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How do we choose to pay using evolving retail payment technologies? Some additional results from Japan

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Abstract

Using Japanese individual household datasets, we obtain the following results that are consistent with findings in most advanced economies. For our first set of findings, persons using electronic money (contactless prepaid cards available in Japan after 2001) for day-to-day transaction values of less than 5,000 yen have lower cash holdings than cash users. Second, the average cash holdings of credit card users for both day-to-day and regular payments are less than that of cash users for day-to-day payments not using credit cards for regular payments. Our second set of findings contributes to the related literature in at least two respects. First, we combine the choice of payment methods for both day-to-day and regular payments. Second, we pay due attention to institutional details about the use of credit cards in Japan and propose unique identifying assumptions excluding those persons using credit cards for day-to-day transactions but not regular payments, and those using cash for day-to-day transactions but credit cards for regular payments.

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Using Japanese individual household datasets, we obtain the following results that are consistent with findings in most advanced economies. For our first set of findings, persons using electronic money (contactless prepaid cards available in Japan after 2001) for day-to-day transaction values of less than 5,000 yen have lower cash holdings than cash users. Second, the average cash holdings of credit card users for both day-to-day and regular payments are less than that of cash users for day-to-day payments not using credit cards for regular payments. Our second set of findings contributes to the related literature in at least two respects. First, we combine the choice of payment methods for both day-to-day and regular payments. Second, we pay due attention to institutional details about the use of credit cards in Japan and propose unique identifying assumptions excluding those persons using credit cards for day-to-day transactions but not regular payments, and those using cash for day-to-day transactions but credit cards for regular payments.

***Keywords*:** cash demand, credit cards, electronic money, automatic withdrawals
JEL codes: D14, E41, E52
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1. Introduction

Using the Survey of Household Finances (SHF) conducted by the Central Council for Financial Services Information from 2007 to 2014, Fujiki and Tanaka (2018) showed that Japanese credit card users tended to have smaller cash holdings than cash users for day-to-day transaction values of more than 1,000 yen. However, they also found that credit card users tended to have larger cash holdings than cash users for day-to-day transaction values of less than 1,000 yen. This raises two interesting questions concerning their results.

First, does the latter result infer that persons using noncash payment methods for day-to-day transaction values of less than 1,000 yen have larger cash holdings than cash users? Second, should we consider heterogeneity among credit card and cash users for day-to-day transaction values of less than 1,000 yen as necessarily leading to this finding? To address these questions, we employ identical statistical methods as in Fujiki and Tanaka (2018) along with the SHF data from 2007 to 2017. We respond to the first question in the negative as we find that persons using electronic money (contactless prepaid cards available in Japan after 2001) for day-to-day transaction values of less than 5,000 yen have lower cash holdings than cash users. In response to the second question, we first classify credit card and cash users for day-to-day transaction values of less than

1,000 into four groups depending on their use of credit cards for regular payments, including for monthly telephone and electricity bills. We argue that we should consider the heterogeneity of two of these groups, as once excluded from the analysis, we are able resolve the somewhat puzzling result in Fujiki and Tanaka (2018).

In a first adjustment, we exclude credit card users for day-to-day transactions but not regular payments. According to JCB (2018), which questions respondents about the main reason they use credit cards, 50% reply that they emphasize the ease of accumulating points or mileage services, while 30% respond that they emphasize low or free membership fees. Based on these observations, we argue that credit card users for day-to-day transactions for values of less than 1,000 yen but not regular payments exhibit a special preference because they are willing to forego the opportunity to accumulate points through credit card usage by making bill payments. Similarly, credit card users for day-to-day transactions for values of less than 1,000 yen but not regular payments are heterogeneous in the sense that they tend to have larger cash holdings, older household heads, more household heads without a job, higher average disposable incomes and more financial assets compared with the other three groups.

In a second adjustment, we exclude cash users for day-to-day transactions using credit cards for regular payments. This aligns with the approach by Fujiki and Tanaka

(2018) aimed at comparing persons using cash only and those using noncash payment methods. Regarding the two remaining groups, we find that the average cash holdings of credit card users for both day-to-day and regular payments are less than for cash users for day-to-day payments, but not credit cards for regular payments.

As a result, this paper improves on the findings by Fujiki and Tanaka (2018). Although Fujiki (2019) considered the choice of regular payment methods, the analysis therein did not consider the combination of day-to-day and regular payment methods. While Fujiki and Tanaka (2018) survey the related Japanese literature, our analysis also relates to work on the choice of consumer payment method and the demand for cash outside of Japan. In this regard, relevant studies include Esselink and Hernández (2017) in the Eurozone, Greene et al. (2017) for the US, Henry et al. (2018) for Canada, Politronacci et al. (2018) for France, Jonker et al. (2018) for the Netherlands, Lippi and Secchi (2009) for Italy, and Schautzer and Stix (2019) for Austria. Also included is Bagnall et al. (2016) and their analysis of cross-country payment diary surveys.

While the two main findings in our paper are consistent with the results in that body of work, we also contribute to the literature in at least two respects. First, we combine the choice of payment methods for both day-to-day and regular payments. Second, we use identifying assumptions that exclude people using credit cards for day-to-day transactions but not regular payments, and those using cash for day-to-day transactions but credit cards for regular payments. This approach pays due care to the institutional features of the use of credit cards in Japan.

The remainder of the paper is organized as follows. Section 2 explains the data used in our analysis and Section 3 outlines the empirical models. Section 4 reports the estimation results and Section 5 concludes. In addition to the main text, Appendix 1 discusses the institutional background of the use of electronic money, debit cards, credit cards, automatic withdrawals, and cash in Japan and Appendix 2 details the replication of the results in Fujiki and Tanaka (2018).

2. Data

2.1. Choice of payment method

We use repeated cross-sectional datasets for Japanese family households from the SHF from 2007 to 2017. The SHF asks respondents to identify their two most frequently used payment methods for day-to-day transaction values of less than or equal to 1,000 yen (hereafter ≤1k), more than 1,000 yen and less than or equal to 5,000 yen (1k–5k) , more than 5,000 yen and less than or equal to 10,000 yen (5k–10k), more than 10,000 yen and less than or equal to 50,000 yen (10k–50k), and more than 50,000 yen (>50k) from four different payment methods: cash, credit cards, electronic money (including debit card), and other payment methods. We assume that the SHF data more effectively capture the use of electronic money rather than debit cards because the use of debit cards has not been common in Japan until recently, as shown in Appendix 1.

Following Fujiki and Tanaka (2018), we construct an aggregate dummy variable for the five payment methods: cash (respondents chose cash exclusively), card (credit card exclusively, cash and credit card, or credit card and other), emoney (electronic money exclusively, cash and electronic money, or electronic money and other), other (other exclusively or cash and other), and card and emoney (credit card and electronic money).

Among the possible payment methods, electronic money is typically a prepaid card using Sony's FeliCa contactless IC card technology. Electronic money is mostly for low value transactions at convenience stores, train and subway stations, and supermarkets. As it takes only 0.2 seconds per transaction, electronic money is a close substitute for cash for small value transactions. For other payments, according to JCB (2018), Japanese credit card holders mostly use their credit cards for payments for online shopping, groceries, and utility bills. Of these, 90% of Japanese credit card holders choose to pay with a one-time payment (within 55 days) free from interest rate charges, rather than through revolving payments, and 97% of credit card transactions are for shopping rather than for cash. See Appendix 1 for further details about electronic money and credit cards.

From the data, we remove respondents who did not report their choice of payment method or cash holdings and those whose cash holdings exceed 9 million yen, which appear to be outliers. The upper panel of Table 1 details the proportion of observations for the aggregate payment method choice for day-to-day transactions and the number of observations. There are just three major payment choices of survey respondents, as shown in the shaded area: cash only and card for all ranges of transaction values, and electronic money for transaction values of 1k–5k and ≤1k. This is consistent with the findings in Fujiki and Tanaka (2018). In the following analysis, we concentrate on these major choices.

The lower panel of Table 1 details the mean cash holdings by choice of aggregate payment method. Respondents choosing card (hereafter card users) tend to have smaller cash holdings compared with respondents choosing cash only (hereafter cash only users) for transaction values of more than 1k, and higher cash holdings for transaction values of ≤1k, as also reported in Fujiki and Tanaka (2018). However, respondents choosing emoney (hereafter emoney users) tend to have smaller cash holdings compared with cash only users for transaction values of 1k–5k and ≤1k.

The SHF also asks respondents about their two major payment methods for regular payments from among the five options of cash, credit cards, electronic money, automatic withdrawals, and other. Cash payments usually mean that customers receive barcode-based utility bills via mail, and then they visit a convenience store to pay these bills by withdrawing cash from a convenience store automated teller machine (ATM) on a 24/7/365 basis. Automatic withdrawal (a direct debit or *kouza furikae* in Japanese) refers to an arrangement whereby a depositor will grant permission to a seller to take payments from the depositor's bank account automatically and regularly, for example, monthly.

Many Japanese banks have offered automatic withdrawal services for the payment of bills for utilities, public television services, credit cards, internet providers, newspapers, and insurance premiums since the early 1970s. As 90% of Japanese credit card holders choose to pay using a one-time payment, from the consumer perspective, credit cards are a close substitute for automatic withdrawals using regular payments, with the additional advantage of the accumulation of points with the use of credit card payments. See Appendix 1 for further details about bill payments by cash and automatic withdrawals.

After dropping households not responding to this question from the sample, we find that more than 98% of respondents choose one of the following six choices: automatic withdrawal only, cash and automatic withdrawal, cash only, credit card and automatic withdrawal, credit card only, and credit card and cash. Table 2 provides the proportions of the six major choices, along with the sum of all remaining choices in the row labeled 'All the rest'. We refer to the sum of the three choices not involving credit cards (automatic withdrawal only, automatic withdrawal and cash, and cash only) as *NCC* (No Credit Card users for regular payments), which represents the payment behavior of about 76% of the sample households (after excluding 'All the rest').

We then refer to the sum of the three remaining choices involving credit cards (credit card and automatic withdrawal, credit card only, and credit card and cash) as *CC* (Credit Card users for regular payments), which explains the payment behavior of another 24% of the sample households (after again excluding 'All the rest'). Table 3 details the choice of day-to-day payment methods conditional on the choice of aggregate regular payments methods, either *NCC* or *CC*. This shows that *CC* households chose card and emoney more frequently than those choosing *NCC*. The second panel of Table 3 indicates that card users choosing *CC* have smaller cash holdings than cash only users choosing *NCC* for all transaction values. It also shows that card users choosing *NCC* for transaction values of ≤1k have relatively large cash holdings compared with other users.

This finding appears to correspond with the discussion in Section 1 where we suggested card users choosing *NCC* have a unique preference in that they seem to prefer cash to other credit card users for day-to-day transactions. Thus, the question arises regarding what kind of demographic variables are associated with card users choosing *NCC*. Table 4 compares the mean cash holdings, age, disposable income, financial assets outstanding, the probability that the person has no job, the proportion of persons placing an emphasis on online banking services in selecting financial institutions, and the probability that the person is self-employed for transaction values of ≤1k across the choice of payment methods. We explain the details of these demographic variables in the following section. As shown in Table 4, card users choosing *NCC* for transaction values of ≤1k are on average older, have higher incomes and more financial assets outstanding, and about a quarter of them have no job, which is similar to the cash only users choosing *NCC*.

2.2. Demographic variables

Table 5 reports the means of the outstanding amount of cash holdings (*Cash*) for transaction values of 10k–50k, which includes the maximum number of observations (35,917) when we focus on the choice of cash only and cards. Table 5 also details the means of the following demographic variables: a dummy variable identifying respondents who have made mattress deposits (*Mattress deposit*) to reduce investment risk, the household size (*H_sizen*), where n = 3, 4, 5, and 6, where n is the number of household members, and the log of passengers per kilometer, *ln(Passengers km)*. We also include dummy variables for the categories of annual disposable income (*Income*) and amount of financial assets (*Assets*), and for respondents who either know about the Deposit Insurance Corporation of Japan and its role or have heard of it (*Know Deposit Insurance* and *Heard of Deposit Insurance*, respectively).

We include dummy variables for those placing an emphasis on lower service charges and online banking services offered via the Internet when selecting a financial institution (*Lower service charges* and *Online banking*, respectively), and for indicating whether a respondent has debt (*Debt*) and whether the respondent is a homeowner (*Homeowner*). Additional dummy variables include those for the age (in years) of the household head (*Age*), if the household has a male household head (*Male*), and the mean of each respondent's job situation, being whether the household head is a full- (*Full-time*) or part-time (*Part-time*) worker, self-employed, or a student. Additional dummy variables include the highest educational attainment of each survey respondent (senior high school, vocational college, junior college, university, or graduate school). We use dummy variables indicating a spouse for the survey respondent's job situation and educational attainment indicated by an S_ preceding the variable names, and a dummy variable for a household without a spouse (*No_spouse*). Lastly, we employ dummy variables to represent the city size (based on population) where the respondent is residing, comprising the 20 largest cities (*Top 20 cities*), cities with more than 40,000 households (*Cities_40k_*), cities with 20,000–40,000 households (*Cities_20k_40k)*, and dummy variables denoting the survey year (*Year*_2007–*Year*_2016). The remaining variables followed by _NA identify dummy variables for households not reporting the variable. Compared with the sample in Fujiki and Tanaka (2018), we have added three more waves of the SHF (2015–2017) and several additional dummy variables for households not reporting some demographic variables.

3. Empirical model

We employ the three econometric methods used by Fujiki and Tanaka (2018), which in turn applies those in Dubin and McFadden (1984). First, we run a multinomial logit model of the choice of payment method, as shown in equation (1):

$$Payment\ method_{ijt} = X_{ijt}\delta_j + \nu_{ijt}, \tag{1}$$

where *Payment method* is an indicator variable for the choice of payment method *j* by an individual *i* at time *t*, X_{ijt} is a vector of the demographic variables explained in Section

2.2, δ_j is a vector of parameters to be estimated, and ν_{ijt} are unobservable preferences for payment method *j* of a household *i*, taking cash only users as the base group.

Second, we estimate cash demand conditional on the choice of payment method *j* by a household i, $(\bar{C}_{ijt}|\text{j chosen})$, as shown in equation (2):

$$(\bar{C}_{ijt}|\text{j chosen}) = X_{ijt}\beta + (\sigma\sqrt{6}/\pi)\sum_{k=1}^{K} R(j)_k Z_{ijt} + u_{ijt}, \qquad (2)$$

$$Z_{ijt}{=}{-}logP_{ikt}\ if\ k = j, Z_{ijt} = (P_{ikt}/(1 - P_{ikt}))logP_{ikt}\ if\ k \neq,$$

where Z_{ijt} is the sample selection adjustment terms related to P_{ikt}, which can be estimated from the forecast value of the probability of household *i* selecting the *k*-th choice conditional on the household making the *j*-th choice using the estimates of equation (1), and β and $R(j)_k$ are parameters to be estimated. Given $E(u_{ijt}) = 0$ and $Var(u_{ijt}) = \sigma_j{}^2$, we estimate equation (2) using the STATA 14 command reg. We follow Dubin (1982) to compute the standard errors of the parameter estimates.

Third, we report the estimates of the average treatment effects (ATEs) and the average treatment effects on the treated (ATETs) using the inverse probability weighting (IPW) on the cash holdings according to the choice of credit card and electronic money against the choice of cash, the main purpose being as a robustness check. To compute propensity scores, we run a logistic regression, equation (3), using the subsamples of households choosing the *j*-th payment method and *j*+1-th payment method:

$$D_{ij(j+1)t} = X_{ij(j+1)t}\theta_{j(j+1)} + \upsilon_{it}, \tag{3}$$

where $D_{ij(j+1)t}$ is an indicator variable that takes a value of zero for household i choosing the j-th payment method and one for household i choosing j+1 at time t, $X_{ij(j+1)t}$ is a vector of the demographic variables for the household i, $\theta_{j(j+1)}$ is a vector of parameters to be estimated, and υ_{it} is a disturbance term.

4. Regression results

We first estimate equation (1). For transaction values of >50k, 10k–50k, and 5k–10k, *j* is cash only or card, and we estimate logit models. For transaction values of 1k–5k and ≤1k, *j* is cash only, card, or emoney and we estimate multinomial logit models. See the parameter estimates in Appendix Table 1 and marginal effects in Appendix Table 2. We then run equation (2) for transaction values of >50k, 10k–50k, and 5k–10k, where *j* is cash only or card. For transaction values of 1k–5k and ≤1k, *j* is cash only, card, or emoney. See the parameter estimates in Appendix Table 3. Finally, we run equation (3) for transaction values of >50k, 10k–50k, and 5k–10k, where *j* is cash only and *j*+1 is card, and for transaction values of 1k–5k and ≤1k, where *j* is cash only and *j*+1 is card or emoney. For details, see Appendix Table 4 for the ATEs and ATETs, Appendix Table 5 for the logit model estimates and Appendix Table 6 for the standardized differences.

We begin by replicating the results in Fujiki and Tanaka (2018) using the data from 2007 to 2014. The row labeled 'Result 1' in Table 6 reports the differences in the unconditional average of cash holdings in the fourth column. The fifth column details the means of the predicted cash holdings conditional on the choice of payment methods using the estimates of equation (2), with the t-tests indicating whether the mean cash holdings for cash users, emoney users, and cash only users significantly differ. As shown, credit card users on average tend to have smaller cash holdings than cash only users for day-to-day transaction values of more than 1k. Similarly, the sixth and seventh columns show that card users tend to have larger cash holdings than cash only users for day-to-day transaction values of ≤1k, while the ATEs and ATETs are not statistically significantly different from zero. These results are very similar to those in Fujiki and Tanaka (2018) using data from 2007 to 2014 and reported in the row labeled 'Result 2'. In addition, although replicating the results in Fujiki and Tanaka (2018), we found some coding errors in the computer program, which we explain in Appendix 2. Nevertheless, there is little change in the results, even after correcting these errors, as reported in the row labeled 'Result 3'.

We now examine our first question, namely, do these results indicate that persons using noncash payment methods for day-to-day transaction values of ≤1k have larger cash holdings than cash users? Our answer is no, because the row labeled 'Result 4' indicates that electronic money users tend to have smaller cash holdings than cash only users for day-to-day transaction values of 1k–5k and for ≤1k irrespective of the choice of estimation method.

We now move to the analysis combining the data for day-to-day payment methods and regular payments that takes into account the heterogeneity of the four groups of users. Hereafter, we use the following notation for the combination of choices of I and J for day-to-day transactions and regular payments, where I = *Cash* (cash only), *Card*, and *Emoney* for day-to-day transactions and J = *CC* and *NCC* for regular payments.

For day-to-day transaction values of >50k, 10k–50k, and 5k–10k, we run equation (1) for the choice of *Card & NCC*, *Cash & CC*, and *Card & CC*, taking *Cash & NCC* as the base case. See the estimates of the multinomial logit model in Appendix Table 7 and the marginal effects in Appendix Table 8. For transaction values of 1k–5k and ≤1k, we run equation (1) for the choice of *Card & NCC*, *Emoney & NCC*, *Cash & CC*, *Card & CC*, and *Emoney & CC*, taking *Cash & NCC* as the base case. See the estimates of the multinomial logit models in Appendix Table 9 and the marginal effects in Appendix Table 10. We then estimate equation (2) for the choice of *Cash & NCC*, *Card & NCC*, *Cash & CC*, and *Card & CC* for day-to-day transaction values of >50k, 10k–50k, and

5k–10k. We also estimate equation (2) for the choice of *Cash & NCC*, *Card & NCC*, *Emoney & NCC*, *Cash & CC*, *Card & CC*, and *Emoney & CC* for transaction values of 1k–5k and ≤1k. These results are in Appendix Table 11.

The row labeled 'Result 5' in Table 6 reports the differences in the unconditional average cash holdings, the conditional mean cash holdings using the estimates from equation (2), and the estimates of the ATEs and ATETs from equation (3) taking j = *Cash & NCC* and j+1 = *Card & CC*. As shown, the differences in the mean predicted cash holdings of those choosing *Card & CC* and those choosing *Cash & NCC* are statistically significantly negative, even for transaction values of ≤1k, as shown in the fifth column. While the ATETs support this finding, the ATEs are not statistically significant for transaction values of ≤1k. However, the results from the ATETs are sufficient to show that those choosing *Card & CC* have smaller cash holdings than those choosing *Cash & NCC*. For details, see the ATEs and ATETs in Appendix Table 12, the logit model estimates used to compute the propensity scores in Appendix Table 13, and the standardized differences of these models in Appendix Table 14.

The results in Table 6 suggest that credit card users tend to have smaller cash holdings than cash only users by about 30,000 yen. A back-of-the-envelope calculation suggests that the maximum impact on aggregate cash demand if all Japanese cash users became credit card users would be very small. First, according to forecasts by the National Institute of Population and Social Security Research, there were 34,904,000 non-single-person Japanese households in 2017.[1] Second, Table 1 shows that about 40% of family households are cash only users for transaction values of >50k. Hence, if all Japanese cash only user households with day-to-day transaction values of >50k reduced their cash holdings by 30,000 yen as they became credit card user households, the resulting decrease in overall cash demand would be 34,904,000 households × 40% × 30,000 yen/household = 419 billion yen. Notably, this represents just 0.4% of the 105 trillion yen in cash in circulation in Japan in 2017.

5. Conclusion

We employ the same statistical methods as in Fujiki and Tanaka (2018) and improve their results in two respects. First, we find electronic money users tend to have smaller cash holdings than cash only users for day-to-day transaction values of less than 5,000 yen. Second, we obtain a consistent result that credit card users choosing credit cards for both day-to-day transactions and regular payments tend to have smaller cash holdings compared with cash only users for day-to-day transactions who do not use credit cards

[1] For details of the projection of the number of Japanese households, see the website of the National Institute of Population and Social Security Research. We use the 2017 estimates for the result in http://www.ipss.go.jp/pp-ajsetai/j/HPRJ2018/hprj2018_gaiyo_kekka1.xls

for regular payments for all ranges of day-to-day transaction values. Underpinning this improvement is that we take into account the heterogeneity among credit card and cash users for day-to-day transaction values of less than 1,000 yen, and exclude those using credit cards for day-to-day transactions but not regular payments, and those using cash for day-to-day transactions but also using credit cards for regular payments. We argue that this exclusion assumption pays due attention to the institutional features explaining the main reason for the choice of credit cards in Japan, namely, the accumulation of points for credit card payments.

These findings are consistent with those elsewhere in advanced economies, but our second finding contributes to the literature in two respects. First, it combines the choice of payment methods for both day-to-day and regular payments. Second, it proposes an identifying assumption unique to Japanese institutional features concerning the use of credit cards. Note that our results depend heavily on the institutional features of Japanese retail payments, as explained in Appendix 1. We should also keep in mind that the results in this paper will not hold as retail payment technologies continue to evolve.

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Table 1 Proportion of observations and mean cash holdings for aggregate payment method choices for day-to-day transactions

Choice of payment method 2007-2017

	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
cash only	0.376	0.466	0.668	0.759	0.863
card	0.575	0.502	0.291	0.172	0.047
emoney	0.008	0.010	0.027	0.056	0.083
other	0.037	0.015	0.006	0.004	0.004
card and emoney	0.005	0.006	0.008	0.009	0.003
Number of observations	36,773	37,089	36,826	36,844	36,466

Mean cash holdings by choice of payment method

	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
cash only	15.63	15.24	14.24	14.10	14.01
card	13.09	12.94	12.98	13.58	15.24
emoney	20.97	20.27	15.15	12.00	11.84
other	12.17	10.54	16.48	20.49	18.35
card and emoney	10.76	13.00	11.62	13.23	13.90

Note: In units of 10,000 yen.

Table 2 Choice of regular payment methods

automatic withdrawal only	0.465	
automatic withdrawal and cash	0.214	
cash only	0.075	
NCC		0.762
credit card and automatic withdrawal	0.144	
credit card only	0.058	
credit card and cash	0.033	
CC		0.238
All the rest	0.012	0.000
Total	1	1

Table 3 Choice of regular and day-to-day payment methods and cash holdings

Choice of regular and day-to-day payment method 2007-2017

Regular	Day-to-day	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
NCC	cash only	0.505	0.602	0.809	0.858	0.922
	card	0.495	0.398	0.191	0.099	0.025
	emoney				0.044	0.053
Number of observations		25,845	26,700	26,443	27,226	27,024
Regular	Day-to-day	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
CC	cash only	0.069	0.115	0.345	0.495	0.711
	card	0.931	0.885	0.655	0.413	0.119
	emoney				0.092	0.171
Number of observations		8,724	8,813	8,449	8,670	8,810

Mean cash holdings by choice of regular and day-to-day payment method 2007-2017

Regular	Day-to-day	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
NCC	cash only	15.74	15.35	14.46	14.39	14.26
	card	13.20	12.96	12.98	14.08	18.28
	emoney				11.81	11.78
CC	cash only	13.31	13.86	12.59	12.53	12.95
	card	12.88	12.84	13.00	13.27	13.37
	emoney				11.26	11.34

Note: In units of 10,000 yen.

Table 4 Summary statistics by choice of payment method for transaction values of ≤1,000 yen

Regular	Day-to-day	Cash	Age	Income	Assets	No job	Online	Selfemployed
NCC	cash only	14.26	58.58	471.20	1115.75	0.27	0.04	0.15
	card	18.28	56.90	513.49	1539.33	0.24	0.09	0.12
	emoney	11.78	52.10	557.83	1343.25	0.14	0.12	0.10
CC	cash only	12.95	49.45	578.97	1260.03	0.12	0.15	0.09
	card	13.37	48.77	589.91	1561.03	0.12	0.27	0.09
	emoney	11.34	46.34	649.47	1343.13	0.06	0.29	0.06
	Average	13.86	55.89	506.55	1180.63	0.22	0.08	0.13

Note: Cash denotes cash holdings, Income denotes disposable income, Assets denotes financial assets outstanding, No job denotes the probability that the person has no job, Online denotes the proportion of persons placing an emphasis on online banking services in selecting financial institutions, and Self-employed denotes the probability that the person is self-employed. Cash, Income, Assets are in units of 10,000 yen.

Table 5 Means of demographic variables

Variable	mean
Cash	14.690
Mattress deposit	0.014
H_size3	0.249
H_size4	0.239
H_size5	0.099
H_size6	0.040
H_size_6_	0.059
ln(Passengers km)	-3.345
Income_200_260	0.061
Income_260_300	0.105
Income_300_370	0.073
Income_370_407	0.086
Income_407_500	0.145
Income_500_600	0.092
Income_600_700	0.065
Income_700_900	0.081
Income_900_	0.079
Asset_0	0.253
Asset_110_270	0.068
Asset_270_430	0.068
Asset_430_600	0.060
Asset_600_900	0.078
Asset_900_1200	0.067
Asset_1200_1694	0.074
Asset_1694_2400	0.067
Asset_2400_3900	0.071
Asset_3900_	0.070
Know_Dep_Ins	0.402
Hear_Dep_Ins	0.387
Lower_service_charge	0.094
Online_banking	0.081
Debt	0.414
Homeowner	0.724

Variable	mean
Age35_39	0.079
Age40_44	0.096
Age45_49	0.096
Age50_54	0.107
Age55_59	0.114
Age60_64	0.125
Age65_69	0.113
Age70_74	0.086
Age75_	0.102
Male	0.922
Full_time	0.536
Part_time	0.064
Self_employed	0.128
Student	0.003
S_Full_time	0.152
S_Part_time	0.250
S_Self_employed	0.046
S_Student	0.001
Senior_high	0.392
Vocational_college	0.073
Junior_college	0.037
University	0.269
Graduate	0.027
S_Senior_high	0.391
S_Vocational_college	0.088
S_Junior_college	0.134
S_University	0.111
S_Graduate	0.005
No_spouse	0.109
Top20cities	0.234
Cities_40k_	0.402
Cities_20k_40k	0.252

Variable	mean
Year_2007	0.079
Year_2008	0.094
Year_2009	0.100
Year_2010	0.099
Year_2011	0.090
Year_2012	0.097
Year_2013	0.093
Year_2014	0.095
Year_2015	0.082
Year_2016	0.082
Mattress_NA	0.007
H_size_NA	0.010
Income_NA	0.103
Asset_NA	0.056
Dep_Ins_NA	0.004
Banking_NA	0.005
Debt_NA	0.005
Homeowner_NA	0.008
Age_NA	0.006
Male_NA	0.003
job_NA	0.050
S_job_NA	0.056
Education_NA	0.093
S_Education_NA	0.080
N	35,917

Table 6 Differences in mean cash holdings

Results	Sample period and data	Transaction values	Unconditional mean	Predicted value by a conditional cash demand function	ATE (IPW)	ATET (IPW)
Result 1	2007-2017	>50k	-2.541	-2.553 ***	-3.140***	-3.085***
	card vs cash only	10k - 50k	-2.306	-2.306 ***	-3.315***	-3.115***
		5k - 10k	-1.265	-1.241 ***	-2.830***	-2.335***
		1k - 5k	-0.518	-0.455 ***	-2.431***	-1.909***
		≤1k	1.230	1.265 ***	-0.525	-0.541
Result 2	2007-2014	>50k	-3.018	-3.018 ***	-3.524***	-3.624***
	card vs cash only	10k - 50k	-2.489	-2.489 ***	-3.315***	-3.312***
	Fujiki and Tanaka (2018a)	5k - 10k	-1.370	-1.370 ***	-2.596***	-2.028***
	Tables 7 and 8	1k - 5k	-0.386	-0.386 ***	-2.031***	-1.221*
		≤1k	1.063	1.062 ***	-0.843	-0.019
Result 3	2007-2014	>50k	-3.020	-3.020 ***	-3.506***	-3.627***
	card vs cash only	10k - 50k	-2.490	-2.490 ***	-3.256***	-3.222***
	Correction	5k - 10k	-1.374	-1.374 ***	-2.565***	-1.920***
		1k - 5k	-0.396	-0.396 ***	-2.063***	-1.137*
		≤1k	1.065	1.065 ***	-1.108	-0.202
Result 4	2007-2017	1k - 5k	-2.103	-2.061 ***	-2.370***	-2.324***
	emoney vs cash only	≤1k	-2.169	-2.133 ***	-2.561***	-2.586***
Result 5	2007-2017	>50k	-2.858	-2.870 ***	-3.450***	-3.261**
	Card & *CC* and *Cash* & *NCC*	10k - 50k	-2.507	-2.495 ***	-3.719***	-3.241***
		5k - 10k	-1.463	-1.388 ***	-2.913***	-2.785***
		1k - 5k	-1.124	-1.036 ***	-2.905***	-2.862***
		≤1k	-0.890	-0.855 ***	-2.044	-2.916**

Notes: In units of 10,000 yen. IPW stands for Inverse probability weights.
* p<0.10, ** p<0.05, *** p<0.01

Appendix 1. Historical background of payment methods in Japan

Appendix 1 explains the evolution of Japanese retail payment technologies and follows Hiraki (2018), Honda (2018), Nagaoka (2008), Nemoto (2008), and Tsutsumi (2015).

A1. 1. Electronic money

Japanese electronic money is typically a prepaid card based on noncontact integrated circuit (IC) forms based on near-field communication (NFC) technology, similar to Octopus in Hong Kong, and has been available since 2001. According to JCB (2018), 83% of respondents have access to electronic money and 73% actually use it. Regarding the places of use, 50% of respondents reply that they use electronic money in convenience stores, 48% in train, subway, and bus stations, 34% in supermarkets, and 25% in vending machines.

There are three main types of electronic money: those provided by electronic money service providers ("Rakuten Edy," with 105 million issued as of 2017), public transportation companies (such as "Suica" by the East Japan Railway and "PASMO" by private train companies in Tokyo, with 64 and 34 million issued as of 2017, respectively) and retailers, especially by supermarkets ("WAON" by AEON, with 67 million issued as of 2017) or convenience stores ("nanaco" by Seven Card Services, with 56 million issued as of 2017).[2]

Those electronic monies use Sony FeliCa contactless IC card technology, rather than globally available type A or B contactless technology; hence, they are not available for use outside of Japan. However, the success of Japanese electronic money led Apple Pay to make its iPhone 7 and 8 sold in Japan compatible with FeliCa.

To protect the users of electronic money, an issuer of prepaid payment instruments is regulated by the Payment Services Act, Article 14, which states that an issuer must make a security deposit for issuance to the official depository nearest to its principal business office in an amount equivalent to not less than half the amount of that unused base date balance.

Most electronic money providers offer the service of automatic reloading from credit cards. For example, if the amount of money deposited as electronic money is less than 2,000 yen, there will be an automatic charge of 3,000 yen in the case of PASMO, the electronic money issued by private train companies.[3] However, there are strict upper limits on the total amount of reloading within a month (50,000 yen in the case of PASMO) and within a day (10,000 yen in the case of PASMO). The strict upper limits for the

[2] See Hiraki (2018) for the number of instruments issued as of 2017.
[3] For details of the service provided by PASMO, see https://www.pasmo.co.jp/use/autocharge/

total amount of reloading suggest that electronic money is primarily for low value transactions. Indeed, according to the Bank of Japan (2019), the average settlement value made by electronic money was just 957 yen in 2017. The key benefit of electronic money lies in its high-speed contactless payment (typically 0.2 seconds thanks to the use of the FeliCa technology). Given this very fast transaction speed, its wide acceptance including three nationwide chains of convenience stores, and its automatic reloading service and widespread point services, we do not discern any major difference between credit cards and electronic money when used to pay for small value transactions.

In sum, apart from the strict upper limits of automatic reloading, electronic money is a close substitute for credit cards for small value transactions, with the additional advantage of high-speed transactions. This allows electronic money, rather than credit cards, to replace the use of cash for small value transactions.

The discussion is consistent with the recent and rapid acceptance of contactless debit and credit card payments in the Netherlands discussed in Jonker et al. (2018) and in Canada in Henry et al. (2018), which have led to a substantial reduction in the use of cash, especially for small value transactions. Note that contactless international credit and debit cards have only recently become available in Japan. Because the speed of the contactless NFC technology is the key advantage of electronic money in Japan, we anticipate that electronic money, and not debit or credit cards, is the preferred payment instrument for small value transactions in Japan to date.

A1. 2. Debit card

According to the Bank of Japan (2019), 5.1 billion yen of transactions were made by electronic money in 2017, while the Japan Consumer Credit Association (2018) showed that the volume of transactions made by debit cards (including both cash withdrawal cards accepted only within Japan and international brand debit cards) was only 0.9 billion yen in 2017. Given the success of electronic money, we could well wonder why Japanese people do not use debit cards frequently. There are two kinds of debit cards in Japan, one for domestic debit cards, called J-Debit, and the other being international brand debit cards.

First, J-Debit is the brand name of a bank cash withdrawal card (also accepted in member shops) introduced in 1999 by several major Japanese banks. However, J-Debit did not perform well due to a number of weaknesses. First, the number of member shops was only about one-tenth of those of credit cards. Second, J-Debit is for domestic purchases at member shops only (it cannot be used for internet purchases) because the magnetic stripes on Japanese bank cash withdrawal cards are not compatible with the international standard. Third, holders can only use J-Debit during bank business hours because it requires instantaneous authorization from banks. Although Japanese banks were not enthusiastic about J-Debit, recent advances in QR code base smartphone applications linked to bank accounts, such as the Japanese payment service "Origami" or China's "UnionPay," together with the Japanese government's vision for a cashless economy, have led to a plan to introduce "Bank Pay" in the fall of 2019. Bank Pay is essentially a debit card using a QR code. However, it uses venture business technology to link the QR code application to almost all Japanese financial institution accounts and merchants do not need special terminals for its use. For this reason, it may be widely accepted by merchants and help extend the use of debit cards in terms of QR code applications.

Second, in 2006, Suruga Bank, a Japanese regional bank, started issuing international brand debit cards with VISA, which solves the three problems of J-Debit. The major banks and the JCB, the Japanese international brand credit card, also started issuing brand debit cards in 2013 and 2014, respectively. By the end of 2017, as many as 46 banks in Japan were issuing international debit cards, and the volume of transactions made by brand debit cards increased substantially (Bank of Japan, 2018). Some of these brand debit cards allow contactless payments for small value transactions. In an analysis of these changes, the Japan Consumer Credit Association (2018) declared that purchases made by international brand debit cards exceeded those made by J-Debit in 2016.

A1. 3. Automatic withdrawals to make regular payments

Automatic withdrawal (direct debit or *kouza furikae* in Japanese) refers to an arrangement whereby a depositor will give permission to companies to take the payments from the depositor's bank account automatically and regularly, for example, monthly.[4] The automatic withdrawal service made by Japanese banks began in 1955 with payments for telephone bills. Following the launch of the first online banking network system for Japanese banks in the early 1970s, many started to offer the service of automatic withdrawals for other bill payments. These included the payment of utility bills (such as gas, water, and electricity), and the bills for public television, credit cards, internet providers, newspapers, and insurance premiums, as part of the banking services package (*sogo kouza* in Japanese) commencing in 1972.

In the 1960s, Japanese city banks had relatively few branches compared with regional banks, and needed an efficient way to attract consumer deposits to increase their business loans. Note that at the time, both lending rates and deposits rates were highly

[4] Automatic withdrawal differs from the recurring bill-pay transfers. In recurring bill-pay transfers, customers allow their bank to send payments to the company. In automatic withdrawals, customers allow the company to take payments from their bank account.

regulated and as lending rates were lower than market-based borrowing rates, there was an excess demand for bank loans. Under such circumstances, it made sense for banks to accept more deposits from consumers and to lend the new funds to large enterprises to be profitable. By the early 1960s, workers would typically receive their monthly salary in cash (note that there are no personal checks in Japan), retain the necessary amount of cash for monthly consumption at home, and then deposit any remaining cash into the bank branch holding their account. Workers could withdraw deposits only at the branch where they held the account, usually near their home, because there was no online network to share depositor information between bank branches. Hence, workers preferred to keep some amount of cash at home to prepare for unexpected expenses. Banks wanted a mechanism to induce these workers to deposit all of their monthly salary so that the banks could attract a larger amount of deposits, which is why they developed the *sogo kouza* banking services package.

Sogo kouza increased the amount of bank deposits by providing the following four related banking services to depositors: direct payroll deposits (available since 1969), a cash card for online cash dispensers (CDs) and ATMs (available since 1971), automatic withdrawal for regularly scheduled payments (available since 1955), and an overdraft from saving deposits (available since 1972). With direct payroll deposits, workers deposited in the bank all their salary, rather than the salary net of the necessary amount of cash for monthly consumption, just as the city banks had hoped. Then, using a cash card for online CDs and ATMs, workers could withdraw money anywhere they wanted including, for example, at a bank ATM located close to their workplace. This effectively reduced precautionary cash holding, and increased bank deposits. In addition, by using automatic withdrawal for regularly scheduled payments such as utility bills, workers did not have to withdraw cash from their bank accounts to pay those bills.

Given this situation, utility bill payments just became a transfer from the deposit account of workers to the deposit account of the utility company (assuming that the worker and the utility company both held deposit accounts at the same bank), which also helped maintain the amount of bank deposits. In the end, workers may have experienced a shortage of cash, especially if regularly scheduled payments, such as utility bills, were due just before payday. To assist these workers, city banks offered an overdraft service that allowed workers to borrow from the bank up to a certain proportion (usually 90%) of their saving deposits. In most cases, the companies, not the depositors, pay the fees for automatic withdrawal to the banks.

With the introduction of *sogo kouza*, and given the saving in time from the use of the automatic withdrawal service, it has been the default payment method for regularly scheduled payments up until recently. In evidence, Figure 1 plots the proportion of the two most-favored methods of payment from among five options: cash, credit cards, debit cards, automatic withdrawals, and other, for the periods 1991–1994, 2000, and 2002–2006, as reported in the SHF. The success of *sogo kouza* is clearly illustrated with survey respondents choosing cash (the thick line) and automatic withdrawal (the dashed line) accounting for 80–90% and 60–70% of all respondents, respectively.

However, Japanese banks incurred a huge amount of losses following the collapse of the Japanese real estate bubble in the late 1980s, which made them very reluctant to provide new and innovative services for depositors. In particular, the cost of investment to maintain their online banking system and keep ATM networks up to date has become a heavy burden on city banks. Moreover, the deregulation of the Japanese financial services industry at the end of 1990s, the long-lasting low interest rate environment since 1995, rapid population aging, and the resulting decrease in the number of visitors to their branches, have made the city bank's business model as originating from *sogo kouza* perilous. Consequently, Japanese banks only provided new services for consumers if they faced serious outside challenges.

First, Japanese banks eventually started modifying their ATMs to accept credit cards issued outside Japan in preparation for the 2020 Tokyo Olympic Games and under pressure from the Japanese government. Behind this lies the fact that Japanese ATMs located at commercial banks can read the magnetic stripes of cash cards following the Japanese Banking Association standard, but not those of credit cards issued outside of Japan whose magnetic stripes follow the international standard. In contrast, Seven Bank, a new bank with a narrow range of services operated by the 7-Eleven chain of convenience stores since 2001, and Japanese postal banks have ATMs that accept credit cards issued outside Japan.

Second, Japanese banks introduced QR code-based smartphone applications linked to bank accounts, which enables the person-to-person transfer of deposits as a way to cope with the challenges made by FinTech companies. For example, the social networking service (SNS) application "LINE" allows person-to-person payments linked to the user's bank account. To respond to this unfavorable business situation, Mizuho Bank, one of the three largest banks in Japan, introduced a QR code application (J-Coin Pay) linked to bank accounts on March 1, 2019. Some 60 Japanese financial institutions plan to introduce this application. Both J-Coin Pay and Line Pay enable depositors to make person-to-person transfers of deposits without using cash; thus, they resemble a prepaid card or a debit card that makes person-to-person transfers of deposits. The success of these QR code-based applications may substantially reduce the benefits of branches and ATMs for depositors, and the long-lasting tradition of frequent use of ATMs by Japanese people originating from the innovation of *sogo kouza* may well change.

A1. 4. Credit cards

This subsection explains the industry structure, followed by the consumer choice of payment methods.

A1. 4.1. Industry structure

The Japanese credit card industry has the following two unique features that could affect the choice of payment method. First, to protect installment credit companies, it was not until 1982 that the law permitted Japanese banks to issue credit cards. Instead, bank subsidiaries issued credit cards domestically after the 1960s. Because of these regulations, banks have focused on large-size consumer lending (such as housing), while the credit card, installment credit, and consumer credit companies provide small-size consumer (uncollateralized) lending.

Second, the Japanese government allowed the use of revolving payment only for credit cards issued by installment credit companies until 1982. Reflecting this regulation, the default payment method is a one-time payment using automatic withdrawal from the card holder's banking account (on average, within 40 business days, no interest rate charge), rather than revolving payment.

Reflecting those regulations, Japanese credit card companies have three origins: installment credit companies, bank subsidiaries and banks, and retailers. The first of these, installment credit companies, date back to 1951. They provided members with shopping coupons for purchases in department stores, but the government placed an upper limit on coupon purchases to help small shops compete with the department stores. They then invented a new system of installment credit, known as *shopping credit*, especially for durable goods such as cars, sewing machines, televisions, and air conditioners, for all consumers rather than only for the members of the installment credit companies.

One drawback of this scheme was that unlike a purchase made by credit card, a consumer needed to make a contract with the installment credit companies for each purchase of goods. However, rapid economic growth after the 1960s and the increased demand for durable goods led to the rapid expansion of the sales of installment credit companies, with sales through *shopping credit* increasing from 11 billion yen in 1969 to 4 trillion yen in 1975.

Installment credit companies started issuing credit cards in 1966, and these incorporated both credit card cashing and credit card shopping. The Installment Sales Act regulates credit card shopping (in three or more installments over a period of two or more months), and the Money Lending Business Act regulates credit card cashing. Both credit card shopping and credit card cashing originally had strict upper limits linked to the annual income of the credit card holder. Following the tradition of installment payment, their credit card payments included so-called “Japanese payment options,” such as bonus payments (e.g., a worker purchases an air conditioner between April 1 and June 15, and has no interest rate charges if they pay by credit card on August 10). However, due to the massive reimbursement of overpayments after the Supreme Court decision on so-called “gray-zone interest rates” in January 2006, many consumer installment credit companies that relied on credit card cashing could not sustain their business and ultimately merged with the credit card companies operated by the large city banks.

The second group of credit card companies comprises subsidiaries of the Japanese city banks established in the 1960s. The Ministry of Finance did not allow city banks to issue credit cards, nor did it permit their subsidiary credit card companies to use revolving payment to protect the installment credit industries until 1982. In May 1961, the JCB became the first private business to provide an automatic withdrawal service from a bank account to pay for credit card bills. Since then, the issuance of consumer credit cards is usually on the basis of automatic withdrawal from the bank account of the card holder or a family member of the card holder in Japan.

In 1980, there were revisions to the foreign exchange law admitting free international transactions. Taking advantage of this opportunity, bank subsidiaries started to issue credit cards for international purchases jointly with VISA and MasterCard. To become an international credit card, Japanese credit cards needed to have magnetic stripes on both sides of the card, one on the front for the Japanese bank network and another on the back for international networks. The spread of credit authorization terminals and information exchange systems in 1983 made the authorization of the use of credit cards automatic and fast, and thereby contributed significantly to the increase in the number of member merchants accepting credit cards.

It was only in 1982 that the banks could issue credit cards themselves, in exchange for the use of bank ATM networks for non-bank credit card companies. Regional banks invented a cash withdrawal card with credit card in 1982, but they exited from the business in 2008. In 2006, the credit card business was reclassified as a bank lending activity by regulators, and the credit card companies operated by city banks merged with the consumer credit and consumer installment companies.

The third group of credit card companies comprises retailers, train companies, airlines, and manufacturers. For example, department stores and chain stores adopted point-of-sale systems after realizing that the customer information obtained would help their businesses. Likewise, the Toyota automobile company introduced the first IC card credit card in 2001 in Japan.

A1. 4.2. Choice of credit card for payment

The use of credit cards became popular in Japan especially after the 1990s, reflecting the increase in overseas travel and internet transactions by Japanese people. Young people especially began to use credit cards not only for day-to-day internet transactions, but also for regularly scheduled payments, for example, paying for cell phone bills; in contrast, older people took for granted that the main method used to pay for utility bills remained automatic withdrawal. Figure 1 shows that respondents choosing credit cards (the dotted line) increased from 10% in 1991 to 26% in 2006.

According to JCB (2018), Japanese credit card holders mostly use their credit cards for payments for online shopping, groceries, and utility bills. In response to the question on the main reason for using credit cards, 50% of respondents reply that they emphasize the ease of accumulating points or mileage services, while 30% respond that they emphasize low or free membership fees. Based on those results, it is reasonable to expect that some Japanese may start to pay their utility bills by credit cards, given that many major credit cards offer discounts based on the accumulation of points from their use. Hence, regarding the choice of payment methods for regular payments, the benefit of using credit cards over automatic withdrawal lies in the easy accumulation of points, while the cost is the credit card membership fee. However, large retailers, such as department stores, often issue credit cards free of membership fees. In this case, the benefit of using credit cards will exceed the benefit of automatic withdrawal.

Outsiders might expect that Japanese people would use credit cards to take advantage of revolving payments or cashing. However, the Japan Consumer Credit Association (2018) concludes that credit cards bills settled after two months account for only 10% of total credit card bill payments during 2017, with most Japanese credit card holders choosing to pay using a one-time payment (within 55 days). In other words, 90% of Japanese credit card holders have sufficient bank deposits to pay their credit card bills in the month after the purchase of goods and services using their credit cards. Moreover, credit card cashing explains only about 3% of total credit card lending, with the other 97% being credit card shopping. Note that 80% of shopping credit (without using credit cards) by consumer installment companies runs over two months or more and about 70% of shopping credit is for automobile purchases.

In summary, credit cards are a close substitute for automatic withdrawals for regular payments, with the additional advantage of the accumulation of points with the use of credit card payments. Therefore, if a household chooses to pay by credit cards for regular payments because the household appreciates the accumulation of points, the household also tends to choose credit cards to pay for day-to-day transactions compared with choosing to pay using automatic withdrawals for regular payments. We demonstrated this finding in Section 2 using Japanese household survey data.

A1. 5. Bill payment at convenience stores using cash

Bill payment at convenience stores originates from the history of poor services offered by Japanese banks for bill payment. Under this system, it is possible for depositors to pay their bills using bank transfers (*kouza furikomi* in Japanese). For example, a depositor may transfer funds from their own bank account to a bank account held by the utility companies at ATMs, at the bank counter, or using the internet banking service. However, to do this, the depositor must spend time every month either going to an ATM, to a bank branch, or making internet transactions. Moreover, Japanese banks were traditionally very reluctant to accept utility bill payments because utility companies did not pay sufficient service charges to the banks and instead induced depositors to use automatic withdrawal for bill payments.

This negative attitude of the banks toward bill payment allowed convenience stores in Japan to penetrate retail payment services. One convenience store chain began accepting utility bill payment as early as 1987. Convenience stores also started accepting payment of some regional taxes and even premiums for national health insurance by 2003. Nowadays, most convenience stores accept over-the-counter payments for not only utility bills, but also many other kinds of bills, for example, for mail-order shopping, online shopping debits, and even for such mobile downloads as ringtones, games, and applications.

Behind these payments at convenience store chains lie payment acceptance service companies, which allow Japanese people to pay their bills at convenience stores on a 24/7/365 basis using a unified barcode for bills. Therefore, frequent visitors to convenience stores may well pay their utility bills with cash by withdrawing money from the ATM in the convenience store, which are available on a 24/7/365 basis, instead of paying utility bills via bank transfers or automatic withdrawal. Section 2.1 shows that some people even use cash for regular payments. In practice, this means that they receive barcode-based utility bills via mail, and then visit a convenience store to pay by withdrawing cash from the ATM in the same convenience store. However, recent innovations in convenience stores could decrease the frequency of the choice of cash for bill payment, thanks to the prevalence of smartphone applications. For example, Lawson, one of the three largest convenience store chains in Japan, accepts bill payment for some power supply companies, including the Tokyo Electric Power Company, using smartphone applications such as LINE, a social networking service (SNS) application that allows person-to-person payments linked to the user's bank account.[5]

[5] For details of LINE, see https://line.me/en/pay Bill payment service information in Japanese is available at https://line.me/ja/pay/merchant/invoiceline#md_card (accessed March 31, 2019).

Appendix Table 1 Results of logit and multinomial logit models

	Logit model for card and cash only			Multinomial logit model for card, emoney and cash only			
	>50k	10k-50k	5k-10k	1k-5k		≤1k	
				card	emoney	card	emoney
Mattress deposit	-0.165	-0.089	-0.205*	0.006	0.356**	-0.189	0.095
H_size3	0.009	0.032	0.013	0.034	0.016	0.019	-0.094
H_size4	-0.005	-0.008	0.026	0.038	0.074	0.052	-0.086
H_size5	-0.067	-0.072	-0.118**	-0.059	-0.027	-0.105	-0.197**
H_size6	-0.064	-0.019	0.081	0.263*	-0.098	-0.24	-0.282
H_size_6_	-0.133	-0.13	-0.209**	-0.377***	-0.041	0.141	-0.005
ln(Passengers km)	0.045***	0.086***	0.121***	0.139***	-0.055***	0.135***	0.035**
Income_200_260	0.117*	0.168***	0.094	0.03	0.115	0.132	0.328**
Income_260_300	0.317***	0.309***	0.224***	0.197***	0.057	-0.065	0.168
Income_300_370	0.385***	0.427***	0.323***	0.222***	0.172	-0.047	0.364***
Income_370_407	0.506***	0.454***	0.333***	0.233***	-0.033	0.055	0.248**
Income_407_500	0.601***	0.533***	0.362***	0.296***	0.079	0.166	0.304***
Income_500_600	0.649***	0.614***	0.450***	0.297***	0.216*	0.07	0.378***
Income_600_700	0.680***	0.631***	0.431***	0.238***	0.105	-0.063	0.471***
Income_700_900	0.734***	0.670***	0.428***	0.281***	0.141	-0.011	0.390***
Income_900_	0.944***	0.850***	0.521***	0.285***	0.318**	0.077	0.607***
Asset_0	-0.03	-0.027	-0.123**	-0.068	-0.122	0.084	-0.116
Asset_110_270	0.253***	0.265***	0.172**	0.113	0.022	0.242	0.026
Asset_270_430	0.104	0.134**	0.159**	0.209**	0.101	0.285*	0.151
Asset_430_600	0.195***	0.242***	0.194***	0.230***	-0.018	0.364**	0.209*
Asset_600_900	0.435***	0.405***	0.311***	0.311***	0.324***	0.449***	0.192*
Asset_900_1200	0.320***	0.357***	0.342***	0.339***	0.121	0.434***	0.274**
Asset_1200_1694	0.323***	0.386***	0.398***	0.453***	0.324**	0.585***	0.316***
Asset_1694_2400	0.379***	0.348***	0.402***	0.450***	0.119	0.569***	0.243**
Asset_2400_3900	0.453***	0.428***	0.535***	0.552***	0.402***	0.679***	0.386***
Asset_3900_	0.465***	0.506***	0.548***	0.635***	0.453***	0.737***	0.427***
Know_Dep_Ins	0.259***	0.396***	0.447***	0.526***	0.688***	0.532***	0.639***
Hear_Dep_Ins	0.160***	0.204***	0.253***	0.314***	0.494***	0.414***	0.420***
Lower_service_charge	0.308***	0.367***	0.356***	0.379***	0.417***	0.413***	0.458***
Online_banking	0.929***	0.890***	0.794***	0.787***	0.660***	0.813***	0.741***
Debt	0.562***	0.415***	0.229***	0.134***	0.217***	0	0.238***
Homeowner	-0.034	0.03	0.084**	0.161***	-0.194***	0.274***	-0.159***
Age35_39	0.08	0.031	0.009	0.044	0.219**	-0.083	0.062
Age40_44	0.041	-0.03	-0.032	-0.064	0.025	-0.191*	-0.02
Age45_49	0.012	-0.109*	-0.174***	-0.102	0.071	-0.286**	-0.014
Age50_54	-0.107*	-0.228***	-0.242***	-0.213***	-0.07	-0.486***	-0.251***
Age55_59	-0.404***	-0.480***	-0.445***	-0.321***	-0.159	-0.471***	-0.429***
Age60_64	-0.526***	-0.636***	-0.652***	-0.634***	-0.557***	-0.742***	-0.748***
Age65_69	-0.687***	-0.872***	-0.788***	-0.719***	-0.840***	-0.985***	-1.165***
Age70_74	-0.831***	-0.963***	-0.931***	-0.809***	-1.163***	-1.070***	-1.504***
Age75_	-1.127***	-1.160***	-1.141***	-1.171***	-1.583***	-1.517***	-1.724***
Male	-0.487***	-0.486***	-0.414***	-0.428***	-0.338***	-0.246*	-0.260**
Full_time	0.081*	0.055	0.01	-0.002	0.095	-0.203*	0.011
Part_time	0.061	0.064	0.014	0.008	0.031	-0.087	0.02
Self_employed	-0.108**	-0.146***	-0.190***	-0.136**	-0.078	-0.218*	-0.210**
Student	0.244	0.231	-0.029	-0.355	-0.18	-0.247	-0.452
S_Full_time	-0.058	-0.116***	-0.227***	-0.214***	-0.221***	-0.13	-0.160***
S_Part_time	0.029	0.072**	-0.007	-0.007	-0.108*	-0.085	-0.125**
S_Self_employed	-0.118*	-0.176***	-0.227***	-0.271***	-0.238*	-0.322**	-0.250**
S_Student	-0.193	-0.11	-0.046	-0.226	-0.303	-0.051	0.27
Senior_high	0.104**	0.102**	0.172***	0.186**	-0.196*	0.325**	-0.014
Vocational_college	0.315***	0.269***	0.363***	0.326***	-0.027	0.472***	0.178
Junior_college	0.422***	0.380***	0.421***	0.482***	-0.026	0.613***	0.098
University	0.568***	0.542***	0.479***	0.448***	0.082	0.542***	0.224*
Graduate	0.987***	0.836***	0.757***	0.686***	0.394**	0.781***	0.474***
S_Senior_high	0.322***	0.345***	0.176**	0.200**	0.421**	0.079	0.260*
S_Vocational_college	0.416***	0.455***	0.249***	0.284***	0.625***	0.192	0.369**
S_Junior_college	0.503***	0.556***	0.397***	0.370***	0.472***	0.139	0.205
S_University	0.587***	0.658***	0.504***	0.450***	0.559***	0.265	0.428***
S_Graduate	0.638**	0.491**	0.234	0.424**	0.514	0.151	0.646***
No_spouse	-0.11	-0.056	-0.218**	-0.186	0.236	-0.011	0.127
Top20cities	0.400***	0.481***	0.377***	0.339***	0.098	0.281***	0.257***
Cities_40k_	0.196***	0.217***	0.171***	0.171***	0.094	0.159	0.137*
Cities_20k_40k	-0.043	0.014	-0.016	-0.021	-0.046	0.006	0.011
N	34,962	35,917	35,297		36,353		36,302
pseudoRsq	0.161	0.160	0.139		0.117		0.125
LLR	-19,684.6	-20,880.3	-18,660.9		-21,500.0		-15,074.7
% correctly classified	70.72%	69.37%	73.61%				
Area under ROC curve	0.7615	0.7602	0.748				

* p<0.10, ** p<0.05, *** p<0.01

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 2 Marginal effects

	>50k	10k–50k	5k–10k	1k–5k			≤1k		
Variable	card	card	card	cash only	card	emoney	cash only	card	emoney
Mattress deposit	-0.032	-0.018	-0.036 *	-0.014	-0.004	0.018 **	0.001	-0.009	0.008
H_size3	0.002	0.006	0.002	-0.005	0.004	0.000	0.005	0.001	-0.007 *
H_size4	-0.001	-0.002	0.005	-0.007	0.004	0.003	0.003	0.003	-0.006
H_size5	-0.013	-0.014	-0.021 **	0.008	-0.007	-0.001	0.016 **	-0.003	-0.013 **
H_size6	-0.012	-0.004	0.014	-0.027	0.035 *	-0.009	0.026 *	-0.009	-0.018
H_size_6_	-0.025	-0.026	-0.037 **	0.045 **	-0.048 ***	0.003	-0.005	0.006	-0.001
ln(Passengers km)	0.009 ***	0.017 ***	0.021 ***	-0.014 ***	0.019 ***	-0.005 ***	-0.007 ***	0.006 ***	0.001
Income_200_260	0.022 *	0.033 ***	0.016	-0.008	0.002	0.005	-0.025 **	0.004	0.022 **
Income_260_300	0.061 ***	0.061 ***	0.039 ***	-0.025 **	0.025 **	0.000	-0.008	-0.004	0.012
Income_300_370	0.074 ***	0.085 ***	0.057 ***	-0.032 ***	0.026 **	0.006	-0.021 **	-0.004	0.025 ***
Income_370_407	0.097 ***	0.090 ***	0.059 ***	-0.026 **	0.031 ***	-0.005	-0.018 *	0.001	0.017 **
Income_407_500	0.115 ***	0.106 ***	0.064 ***	-0.037 ***	0.037 ***	0.000	-0.025 ***	0.005	0.020 ***
Income_500_600	0.124 ***	0.122 ***	0.079 ***	-0.042 ***	0.035 ***	0.007	-0.026 ***	0.001	0.026 ***
Income_600_700	0.130 ***	0.125 ***	0.076 ***	-0.031 ***	0.029 ***	0.002	-0.027 ***	-0.006	0.033 ***
Income_700_900	0.140 ***	0.133 ***	0.075 ***	-0.038 ***	0.034 ***	0.003	-0.024 **	-0.003	0.027 ***
Income_900_	0.181 ***	0.169 ***	0.092 ***	-0.045 ***	0.032 ***	0.012 *	-0.041 ***	-0.001	0.041 ***
Asset_0	-0.006	-0.005	-0.022 **	0.012	-0.007	-0.005	0.004	0.004	-0.009
Asset_110_270	0.048 ***	0.053 ***	0.030 **	-0.014	0.014	0.000	-0.011	0.010	0.000
Asset_270_430	0.020	0.027 **	0.028 **	-0.028 **	0.026 **	0.002	-0.020 **	0.012 *	0.009
Asset_430_600	0.037 ***	0.048 ***	0.034 ***	-0.026 **	0.030 ***	-0.004	-0.027 ***	0.015 **	0.012
Asset_600_900	0.083 ***	0.081 ***	0.055 ***	-0.048 ***	0.036 ***	0.012 *	-0.029 ***	0.018 ***	0.010
Asset_900_1200	0.061 ***	0.071 ***	0.060 ***	-0.044 ***	0.042 ***	0.001	-0.033 ***	0.017 **	0.016 **
Asset_1200_1694	0.062 ***	0.077 ***	0.070 ***	-0.064 ***	0.054 ***	0.010	-0.041 ***	0.024 ***	0.018 **
Asset_1694_2400	0.073 ***	0.069 ***	0.071 ***	-0.056 ***	0.057 ***	0.000	-0.036 ***	0.023 ***	0.013
Asset_2400_3900	0.087 ***	0.085 ***	0.094 ***	-0.079 ***	0.066 ***	0.013 *	-0.049 ***	0.027 ***	0.022 ***
Asset_3900_	0.089 ***	0.101 ***	0.097 ***	-0.090 ***	0.076 ***	0.014 **	-0.054 ***	0.030 ***	0.025 ***
Know_Dep_Ins	0.050 ***	0.079 ***	0.079 ***	-0.086 ***	0.059 ***	0.028 ***	-0.060 ***	0.019 ***	0.041 ***
Hear_Dep_Ins	0.031 ***	0.041 ***	0.045 ***	-0.055 ***	0.034 ***	0.021 ***	-0.042 ***	0.015 ***	0.026 ***
Lower_service_charge	0.059 ***	0.073 ***	0.063 ***	-0.059 ***	0.043 ***	0.016 ***	-0.044 ***	0.015 ***	0.029 ***
Online_banking	0.178 ***	0.177 ***	0.140 ***	-0.115 ***	0.093 ***	0.023 ***	-0.076 ***	0.031 ***	0.046 ***
Debt	0.107 ***	0.082 ***	0.040 ***	-0.024 ***	0.014 ***	0.009 ***	-0.015 ***	-0.002	0.016 ***
Homeowner	-0.006	0.006	0.015 **	-0.011 **	0.024 ***	-0.012 ***	0.000	0.013 ***	-0.013 ***
Age35_39	0.015	0.006	0.002	-0.013	0.003	0.010 *	-0.001	-0.004	0.005
Age40_44	0.008	-0.006	-0.006	0.006	-0.009	0.002	0.008	-0.008 *	0.000
Age45_49	0.002	-0.022 *	-0.031 ***	0.009	-0.014	0.005	0.012	-0.012 **	0.001
Age50_54	-0.021 *	-0.045 ***	-0.043 ***	0.027 ***	-0.027 ***	-0.001	0.034 ***	-0.020 ***	-0.014 **
Age55_59	-0.077 ***	-0.095 ***	-0.078 ***	0.043 ***	-0.039 ***	-0.004	0.044 ***	-0.018 ***	-0.026 ***
Age60_64	-0.101 ***	-0.126 ***	-0.115 ***	0.094 ***	-0.074 ***	-0.020 ***	0.074 ***	-0.028 ***	-0.047 ***
Age65_69	-0.131 ***	-0.173 ***	-0.139 ***	0.114 ***	-0.081 ***	-0.033 ***	0.109 ***	-0.036 ***	-0.074 ***
Age70_74	-0.159 ***	-0.192 ***	-0.164 ***	0.137 ***	-0.089 ***	-0.048 ***	0.134 ***	-0.037 ***	-0.097 ***
Age75_	-0.215 ***	-0.231 ***	-0.201 ***	0.194 ***	-0.130 ***	-0.064 ***	0.164 ***	-0.055 ***	-0.109 ***
Male	-0.093 ***	-0.097 ***	-0.073 ***	0.062 ***	-0.051 ***	-0.011 *	0.025 ***	-0.009	-0.016 **
Full_time	0.015 *	0.011	0.002	-0.003	-0.002	0.005	0.007	-0.009 **	0.002
Part_time	0.012	0.013	0.002	-0.002	0.001	0.001	0.002	-0.004	0.002
Self_employed	-0.021 **	-0.029 ***	-0.033 ***	0.019 *	-0.017 *	-0.002	0.021 **	-0.008	-0.013 *
Student	0.047	0.046	-0.005	0.048	-0.043	-0.004	0.037	-0.008	-0.029
S_Full_time	-0.011	-0.023 ***	-0.040 ***	0.033 ***	-0.025 ***	-0.008 **	0.015 ***	-0.005	-0.010 **
S_Part_time	0.006	0.014 **	-0.001	0.005	0.001	-0.005 *	0.011 **	-0.003	-0.008 **
S_Self_employed	-0.023 *	-0.035 ***	-0.040 ***	0.040 ***	-0.032 ***	-0.008	0.028 ***	-0.012 *	-0.015 *
S_Student	-0.037	-0.022	-0.008	0.037	-0.025	-0.012	-0.015	-0.004	0.019
Senior_high	0.020 **	0.020 **	0.030 ***	-0.014	0.027 ***	-0.012 **	-0.011	0.014 **	-0.003
Vocational_college	0.060 ***	0.053 ***	0.064 ***	-0.037 ***	0.043 ***	-0.006	-0.029 ***	0.020 ***	0.009
Junior_college	0.081 ***	0.076 ***	0.074 ***	-0.055 ***	0.063 ***	-0.008	-0.029 **	0.026 ***	0.003
University	0.109 ***	0.108 ***	0.084 ***	-0.055 ***	0.057 ***	-0.002	-0.034 ***	0.022 ***	0.012
Graduate	0.189 ***	0.166 ***	0.133 ***	-0.094 ***	0.083 ***	0.011	-0.059 ***	0.031 ***	0.027 ***
S_Senior_high	0.062 ***	0.069 ***	0.031 **	-0.039 ***	0.020 *	0.019 **	-0.019 *	0.002	0.017 *
S_Vocational_college	0.080 ***	0.090 ***	0.044 ***	-0.056 ***	0.028 **	0.028 ***	-0.030 **	0.006	0.024 **
S_Junior_college	0.096 ***	0.111 ***	0.070 ***	-0.060 ***	0.041 ***	0.019 **	-0.018	0.005	0.013
S_University	0.112 ***	0.131 ***	0.089 ***	-0.073 ***	0.051 ***	0.022 **	-0.037 ***	0.009	0.028 **
S_Graduate	0.122 **	0.098 **	0.041	-0.068 **	0.048 *	0.020	-0.046 **	0.002	0.043 ***
No_spouse	-0.021	-0.011	-0.038 **	0.013	-0.027 *	0.015	-0.008	-0.001	0.009
Top20cities	0.076 ***	0.096 ***	0.067 ***	-0.043 ***	0.042 ***	0.000	-0.027 ***	0.011 **	0.016 ***
Cities_40k_	0.037 ***	0.043 ***	0.030 ***	-0.023 ***	0.021 ***	0.002	-0.014 **	0.006	0.008
Cities_20k_40k	-0.008	0.003	-0.003	0.004	-0.002	-0.002	-0.001	0.000	0.001

Notes: The marginal effects for the choice of cash only for transaction values of 50k –, 10k – 50k, and 5k – 10k have the same absolute values with opposite sign as the marginal effects for card, hence they are not reported. We do not report the results for dummy variables for observation years, constant and non-available observations.

Appendix Table 3 Conditional cash demand

	card and cash						card, emoney and cash			
	>50k		10k-50k		5k-10k		1k-5k		≤1k	
Mattress deposit	26.839	***	26.349	***	24.007	***	24.938	***	25.531	***
H_size3	-1.252	**	-1.312	**	-1.450	**	-1.804	***	-1.747	***
H_size4	-1.696	**	-1.680	**	-1.656	**	-2.074	***	-2.289	***
H_size5	-1.971	**	-1.747	**	-1.375		-1.897	**	-2.377	***
H_size6	-0.225		0.454		0.217		0.575		-0.147	
H_size_6_	-1.292		-1.978		-1.297		-1.992		-1.641	
ln(Passengers km)	0.409	***	0.406	***	0.266	*	0.294		0.366	*
Income_200_260	0.536		0.858		1.073		1.073		1.704	
Income_260_300	1.938	*	2.279	**	2.330	**	2.514	***	3.259	***
Income_300_370	1.644		2.209	**	2.130	*	2.378	**	3.558	***
Income_370_407	3.368	***	3.243	***	3.238	***	3.466	***	4.331	***
Income_407_500	3.514	***	3.757	***	3.458	***	3.506	***	4.217	***
Income_500_600	4.310	***	4.810	***	4.569	***	4.170	***	5.624	***
Income_600_700	5.803	***	6.455	***	5.835	***	5.660	***	7.447	***
Income_700_900	6.892	***	6.831	***	6.282	***	6.574	***	7.562	***
Income_900_	13.582	***	13.327	***	13.832	***	13.175	***	14.452	***
Asset_0	0.210		0.442		0.607		0.311		-0.092	
Asset_110_270	1.972		1.805		1.688		1.477		1.701	
Asset_270_430	3.141	**	2.746	**	2.554	**	2.751	**	3.128	***
Asset_430_600	4.536	***	4.607	***	4.619	***	4.286	***	4.569	***
Asset_600_900	6.388	***	6.045	***	5.842	***	6.548	***	6.331	***
Asset_900_1200	3.650	***	2.906	**	2.767	**	2.596	**	3.760	***
Asset_1200_1694	3.923	***	3.611	***	3.084	**	3.148	**	4.496	***
Asset_1694_2400	6.948	***	6.549	***	6.208	***	5.862	***	6.972	***
Asset_2400_3900	9.497	***	8.571	***	9.244	***	9.306	***	9.728	***
Asset_3900_	17.172	***	17.185	***	16.665	***	16.959	***	17.622	***
Know_Dep_Ins	1.371	**	1.021		0.912		0.786		2.449	***
Hear_Dep_Ins	-0.076		-0.531		-0.356		-0.333		0.630	
Lower_service_charge	-2.147	***	-2.033	***	-2.358	***	-2.541	***	-2.103	**
Online_banking	3.285	***	3.053	***	2.403	***	1.691		2.944	**
Debt	-1.389	**	-1.608	***	-2.104	***	-2.047	***	-1.127	**
Homeowner	1.107	*	1.003	*	0.911		0.913		0.440	
Age35_39	-0.376		-0.581		-0.613		-0.479		-0.164	
Age40_44	-0.187		-0.295		-0.557		-0.637		-0.512	
Age45_49	-0.297		-0.317		-0.196		-0.407		-0.309	
Age50_54	-0.192		0.198		0.130		0.443		-0.158	
Age55_59	1.240		1.445		1.712		2.105	*	0.859	
Age60_64	3.022	**	3.227	***	3.802	***	4.105	***	2.201	
Age65_69	5.243	***	6.062	***	5.923	***	6.215	***	3.540	**
Age70_74	5.384	***	6.138	***	6.325	***	6.290	***	3.059	
Age75_	7.544	***	7.772	***	7.809	***	8.077	***	4.644	**
Male	2.780	**	2.941	**	3.529	***	3.168	**	2.142	*
Full_time	0.578		0.010		-0.117		0.464		1.038	
Part_time	-1.416		-1.678		-1.116		-1.078		-0.675	
Self_employed	3.731	***	3.262	***	3.526	***	3.731	***	3.794	***
Student	17.678	***	15.007	***	14.176	***	12.102	***	16.795	***
S_Full_time	-0.870		-0.908		-1.017		-0.793		-1.133	
S_Part_time	-1.126	*	-1.218	**	-1.394	**	-1.280	**	-1.548	**
S_Self_employed	2.759	**	3.417	***	3.097	***	2.723	**	2.452	**
S_Student	-0.136		-2.382		-1.985		-0.715		-2.914	
Senior_high	-0.190		-0.483		-0.314		-0.850		-0.833	
Vocational_college	-0.352		-0.919		-0.813		-1.295		-0.622	
Junior_college	2.898	**	2.563	*	2.037		2.000		2.261	
University	-0.412		-0.749		-0.947		-1.353		-0.580	
Graduate	-1.796		-3.013	*	-3.171	*	-4.163	**	-3.079	*
S_Senior_high	1.112		0.552		0.565		1.092		1.909	**
S_Vocational_college	0.978		0.409		0.513		0.927		1.850	
S_Junior_college	1.583		0.553		0.398		0.788		1.350	
S_University	2.181	*	1.321		1.171		0.972		2.115	*
S_Graduate	-0.193		1.721		1.742		-1.477		0.652	
No_spouse	3.964	***	3.259	**	3.505	**	3.667	***	4.135	***
Top20cities	1.379		1.248		1.001		0.406		1.119	
Cities_40k_	0.470		0.351		0.360		-0.078		0.287	
Cities_20k_40k	0.008		0.112		0.230		0.348		-0.373	
$R(card)_{card}$	-0.258	***	-0.222	***	-0.148	**	-0.079		-0.024	
$R(card)_{emoney}$							-0.246		0.511	*
$R(card)_{cash}$	-0.567	***	-0.455	***	-0.374	**	-0.228		-0.094	
$R(emoney)_{card}$							0.011		0.634	
$R(emoney)_{emoney}$							-0.059		0.067	
$R(emoney)_{cash}$							-0.311		0.271	
$R(cash)_{card}$	-0.569	***	-0.496	***	-0.624	***	-0.608	**	-0.365	
$R(cash)_{emoney}$							-0.225		0.774	**
$R(cash)_{cash}$	-0.133	**	-0.124	*	-0.282	***	-0.323	**	0.128	
N	34962		35917		35297		36353		36302	
Adjusted Rsq	0.047		0.046		0.045		0.045		0.046	

* p<0.10, ** p<0.05, *** p<0.01

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 4 Propensity-score matching results

Goodness of fit statistics for the Logit models

	card vs cash only					emoney vs cash only	
	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k	1k - 5k	≤1k
N	34,962	35917	35,297	34,293	33,273	30,017	34,572
pseudoRsq	0.161	0.16	0.139	0.122	0.093	0.119	0.159
LLR	-19684.57	-20880.25	-18660.86	-14,414	-21,480	-6615.283	-8637.621
% correctly classified	70.72%	69.37%	73.61%	82.06%	94.79%	93.14%	91.20%
Area under ROC curve	0.7615	0.7602	0.748	0.7426	0.7353	0.7642	0.7944

Notes: The row labeled N provides the sample size of the logistic treatment model.
The low labelled pseudoRsq and LLR report the pseudo R2 and the log-likelihood ratio respectively.
The low labelled % correctly classified reports the percentage of observations correctly classified.
The low labelled Area under ROC curve reports the area under the ROC curve.

Propensity-score matching

	card vs cash only					emoney vs cash only	
	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k	1k - 5k	≤1k
ATE: Psmatch	-3.343***	-2.903***	-3.608***	-2.833***	-0.775	-1.801*	-2.518***
	(0.762)	(0.589)	(0.500)	(0.571)	(1.727)	(0.985)	-0.965
ATE: IPW	-3.140***	-3.315***	-2.830***	-2.431***	-0.525	-2.370***	-2.561***
	(0.591)	(0.532)	(0.427)	(0.496)	(1.169)	(0.781)	-0.741
ATET: Psmatch	-3.055***	-2.843***	-3.579***	-3.436***	-1.086	-3.630***	-2.284**
	-1.068	-0.759	-0.793	-1.031	-1.591	(1.257)	-1.16
ATET: IPW	-3.085***	-3.115***	-2.335***	-1.909***	-0.541	-2.324***	-2.586***
	-0.739	-0.706	-0.547	-0.597	-1.149	(0.745)	-0.681

Note: Standard errors in parentheses. Cash is in units of 10,000 yen.
Psmatch stands for propensity-score matching and IPW stands for inverse probability weight.
* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 5 Logit models used for computing propensity scores

	Logit models for PS match			
	card versus cash only		emoney versus cash only	
	1k-5k	≤1k	1k-5k	≤1k
Mattress deposit	-0.024	-0.221	0.405**	0.127
H_size3	0.033	0.019	0.001	-0.097*
H_size4	0.031	0.041		-0.098
H_size5	-0.073	-0.133	-0.065	-0.223***
H_size6	0.273*	-0.259	-0.146	-0.264
H_size_6_	-0.387***	0.149	-0.084	-0.057
ln(Passengers km)	0.140***	0.136***	-0.055***	
Income_200_260	0.027	0.129	0.013	0.337***
Income_260_300	0.197***	-0.07		0.174
Income_300_370	0.225***	-0.044	0.025	0.372***
Income_370_407	0.236***	0.062	-0.159*	0.253**
Income_407_500	0.300***	0.171	-0.07	0.334***
Income_500_600	0.302***	0.079		0.401***
Income_600_700	0.227***	-0.088	-0.051	0.499***
Income_700_900	0.284***	-0.009	-0.057	0.424***
Income_900_	0.294***	0.081		0.646***
Asset_0	-0.063	0.084		
Asset_110_270	0.122	0.254	0.089	0.062
Asset_270_430	0.213**	0.289*	0.156	0.187**
Asset_430_600	0.240***	0.375**	0.02	0.260***
Asset_600_900	0.309***	0.444***	0.341***	0.229***
Asset_900_1200	0.338***	0.436***		0.301***
Asset_1200_1694	0.450***	0.592***	0.322***	0.350***
Asset_1694_2400	0.465***	0.581***	0.077	0.296***
Asset_2400_3900	0.564***	0.694***	0.361***	0.428***
Asset_3900_	0.642***	0.752***	0.389***	0.446***
Know_Dep_Ins	0.517***	0.517***	0.616***	0.675***
Hear_Dep_Ins	0.307***	0.399***	0.402***	0.438***
Lower_service_charge	0.371***	0.397***		0.460***
Online_banking	0.775***	0.791***	0.778***	0.777***
Debt	0.134***	-0.008		0.226***
Homeowner	0.156***	0.274***	-0.152***	-0.156***
Age35_39	0.047	-0.086	0.531***	0.069
Age40_44	-0.055	-0.175	0.370***	-0.037
Age45_49	-0.083	-0.266**	0.418***	-0.048
Age50_54	-0.203***	-0.474***	0.312***	-0.289***
Age55_59	-0.312***	-0.458***	0.191**	-0.476***
Age60_64	-0.624***	-0.733***		-0.768***
Age65_69	-0.711***	-0.971***	-0.368***	-1.167***
Age70_74	-0.799***	-1.064***	-0.686***	-1.487***
Age75_	-1.164***	-1.512***	-1.063***	-1.698***
Male	-0.413***	-0.221	-0.364***	-0.259**
Full_time	-0.004	-0.200*	0.296***	0.104
Part_time	0.002	-0.082	0.077	0.09
Self_employed	-0.135*	-0.212*		-0.141
Student	-0.38	-0.226	0.186	-0.367
S_Full_time	-0.214***	-0.131	-0.058	-0.147**
S_Part_time	-0.011	-0.093	-0.002	-0.094*
S_Self_employed	-0.281***	-0.326**	-0.087	-0.199
S_Student	-0.145	-0.05	-0.302	0.431
Senior_high	0.185**	0.329**	-0.165	-0.026
Vocational_college	0.326***	0.479***	0.076	0.172
Junior_college	0.480***	0.619***	0.025	0.1
University	0.451***	0.546***	0.125	0.234**
Graduate	0.672***	0.756***	0.475***	0.478***
S_Senior_high	0.202**	0.079	0.505***	0.276*
S_Vocational_college	0.282***	0.202	0.760***	0.393**
S_Junior_college	0.362***	0.125	0.597***	0.235
S_University	0.447***	0.261	0.756***	0.446***
S_Graduate	0.409**	0.122	0.796**	0.712***
No_spouse	-0.178	-0.014	0.349*	0.177
Top20cities	0.342***	0.278***	0.15	
Cities_40k_	0.175***	0.161	0.150*	-0.062
Cities_20k_40k	-0.011	0.013	0.02	-0.187***
N	34,293	33,273	30,017	34,572
pseudoRsq	0.122	0.093	0.119	0.159
LLR	-14,414.4	-21,479.7	-6,615.3	-8,637.6
% correctly classified	82.06%	94.79%	93.14%	91.20%
Area under ROC curve	0.7426	0.7353	0.7642	0.7944

Notes: If some variables have an absolute value of standardized difference after matching of more than 0.1, we drop the variable with the largest absolute value of the standardized difference and match again using the remaining common covariates as explanatory variables. We continue until all of the absolute values of the standardized differences after matching are less than 0.1. We do not report the results for dummy variables for observation years, constant and non-available observations.

Appendix Table 6 Standardized differences

	Logit model for card and cash only			Logit models			
				card versus cash only		emoney versus cash only	
	>50k	10k-50k	5k-10k	1k-5k	≤1k	1k-5k	≤1k
Mattress deposit	-0.001	0.002	-0.001	-0.003	-0.023	0.037	0.032
H_size3	0.011	0.004	0.000	0.006	0.032	-0.007	0.004
H_size4	0.009	0.002	0.011	0.020	0.012		0.052
H_size5	-0.016	-0.003	0.008	0.017	0.009	0.062	0.032
H_size6	0.001	0.011	0.015	0.014	-0.033	-0.044	-0.006
H_size_6_	-0.002	0.014	0.014	0.014	-0.009	0.003	-0.005
ln(Passengers km)	0.014	-0.002	0.003	0.028	0.066	0.020	
Income_200_260	0.000	0.007	0.013	-0.007	-0.040	-0.001	-0.007
Income_260_300	-0.006	0.001	0.002	-0.006	-0.012		-0.032
Income_300_370	-0.008	-0.005	0.002	0.011	0.031	0.008	-0.001
Income_370_407	-0.005	0.001	0.010	0.025	0.040	0.029	0.002
Income_407_500	0.004	0.000	0.007	0.001	-0.012	0.019	0.006
Income_500_600	-0.002	0.000	0.000	-0.007	-0.002		0.002
Income_600_700	0.004	0.000	0.001	0.003	0.022	0.022	0.024
Income_700_900	-0.002	-0.002	-0.005	0.006	-0.003	0.023	-0.007
Income_900_	0.030	0.012	0.006	0.017	0.044		0.029
Asset_0	-0.016	-0.004	-0.010	-0.023	-0.022		
Asset_110_270	-0.004	0.001	0.007	0.006	0.044	-0.025	-0.045
Asset_270_430	0.009	0.000	0.000	0.011	-0.011	-0.006	-0.003
Asset_430_600	-0.005	-0.002	0.004	0.001	-0.009	-0.010	-0.013
Asset_600_900	0.015	-0.001	-0.006	0.001	-0.005	0.000	-0.011
Asset_900_1200	0.001	-0.008	0.002	-0.006	0.007		0.000
Asset_1200_1694	0.001	-0.001	-0.006	0.003	0.009	0.012	0.005
Asset_1694_2400	0.003	-0.001	-0.004	-0.005	-0.012	-0.054	-0.045
Asset_2400_3900	0.006	0.014	0.003	-0.005	0.015	0.016	-0.014
Asset_3900_	0.008	0.002	0.005	0.011	0.021	-0.002	0.000
Know_Dep_Ins	0.009	-0.002	0.000	0.015	0.055	0.021	0.004
Hear_Dep_Ins	-0.005	0.002	0.004	0.002	-0.047	0.006	-0.003
Lower_service_charge	0.006	-0.001	0.006	0.016	0.039		0.041
Online_banking	0.013	-0.013	-0.002	0.014	0.002	0.065	0.049
Debt	-0.007	0.006	0.018	0.032	0.022		0.059
Homeowner	0.002	-0.002	-0.019	-0.038	-0.004	-0.036	-0.055
Age35_39	-0.001	0.002	0.005	0.007	-0.020	0.015	0.031
Age40_44	-0.014	-0.014	0.005	0.014	0.009	0.037	0.019
Age45_49	0.010	0.007	0.000	0.007	0.026	0.012	0.007
Age50_54	-0.004	0.001	0.000	-0.003	0.006	0.017	0.008
Age55_59	0.005	0.002	-0.004	0.001	-0.021	0.020	0.008
Age60_64	0.000	0.003	-0.004	0.001	-0.006		-0.012
Age65_69	-0.002	0.003	0.000	-0.020	0.030	-0.007	-0.016
Age70_74	-0.003	-0.001	-0.007	-0.016	0.002	-0.063	-0.043
Age75_	0.001	0.002	0.003	0.001	-0.034	-0.060	-0.035
Male	0.004	0.003	-0.003	-0.012	-0.016	-0.021	-0.028
Full_time	0.012	-0.002	-0.006	0.006	0.019	0.058	0.056
Part_time	-0.006	0.005	0.016	0.018	0.022	0.005	0.012
Self_employed	-0.009	0.002	0.015	0.032	-0.019		-0.013
Student	0.011	0.007	-0.007	-0.002	-0.009	-0.015	-0.030
S_Full_time	0.000	0.004	0.010	0.011	0.021	-0.010	0.010
S_Part_time	-0.009	-0.002	0.013	0.015	0.026	0.046	0.012
S_Self_employed	-0.003	0.003	0.004	0.006	-0.050	0.020	0.010
S_Student	0.003	0.000	-0.001	-0.004	-0.025	-0.022	-0.005
Senior_high	-0.008	0.002	-0.007	-0.018	-0.045	-0.002	-0.027
Vocational_college	0.001	0.003	0.002	0.009	0.000		0.009
Junior_college	0.012	0.003	-0.001	-0.005	-0.023	0.026	0.011
University	-0.003	-0.005	0.012	0.027	0.039	0.030	0.017
Graduate	0.021	0.000	-0.003	0.006	0.033	0.003	0.013
S_Senior_high	-0.008	-0.001	-0.009	-0.019	-0.037	-0.026	-0.050
S_Vocational_college	-0.012	-0.004	0.011	0.002	-0.008	-0.006	-0.032
S_Junior_college	0.009	0.001	0.004	0.023	0.031	0.030	0.036
S_University	0.015	0.005	-0.001	0.005	0.035	0.036	0.032
S_Graduate	0.015	-0.002	-0.001	0.002	-0.001	-0.003	0.009
No_spouse	-0.003	0.003	0.007	0.024	0.004	-0.005	0.038
Top20cities	0.001	-0.003	0.002	0.016	0.006	0.032	
Cities_40k_	0.005	0.005	0.004	0.021	0.045	0.036	0.037
Cities_20k_40k	-0.008	-0.005	-0.005	-0.035	-0.028	-0.054	-0.054

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 7 Multinomial logit regression for transaction values of ≥5,000 yen

	Card & NCC			*Cash & CC*			*Card & CC*		
	>50k	10k - 50k	5k - 10k	>50k	10k - 50k	5k - 10k	>50k	10k - 50k	5k - 10k
Mattress deposit	-0.149	-0.057	-0.128	0.188	0.135	0.089	-0.204	-0.11	-0.279*
H_size3	0.013	0.042	0.027	0.094	0.101	0.026	0.001	0.028	0.001
H_size4	0.003	-0.002	0.024	0.085	0.107	0.001	-0.013	-0.013	0.012
H_size5	0.008	-0.003	-0.019	0.239	0.121	-0.026	-0.194***	-0.188***	-0.265***
H_size6	-0.063	-0.03	0.115	-0.737**	-0.647**	-0.234	-0.172	-0.132	-0.07
H_size_6_	-0.103	-0.112	-0.131	0.615**	0.317	0.229	-0.143	-0.117	-0.224
ln(Passengers km)	0.034***	0.076***	0.121***	0.058**	0.036	0.041***	0.084***	0.112***	0.135***
Income_200_260	0.173***	0.257***	0.164*	0.133	0.129	0.039	-0.06	-0.035	-0.037
Income_260_300	0.350***	0.373***	0.260***	0.553***	0.582***	0.313***	0.299***	0.302***	0.228**
Income_300_370	0.418***	0.452***	0.340***	0.578***	0.311*	0.362***	0.399***	0.437***	0.355***
Income_370_407	0.506***	0.464***	0.318***	0.590***	0.515***	0.435***	0.581***	0.522***	0.434***
Income_407_500	0.590***	0.541***	0.370***	0.507**	0.500***	0.492***	0.677***	0.594***	0.458***
Income_500_600	0.603***	0.608***	0.481***	0.406*	0.558***	0.609***	0.774***	0.729***	0.596***
Income_600_700	0.650***	0.626***	0.438***	0.595**	0.615***	0.661***	0.828***	0.764***	0.606***
Income_700_900	0.696***	0.641***	0.384***	0.667***	0.596***	0.629***	0.906***	0.829***	0.651***
Income_900_	0.884***	0.807***	0.408***	0.683***	0.643***	0.642***	1.178***	1.070***	0.817***
Asset_0	0.004	0.007	-0.147**	-0.232	-0.207	-0.212**	-0.156**	-0.149**	-0.179**
Asset_110_270	0.206***	0.210***	0.039	0.149	0.205	0.111	0.366***	0.384***	0.345***
Asset_270_430	0.048	0.043	-0.002	0.311	0.139	0.117	0.269***	0.291***	0.374***
Asset_430_600	0.167**	0.181**	0.076	0.329	0.068	0.103	0.346***	0.378***	0.361***
Asset_600_900	0.357***	0.325***	0.208**	-0.065	0.083	0.154	0.596***	0.555***	0.491***
Asset_900_1200	0.260***	0.260***	0.208**	0.294	0.046	0.151	0.533***	0.560***	0.561***
Asset_1200_1694	0.234***	0.272***	0.285***	0.289	0.127	0.238**	0.581***	0.618***	0.631***
Asset_1694_2400	0.322***	0.260***	0.287***	0.186	0.109	0.149	0.569***	0.547***	0.590***
Asset_2400_3900	0.405***	0.378***	0.462***	0.243	0.316*	0.237**	0.644***	0.618***	0.709***
Asset_3900_	0.417***	0.442***	0.409***	0.425*	0.136	0.186	0.691***	0.688***	0.769***
Know_Dep_Ins	0.150***	0.287***	0.337***	0.395***	0.435***	0.352***	0.598***	0.687***	0.703***
Hear_Dep_Ins	0.115***	0.162***	0.193***	0.175	0.243***	0.141**	0.329***	0.340***	0.382***
Lower_service_charge	0.221***	0.277***	0.296***	0.259*	0.243**	0.287***	0.537***	0.575***	0.549***
Online_banking	0.702***	0.714***	0.687***	0.884***	0.900***	0.826***	1.448***	1.391***	1.273***
Debt	0.614***	0.462***	0.345***	0.541***	0.329***	0.300***	0.550***	0.404***	0.207***
Homeowner	-0.061*	-0.001	0.052	0.147	0.102	0.074	0.090**	0.139***	0.193***
Age35_39	0.126	0.075	0.073	-0.327*	-0.232*	-0.212**	-0.071	-0.111	-0.131*
Age40_44	0.175**	0.073	0.077	-0.541***	-0.582***	-0.518***	-0.284***	-0.339***	-0.338***
Age45_49	0.193**	0.067	0.049	-0.848***	-0.793***	-0.670***	-0.497***	-0.593***	-0.639***
Age50_54	0.124*	0.004	0.031	-1.090***	-0.886***	-0.843***	-0.764***	-0.840***	-0.845***
Age55_59	-0.11	-0.172**	-0.11	-1.336***	-1.146***	-1.205***	-1.282***	-1.327***	-1.273***
Age60_64	-0.174**	-0.289***	-0.245***	-1.542***	-1.535***	-1.425***	-1.608***	-1.654***	-1.643***
Age65_69	-0.298***	-0.475***	-0.330***	-1.692***	-1.493***	-1.589***	-1.896***	-2.018***	-1.911***
Age70_74	-0.442***	-0.565***	-0.461***	-1.747***	-1.608***	-1.661***	-2.054***	-2.148***	-2.070***
Age75_	-0.693***	-0.719***	-0.641***	-2.045***	-1.910***	-1.933***	-2.521***	-2.490***	-2.377***
Male	-0.483***	-0.465***	-0.504***	-0.243	-0.137	-0.373***	-0.557***	-0.546***	-0.421***
Full_time	0.067	0.048	-0.003	0.033	0.11	0.022	0.042	0.003	-0.007
Part_time	0.045	0.084	-0.053	0.04	0.231	-0.019	0.055	0.028	0.057
Self_employed	-0.055	-0.058	-0.137*	-0.07	0.071	-0.249**	-0.378***	-0.432***	-0.412***
Student	0.217	0.244	-0.036	-13.662***	-0.258	-0.208	0.079	0.084	-0.129
S_Full_time	0.037	-0.014	-0.112**	-0.015	-0.078	-0.156**	-0.263***	-0.314***	-0.404***
S_Part_time	0.045	0.082**	0.032	-0.005	-0.086	0.008	-0.005	0.021	-0.051
S_Self_employed	-0.125*	-0.226***	-0.277***	-0.077	-0.161	-0.001	-0.1	-0.118	-0.153
S_Student	-0.306	-0.172	-0.568	-13.702***	-0.729	-1.139	-0.241	-0.189	-0.028
Senior_high	0.122**	0.121**	0.196***	0.279	0.357**	0.182*	0.147*	0.142*	0.202**
Vocational_college	0.291***	0.233***	0.263***	0.409*	0.395**	0.269**	0.459***	0.405***	0.522***
Junior_college	0.353***	0.342***	0.349***	0.347	0.608***	0.437***	0.661***	0.592***	0.643***
University	0.548***	0.524***	0.504***	0.684***	0.654***	0.545***	0.763***	0.710***	0.653***
Graduate	0.906***	0.748***	0.647***	1.032***	0.830***	0.608***	1.273***	1.096***	1.027***
S_Senior_high	0.323***	0.354***	0.177**	-0.021	0.063	0.251**	0.361***	0.358***	0.172
S_Vocational_college	0.422***	0.444***	0.292***	0.317	0.137	0.400***	0.483***	0.492***	0.245**
S_Junior_college	0.458***	0.497***	0.367***	0.213	0.133	0.441***	0.647***	0.680***	0.492***
S_University	0.516***	0.629***	0.517***	0.199	0.382*	0.481***	0.727***	0.789***	0.578***
S_Graduate	0.506*	0.556**	0.233	0.107	0.854*	0.524*	0.777***	0.776***	0.373
No_spouse	-0.059	0.005	-0.185	-0.008	-0.066	-0.058	-0.230*	-0.193	-0.385***
Top20cities	0.327***	0.443***	0.360***	0.162	0.360***	0.351***	0.623***	0.654***	0.540***
Cities_40k_	0.146***	0.194***	0.131**	-0.037	0.163	0.142*	0.325***	0.317***	0.266***
Cities_20k_40k	-0.068	0.015	-0.056	-0.171	0.034	-0.026	0	0.026	0.018
N							34569	35513	34892
pseudoRsq							0.143	0.138	0.129
LLR							-34000.0	-35300.0	-32800.0

* p<0.10, ** p<0.05, *** p<0.01

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 8 Marginal effects for multinomial logit regression for transaction values of ≥5,000 yen

	Cash & NCC						*Card & NCC*						*Cash & CC*						*Card & CC*					
	>50k		10k –50k		5k –10k		>50k		10k –50k		5k –10k		>50k		10k –50k		5k –10k		>50k		10k –50k		5k –10k	
Mattress deposit	0.029		0.012		0.024		-0.016		-0.005		-0.009		0.005		0.005		0.013		-0.017		-0.012		-0.029	*
H_size3	-0.002		-0.008		-0.003		0.002		0.006		0.003		0.002		0.002		0.002		-0.001		0.000		-0.001	
H_size4	0.000		0.000		-0.003		0.001		0.000		0.003		0.001		0.003		0.000		-0.003		-0.002		0.001	
H_size5	0.008		0.010		0.020	**	0.017	*	0.011		0.005		0.005	*	0.005		0.003		-0.030	***	-0.027	***	-0.028	***
H_size6	0.021		0.019		0.005		0.006		0.009		0.019		-0.011	**	-0.016	**	-0.018		-0.016		-0.011		-0.007	
H_size_6_	0.017		0.017		0.015		-0.014		-0.017		-0.013		0.012	**	0.011	*	0.023	**	-0.015		-0.011		-0.026	
ln(Passengers km)	-0.009	***	-0.016	***	-0.020	***	0.000		0.007	***	0.010	***	0.000		-0.001		-0.001		0.009	***	0.010	***	0.011	***
Income_200_260	-0.020	*	-0.031	**	-0.012		0.043	***	0.053	***	0.020	*	0.001		0.002		0.001		-0.024	*	-0.024	*	-0.009	
Income_260_300	-0.063	***	-0.070	***	-0.049	***	0.048	***	0.049	***	0.021	**	0.006		0.010	**	0.015	*	0.010		0.011		0.012	
Income_300_370	-0.077	***	-0.085	***	-0.065	***	0.054	***	0.058	***	0.026	***	0.005		0.001		0.016	*	0.018		0.026	**	0.023	**
Income_370_407	-0.098	***	-0.094	***	-0.072	***	0.057	***	0.052	***	0.021	**	0.004		0.006		0.020	**	0.037	***	0.035	***	0.031	***
Income_407_500	-0.113	***	-0.107	***	-0.080	***	0.068	***	0.063	***	0.025	***	0.001		0.004		0.023	***	0.043	***	0.040	***	0.031	***
Income_500_600	-0.119	***	-0.124	***	-0.102	***	0.063	***	0.066	***	0.033	***	-0.001		0.004		0.028	***	0.057	***	0.054	***	0.041	***
Income_600_700	-0.129	***	-0.129	***	-0.102	***	0.068	***	0.067	***	0.027	***	0.002		0.005		0.032	***	0.060	***	0.057	***	0.043	***
Income_700_900	-0.140	***	-0.135	***	-0.099	***	0.071	***	0.066	***	0.020	*	0.002		0.004		0.029	***	0.067	***	0.065	***	0.050	***
Income_900_	-0.178	***	-0.170	***	-0.112	***	0.089	***	0.082	***	0.018	*	0.000		0.002		0.027	***	0.089	***	0.086	***	0.067	***
Asset_0	0.009		0.010		0.032	***	0.016		0.014		-0.010		-0.003		-0.005		-0.010		-0.022	**	-0.019	**	-0.012	
Asset_110_270	-0.046	***	-0.051	***	-0.030	**	0.013		0.014		-0.006		-0.001		0.001		0.001		0.034	***	0.037	***	0.035	***
Asset_270_430	-0.022	*	-0.024	*	-0.029	**	-0.015		-0.013		-0.012		0.004		0.001		0.002		0.033	***	0.036	***	0.039	***
Asset_430_600	-0.041	***	-0.046	***	-0.034	**	0.005		0.009		-0.002		0.003		-0.003		0.000		0.034	***	0.039	***	0.036	***
Asset_600_900	-0.076	***	-0.074	***	-0.055	***	0.027	**	0.026	**	0.009		-0.006		-0.005		-0.001		0.055	***	0.053	***	0.046	***
Asset_900_1200	-0.062	***	-0.066	***	-0.059	***	0.009		0.013		0.008		0.001		-0.005		-0.002		0.053	***	0.058	***	0.054	***
Asset_1200_1694	-0.062	***	-0.072	***	-0.074	***	-0.001		0.010		0.014		0.000		-0.004		0.002		0.062	***	0.065	***	0.058	***
Asset_1694_2400	-0.072	***	-0.066	***	-0.067	***	0.021		0.013		0.016		-0.002		-0.003		-0.004		0.053	***	0.056	***	0.055	***
Asset_2400_3900	-0.086	***	-0.087	***	-0.093	***	0.032	**	0.030	**	0.033	***	-0.002		0.001		-0.002		0.056	***	0.056	***	0.061	***
Asset_3900_	-0.091	***	-0.097	***	-0.090	***	0.029	**	0.040	***	0.026	**	0.001		-0.005		-0.006		0.061	***	0.063	***	0.070	***
Know_Dep_Ins	-0.052	***	-0.081	***	-0.087	***	-0.022	***	0.006		0.016	***	0.003		0.004		0.008	**	0.071	***	0.071	***	0.062	***
Hear_Dep_Ins	-0.033	***	-0.043	***	-0.046	***	-0.004		0.007		0.011	*	0.001		0.003		0.001		0.037	***	0.034	***	0.034	***
Lower_service_charge	-0.057	***	-0.071	***	-0.071	***	0.000		0.013		0.017	***	0.000		0.000		0.007		0.057	***	0.058	***	0.047	***
Online_banking	-0.170	***	-0.181	***	-0.172	***	0.023	**	0.038	***	0.037	***	0.003		0.008	**	0.028	***	0.143	***	0.135	***	0.107	***
Debt	-0.110	***	-0.084	***	-0.054	***	0.085	***	0.062	***	0.032	***	0.002		0.002		0.014	***	0.023	***	0.021	***	0.008	*
Homeowner	0.002		-0.009		-0.020	***	-0.022	***	-0.011	*	0.000		0.002		0.002		0.001		0.018	***	0.018	***	0.019	***
Age35_39	-0.011		0.000		0.012		0.036	***	0.025	*	0.015		-0.006	**	-0.006	*	-0.014	**	-0.020	**	-0.019	**	-0.013	*
Age40_44	-0.005		0.018		0.038	***	0.067	***	0.044	***	0.026	***	-0.009	***	-0.014	***	-0.033	***	-0.054	***	-0.047	***	-0.030	***
Age45_49	0.006		0.036	***	0.066	***	0.092	***	0.062	***	0.032	***	-0.013	***	-0.018	***	-0.038	***	-0.084	***	-0.080	***	-0.060	***
Age50_54	0.030	**	0.060	***	0.088	***	0.101	***	0.067	***	0.038	***	-0.015	***	-0.018	***	-0.047	***	-0.116	***	-0.109	***	-0.079	***
Age55_59	0.088	***	0.113	***	0.142	***	0.096	***	0.068	***	0.038	***	-0.016	***	-0.020	***	-0.064	***	-0.169	***	-0.162	***	-0.116	***
Age60_64	0.114	***	0.152	***	0.186	***	0.112	***	0.071	***	0.035	***	-0.017	***	-0.027	***	-0.072	***	-0.209	***	-0.196	***	-0.149	***
Age65_69	0.145	***	0.196	***	0.217	***	0.111	***	0.059	***	0.034	***	-0.017	***	-0.021	***	-0.078	***	-0.239	***	-0.233	***	-0.173	***
Age70_74	0.172	***	0.216	***	0.240	***	0.093	***	0.051	***	0.024	*	-0.016	***	-0.023	***	-0.078	***	-0.249	***	-0.244	***	-0.186	***
Age75_	0.230	***	0.259	***	0.286	***	0.080	***	0.046	***	0.014		-0.018	***	-0.027	***	-0.090	***	-0.293	***	-0.278	***	-0.210	***
Male	0.092	***	0.091	***	0.083	***	-0.057	***	-0.054	***	-0.044	***	0.002		0.005		-0.013		-0.037	***	-0.042	***	-0.026	**
Full_time	-0.011		-0.007		0.000		0.011		0.009		0.000		0.000		0.003		0.002		0.000		-0.004		-0.001	
Part_time	-0.009		-0.014		0.001		0.005		0.013		-0.008		0.000		0.005		-0.002		0.004		-0.004		0.008	
Self_employed	0.027	***	0.032	***	0.048	***	0.021	*	0.018	*	-0.002		0.001		0.006		-0.009		-0.049	***	-0.056	***	-0.037	***
Student	0.042		-0.032		0.020		0.131	***	0.046		0.002		-0.233	***	-0.010		-0.013		0.060	*	-0.004		-0.009	
S_Full_time	0.009		0.021	***	0.042	***	0.031	***	0.020	**	0.000		0.001		0.000		-0.003		-0.041	***	-0.042	***	-0.039	***
S_Part_time	-0.005		-0.010		0.000		0.010		0.016	**	0.005		0.000		-0.003		0.001		-0.005		-0.002		-0.007	
S_Self_employed	0.022	*	0.036	***	0.032	**	-0.019		-0.036	***	-0.029	***	0.000		-0.002		0.006		-0.003		0.001		-0.009	
S_Student	0.125	*	0.040		0.095		0.043		-0.015		-0.052		-0.229	***	-0.017		-0.076		0.060		-0.008		0.034	
Senior_high	-0.025	***	-0.027	***	-0.036	***	0.012		0.011		0.016	*	0.003		0.008	*	0.007		0.009		0.008		0.014	
Vocational_college	-0.063	***	-0.057	***	-0.066	***	0.022		0.015		0.014		0.003		0.006		0.007		0.039	***	0.037	***	0.046	***
Junior_college	-0.081	***	-0.084	***	-0.088	***	0.018		0.022		0.019		0.000		0.009		0.016		0.063	***	0.053	***	0.053	***
University	-0.113	***	-0.114	***	-0.105	***	0.050	***	0.050	***	0.035	***	0.004		0.008	*	0.021	***	0.059	***	0.056	***	0.048	***
Graduate	-0.187	***	-0.166	***	-0.143	***	0.083	***	0.066	***	0.042	***	0.005		0.008		0.017		0.099	***	0.092	***	0.085	***
S_Senior_high	-0.060	***	-0.065	***	-0.036	***	0.040	***	0.045	***	0.013		-0.004		-0.004		0.013		0.024	*	0.024	*	0.010	
S_Vocational_college	-0.081	***	-0.085	***	-0.056	***	0.049	***	0.054	***	0.023	*	0.000		-0.004		0.021	**	0.031	**	0.036	**	0.012	
S_Junior_college	-0.093	***	-0.103	***	-0.080	***	0.044	***	0.051	***	0.025	**	-0.003		-0.006		0.019	*	0.052	***	0.058	***	0.036	***
S_University	-0.105	***	-0.129	***	-0.099	***	0.050	***	0.068	***	0.040	***	-0.004		-0.001		0.018	*	0.059	***	0.062	***	0.041	***
S_Graduate	-0.106	**	-0.124	***	-0.065	*	0.044		0.050		0.011		-0.005		0.013		0.029		0.067	**	0.061	**	0.025	
No_spouse	0.020		0.012		0.042	**	0.007		0.015		-0.011		0.001		0.000		0.005		-0.028	*	-0.026		-0.036	**
Top20cities	-0.075	***	-0.097	***	-0.078	***	0.017	*	0.040	***	0.024	***	-0.003		0.001		0.011	*	0.060	***	0.056	***	0.043	***
Cities_40k_	-0.035	***	-0.045	***	-0.034	***	0.004		0.015	*	0.007		-0.003		0.000		0.004		0.034	***	0.029	***	0.023	***
Cities_20k_40k	0.010		-0.004		0.004		-0.014		0.001		-0.007		-0.002		0.001		-0.002		0.007		0.002		0.004	

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 9 Multinomial logit regression for transaction values of <5,000 yen

	Card & NCC		*Emoney NCC*		*Cash & CC*		*Card & CC*		*Emoney & CC*	
	1k - 5k	≤1k	1k - 5k	≤1k	1k - 5k	≤1k	1k - 5k	≤1k	1k - 5k	≤1k
Mattress deposit	0.167	-0.038	0.348	0.247	0.118	0.009	-0.108	-0.289	0.397	-0.026
H_size3	0.021	0.117	0.058	-0.139*	0.019	0.01	0.046	-0.068	-0.074	-0.055
H_size4	0.016	0.104	0.081	-0.037	0.021	0.024	0.052	0.014	0.038	-0.121
H_size5	-0.055	-0.093	0.099	-0.012	-0.133*	-0.114*	-0.150*	-0.193	-0.371**	-0.509***
H_size6	0.345	-0.039	-0.044	-0.261	-0.258	-0.128	0.089	-0.46	-0.261	-0.31
H_size_6_	-0.449**	0.143	-0.001	0.089	0.076	-0.021	-0.292	0.123	-0.145	-0.165
ln(Passengers km)	0.142***	0.150***	-0.041**	0.040**	0.046***	0.058***	0.154***	0.154***	-0.049**	0.071***
Income_200_260	0.092	0.261	0.114	0.292*	0.029	-0.06	-0.064	-0.06	0.159	0.402*
Income_260_300	0.231**	0.117	0.034	0.208	0.302***	0.310***	0.212*	-0.155	0.242	0.273
Income_300_370	0.256**	0.113	0.153	0.324**	0.385***	0.332***	0.253**	-0.156	0.465*	0.642***
Income_370_407	0.219**	0.274	-0.159	0.15	0.424***	0.437***	0.320***	0.012	0.400*	0.601***
Income_407_500	0.392***	0.408**	-0.055	0.227*	0.534***	0.463***	0.360***	0.1	0.562**	0.679***
Income_500_600	0.329***	0.219	0.205	0.288**	0.596***	0.556***	0.456***	0.135	0.658***	0.826***
Income_600_700	0.259**	-0.054	0.069	0.334**	0.644***	0.540***	0.422***	0.056	0.593**	0.967***
Income_700_900	0.253**	0.017	0.107	0.318**	0.646***	0.611***	0.524***	0.15	0.624***	0.877***
Income_900_	0.230**	0.094	0.23	0.476***	0.752***	0.697***	0.599***	0.302	0.938***	1.200***
Asset_0	-0.107	-0.084	-0.132	-0.055	-0.196**	-0.181***	-0.099	0.163	-0.276	-0.361**
Asset_110_270	-0.045	0.038	-0.063	0.048	0.172*	0.195**	0.318***	0.498**	0.196	0.115
Asset_270_430	0.082	0.051	-0.047	0.032	0.169*	0.198**	0.402***	0.575***	0.303	0.334**
Asset_430_600	0.039	0.111	-0.084	0.155	0.127	0.181**	0.427***	0.629***	0.115	0.337**
Asset_600_900	0.291**	0.244	0.350**	0.326**	0.286***	0.294***	0.484***	0.768***	0.467**	0.254
Asset_900_1200	0.320***	0.245	0.01	0.177	0.318***	0.287***	0.540***	0.759***	0.361*	0.488***
Asset_1200_1694	0.313***	0.396*	0.265	0.365**	0.291***	0.375***	0.721***	0.923***	0.625***	0.513***
Asset_1694_2400	0.380***	0.451**	0.018	0.261	0.231**	0.294***	0.633***	0.832***	0.409*	0.410**
Asset_2400_3900	0.529***	0.469**	0.555***	0.587***	0.337***	0.366***	0.716***	1.028***	0.337	0.448***
Asset_3900_	0.496***	0.427*	0.643***	0.638***	0.312***	0.397***	0.867***	1.125***	0.35	0.471***
Know_Dep_Ins	0.370***	0.363***	0.632***	0.511***	0.347***	0.428***	0.819***	0.891***	1.023***	1.096***
Hear_Dep_Ins	0.176***	0.235*	0.484***	0.350***	0.106**	0.190***	0.495***	0.663***	0.656***	0.679***
Lower_service_charge	0.310***	0.357***	0.509***	0.536***	0.325***	0.353***	0.591***	0.655***	0.523***	0.628***
Online_banking	0.664***	0.574***	0.654***	0.728***	0.813***	0.838***	1.296***	1.414***	1.270***	1.399***
Debt	0.237***	0.031	0.291***	0.288***	0.244***	0.184***	0.157***	0.066	0.246***	0.275***
Homeowner	0.120**	0.264**	-0.259***	-0.235***	0.061	0.103**	0.253***	0.367***	-0.012	0.026
Age35_39	0.113	-0.115	0.122	0.129	-0.225***	-0.176***	-0.098	-0.174	0.174	-0.097
Age40_44	0.065	-0.087	-0.168	-0.116	-0.502***	-0.471***	-0.376***	-0.530***	-0.093	-0.250**
Age45_49	0.151	-0.181	-0.002	0.066	-0.709***	-0.685***	-0.599***	-0.755***	-0.324**	-0.527***
Age50_54	0.062	-0.168	-0.038	-0.089	-0.877***	-0.827***	-0.820***	-1.155***	-0.778***	-0.985***
Age55_59	0.056	-0.214	-0.226	-0.340**	-1.241***	-1.223***	-1.202***	-1.311***	-0.943***	-1.352***
Age60_64	-0.220*	-0.147	-0.582***	-0.626***	-1.497***	-1.458***	-1.623***	-1.989***	-1.572***	-1.920***
Age65_69	-0.229*	-0.272	-0.730***	-0.907***	-1.637***	-1.583***	-1.852***	-2.452***	-2.388***	-2.668***
Age70_74	-0.234*	-0.259	-1.091***	-1.334***	-1.639***	-1.649***	-2.038***	-2.631***	-2.576***	-2.851***
Age75_	-0.542***	-0.775***	-1.526***	-1.594***	-1.889***	-1.988***	-2.580***	-3.072***	-3.014***	-3.192***
Male	-0.466***	-0.582**	-0.439***	-0.361**	-0.300***	-0.373***	-0.488***	-0.15	-0.3	-0.279
Full_time	0.087	-0.034	0.027	-0.025	0.094	0.065	-0.095	-0.354**	0.213	0.052
Part_time	0.041	-0.096	0.028	-0.013	0.098	0.035	-0.028	-0.09	0.034	0.062
Self_employed	-0.032	-0.031	-0.185	-0.272**	-0.243***	-0.249***	-0.399***	-0.566***	-0.204	-0.436**
Student	-0.089	0.486	-0.065	-0.508	0.173	0.068	-0.519	-0.818	-0.254	-0.388
S_Full_time	-0.086	0.127	-0.376***	-0.196**	-0.243***	-0.259***	-0.422***	-0.427***	-0.254**	-0.347***
S_Part_time	0.006	-0.038	-0.047	-0.059	-0.018	0.002	-0.044	-0.123	-0.231**	-0.205***
S_Self_employed	-0.294**	-0.499*	-0.197	-0.204	0.035	-0.013	-0.216*	-0.185	-0.303	-0.305*
S_Student	-1.504	-12.538***	-0.279	0.810*	-0.38	-0.065	0.011	0.467	-0.584	-0.471
Senior_high	0.143	0.504**	-0.113	-0.025	0.153*	0.177**	0.279**	0.104	-0.32	0.101
Vocational_college	0.132	0.588**	0.045	0.14	0.291***	0.355***	0.562***	0.361	0.022	0.465**
Junior_college	0.443***	0.774***	0.022	-0.002	0.476***	0.479***	0.721***	0.557**	0.178	0.580**
University	0.454***	0.733***	0.116	0.172	0.503***	0.476***	0.667***	0.484**	0.354	0.610***
Graduate	0.531***	0.725**	0.359	0.547***	0.600***	0.708***	1.034***	0.911***	0.780***	1.000***
S_Senior_high	0.298**	0.062	0.314*	0.321*	0.251**	0.231**	0.075	0.171	1.766***	0.321
S_Vocational_college	0.388***	0.181	0.674***	0.490**	0.374***	0.318***	0.18	0.314	1.829***	0.419
S_Junior_college	0.448***	0.115	0.466**	0.370*	0.493***	0.486***	0.364***	0.373	1.804***	0.334
S_University	0.485***	0.182	0.459**	0.440**	0.439***	0.446***	0.449***	0.518**	1.954***	0.660**
S_Graduate	0.526	0.173	0.125	0.820**	0.479*	0.556**	0.496*	0.514	2.134***	0.915**
No_spouse	-0.014	-0.202	0.057	0.187	-0.025	-0.159	-0.516***	0.016	1.492**	-0.053
Top20cities	0.287***	0.166	0.025	0.324***	0.339***	0.401***	0.535***	0.568***	0.449***	0.431***
Cities_40k_	0.154**	0.15	0.014	0.183*	0.178***	0.227***	0.258***	0.284**	0.320**	0.194*
Cities_20k_40k	-0.055	-0.027	-0.115	0.051	-0.03	0.021	0.002	0.044	0.071	-0.064
N									35896	35834
pseudoRsq									0.125	0.14
LLR									-36300.0	-30700.0

* p<0.10, ** p<0.05, *** p<0.01

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 10 Marginal effects for multinomial logit regression for transaction values of <5,000 yen

	Cash & NCC				*Card & NCC*				*Emoney NCC*				*Cash & CC*				*Card & CC*				*Emoney & CC*			
	1k –5k		≤1k		1k –5k		≤1k		1k –5k		≤1k		1k –5k		≤1k		1k –5k		≤1k		1k –5k		≤1k	
Mattress deposit	-0.020		-0.002		0.009		-0.001		0.010		0.010		0.009		0.002		-0.016		-0.008		0.007		-0.001	
H_size3	-0.005		0.003		0.001		0.002		0.002		-0.005	*	0.001		0.003		0.003		-0.002		-0.002		-0.002	
H_size4	-0.006		-0.001		0.000		0.002		0.002		-0.001		0.001		0.005		0.003		0.001		0.000		-0.005	
H_size5	0.019	**	0.024	***	-0.001		-0.001		0.005		0.002		-0.009		-0.007		-0.008		-0.003		-0.006	**	-0.016	***
H_size6	0.000		0.031		0.026	*	0.001		-0.001		-0.007		-0.029	*	-0.007		0.010		-0.010		-0.005		-0.007	
H_size_6_	0.029		-0.001		-0.028	**	0.003		0.002		0.004		0.018		-0.003		-0.020		0.004		-0.001		-0.006	
ln(Passengers km)	-0.015	***	-0.012	***	0.008	***	0.002	***	-0.002	***	0.000		0.001		0.005	***	0.011	***	0.003	***	-0.002	***	0.001	*
Income_200_260	-0.007		-0.010		0.006		0.004		0.003		0.010	*	0.002		-0.016		-0.008		-0.003		0.003		0.014	*
Income_260_300	-0.041	***	-0.039	***	0.010		0.001		-0.002		0.004		0.023	**	0.036	***	0.008		-0.008		0.002		0.006	
Income_300_370	-0.054	***	-0.051	***	0.010		0.000		0.001		0.007		0.029	***	0.034	***	0.008		-0.009	*	0.006		0.019	**
Income_370_407	-0.051	***	-0.060	***	0.007		0.003		-0.009	**	0.000		0.033	***	0.048	***	0.015	*	-0.005		0.005		0.016	**
Income_407_500	-0.071	***	-0.069	***	0.017	***	0.005		-0.008	*	0.002		0.041	***	0.048	***	0.013	*	-0.004		0.007		0.018	***
Income_500_600	-0.082	***	-0.080	***	0.010		0.001		0.000		0.003		0.044	***	0.058	***	0.019	**	-0.004		0.008	*	0.022	***
Income_600_700	-0.077	***	-0.078	***	0.006		-0.004		-0.004		0.005		0.051	***	0.056	***	0.017	*	-0.006		0.007		0.027	***
Income_700_900	-0.083	***	-0.085	***	0.004		-0.003		-0.003		0.004		0.049	***	0.065	***	0.025	***	-0.004		0.007		0.023	***
Income_900_	-0.097	***	-0.106	***	0.000		-0.002		-0.001		0.008		0.057	***	0.070	***	0.027	***	-0.002		0.013	***	0.033	***
Asset_0	0.026	***	0.024	**	-0.003		-0.001		-0.002		0.000		-0.015	**	-0.020	**	-0.002		0.007		-0.004		-0.011	**
Asset_110_270	-0.024	*	-0.030	**	-0.008		0.000		-0.004		-0.001		0.011		0.020	*	0.022	**	0.012	**	0.002		0.000	
Asset_270_430	-0.034	***	-0.035	***	0.000		0.000		-0.005		-0.003		0.008		0.017		0.027	***	0.013	**	0.004		0.008	
Asset_430_600	-0.028	**	-0.037	***	-0.002		0.001		-0.005		0.002		0.005		0.013		0.031	***	0.014	**	0.000		0.008	
Asset_600_900	-0.063	***	-0.055	***	0.011		0.002		0.006		0.007		0.013		0.026	**	0.027	***	0.017	***	0.005		0.002	
Asset_900_1200	-0.062	***	-0.054	***	0.013		0.002		-0.005		0.001		0.017	*	0.023	**	0.033	***	0.016	***	0.003		0.011	**
Asset_1200_1694	-0.075	***	-0.072	***	0.010		0.005		0.002		0.007		0.009		0.031	***	0.046	***	0.020	***	0.008	*	0.010	*
Asset_1694_2400	-0.063	***	-0.059	***	0.017	**	0.006		-0.005		0.004		0.006		0.023	**	0.041	***	0.018	***	0.004		0.008	
Asset_2400_3900	-0.090	***	-0.077	***	0.024	***	0.006		0.011	**	0.015	**	0.012		0.028	**	0.043	***	0.022	***	0.001		0.007	
Asset_3900_	-0.095	***	-0.083	***	0.020	**	0.005		0.013	**	0.017	***	0.006		0.030	***	0.055	***	0.025	***	0.000		0.007	
Know_Dep_Ins	-0.095	***	-0.090	***	0.010	**	0.003		0.012	***	0.010	***	0.009	*	0.030	***	0.049	***	0.016	***	0.015	***	0.030	***
Hear_Dep_Ins	-0.051	***	-0.051	***	0.004		0.002		0.011	***	0.008	***	-0.005		0.007		0.031	***	0.014	***	0.010	***	0.019	***
Lower_service_charge	-0.074	***	-0.071	***	0.010	**	0.004	*	0.010	***	0.014	***	0.014	***	0.027	***	0.034	***	0.012	***	0.006	***	0.015	***
Online_banking	-0.161	***	-0.150	***	0.021	***	0.005	*	0.008	**	0.013	***	0.043	***	0.073	***	0.075	***	0.026	***	0.015	***	0.033	***
Debt	-0.040	***	-0.031	***	0.011	***	-0.001		0.006	***	0.008	***	0.017	***	0.018	***	0.004		-0.001		0.003		0.007	***
Homeowner	-0.016	***	-0.014	**	0.006		0.004	**	-0.010	***	-0.011	***	0.002		0.011	**	0.019	***	0.009	***	-0.002		-0.001	
Age35_39	0.010		0.020	*	0.010		-0.001		0.005		0.007		-0.023	***	-0.021	***	-0.006		-0.003		0.005		-0.001	
Age40_44	0.049	***	0.062	***	0.014	*	0.001		-0.001		0.002		-0.043	***	-0.053	***	-0.021	***	-0.010	***	0.002		-0.001	
Age45_49	0.068	***	0.088	***	0.023	***	0.000		0.006		0.011	**	-0.060	***	-0.077	***	-0.035	***	-0.014	***	-0.001		-0.008	**
Age50_54	0.097	***	0.119	***	0.022	***	0.002		0.007		0.009	*	-0.070	***	-0.086	***	-0.047	***	-0.022	***	-0.009	**	-0.022	***
Age55_59	0.142	***	0.173	***	0.030	***	0.003		0.005		0.004		-0.098	***	-0.130	***	-0.070	***	-0.021	***	-0.009	**	-0.029	***
Age60_64	0.201	***	0.221	***	0.019	**	0.006		-0.002		-0.001		-0.109	***	-0.146	***	-0.092	***	-0.036	***	-0.018	***	-0.044	***
Age65_69	0.230	***	0.260	***	0.024	***	0.005		-0.004		-0.008		-0.115	***	-0.147	***	-0.103	***	-0.044	***	-0.033	***	-0.067	***
Age70_74	0.247	***	0.282	***	0.027	***	0.006		-0.014	**	-0.022	***	-0.109	***	-0.148	***	-0.116	***	-0.047	***	-0.035	***	-0.071	***
Age75_	0.312	***	0.340	***	0.016		-0.001		-0.023	***	-0.027	***	-0.117	***	-0.181	***	-0.148	***	-0.055	***	-0.040	***	-0.077	***
Male	0.072	***	0.059	***	-0.022	***	-0.009	*	-0.009	*	-0.009		-0.013		-0.039	***	-0.026	***	0.001		-0.001		-0.004	
Full_time	-0.008		-0.001		0.005		-0.001		0.000		-0.001		0.009		0.011		-0.011	*	-0.010	***	0.004		0.002	
Part_time	-0.008		-0.002		0.002		-0.002		0.000		-0.001		0.010		0.005		-0.005		-0.003		0.000		0.002	
Self_employed	0.040	***	0.047	***	0.005		0.001		-0.003		-0.006		-0.015	*	-0.020	**	-0.026	***	-0.012	**	-0.001		-0.010	
Student	0.020		0.017		-0.002		0.010		0.000		-0.017		0.029		0.023		-0.042		-0.021		-0.003		-0.011	
S_Full_time	0.047	***	0.040	***	0.002		0.004	*	-0.008	***	-0.003		-0.013	**	-0.025	***	-0.026	***	-0.008	***	-0.002		-0.008	***
S_Part_time	0.006		0.007		0.002		0.000		-0.001		-0.001		0.000		0.004		-0.002		-0.003		-0.004	**	-0.007	***
S_Self_employed	0.027	**	0.020		-0.017	**	-0.008	*	-0.004		-0.006		0.012		0.007		-0.013		-0.003		-0.005		-0.009	
S_Student	0.100		0.143	***	-0.097		-0.228	***	-0.002		0.042	**	-0.019		0.031		0.025		0.021		-0.007		-0.009	
Senior_high	-0.023	**	-0.026	**	0.007		0.008	**	-0.005		-0.003		0.011		0.020	*	0.020	**	0.001		-0.009	*	0.001	
Vocational_college	-0.050	***	-0.058	***	0.001		0.009	*	-0.003		0.000		0.017	*	0.035	***	0.038	***	0.005		-0.004		0.010	
Junior_college	-0.084	***	-0.074	***	0.018	**	0.011	**	-0.006		-0.008		0.029	**	0.049	***	0.044	***	0.009		-0.002		0.013	
University	-0.087	***	-0.077	***	0.019	**	0.011	***	-0.003		-0.001		0.032	***	0.047	***	0.038	***	0.007		0.001		0.014	*
Graduate	-0.121	***	-0.121	***	0.018		0.009		0.002		0.009		0.031	**	0.066	***	0.062	***	0.015	**	0.008		0.023	***
S_Senior_high	-0.054	***	-0.039	***	0.013		0.000		0.005		0.009		0.012		0.022	*	-0.010		0.001		0.034	***	0.007	
S_Vocational_college	-0.077	***	-0.056	***	0.016	*	0.001		0.015	**	0.014	*	0.019		0.029	**	-0.007		0.004		0.034	***	0.009	
S_Junior_college	-0.092	***	-0.069	***	0.017	*	0.000		0.007		0.008		0.029	**	0.053	***	0.006		0.005		0.032	**	0.004	
S_University	-0.095	***	-0.075	***	0.019	**	0.000		0.007		0.010		0.021	*	0.042	***	0.013		0.008		0.035	***	0.015	
S_Graduate	-0.097	**	-0.099	***	0.022		-0.001		-0.004		0.022	*	0.024		0.050	*	0.016		0.005		0.039	***	0.022	*
No_spouse	0.011		0.015		0.001		-0.003		0.002		0.009		0.000		-0.021		-0.048	***	0.002		0.033	**	0.000	
Top20cities	-0.062	***	-0.064	***	0.010	*	0.001		-0.004		0.006		0.019	***	0.039	***	0.032	***	0.010	***	0.005		0.008	*
Cities_40k_	-0.033	***	-0.036	***	0.006		0.001		-0.002		0.004		0.010		0.023	***	0.015	**	0.005		0.004		0.003	
Cities_20k_40k	0.006		-0.002		-0.003		-0.001		-0.003		0.002		-0.002		0.003		0.001		0.001		0.002		-0.003	

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 11 Conditional cash demand functions

	>50k		10k-50k		5k-10k		1k-5k		≤1k	
Mattress deposit	26.973	***	26.496	***	24.113	***	24.139	***	25.348	***
H_size3	-1.366	**	-1.417	**	-1.470	**	-1.864	***	-1.876	***
H_size4	-1.830	***	-1.850	**	-1.766	***	-2.023	***	-2.437	***
H_size5	-2.228	**	-1.965	**	-1.653	*	-2.375	**	-2.635	***
H_size6	0.085		0.838		-0.089		-0.504		-0.127	
H_size_6_	-1.470		-2.136		-1.239		-1.266		-2.183	
ln(Passengers km)	0.377	**	0.371	**	0.150		0.202		0.104	
Income_200_260	0.243		0.520		0.792		0.551		0.395	
Income_260_300	1.355		1.574		1.918	*	2.125	**	3.261	***
Income_300_370	1.194		1.855		1.863		2.236	*	3.749	***
Income_370_407	2.907	**	2.772	**	3.058	***	3.842	***	4.646	***
Income_407_500	3.018	***	3.161	***	3.058	***	3.240	**	4.123	***
Income_500_600	3.912	***	4.197	***	3.991	***	4.425	***	6.389	***
Income_600_700	5.371	***	5.926	***	5.516	***	6.356	***	8.997	***
Income_700_900	6.266	***	6.211	***	6.182	***	7.477	***	9.048	***
Income_900_	12.928	***	12.903	***	13.940	***	14.499	***	15.863	***
Asset_0	0.216		0.445		0.744		0.323		-0.411	
Asset_110_270	1.817		1.598		1.907		2.659	**	2.195	*
Asset_270_430	2.678	**	2.454	**	2.751	**	3.437	***	3.291	**
Asset_430_600	4.341	***	4.626	***	4.786	***	5.573	***	4.690	***
Asset_600_900	6.210	***	6.007	***	5.781	***	6.582	***	6.040	***
Asset_900_1200	3.508	***	2.987	**	2.821	**	2.968	**	3.657	***
Asset_1200_1694	3.858	***	3.621	***	2.973	**	4.162	***	4.123	***
Asset_1694_2400	6.839	***	6.570	***	6.123	***	6.219	***	6.159	***
Asset_2400_3900	9.285	***	8.251	***	8.788	***	8.937	***	8.567	***
Asset_3900_	16.724	***	16.858	***	16.408	***	17.060	***	16.589	***
Know_Dep_Ins	1.396	*	0.876		0.864		1.944	**	2.262	**
Hear_Dep_Ins	-0.085		-0.588		-0.376		0.482		0.223	
Lower_service_charge	-2.003	**	-1.956	**	-2.357	***	-1.782	*	-2.489	**
Online_banking	3.234	***	2.705	***	1.999	*	3.884	***	4.056	***
Debt	-2.174	***	-2.260	***	-2.875	***	-2.677	***	-1.139	*
Homeowner	1.167	*	1.046	*	0.997	*	1.403	**	0.539	
Age35_39	-0.416		-0.555		-0.755		-0.905		-0.659	
Age40_44	-0.405		-0.188		-0.825		-1.713		-1.637	
Age45_49	-0.591		-0.344		-0.823		-3.004		-2.538	
Age50_54	-0.411		0.177		-0.597		-2.633		-2.733	
Age55_59	0.958		1.336		0.896		-2.472		-2.654	
Age60_64	2.755		3.432		2.977		-0.624		-2.041	
Age65_69	5.092	**	6.266	***	5.065	*	0.748		-0.192	
Age70_74	5.249	**	6.364	***	5.502	**	0.359		-0.393	
Age75_	7.444	***	7.961	***	6.882	**	1.773		1.805	
Male	2.927	**	3.083	**	4.182	***	3.590	**	3.227	**
Full_time	0.428		-0.104		-0.098		-0.105		1.319	
Part_time	-1.442		-1.881	*	-0.884		-1.270		-0.203	
Self_employed	3.567	***	3.058	***	3.468	***	2.659	**	3.355	***
Student	18.090	***	14.919	***	14.241	***	10.981	***	16.317	***
S_Full_time	-1.126		-1.223		-1.213		-1.687	*	-2.226	**
S_Part_time	-1.133	*	-1.250	*	-1.550	**	-1.447	**	-1.364	**
S_Self_employed	2.941	**	3.764	***	3.528	***	3.382	**	3.982	***
S_Student	0.915		-1.717		0.252		3.670		-1.140	
Senior_high	-0.145		-0.495		-0.381		-0.800		-1.341	
Vocational_college	-0.434		-0.988		-0.631		-0.261		-1.037	
Junior_college	2.983	**	2.390		2.185		2.447		2.195	
University	-0.769		-1.194		-1.354		-1.196		-1.024	
Graduate	-2.173		-3.332	*	-3.337	*	-2.761		-2.830	
S_Senior_high	0.792		0.183		0.308		0.265		1.781	*
S_Vocational_college	0.473		0.008		0.005		-0.016		1.515	
S_Junior_college	1.118		0.171		-0.072		0.335		1.925	
S_University	1.832		0.706		0.466		0.929		2.603	*
S_Graduate	-0.320		0.638		1.282		-0.773		0.797	
No_spouse	3.674	**	3.032	**	3.537	**	2.480	*	3.660	**
Top20cities	1.242		0.792		0.581		0.963		1.428	
Cities_40k_	0.456		0.081		0.193		0.063		0.181	
Cities_20k_40k	0.048		0.031		0.328		0.540		-0.427	
uij(Cash & NCC)Cash & NCC	-0.005		-0.003		-0.005		0.018		0.003	
uij(Cash & NCC)Cash & CC	0.000		0.000		0.005		0.015		0.050	*
uij(Cash & NCC)Card & NCC	-0.059	***	-0.060	***	-0.078	**	-0.128	**	-0.194	**
uij(Cash & NCC)Card & CC	-0.009		-0.006		-0.009		0.077	*	-0.040	
uij(Cash & NCC)Emoney & NCC							-0.010		-0.002	
uij(Cash & NCC)Emoney & CC							0.044		0.054	
uij(Cash & CC)Cash & NCC	-0.014		-0.015		-0.023		-0.018		0.021	
uij(Cash & CC)Cash & CC	-0.006		-0.003		-0.007		-0.006		0.003	
uij(Cash & CC)Card & NCC	-0.043		-0.030		-0.048		-0.034		-0.081	
uij(Cash & CC)Card & CC	-0.030		-0.026		-0.010		0.030		0.015	
uij(Cash & CC)Emoney & NCC							-0.028		-0.031	
uij(Cash & CC)Emoney & CC							-0.017		0.058	*
uij(Card & NCC)Cash & NCC	-0.020	***	-0.015	*	-0.015		-0.035	*	-0.086	
uij(Card & NCC)Cash & CC	-0.033		-0.024		-0.020		0.003		0.000	
uij(Card & NCC)Card & NCC	-0.007	**	-0.006		-0.006		-0.011	**	-0.020	
uij(Card & NCC)Card & CC	-0.015	*	-0.016		-0.013		-0.005		-0.026	
uij(Card & NCC)Emoney & NCC							0.009		0.017	
uij(Card & NCC)Emoney & CC							-0.063		-0.080	
uij(Card & CC)Cash & NCC	-0.009		-0.003		0.008		-0.001		0.023	
uij(Card & CC)Cash & CC	-0.029		-0.043		-0.033		-0.001		0.021	
uij(Card & CC)Card & NCC	-0.012		-0.011		-0.003		0.011		0.028	
uij(Card & CC)Card & CC	-0.001		-0.001		0.002		0.001		0.005	
uij(Card & CC)Emoney & NCC							-0.041	*	-0.067	*
uij(Card & CC)Emoney & CC							0.031		0.037	
uij(Emoney & NCC)Cash & NCC							-0.004		0.004	
uij(Emoney & NCC)Cash & CC							0.001		0.013	
uij(Emoney & NCC)Card & NCC							-0.032		-0.042	
uij(Emoney & NCC)Card & CC							0.019		-0.008	
uij(Emoney & NCC)Emoney & NCC							-0.001		0.000	
uij(Emoney & NCC)Emoney & CC							-0.001		0.017	
uij(Emoney & CC)Cash & NCC							0.008		-0.005	
uij(Emoney & CC)Cash & CC							-0.014		0.020	
uij(Emoney & CC)Card & NCC							-0.024		-0.007	
uij(Emoney & CC)Card & CC							0.031		0.012	
uij(Emoney & CC)Emoney & NCC							-0.024		-0.008	
uij(Emoney & CC)Emoney & CC							0.000		0.000	
N	34569		35513		34892		35896		35834	
Adjusted Rsq	0.047		0.046		0.046		0.046		0.046	

* p<0.10, ** p<0.05, *** p<0.01

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Appendix Table 12 Results for the propensity-score matching

Goodness of fit statistics for the Logit models

	Card & CC vs Cash & NCC				
	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
N	21,170	23875	26,915	26,940	25,973
pseudoRsq	0.328	0.31	0.268	0.245	0.17
LLR	-9470.106	-10414.46	-10005.99	-7974.523	-3636.369
% correctly classified	79.24%	79.79%	83.88%	88.35%	96.00%
Area under ROC curve	0.8603	0.8533	0.8393	0.8348	0.8051

Notes: The row labeled N provides the sample size of the logistic treatment model.
The low labelled pseudoRsq and LLR report the pseudo R2 and the log-likelihood ratio respectively.
The low labelled % correctly classified reports the percentage of observations correctly classified.
The low labelled Area under ROC curve reports the area under the ROC curve.

Propensity-score matching

	Card & CC vs Cash & NCC				
	>50k	10k - 50k	5k - 10k	1k - 5k	≤1k
ATE: Psmatch	-2.488***	-2.932***	-2.712***	-3.390***	-2.894
	(0.895)	(0.797)	(0.752)	(0.985)	(3.439)
ATE: IPW	-3.450***	-3.719***	-2.913***	-2.905***	-2.044
	(0.835)	(0.685)	(0.706)	(0.788)	(1.856)
ATET: Psmatch	-1.062	-2.586*	-1.868*	-4.001***	-2.971*
	(1.281)	(1.368)	(0.982)	(1.355)	(1.784)
ATET: IPW	-3.261**	-3.241***	-2.785***	-2.862***	-2.916**
	(1.427)	(1.200)	(0.888)	(0.936)	(1.373)

Note: Standard errors in parentheses. Cash is in units of 10,000 yen.
Psmatch stands for propensity-score matching and IPW stands for inverse probability weight.
* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 13 Logit models to compute propensity score

	>50k	10k-50k	5k-10k	1k-5k	≤1k
Mattress deposit	-0.252	-0.114	-0.303*	-0.18	-0.367
H_size3	-0.017	0.021	-0.012	0.027	0.052
H_size4	-0.012	-0.016	0.001	0.047	0.133
H_size5	-0.234***	-0.217***	-0.300***	-0.162**	-0.148
H_size6	-0.076	-0.132	-0.013		-0.414*
H_size_6_	-0.313**	-0.194	-0.305**	-0.236**	
ln(Passengers km)	0.093***	0.116***	0.138***	0.160***	
Income_200_260	-0.087	-0.058	-0.039	-0.075	
Income_260_300	0.297***	0.315***	0.234**	0.229**	
Income_300_370	0.335***	0.386***	0.363***	0.253**	
Income_370_407	0.514***	0.461***	0.449***	0.368***	
Income_407_500	0.655***	0.575***	0.464***	0.405***	0.199**
Income_500_600	0.743***	0.692***	0.579***	0.509***	0.268**
Income_600_700	0.850***	0.758***	0.602***	0.428***	0.064
Income_700_900	0.864***	0.805***	0.664***	0.574***	0.189
Income_900_	1.185***	1.035***	0.816***	0.646***	0.244*
Asset_0	-0.178**	-0.204***	-0.201**	-0.224***	
Asset_110_270	0.392***	0.366***	0.333***	0.205**	0.466***
Asset_270_430	0.329***	0.282***	0.360***	0.306***	0.445***
Asset_430_600	0.355***	0.326***	0.315***	0.340***	0.431***
Asset_600_900	0.670***	0.583***	0.443***	0.335***	0.571***
Asset_900_1200	0.573***	0.530***	0.516***	0.442***	0.548***
Asset_1200_1694	0.618***	0.606***	0.619***	0.591***	0.693***
Asset_1694_2400	0.568***	0.483***	0.510***	0.548***	0.494***
Asset_2400_3900	0.662***	0.581***	0.664***	0.631***	0.727***
Asset_3900_	0.731***	0.639***	0.709***	0.791***	0.768***
Know_Dep_Ins	0.543***	0.647***	0.698***	0.806***	0.692***
Hear_Dep_Ins	0.283***	0.292***	0.369***	0.482***	0.446***
Lower_service_charge	0.543***	0.571***	0.551***	0.560***	
Online_banking	1.455***	1.362***	1.250***	1.241***	1.609***
Debt	0.517***	0.377***	0.182***	0.204***	0.154*
Homeowner	0.108**	0.165***	0.186***		0.053
Age35_39	-0.026	-0.066	-0.135*	-0.076	0.830***
Age40_44	-0.258***	-0.327***	-0.377***	-0.375***	0.639***
Age45_49	-0.439***	-0.521***	-0.587***	-0.503***	0.496***
Age50_54	-0.695***	-0.765***	-0.809***	-0.723***	0.158
Age55_59	-1.244***	-1.280***	-1.228***	-1.076***	0.044
Age60_64	-1.517***	-1.543***	-1.604***	-1.481***	-0.222*
Age65_69	-1.808***	-1.911***	-1.874***	-1.694***	
Age70_74	-1.976***	-2.056***	-2.064***	-1.901***	
Age75_	-2.459***	-2.417***	-2.356***	-2.452***	
Male	-0.575***	-0.543***	-0.458***	-0.443***	-0.287
Full_time	0.065	0.038	0.017	-0.09	0.471***
Part_time	0.002	-0.028	0.03	-0.074	
Self_employed	-0.385***	-0.429***	-0.409***	-0.419***	
Student	0.074	0.144	-0.075	-0.557	-0.036
S_Full_time	-0.284***	-0.320***	-0.447***	-0.486***	
S_Part_time	-0.049	-0.002	-0.07	-0.047	0.073
S_Self_employed	-0.032	-0.081	-0.200*	-0.298**	-0.125
S_Student	-0.209	-0.093	-0.014	0.057	0.576
Senior_high	0.152*	0.131	0.202**	0.303**	
Vocational_college	0.474***	0.406***	0.513***	0.585***	0.453***
Junior_college	0.701***	0.648***	0.649***	0.797***	0.569***
University	0.737***	0.654***	0.622***	0.661***	0.507***
Graduate	1.224***	1.054***	0.996***	1.002***	0.956***
S_Senior_high	0.354***	0.356***	0.181	0.059	0.149
S_Vocational_college	0.441***	0.462***	0.240*	0.137	0.368**
S_Junior_college	0.681***	0.707***	0.499***	0.326**	0.424**
S_University	0.725***	0.804***	0.581***	0.434***	0.731***
S_Graduate	0.847***	0.820***	0.416*	0.329	0.730*
No_spouse	-0.254*	-0.175	-0.428***	-0.569***	0.113
Top20cities	0.580***	0.606***	0.532***	0.523***	0.418***
Cities_40k_	0.283***	0.273***	0.286***	0.282***	
Cities_20k_40k	-0.012	0.01	0.036	0.039	
N	21170	23875	26915	26940	25973
pseudoRsq	0.328	0.31	0.268	0.245	0.17
LLR	-9470.106	-10414.46	-10005.99	-7974.523	-3636.369
% correctly classified	79.24%	79.79%	83.88%	88.35%	96.00%
Area under ROC curve	0.8603	0.8533	0.8393	0.8348	0.8051

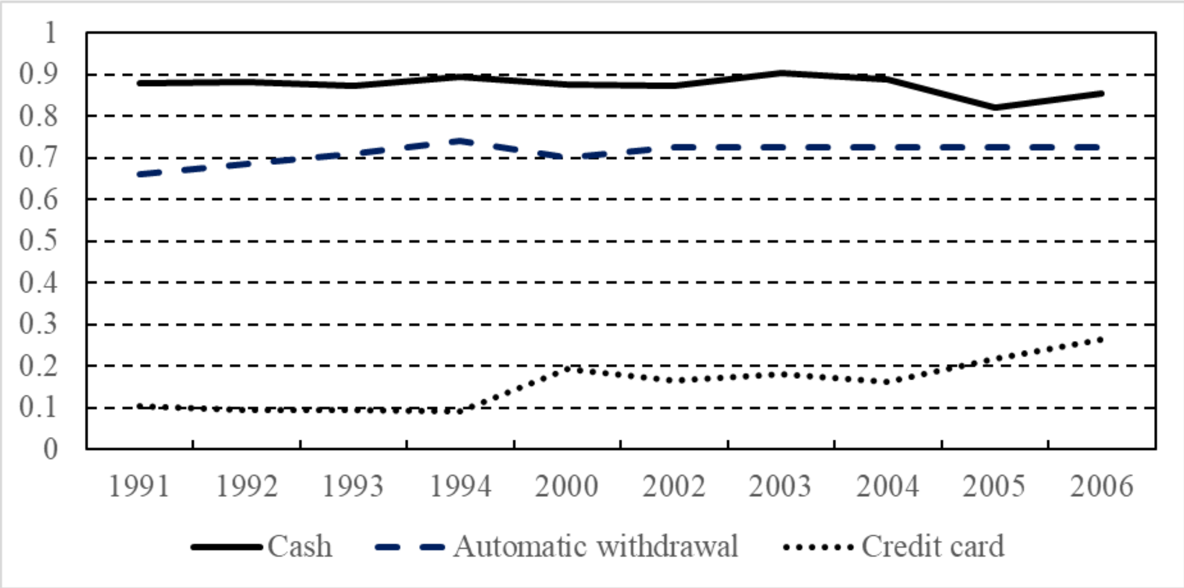
Notes: If some variables have an absolute value of standardized difference after matching of more than 0.1, we drop the variable with the largest absolute value of the standardized difference and match again using the remaining common covariates as explanatory variables. We continue until all of the absolute values of the standardized differences after matching are less than 0.1. We do not report the results for dummy variables for observation years, constant and non-available observations.

Appendix Table 14 Standardized difference

	>50k	10k-50k	5k-10k	1k-5k	≤1k
Mattress deposit	0.009	0.022	0.014	0.011	-0.017
H_size3	0.022	0.002	-0.006	0.011	0.033
H_size4	0.003	0.014	-0.002	0.003	0.053
H_size5	0.010	0.011	0.030	0.051	0.032
H_size6	0.041	0.056	0.094		0.009
H_size_6_	0.048	0.062	0.061	0.081	
ln(Passengers km)	0.003	0.009	-0.003	0.034	
Income_200_260	0.024	0.019	0.009	-0.016	
Income_260_300	-0.004	0.009	0.000	0.023	
Income_300_370	0.006	0.008	-0.016	-0.016	
Income_370_407	0.002	0.008	0.015	0.042	
Income_407_500	0.026	0.031	0.037	0.001	-0.006
Income_500_600	0.001	-0.007	-0.026	-0.037	0.004
Income_600_700	-0.009	-0.013	-0.014	-0.014	0.005
Income_700_900	-0.002	-0.004	-0.005	0.001	-0.041
Income_900_	0.032	0.025	0.032	0.071	0.031
Asset_0	0.006	0.004	-0.014	-0.034	
Asset_110_270	-0.007	0.006	0.013	-0.005	-0.017
Asset_270_430	-0.015	-0.016	-0.035	-0.031	-0.006
Asset_430_600	0.008	0.008	0.024	0.037	0.006
Asset_600_900	0.021	-0.003	-0.005	-0.010	-0.015
Asset_900_1200	-0.007	-0.019	0.004	-0.021	0.013
Asset_1200_1694	-0.019	-0.008	-0.015	-0.004	0.019
Asset_1694_2400	-0.020	-0.018	-0.029	-0.027	-0.084
Asset_2400_3900	0.005	0.020	0.008	-0.011	-0.005
Asset_3900_	0.008	0.002	0.018	0.034	0.036
Know_Dep_Ins	0.009	-0.002	-0.001	0.018	0.036
Hear_Dep_Ins	-0.022	-0.025	0.007	-0.013	-0.012
Lower_service_charge	0.017	0.013	0.015	0.021	
Online_banking	0.002	-0.006	0.003	0.009	0.028
Debt	0.023	0.040	0.017	0.022	0.028
Homeowner	-0.028	-0.027	-0.049		-0.052
Age35_39	-0.001	0.003	0.005	0.009	0.020
Age40_44	-0.023	-0.018	-0.002	0.001	-0.023
Age45_49	0.018	0.014	-0.014	-0.006	0.047
Age50_54	-0.006	0.001	-0.003	-0.005	0.026
Age55_59	0.003	-0.006	-0.025	0.010	-0.026
Age60_64	-0.016	-0.003	0.014	0.018	0.032
Age65_69	-0.017	-0.016	-0.016	-0.014	
Age70_74	0.015	0.008	-0.031	-0.052	
Age75_	0.010	0.005	0.054	0.037	
Male	0.015	0.011	-0.004	-0.015	0.025
Full_time	-0.013	-0.019	-0.033	-0.025	0.011
Part_time	0.009	0.020	0.026	0.027	
Self_employed	-0.020	-0.016	0.021	0.035	
Student	-0.007	-0.010	-0.024	-0.037	-0.063
S_Full_time	0.010	0.009	0.008	-0.001	
S_Part_time	-0.001	0.004	0.003	0.010	0.016
S_Self_employed	0.000	-0.003	0.002	-0.040	-0.067
S_Student	-0.001	0.006	0.000	-0.006	-0.028
Senior_high	-0.006	-0.010	-0.025	-0.032	
Vocational_college	-0.012	-0.001	0.020	0.033	-0.005
Junior_college	0.009	0.001	-0.004	-0.008	-0.033
University	-0.010	0.003	0.016	0.037	0.056
Graduate	0.017	-0.008	-0.013	-0.004	0.015
S_Senior_high	-0.036	-0.025	-0.046	-0.036	0.028
S_Vocational_college	0.010	0.015	0.030	-0.009	0.015
S_Junior_college	0.001	-0.002	0.003	0.031	0.051
S_University	0.017	0.010	-0.007	-0.011	0.022
S_Graduate	0.012	0.007	-0.004	-0.002	0.009
No_spouse	0.020	0.033	0.056	0.078	-0.058
Top20cities	-0.019	-0.006	-0.016	-0.001	0.005
Cities_40k_	0.009	0.006	0.005	0.046	
Cities_20k_40k	0.003	-0.002	0.013	-0.061	

Note: We do not report the results for dummy variables for observation years, constant and nonavailable observations.

Figure 1 Proportion of observations for payment method choice for all payments (choose up to two out of five choices)



Appendix 2 Details of replication of Fujiki and Tanaka

Appendix 2 reports the coding errors in the Stata programs for Fujiki and Tanaka (2018). The author made these careless coding errors while he was running the Stata programs by himself, hence the coauthor did not have the opportunity to correct them. Fortunately, these corrections have not changed the main conclusion of the paper, even though they affect the parameter estimates. The author made three kinds of errors as below.

First, the author failed to include dummy variables to control for those households that did not report age, education, job status, or the education and job status of the spouse of a household head, those that did not answer the questions on making mattress deposits and whether the household places an emphasis on lower service charges and online banking services in selecting financial institutions, and those that did not respond about whether the household head has a spouse. Together, these comprised the following variables: age_NA, Education_NA, job_NA, S_Education_NA, and S_job_NA, Mattress_NA, Banking_NA, and No_spouse. Second, the author made some coding errors in computing the dummy variable for persons aged over 74 years in that the author only included people aged over 75 (coded age > 75, rather than age >= 75). This involved the proportion of the sample aged over 74 years being 0.098 instead of 0.087. Third, the author made coding errors in computing the standard errors in the second column labeled 50k-in Table 5 on p. 95. If done correctly, the standard errors would have been much smaller and more variables would have been statistically significant.

Together, these inadvertent errors affected the estimation results reported in Tables 3–8, as shown in the revised tables.

Table 3 is now corrected as "Table 3, Revised" in Appendix Table 15 with any changes shown in red. The mean value of age_75 has been corrected, and the mean values of the additional dummies age_NA, Education_NA, S_Education_NA, job_NA, S_job_NA, Mattress_NA, Banking_NA, and No_spouse are now reported.

Regarding the results for the multinomial logit estimation in Revised Table 4 (Appendix Table 16), while the size of the parameter estimates was quite like those reported in the paper, the statistical significance of the estimates of the dummy variables for age, job-status, and education vary. In the revised table, the dummy variables for ages 35 through 49 and those for full-time worker (Fulltime) are not statistically significant. However, the dummy variables for age_NA, Education_NA, S_Education_NA, S_job_NA, and No_spouse become statistically significant for at least some transaction value ranges.

Regarding the results for cash demand in Revised Tables 5 and 6 (Appendix Table 17 and Appendix Table 18), while the overall results are largely the same, the statistical significance of the estimates of some dummy variables, especially those for gender and job status, vary between the tables. In the revised tables, the dummy variables for male household head (Male) and self-employed spouse of the household head (S_selfemployed) for some transaction value ranges, and those for a household without a spouse (No_spouse) have become statistically significant for all transaction value ranges, while those for full-time working spouse of the household head (S_Fulltime) have become statistically significant only for transaction values between 1,000 and 5,000 yen. In addition, the dummy variable for knowledge about the Japanese Deposit Insurance Corporation (Know Deposit Insurance) is not statistically insignificant for transaction values between 5,000 and 10,000 yen in the revised Table 6.

Regarding the forecasts based on cash demand in the revised Table 7 (Appendix Table 19), the results are almost identical to the original results. Regarding the results of the propensity-score matching in the revised Table 8 (Appendix Table 20), the sizes of the estimates of the ATEs using propensity score matching (reported in the rows labelled as ATE: Psmatch) for transaction values more than 10,000 yen have decreased slightly. However, the qualitative nature of the results is unchanged. Appendix Table 21 reports the errata list for the main text of Fujiki and Tanaka (2018).

Appendix Table 15 Revised Table 3 for Fujiki and Tanaka (2018)

	Mean
Know Deposit Insurance	0.414
Heard of Deposit Insurance	0.393
Lower service charges	0.093
Online banking	0.076
Debt	0.420
Homeowner	0.726
age35_39	0.082
age40_44	0.096
age45_49	0.097
age50_54	0.107
age55_59	0.118
age60_64	0.129
age65_69	0.108
age70_74	0.085
age75_	0.098
Male	0.926
Full-time	0.535
Part-time	0.063
Self-employed	0.135
Student	0.003
S_Full-time	0.149
S_Part-time	0.245
S_Self-employed	0.049
S_Student	0.001
Senior high	0.398
Vocational college	0.073
Junior college	0.037
University	0.262
Graduate	0.026
S_Senior high	0.401
S_Vocational college	0.088
S_Junior college	0.133
S_University	0.102
S_Graduate	0.004
Top20cities	0.231
Cities_40k_	0.401
Cities_20k_40k	0.250
age_NA	0.003
Education_NA	0.085
S_Education_NA	0.076
job_NA	0.044
S_job_NA	0.055
Mattress_NA	0.004
Banking_NA	0.002
No_spouse	0.105
N	27003

Appendix Table 16 Revised Table 4 for Fujiki and Tanaka (2018)

	50k -	10k - 50k	5k - 10k	1k - 5k	less 1k
Mattress Deposit	-0.17	-0.072	-0.243*	-0.183	-0.366
Household size	-0.026**	-0.030**	-0.032**	-0.042***	-0.038
ln(Passengers km)	0.046***	0.088***	0.123***	0.140***	0.142***
income_0	0.097	0.17	-0.116	0.078	0.439
income_200_260	0.094	0.05	-0.122	-0.052	-0.017
income_260_301	0.283***	0.221***	0.053	0.102	-0.279
income_301_370	0.349***	0.356***	0.155*	0.119	-0.157
income_370_410	0.519***	0.448***	0.175**	0.1	-0.11
income_410_500	0.639***	0.556***	0.237**	0.246**	0.051
income_500_600	0.562***	0.476***	0.192**	0.177*	-0.003
income_600_700	0.618***	0.542***	0.308***	0.186*	-0.127
income_700_900	0.725***	0.649***	0.320***	0.225**	-0.14
income_900_	0.848***	0.763***	0.283***	0.141	-0.066
income_NA	0.228***	0.229***	0.008	0	-0.282
asset_0	-0.104**	-0.141***	-0.269***	-0.196***	-0.093
asset_250_404	-0.019	-0.028	-0.023	0.052	0
asset_404_600	0.125*	0.162**	0.062	0.056	0.113
asset_600_870	0.306***	0.247***	0.159**	0.214***	0.276*
asset_870_1180	0.220***	0.214***	0.232***	0.227***	0.222
asset_1180_1620	0.179***	0.196***	0.285***	0.354***	0.409***
asset_1620_2350	0.243***	0.220***	0.287***	0.344***	0.430***
asset_2350_3800	0.291***	0.243***	0.381***	0.426***	0.520***
asset_3800_	0.369***	0.423***	0.462***	0.552***	0.533***
asset_NA	0.052	-0.001	-0.087	0.016	0.125
Know Deposit Insurance	0.266***	0.393***	0.451***	0.531***	0.517***
Heard of Deposit Insurance	0.181***	0.200***	0.269***	0.350***	0.418***
Lower service charges	0.317***	0.364***	0.367***	0.379***	0.393***
Online banking	0.880***	0.866***	0.786***	0.758***	0.755***
Debt	0.563***	0.420***	0.249***	0.137***	-0.019
Homeowner	-0.023	0.03	0.075*	0.147***	0.220**
age35_39	0.1	0.025	0.063	0.123	0.071
age40_44	0.075	-0.011	0.009	0.004	-0.081
age45_49	0.044	-0.089	-0.111	-0.008	-0.143
age50_54	-0.098	-0.245***	-0.225***	-0.138	-0.347**
age55_59	-0.406***	-0.495***	-0.412***	-0.240***	-0.360**
age60_64	-0.572***	-0.694***	-0.654***	-0.545***	-0.544***
age65_69	-0.718***	-0.916***	-0.796***	-0.686***	-0.986***
age70_74	-0.891***	-1.067***	-0.919***	-0.776***	-0.906***
age75_	-1.122***	-1.218***	-1.147***	-1.146***	-1.480***
Male	-0.477***	-0.460***	-0.440***	-0.374***	-0.208
Fulltime	0.049	0.034	0.007	0.047	-0.184
Parttime	0.03	0.065	-0.01	-0.026	-0.259
Selfemployed	-0.142**	-0.167***	-0.211***	-0.106	-0.191
Student	0.317	0.107	-0.072	-0.38	0.135
S_Fulltime	-0.073	-0.139***	-0.238***	-0.230***	-0.122
S_Parttime	0.033	0.055	-0.006	-0.008	-0.07
S_Selfemployed	-0.134*	-0.246***	-0.241***	-0.318***	-0.449**
S_Student	-0.078	-0.169	-0.285	-0.093	-0.689
Seniorhigh	0.088	0.071	0.170**	0.197**	0.265
Vocationalcollege	0.277***	0.246***	0.401***	0.356***	0.432**
Juniorcollege	0.367***	0.333***	0.426***	0.486***	0.439*
University	0.554***	0.544***	0.496***	0.462***	0.454**
Graduate	0.939***	0.799***	0.838***	0.755***	0.635***
S_Seniorhigh	0.377***	0.352***	0.198**	0.171	0.147
S_Vocationalcollege	0.512***	0.485***	0.295***	0.299**	0.400*
S_Juniorcollege	0.535***	0.543***	0.421***	0.368***	0.255
S_University	0.629***	0.662***	0.521***	0.458***	0.389*
S_Graduate	0.663**	0.430*	0.256	0.452*	-0.059
yeard2007	-0.543***	-0.638***	-0.628***	-0.646***	-0.802***
yeard2008	-0.534***	-0.649***	-0.699***	-0.690***	-0.804***
yeard2009	-0.371***	-0.484***	-0.463***	-0.501***	-0.727***
yeard2010	-0.291***	-0.443***	-0.353***	-0.373***	-0.441***
yeard2011	-0.246***	-0.318***	-0.275***	-0.310***	-0.417***
yeard2012	-0.191***	-0.251***	-0.310***	-0.332***	-0.343***
yeard2013	-0.035	-0.136**	-0.085	-0.149**	-0.211*
Top20cities	0.388***	0.464***	0.364***	0.373***	0.371***
Cities_40k_	0.162***	0.188***	0.161***	0.170**	0.234*
Cities_20k_40k	-0.06	-0.036	-0.039	0.006	0.069
Constant	-0.024	-0.091	-0.679***	-1.537***	-2.787***
age_NA	-0.057	-0.214	-0.479	-0.809*	-16.499***
Education_NA	0.333***	0.310***	0.338***	0.445***	0.37
S_Educatio_NA	0.193*	0.212*	0.067	-0.069	0.234
job_NA	-0.101	0.032	-0.079	0.061	-0.05
S_job_NA	-0.112	-0.172**	-0.193**	-0.300***	0.006
Mattress_NA	0.126	0.243	-0.041	-0.325	-0.305
Banking_NA	-0.561*	-0.398	-0.147	-0.172	0.152
No_spouse	-0.071	-0.086	-0.265**	-0.206	0.117
N	26810	27003	26784	26826	26583
pseudoRsq	0.132	0.145	0.126	0.117	0.120
LLR	-20469.68	-19289.34	-17518.66	-15792.00	-10048.17

* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 17 Revised Table 5 for Fujiki and Tanaka (2018)

	50k-		10k-50k		5k-10k		1k-5k		less1k	
Mattress deposit	26.792	***	25.754	***	23.543	***	24.039	***	23.437	***
h_size	-0.014		0.000		-0.047		-0.321		-0.338	
ln(Passengers km)	0.212		0.322	*	0.300		0.683	**	0.757	***
income_0	-0.719		-1.023		-0.852		-1.049		-0.102	
income_200_260	-0.775		-0.967		-0.112		0.447		0.509	
income_260_301	-0.172		0.653		1.404		1.938		1.674	
income_301_370	-0.972		-0.115		0.969		1.146		1.503	
income_370_410	-0.780		0.638		1.621		1.777		2.010	
income_410_500	-0.832		0.318		1.190		1.896		2.142	
income_500_600	0.722		1.325		3.004	**	3.734	***	3.281	**
income_600_700	0.812		1.683		3.050	**	3.854	***	4.102	***
income_700_900	1.760		3.658	**	4.430	***	5.049	***	5.035	***
income_900_	7.757	***	9.715	***	11.258	***	11.189	***	11.633	***
income_NA	-0.400		-0.086		0.863		0.554		0.384	
asset_0	0.190		-0.049		-0.191		-1.193		-1.060	
asset_250_404	1.622		2.015		2.940	**	2.471	**	2.731	**
asset_404_600	3.525	***	4.403	***	4.193	***	4.432	***	4.952	***
asset_600_870	5.707	***	6.002	***	5.712	***	7.375	***	6.463	***
asset_870_1180	2.572	*	2.673	**	2.901	**	3.167	**	3.745	***
asset_1180_1620	2.792	**	3.538	***	3.228	***	4.393	***	5.020	***
asset_1620_2350	5.031	***	5.644	***	5.935	***	6.590	***	7.153	***
asset_2350_3800	7.649	***	7.735	***	8.367	***	9.765	***	9.743	***
asset_3800_	16.176	***	16.854	***	17.547	***	18.951	***	18.153	***
asset_NA	0.489		1.058		1.722		1.351		2.209	*
Know Deposit Insurance	0.713		1.672	*	1.629	*	3.521	***	4.187	***
Heard of Deposit Insurance	-0.392		-0.304		0.010		1.367		1.862	**
Lower service charges	-2.281	**	-1.665	*	-2.102	**	-1.142		-1.373	
Online banking	0.585		1.451		1.345		3.625	**	3.630	**
Debt	0.231		-1.012		-1.312	**	-0.692		-0.570	
Homeowner	0.626		1.002		1.050		1.313	*	0.913	
age35_39	-0.304		-0.986		-0.889		-0.503		-0.860	
age40_44	0.462		-0.937		-1.220		-1.112		-1.299	
age45_49	0.300		-1.511		-1.248		-1.151		-1.378	
age50_54	1.713		0.004		-0.430		-0.005		-1.018	
age55_59	2.990	*	1.631		1.310		0.832		-0.481	
age60_64	5.543	***	4.046	**	3.377	**	1.559		0.648	
age65_69	7.007	***	6.248	***	5.545	***	3.005		1.205	
age70_74	8.381	***	6.490	***	4.401	**	1.641		0.525	
age75_	10.348	***	7.454	***	5.918	***	2.718		1.324	
Male	3.335	**	2.389	*	3.320	**	1.982		2.037	
Fulltime	0.528		0.228		0.497		1.118		1.210	
Parttime	-0.544		-1.710		-0.922		-0.836		-0.606	
Selfemployed	4.112	***	3.497	***	4.205	***	3.924	***	3.952	***
Student	17.822	***	16.774	***	15.246	***	15.984	***	16.296	***
S_Fulltime	-0.798		-1.171		-1.373		-1.904	**	-1.359	
S_Parttime	-1.303	*	-1.724	**	-1.863	***	-1.761	**	-1.854	***
S_Selfemployed	2.567	*	2.679	**	2.619	*	0.831		1.246	
S_Student	12.171		5.676		2.850		0.392		1.216	
Seniorhigh	-0.835		-1.284		-1.040		-1.330		-0.771	
Vocationalcollege	-1.422		-2.285	*	-1.692		-1.592		-0.556	
Juniorcollege	0.786		0.667		0.259		1.011		1.444	
University	-2.325	*	-2.252	*	-1.851		-1.241		-0.480	
Graduate	-4.191	**	-5.145	**	-4.568	**	-2.835		-3.066	
S_Seniorhigh	0.535		1.521		1.201		2.072	*	2.278	**
S_Vocationalcollege	-0.167		1.476		0.802		2.313		2.261	
S_Juniorcollege	-0.029		1.864		1.669		2.875	**	2.200	
S_University	0.950		1.788		1.633		2.925	*	3.086	**
S_Graduate	0.938		2.983		3.909		0.388		0.014	
yeard2007	-0.537		-3.535	**	-3.661	*	-5.858	***	-6.992	***
yeard2008	-0.255		-3.024	**	-3.115		-5.112	**	-6.775	***
yeard2009	-1.896		-4.216	***	-4.384	**	-6.187	***	-7.454	***
yeard2010	-1.387		-3.058	**	-3.094	**	-4.211	***	-4.523	***
yeard2011	0.163		-1.077		-1.205		-2.271		-2.334	*
yeard2012	-0.047		-1.518		-1.227		-1.663		-1.810	
yeard2013	0.789		-0.389		-0.719		-0.676		-0.497	
Top20cities	1.478		1.714	*	1.617		2.407	**	2.483	**
Cities_40k_	0.443		0.633		0.834		1.034		1.379	
Cities_20k_40k	1.227		0.479		0.391		0.815		0.430	
R(card) card	-0.195	**	-0.188	**	-0.097		0.133		-0.079	
R(card) emoney	-0.679		0.906		0.011		-0.193		1.015	***
R(card) other	0.863		0.539		0.035		2.293		-0.432	
R(card) card+emoney	-0.168		0.012		0.263		1.699	**		
R(card) cash	-0.410	**	-0.414	**	-0.232		0.491		-0.144	
R(emoney) card	-1.016		-1.162		-0.502		0.530		0.928	
R(emoney) emoney	-0.227		-0.197		-0.038		-0.044		0.133	
R(emoney) other	-0.740		-3.542		1.384		2.473		0.786	
R(emoney) card+emoney	-7.830		4.686		2.971		1.372			
R(emoney) cash	-0.229		-0.403		-0.199		-0.203		0.641	*
R(other) card	0.430		0.168		-1.067		0.084		-0.362	
R(other) emoney	0.152		-2.099		-0.097		-0.880		3.811	
R(other) other	0.217		0.078		-0.249		-0.279		-0.057	
R(other) card+emoney	4.381		2.935		0.671		2.638			
R(other) cash	0.466		0.309		-1.121		-1.614		-0.764	
R(card + emoney) card	0.345		0.352		-0.167		0.519			
R(card + emoney) emoney	0.302		-2.798		3.180		0.504			
R(card + emoney) other	-0.013		4.259		10.363		6.369			
R(card + emoney) card+emoney	0.100		0.062		-0.143		-0.014			
R(card + emoney) cash	0.518		-0.114		-1.547		-0.116			
R(cash) card	-0.436	**	-0.434	**	-0.540	**	0.072		1.007	
R(cash) emoney	-1.533		0.657		0.442		0.587		1.360	***
R(cash) other	1.000	*	0.333		-0.775		-0.649		0.412	
R(cash) card+emoney	0.037		0.609		-0.912		-1.554	**		
R(cash) cash	-0.098		-0.092		-0.348	**	-0.456	*	0.844	**
constant	-0.173		1.334		-0.161		9.638	*	12.541	***
age_NA	7.674		1.696		1.454		0.942		-0.698	
Education_NA	2.195		1.141		0.615		1.050		1.376	
S_Education_NA	-0.446		2.179		0.758		0.391		2.339	
job_NA	-0.586		-0.475		-0.959		1.228		0.475	
S_job_NA	3.545	**	3.950	***	2.541	*	1.144		1.310	
Mattress_NA	-1.467		-1.492		1.125		-2.187		-0.929	
Banking_NA	-5.112		-6.539		-8.603		-3.120		-4.220	
No_spouse	2.896	*	3.993	**	3.566	**	3.401	**	4.164	***
N	26810		27003		26784		26826		26583	
Adjusted Rsq	0.046		0.046		0.046		0.045		0.045	

* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 18 Revised Table 6 for Fujiki and Tanaka (2018)

	50k-		10k-50k		5k-10k		1k-5k		less1k	
Mattress deposit	22.694	***	22.547	***	20.641	***	20.949	***	20.300	***
h_size	-0.255		-0.186		-0.080		-0.315		-0.363	
ln(Passengers km)	0.402	**	0.416	**	0.338	*	0.547	**	0.881	***
income_0	-2.629		-2.765		-1.684		-2.297		-1.748	
income_200_260	-0.902		-0.393		0.719		0.755		0.561	
income_260_301	0.821		1.142		2.020		2.065	*	1.323	
income_301_370	0.050		0.397		1.278		1.318		0.948	
income_370_410	1.343		1.231		2.234	*	2.226	*	1.945	
income_410_500	0.494		0.571		1.384		1.387		1.506	
income_500_600	2.396	*	2.558	*	3.418	***	3.735	***	3.343	**
income_600_700	2.994	**	2.903	**	3.717	***	3.769	***	3.960	***
income_700_900	4.177	***	4.399	***	4.581	***	4.917	***	4.422	***
income_900_	10.292	***	10.211	***	11.511	***	11.077	***	10.777	***
income_NA	0.666		0.551		1.466		1.182		0.386	
asset_0	-0.741		-0.481		-0.242		-0.677		-1.140	
asset_250_404	2.665	**	2.635	**	2.425	**	2.445	**	2.547	**
asset_404_600	4.134	***	4.572	***	4.389	***	4.837	***	4.861	***
asset_600_870	5.968	***	5.624	***	5.574	***	7.032	***	6.585	***
asset_870_1180	3.498	***	2.745	**	2.575	**	2.926	**	3.768	***
asset_1180_1620	3.389	***	3.516	***	2.935	**	3.826	***	5.226	***
asset_1620_2350	6.151	***	5.982	***	5.597	***	6.442	***	7.666	***
asset_2350_3800	8.546	***	7.552	***	8.092	***	9.163	***	10.349	***
asset_3800_	16.258	***	16.358	***	16.649	***	17.543	***	18.480	***
asset_NA	1.471		1.355		1.465		1.389		1.762	
Know Deposit Insurance	1.472	*	1.267	*	1.242		2.093	**	3.056	***
Heard of Deposit Insurance	0.009		-0.419		-0.239		0.289		1.037	
Lower service charges	-2.202	**	-2.021	**	-2.435	***	-2.175	**	-1.893	*
Online banking	1.479		1.548		0.922		1.940		3.241	**
Debt	-0.842		-1.109	*	-1.576	***	-1.355	**	-1.257	*
Homeowner	0.862		0.872		0.719		0.982		1.531	**
age35_39	-0.738		-1.000		-1.068		-0.853		-0.609	
age40_44	-0.699		-0.607		-0.904		-0.862		-0.968	
age45_49	-0.729		-0.909		-0.777		-0.856		-1.409	
age50_54	0.116		0.579		0.449		0.800		-0.199	
age55_59	1.503		1.607		1.847		1.623		0.813	
age60_64	3.684	***	3.452	***	3.909	***	2.871	*	1.859	
age65_69	6.190	***	6.419	***	6.215	***	4.834	***	2.895	
age70_74	6.104	***	6.740	***	5.943	***	4.692	***	3.017	
age75_	8.078	***	8.133	***	7.609	***	6.348	***	3.338	
Male	2.922	**	2.695	*	3.707	***	2.661	*	2.434	
Fulltime	0.912		0.337		0.326		0.976		0.662	
Parttime	-1.052		-1.423		-0.848		-0.632		-1.204	
Selfemployed	4.151	***	3.535	***	3.876	***	4.036	***	3.710	***
Student	18.530	***	14.986	***	13.780	***	14.382	***	19.262	***
S_Fulltime	-0.810		-1.085		-1.330		-1.485	*	-1.310	
S_Parttime	-1.293	*	-1.429	**	-1.671	**	-1.472	**	-1.789	**
S_Selfemployed	2.587	*	2.711	**	2.882	**	1.758		1.513	
S_Student	7.129		4.947		3.613		2.875		1.986	
Seniorhigh	-0.483		-0.920		-0.903		-1.362		-0.303	
Vocationalcollege	-1.187		-1.906		-1.639		-2.158		-0.180	
Juniorcollege	0.978		0.918		0.129		0.369		2.003	
University	-1.471		-1.826		-2.203	*	-2.213	*	-0.343	
Graduate	-3.523	*	-4.646	**	-4.993	**	-4.721	**	-3.017	
S_Seniorhigh	1.763		1.402		1.215		1.869	*	2.480	**
S_Vocationalcollege	1.544		1.006		0.956		1.764		2.543	*
S_Juniorcollege	2.034		1.606		1.367		1.993		2.283	
S_University	2.542	*	1.961		1.684		2.388		3.327	**
S_Graduate	0.619		4.635		4.537		-0.625		-0.359	
yeard2007	-1.972	*	-2.587	**	-2.025	*	-2.825	**	-4.519	***
yeard2008	-1.920	*	-2.183	**	-1.867	*	-2.244	*	-4.421	***
yeard2009	-3.659	***	-3.281	***	-3.339	***	-3.825	***	-5.340	***
yeard2010	-2.526	**	-2.634	***	-2.373	**	-2.800	***	-3.478	***
yeard2011	-0.088		-0.731		-0.293		-0.854		-1.552	
yeard2012	0.078		-0.501		-0.724		-0.572		-1.168	
yeard2013	-0.066		-0.433		-0.270		-0.013		-0.255	
Top20cities	1.631	*	1.914	**	1.560	*	1.753	*	2.602	**
Cities_40k_	0.918		0.978		0.845		0.859		1.432	
Cities_20k_40k	0.695		0.613		0.629		0.862		0.423	
R(card) card	-0.217	**	-0.204	**	-0.133		0.004		0.070	
R(card) cash	-0.429	**	-0.412	***	-0.296		0.088		0.482	*
R(cash) card	-0.432	**	-0.465	***	-0.514	**	-0.170		2.410	**
R(cash) cash	-0.083		-0.120		-0.281	**	-0.343		2.527	
constant	-2.932		-1.246		-1.628		3.824		9.926	**
age_NA	3.610		2.797		2.488		2.098		-0.486	
Education_NA	2.699		1.053		0.906		-0.470		1.183	
S_Educatio~A	-0.014		1.325		0.051		1.058		2.808	
job_NA	-1.232		-0.893		-1.409		0.464		-0.210	
S_job_NA	3.779	***	3.833	***	3.122	**	2.010		1.990	
Mattress_NA	0.179		-0.217		0.921		-0.597		-0.215	
Banking_NA	-6.620		-6.692		-6.766		-0.590		-1.346	
No_spouse	4.019	**	3.356	**	3.832	**	3.594	**	4.666	***
N	25437		26204		25912		25428		24793	
Adjusted Rsq	0.045		0.044		0.045		0.042		0.044	

* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 19 Revised Table 7 for Fujiki and Tanaka (2018)

		50k -	10k - 50k	5k - 10k	1k - 5k	less 1k
card users	mean	12.400	12.301	12.380	13.139	14.514
	N	14947	12985	7276	4266	1080
only cash users	mean	15.421	14.791	13.753	13.535	13.449
	N	10490	13219	18636	21162	23713
Difference		-3.020	-2.490	-1.374	-0.396	1.065
t-statistics		-27.175	-22.919	-10.995	-2.593	3.559
p-value		0.000	0.000	0.000	0.010	0.000

Note: Cash is in units of 10,000 yen.

Appendix Table 20 Revised Table 8 for Fujiki and Tanaka (2018)

Goodness of fit statistics for the Logit models

	50k -	10k - 50k	5k - 10k	1k - 5k	less 1k
N	25437	26204	25912	25428	24793
pseudoRsq	0.16	0.16	0.13	0.12	0.07
LLR	-14566.52	-15277.57	-13322.96	-10170.89	-4108.22
% correctly classified	69.87%	69.36%	74.91%	83.46%	95.64%
Area under ROC curve	0.76	0.76	0.75	0.74	0.72
chi2	25329.94	26195.63	25752.08	24955.19	24169.03
Prob > chi2	0.52	0.35	0.61	0.95	0.99

Propensity-score matching

	50k -	10k - 50k	5k - 10k	1k - 5k	less 1k
ATE: Psmatch	-3.559***	-3.027***	-3.114***	-2.489***	-1.361
	(0.810)	(0.640)	(0.531)	(0.592)	(1.184)
ATE: IPW	-3.506***	-3.256***	-2.565***	-2.063***	-1.108
	(0.688)	(0.603)	(0.475)	(0.580)	(1.074)
ATET: Psmatch	-3.474***	-2.933***	-2.200***	-0.914	-0.209
	(1.068)	(0.909)	(0.747)	(0.852)	(1.787)
ATET: IPW	-3.627***	-3.222***	-1.920***	-1.137*	-0.202
	(0.886)	(0.824)	(0.590)	(0.660)	(1.320)

Note: Standard errors in parentheses. Cash is in units of 10,000 yen.

* p<0.10, ** p<0.05, *** p<0.01

Appendix Table 21 : Errata list for the main text of Fujiki and Tanaka (2018)

Page/Paragraph, Line/	Original text	Corrected text
90/ Right 1, 3/	"in SHF."	"in SHF and those who did not respond to this question, Mattress NA."
90/ Right 2, 7/	"re-spectively)."	"re-spectively), and those who did not respond to these questions, Banking NA."
91/ Right 3, 7/	", and over 74 years."	", over 74 years and age_NA for a household not reporting its age."
92/ Left 1, 2/	"or a student."	"or a student and job NA for a household not reporting its job situation."
92/ Left 2, 3/	"and graduate school."	"graduate school, and Education_NA for a household not reporting its educational attainment."
92/ Left 2, 11/	"survey respondents."	"survey respondents and a dummy variable for a household head without spouse, No spouse."
92/ Right 1, 3-4/	"Fifth, having a young household head tends to correlate positively with the choice of card, while having"	"Fifth, having"
92/ Right 1, 14-15/	"for junior college for day-to-day transaction values more than 1000 yen,"	"for vocational college, junior college,"
94 /Left 2, 5/	"over 74"	"55-59"
94/ left 2, 7-8/	"between 10,000 and 50,000 yen, and from 60–69 and over 74 years for transaction values between"	"exceeding"
94/ left 2, 8-9/	"5000 and 10,000 yen. For transaction values less than or equal to 50,000 yen,"	"5000 yen."
94/Left 2, 10/	"household with a self-employed or student head"	"Household with a self-employed or student head and a self-employed spouse of the household head"
94/Left 2, 12/	"a full- or part-time"	"a part-time"
94/Left 3, 5/	"between 1000 and 5000 yen,"	"between 1000 and 5000 yen, and R(card)cash for transaction values more than 10,000 yen,"
94 /Left 3, 7/	"between 5000 and 10,000 yen and less than 1000"	"exceeding 5000"

94/ Left 3, 8-9/	“values between 1000 and 5000 yen and”	“values”
94/ Left 3, 10/	“between 1000 and 5000 yen are”	“between 1000 and 5000 yen, and R(cash)cash for transaction values less than 10,000 yen are”
94/ Left 4, 3-4/	“R(emoney)card for transaction values between 10,000 and 50,000 yen and less”	“R(emoney)cash for transaction values less”
94/ Left 4, 5-7/	“1000 yen and R(emoney)card+ emoney for transaction values between 5000 and 10,000 yen.”	“1000 yen.”
94/Right 2, 7/	“cash holdings”	“cash holdings except for transaction values between 5000 and 10,000 yen”
94/Right 2, 8-9/	“charges for transaction values more than 1000 yen”	“charges”
94/Right 2, 11/	“with older”	“with male and older”
94/Right 2, 13-14/	“1000 yen except for age 60–64 for transaction values between 1000 and 5000 yen.”	“1000 yen.”
94/Right 3, 2/	“head tend”	“head and those with a self-employed spouse of the household head tend”
94/Right 3, 2-4/	“a full- or part-time worker”	“ a part-time worker ”
94/Right 4, 3/	“more than 5000 yen”	“between 1000 and 10,000 yen”
94/Right 5, 8/	“yen, less”	“yen, between 5000 yen and 10,000 yen, and”
94/Right 5, 8-9/	“values between 10,000 and 50,000 yen and between 5000”	“values between 5000”
94/Right 6, 5/	“a self-employed”	“a male, self-employed”
98/ Left 1, 7/	“verify that most of the”	“dropped four variables whose”
98/ Left1, 8/	“for the covariates are less than 3%”	“are more than 10%”
98/ Left 1, 9/	“summarize.”	“summarize in the case of transaction values less than 1000 yen.”