# Currency Demand, New Technology and the Adoption of Electronic Money: Evidence Using Individual Household Data *

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March 3, 2010

**Abstract**

Accurate information of financial technology and its effect to currency demand is essential for evaluation of monetary policy. We investigate the effect of a new form of such technology, electronic money, to money demand. Specifically, we estimate currency demand functions conditional on electronic money adoption using unique household-level survey data from Japan. Our results indicate that average cash balances do not decrease with the adoption of electronic money. Rather, it seems to increase under some specifications. It suggests that consumers do not significantly substitute cash holding with electronic money holding despite the rapid diffusion of electronic money among households.

Keywords: Currency Demand; Transaction Demands for Money; Electronic Money; Instrumental Quantile Regression
JEL Classification: E41

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During work on this paper, the authors participated in the Research Group on the Survey of Household Finances and received permission from the Central Council for Financial Services Information (CCFSI) to use data from the Survey of Household Finances. The authors would like to thank the CCFSI for providing the requisite data and Fumiko Hayashi for helpful comments on an earlier version of this paper. The authors also appreciate the comments of seminar participants at the Chinese University of Hong Kong and the University of Hong Kong. All remaining errors are our own. This paper was partly prepared when both authors were affiliated with the Institute of Monetary and Economic Studies at the Bank of Japan. The views expressed herein are the authors' and do not necessarily reflect the view of the Bank of Japan.

# 1 Introduction

To what extent does financial innovation change the demand for money by individuals and firms? This is one of the more fundamental questions widely debated among economists and central bankers, as the accurate specification of the money demand function is relevant information for the evaluation of monetary policy. During the 1970s and 1980s, financial innovation led to the debate about whether monetary targeting was an effective form of monetary policy.[1] During the 1990s and the current decade, "plastic money," such as credit and debit cards, attracted academic attention as a type of financial innovation. Economists expected that "plastic money" would change the way consumers and firms undertake retail transactions and thus would change the demand for traditional "paper money," that is, banknotes and checks. In evidence, some empirical research found a link between the diffusion of "plastic money" and reductions in the demand for cash and its elasticity with respect to interest rates and other variables. For example, using aggregate data from 13 countries, Amromin and Chakravorti (2007) found that the diffusion of debit cards and automated teller machine (ATM) networks decreased the demand for small-denomination currency. Studies using household data also suggested that these technologies reduced currency demand.[2]

Recently, a new form of payment technology, so-called electronic money, has been perceived by economists and policy makers.[3] Electronic money is a payment medium that allows buyers and sellers to make secure and instantaneous monetary transactions with a slight touch of the card on a terminal. Because of its high speed of transaction, electronic money has been adopted in many parts of the world, primarily for fare payment in mass transit systems.[4] Japan is the one of the

[1]This line of research has been active since the early 1970s, when the hitherto stable relationship between the measure of aggregate monetary, M1, and other key macro variables, such as interest rates and income, became unstable. This was mainly attributed to a new financial product called a super NOW account in the U.S. See Goldfeld and Sichel (1990) for an extensive literature review on the analysis of the demand for money.

[2]For work on ATM networks and debit cards, see Attanasio, Guiso, and Jappelli (2002) and Lippi and Secchi (2009). For studies of debit cards and electronic funds transfer at point-of-sale (EFTPOS), see Stix (2004). For credit cards, see Duca and Whitesell (1995).

[3]It is also known as a smart card or electronic purse.

[4]Examples include Charlie Card in Boston, Octopus Card in Hong Kong, Oyster in London, ICOCA/PiTaPa in Osaka, OPUS card in Quebec, T-Money in Seoul, Ez-Link in Singapore, Suica/Pasmo in Tokyo, and Metro Card in Washington D.C..

few places where this technology has been successfully adopted to retail payments in recent years. By the end of 2007, there were 73 million cards with electronic money functionality in Japan, representing about two-thirds of the total population.

We contribute to the literature by examining the effect of the use of electronic money, which has distinctly different functions from existing "plastic money," on the demand for currency by households using a unique survey data set from Japan. More specifically, we provide two contributions as detailed below. First, the new data set allows us to correct for the selection bias in estimating the effect of the use of electronic money on the demand for currency. This correction is necessary because if households use electronic money, the benefits of adoption depend on unobservable changes in cash holdings. A conventional estimation strategy using OLS would then provide biased estimates.[5] Second, our new data set allows us to estimate the effect of the use of electronic money on the demand for currency at different quantiles of currency holdings. We consider quantile regression as a promising means to separate the transaction motive for holding cash from the savings (precautionary) motive because households with low cash balances hold cash mainly for transaction motives while those with large balances do so more for precautionary motives.

Our empirical analysis yields the following results. First, households are more likely to adopt electronic money if their disposable income is higher, and if their household head is self-employed, with a tertiary education and with easier access to the new payment technology. Second, using instrumental variable methods, we find a positive and significant difference in currency demand after electronic money adoption. The estimated demand for currency conditional on electronic money adoption status, given various household characteristics suggest that electronic money users hold, ceteris paribus, more currency. These results are at odds with standard theoretical predictions from the transaction money demand model and existing studies on the effects of "plastic money." Third, households at most cash holding quantiles tend to increase cash holdings through the adoption of new payment technologies; however, the parameter estimates are not statistically significant. These particular findings serve as a quick robustness check of the previous results. Together, our three results are consistent with the conclusions obtained from past studies using Japanese aggregate

[5] Attanasio, Guiso, and Jappelli (2002) and Lippi and Secchi (2009) adopt a similar approach when examining the benefits of larger bank branch and ATM networks using survey data on Italian households by controlling for the selection bias in adopting new financial technology (i.e., having a bank account and an ATM card) using an endogenous switching regression model.

data that the impact of electronic money on the demand for currency is limited.

The remainder of the paper is structured as follows. Section 2 describes the definition and background of electronic money in Japan and the data employed in the analysis. We also explain the key differences between this new payment option and existing means, including debit and credit cards. Section 3 introduces our empirical model. Section 4 provides two of the estimation results. First, we report the characteristics of households that adopt electronic money. Second, we report the average change in currency demand from the adoption of electronic money. Section 5 provides a robustness check of the results obtained in Section 4 using instrumental quantile regression. Section 6 concludes.

# 2 Background and Data

## 2.1 Electronic Money and Other Payment Media

In this paper, we use the term "electronic money" to refer to electronic forms of payment at point-of-sale (POS) locations, including debit cards, unless otherwise noted. Within the category of electronic money, one notable recent development in some economies is the remarkable penetration of prepaid noncontact Integrated Circuit (IC) forms, as the case of Japan is described in the next subsection. This can take the form of a plastic card or mobile phone and requires users to load cash in the account using deposit terminals at retail outlets, train stations, and banks. Account balances and transactions are recorded on an embedded chip.[6] Though the deposit process still requires the handling of cash, payments are settled instantly by using the device at a POS location. To highlight the differences between electronic money and other payment instruments, their properties are summarized in Table 1.

First, from the perspective of both consumers and merchants, "plastic money" has an advantage over "paper money" in terms of the time required for transactions. Given the noncontact IC form does not require either the authorization of a central server or a signature at the POS location, it

[6] This particular format is known as stored-value electronic money as opposed to server-type electronic money where balances and transaction records are held on a central server.

has the fastest transaction speed, as shown in the fifth row of Table 1.[7,8]

Second, as shown in the second through fourth rows of Table 1, the fee structures of most "plastic money" are similar for all types. Here, merchants bear an up-front fixed cost covering the adoption of the payment device and pay a few percent of each transaction value. Consumers are required to pay a small initial cost. This is only cost of a credit card as well, as long as they pay their bill within the billing period. However, consumers can gain through royalty programs offered by some types of "plastic money." Third, as shown in the last row of Table 1, prepaid noncontact IC forms record transactions on the card itself and thereby maintains anonymity, in much the same manner as cash. Consequently, card providers do not insure physical loss of the form.

Overall, the electronic money we are interested in, namely, prepaid noncontact IC forms, is similar to conventional "plastic money" in terms of its fee structure but is quite different from conventional "plastic money" in terms of the speed of transaction and anonymity.

## 2.2 Cross-country Comparisons

Both macro and micro evidence suggest that the Japanese use more cash than many other nationalities. As a macro example, the ratio of cash in circulation to nominal GDP has been about 15 to 16 percent since 2003, while the corresponding figure according to the Bank for International Settlements (2009) is only 6 percent in the U.S., 8 percent in the Euro area, and 3 percent in the UK. As a micro example, the Survey of Household Finances (SHF) in 2007 provides the choice of payment method by transaction size and shows that across all sizes of transaction, the majority of Japanese households choose cash. Indeed, the average cash holding of Japanese households is some 159,000 yen, or more than 1,400 U.S. dollars using the 2007 year-end exchange rate. This is a remarkably high level of cash holding, especially compared with other cash-dominant economies. For example, in Italy, the average cash balance is only about 400 euros (some 500 U.S. dollars).

[7] This comparison is based on signature-less transactions for credit cards, as some card issuers have agreements with retailers to omit the signature requirement for small value transactions, typically those worth less than 10,000 yen in the case of Japan. Recently some credit card issuers have introduced a non-IC transaction capability, such as MasterCard Paypass and Visa Touch, with which the payment speed is less than 30 seconds.

[8] One disadvantage of noncontact IC for the consumer is that it typically requires a deposit in advance. While some issuers offer automatic balance transfer programs from credit cards, we believe that at the time when the data in our analysis were surveyed, it was not common practice.

Table 2 compares the average transaction size by payment and withdrawal instrument. We point out two important differences between the Japanese data and those from other economies. First, compared with other economies, the yen value of ATM withdrawals is substantially higher in Japan. This suggests that in Japan, withdrawal costs are very high and/or there are more transactions that must be made in cash. Second, in contrast to other economies, debit cards are used for high-value transactions relative to credit card in Japan. It may reflect the fact that debit cards mainly substitute for personal checks in the U.S., while debit card replaces either credit card or cash payments in Japan, where personal checks have been rarely used historically. Third, in both economies where electronic money data is available, the transaction value is much lower than other payment instruments: 6 dollars in Japan and 24 dollars in France. It indicates that electronic money is used mainly for small value transactions.

### 2.3 Evidence Available from Japanese Aggregate Data

Figure 1 plots the diffusion of noncontact IC technology with the cumulative number of prepaid noncontact IC forms issued by various providers since 2002 in Japan.[9] This payment technology went into use for the first time in 2001 and has since grown exponentially. By the end of 2008, the number of issued IC forms reached 99 million, the number of stores that accept electronic money payment approached 314,000, and the number of transactions per month exceeded 89 million. Figure 2 shows the diffusion of prepaid noncontact IC forms and debit cards in terms of monthly transaction values. It shows that debit cards spread quickly at the early stage but the transaction volume in yen peaked in 2005 stays around 770 million yen per month.[10] Meanwhile the transactions by prepaid non contact IC forms increased in value and exceeded that of debit card by the end of 2008 and its growth does not seem to slow down in near future. As mentioned before, we investigate the effect of electronic money, including debit cards and non contact IC form to currency demand.

To date, Japanese evidence drawing on aggregate data has led to the same policy conclusions as overseas research on "plastic money" has suggested; i.e., the limited impact of electronic money

[9] The providers of electronic money is the owner of the payment network and issue the IC forms to consumer directly. In addition, some retail chains and banks issue their royalty cards or credit cards with electronic money functionality by one of the providers' networks.

[10] Data on debit card usage can be obtained from the web site of the Japan Debit Card Promotion Association (http://www.debitcard.gr.jp/).

on currency demand. In particular, the available evidence provides two main findings as we detail below.

First, the aggregate statistics do not provide any evidence of a trend for currency in circulation to fall because of the diffusion of electronic money. For example, and as shown in Figure 3, the ratio of currency in circulation to nominal GNP has been stable at between 15 and 16 percent since 2003. Consistent with this observation, according to the Bank of Japan (2008) as at the end of March 2008, the value of electronic money outstanding was 1.7 percent of the total value of coins in circulation, 0.1 percent of the total value of banknotes in circulation, and 0.1 percent of the total value of cash (coins and banknotes) in circulation. This is despite the remarkable growth in electronic money, as shown in Figure 4. Nakata (2007) has confirmed these findings using monthly aggregated data by currency denomination.

Second, electronic money is used mainly for transactions of small amounts. For instance, the Bank of Japan (2008) has reported that the average transaction amount of electronic money as a retail payment was ¥696 in fiscal year 2007. Consistent with this, the volume of coins in smaller denominations has recently decreased. Furthermore, the 2007 SHF shows that only 4 percent of Japanese households chose electronic money for daily shopping, and of these consumers, most transactions were for small amounts.[11]

### 2.4 Our Data Set

This paper uses individual household data from the 2007 SHF conducted by the Central Council for Financial Services Information.[12] The SHF employs a stratified two-stage random sampling method first to select 400 survey areas and then randomly to select 15 households consisting of two or more people from each area to obtain a total of 8,000 samples. The number of valid samples eventually reduces to 3,000. To supplement this sample, the SHF collects data for single-person households from a pool of individuals registered with a survey company through the Internet.[13]

[11] The SHF also surveys single-person households. Of these, 25 percent responded that they use electronic money for daily payments.

[12] This survey was formerly known as the "Public Opinion Survey on Household Financial Assets and Liabilities." Information on the survey is available at http://www.shiruporuto.jp/e.

[13] The sampling probability assigned is based on the latest Census (conducted in 2005), by age, gender, and region. All responses are collected through the Internet.

Tables 3 and 4 summarize selected variables for the overall sample along with a breakdown by electronic money adoption. The summary statistics for the family data set and those for the single-person data set differ greatly in many respects. For example, in the single-person data set, distinctly more households use credit cards (54 percent of family households and 74 percent of single-person households) and electronic money (4 percent of family households and 26 percent of single-person households). These contrasting results are suspected to stem partly from the difference in sampling methods. It is not obvious which of the two data sets is better for our purpose. On the one hand, it is clear that the family sample is better because it lies closer to a random sample, whereas the single-person sample is self-selected as an Internet monitored household. On the other hand, the single-person sample is less subject to measurement error as the respondents themselves respond only about their own behavior, not the aggregate behavior of other household members. In this paper, after weighing the advantages and disadvantages of the two data sets carefully, we focus on the family household. We include an analysis using the single household data in the appendix.

Table 5 summarizes the choice of payment type by transaction amount for family households. In the survey, respondents are asked to choose, at most, two major means of payment for each range of transaction values, from cash, credit card, electronic money, bank transfer, and others.[14] Though the SHF's question on electronic money usage groups prepaid and postpaid noncontact IC forms along with debit cards in the same category, our study focuses on the money in prepaid noncontact IC forms and debit cards. We believe that postpaid cards have a small market share, and so this treatment should not significantly bias the results.

Table 5 provides a number of interesting results. First, the fifth row in Table 5 shows that cash payment is still the dominant option for payments made by households relative to credit cards and electronic money. This finding is consistent with the available aggregate data evidence reported in Amromin and Chakravorti (2007). Second, the first column of Table 5 shows that across all ranges of transaction values, more than 50 percent of households choose cash for payment, though the share of cash payment decreases as the payment amount increases. Third, the second column of Table 5 shows that the share of credit card payments increases as the payment amount increases.

[14] The survey question asks: "Which means of payment would you use to make a daily transaction of (1) less than ¥1,000, (2) between ¥1,000 and ¥5,000, (3) between ¥5,000 and ¥10,000, (4) between ¥10,000 and ¥50,000, and (5) more than ¥50,000 ? Choose from cash, credit card, electronic money (including debit card), bank transfer and others."

Both these findings indicate that credit cards are substitutes for cash and that the relative cost (benefit) of credit cards decreases (increases) as the transaction size increases. Fourth, the third column of Table 5 shows that only 4 percent of households use electronic money for daily retail payments. The share of electronic money payments decreases as the payment amount increases; this is a similar trend as found for cash payments. We therefore infer that electronic money may be a closer substitute for cash and that there may then be a need to correct for sample selection bias when we estimate the demand for cash. Fifth, the last row of Table 5 shows the payment choice for recursive payments, such as monthly utility bills.[15] This indicates that bank transfers are the dominant option for payment and that electronic money is rarely chosen for making such payments.

In order to grasp the effect of the use of electronic money on cash balances, we generate Table 6 showing the average cash balance for households by the choice of payment in each transaction range. As the last row of Table 6, labeled "All" shows, the average cash balance for households that use credit cards, ¥115,540, is lower relative to the overall mean, ¥138,320, and yet the average cash balance of electronic money users is ¥141,790, which is higher than the overall mean. However, the third column of Table 6 shows that the average cash balance of electronic money users falls substantially as the transaction amount decreases. Thus, it is not apparent how the adoption of electronic money technology affects the cash-holding behavior of households. At the very least, the findings in the table suggest that we should control for the level and availability of financial technology when estimating the demand function for currency. Unfortunately, while the SHF data set does not contain such information, it does report the location of each household by region and city size. More specifically, there are nine regions and six classifications of city size.[16,17] This classification yields 53 locations. Because of the geographic information found in the SHF data

[15]The survey questions asks: "Which means of payment would you use to make a recurring payment, such as the payment of utility bills? Choose from cash, credit card, debit card, bank transfer, and others."

[16]The regions are Hokkaido, Tohoku, Kanto, Chubu, Hokuriku, Kinki, Shikoku Chugoku and Kyushu.

[17]City size is classified according to (1) the 18 largest cities, (2) cities with more than 40,000 households, (3) cities with more than 20,000 and fewer than or equal 40,000 households, (4) cities with more than 10,000 and fewer than or equal 20,000 households, (5) cities with fewer than 10,000 households, and (6) villages. The largest 18 cities are Chiba, Kitakyushu, Sendai, Hiroshima, Saitama, Kawasaki, Fukuoka, Kyoto, Kobe, Sapporo, Nagoya, Osaka, Yokohama, Tokyo (23 special wards), Shizuoka, Niigata, Hamamatsu and Sakai.

set, a corresponding region–city size pair can match some measure of financial technology to each household obtained from other sources within the SHF data set.

We provide two measures of financial technology for each household. The first measure is the density of electronic money terminals owned by Edy, the largest electronic money providers that serves nationwide.[18] Note that the payment card industry, including the electronic money industry, is a typical two-sided market, where the particular payment card (the so-called platform in the literature) is valuable for shoppers if a sufficient number of retailers accept the card and vice versa. Therefore, there is a positive network externality in adopting the technology for both retailers and consumers within each group.[19] The number of terminals is expected to affect the adoption choice positively. Table 7 provides a summary of the number of Edy terminals per square kilometer. As shown, the terminal density is highest in regions including major metropolitan areas.

The second measure is railroad passenger kilometers, which gauges the usage of the transportation system in a given area in a give period.[20] Underlying the choice of the second measure is the fact that the nation's transportation systems are major providers of electronic money, and thus people who use mass transit for daily commutes are more likely to employ an electronic form of money.[21]

## 3 Empirical Model

Our empirical model is based on the Baumol–Tobin model of the transaction demand for money. In this model, households hold cash to make transactions and decide upon the amount of cash held by minimizing the sum of the cost of transactions and the opportunity cost of holding cash. The cost of transactions includes the time cost of making transactions, which increases with the frequency of withdrawal and decreases with the amount of cash withdrawn in each bank visit. The opportunity

[18] The data are compiled from online data published on the Edy web site as at the end of 2008 (http://www.edy.jp/).

[19] For more details on the theoretical framework of a two-sided market, see Rochet and Tirole (2006). In the context of a payment industry with network externality, see Markose and Loke (2003).

[20] This measure is defined as the product of the distance a vehicle travels and the number of occupants traveling that distance. The data are obtained from the Ministry of Land, Infrastructure and Transportation. We use annual data for fiscal year 2007.

[21] Those transportation related providers are ICOCA, Suica and Pasmo in Figure 1.

cost is measured by the forgone interest that would have been earned if the cash had remained as an interest-bearing asset; for example, in a savings account. In our setup, there is an alternative medium to cash for making a transaction; namely, electronic money. The use of electronic money may further reduce the transaction cost by shortening the transaction time.

In order to adopt electronic money, one needs to pay a one-time fixed fee and deposit a certain amount of money in an electronic money account that does not provide interest rate earnings.[22] Once the deposit is made, one can only use the balance in the card in a mass transit system or at retail outlets where electronic money payments are accepted. The business practice operating for electronic money implies that there is no major difference between the opportunity cost of holding cash and that of holding electronic money at the time of analysis.

A household adopts this technology if the benefit from the technology exceeds the cost of adoption. As the adoption of the technology reduces the cost of payment, currency demand differs for those who adopt the technology and those who do not. We model this discrete decision problem for electronic money adoption as a probit model, in which the costs and benefits of the technology depend on the household characteristics as well as the extent of availability of the payment technology.

The empirical model is given as follows. Let $m_i$ be the average currency holdings of household $i$. Let $d_i$ denote the choice variable that takes a value of one if household $i$ adopts the electronic money payment technology and zero otherwise. More formally, we can write this as follows:

$$d_i = \begin{cases} 1 & \text{if } d_i^* > 0, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $d_i^*$ is a latent variable defined as:

$$d_i^* = \gamma Z_i + u_i. \tag{2}$$

The vector $Z_i$ contains the characteristics of household $i$ that affect the costs and benefits of adopting the technology for household $i$. For example, it includes the measure of accessibility to the technology. The term $u_i$ captures other unobservable factors affecting the adoption decision.

[22] Some electronic money service providers offer a loyalty-point program that can be converted to an electronic money cash rebate or frequent-flier miles in partner airlines. These advantages may be another factor driving the adoption of electronic money.

Therefore, the right-hand side of the equation represents the net benefit of adopting electronic money for household $i$.

Given the definition of $d_i$, we can write the money demand function as follows:

$$\begin{aligned} \log(m_i^1) &= \mu_1 + X_i\beta + \epsilon_i^1 \quad \text{if } d_i = 1, \\ \log(m_i^0) &= \mu_0 + X_i\beta + \epsilon_i^0 \quad \text{if } d_i = 0. \end{aligned} \tag{3}$$

The vector $X_i$ includes standard explanatory variables for transaction money demand, such as measures of income and the assets of household $i$ along with other characteristics, such as the age of the household head, household location, and employment status. Because of the limitations of the data for our analysis, we simplify the model and assume that there is no unobservable gain or loss from adoption; namely $\epsilon_i^1 = \epsilon_i^0$ for all $i$. Our primary objective is to identify $\alpha = \mu_1 - \mu_0$, the average change in money demand due to electronic money adoption. Note that $m_i^1$ and $m_i^0$ are observable only when the household does and does not adopt the electronic money technology, respectively. Thus, we never observe $m_i^1$ and $m_i^0$ at the same time for household $i$. Let the observed transaction money demand be $m_i$; then:

$$\begin{aligned} \log(m_i) &= d_i \cdot \log(m_i^1) + (1 - d_i) \cdot \log(m_i^0) \\ &= \mu_0 + \alpha d_i + X\beta + \epsilon_i^0 + d_i(\epsilon_i^1 - \epsilon_i^0) \\ &= \mu_0 + \alpha d_i + X\beta + \epsilon_i^0. \end{aligned} \tag{4}$$

The last equality is obtained because of the simplifying assumption made earlier on $\epsilon_i^1$ and $\epsilon_i^0$. Given that the adoption choice $d_i$ is likely to correlate with unobservable heterogeneity $\epsilon_i^0$, OLS estimates of the observed money demand on $X$ and the adoption dummy will not yield consistent estimates of $\alpha$.[23,24]

[23] One may argue that it is likely that $\epsilon_i^0 \neq \epsilon_i^1$; thus, the unobservable (counterfactual) change in money demand, $\epsilon_i^0 \neq \epsilon_i^1$, is nonzero and likely to be correlated with the adoption decision $d$ in nontrivial way. For example, a household who holds more cash for transaction purpose may get more benefit from adopting electronic money. Or, a household who has small value of cash tends to derive more disutility from holding cash and thus, gets more benefit from electronic money adoption. In this case, we can impose a parametric form on the joint distribution of these errors and estimate the model by a maximum likelihood estimator or control function approach. We tried these approaches; however, the models did not fit the data well.

[24] In addition, one may also claim that the demand functions under different adoption regimes are different and that an endogenous switching regression model may be more appropriate, as in Attanasio, Guiso, and Jappelli (2002)

Now, partition $Z_i$, a vector of explanatory variables for the adoption model, into two parts: $Z_i = [X_i, W_i]$, where $W_i$ is the set of observable factors that affect adoption behavior but not the transaction money demand directly. We consider the variables that gauge electronic money availability as such variable. The detail of the selection of such variables is postponed to the next section.

As we assume that $u_i$ follows a standard normal distribution, parameter $\gamma$ can be estimated consistently by maximum likelihood estimator.[25] Given this estimate, the model (4) can be inferred by two-stage least squares (2SLS) using the fitted value of $Pr(d = 1)$ from model (1) and (2) and $X$ as instruments.

# 4 Results

## 4.1 Electronic Money Adoption

We begin by reporting the characteristics of households that have adopted electronic money to infer the relevant control variables for our model in equations (1) and (2). We fit the probit model for equation (1) using household disposable income, financial assets, and other characteristics as regressors. The measure of availability of technology, namely, the number of electronic money terminals per square kilometer and the log of passenger kilometers, are also included. In order to capture additional regional variations, such as general price level and lifestyle differences, five city size dummy variables are included.

Table 8 reports the result of the probit estimates with the marginal effect evaluated at the sample mean. The positive coefficient implies that households with a high value of that variable obtain positive net benefits from adopting electronic money.

The results suggest that households are more likely to adopt electronic money if their disposable income is higher: an increase of disposable income by about 2.7 times contributes to a 1 percent increase in the probability of adoption.[26] As disposable income is likely to correlate positively

and Lippi and Secchi (2009). We found that those models yielded qualitatively similar results to those we present in the next section. Nevertheless, the parameters were less precisely estimated, partly because of the small (sub)sample size of electronic money users (4 percent).

[25] However, consistent estimation of the money demand function does not require consistency of $\gamma$.

[26] We also estimate the model with level of disposable income as one of independent variables and we still obtain

with the average volume of transactions for households, this indicates that households with higher disposable incomes obtain greater benefits from the new payment technology.[27] Asset variables may also help gauge the average volume of household transactions; however, the estimates indicate that it is not a significant predictor of electronic money adoption.

The employment status of the household head, such as full-time employment or unemployment, is not significant except in the case of self-employment. If the head of the household is self-employed, the household is 2.3 percent more likely to adopt electronic money. The sector dummies for the head's employment are not significant and are omitted from the model reported in the table. The household is 2.2 percent more likely to adopt electronic money if the household head has a tertiary education.

Estimates of the coefficient for the age of the head of the household are insignificant and are not included in the model reported in the table. However, these results may be a statistical artifact because the survey used asked about the behavior of the household, not the household head as an individual. This point is partially confirmed by the analysis using the single-person household sample reported in the appendix. To see the effects of age on adoption, we instead control for the age distribution within the household (i.e., the share of a particular age group in the household). As these age variables sum to one, we omit the share of household members less than 20 years of age. The estimates obtained indicate that households with a higher proportion of members in their thirties have a significantly higher probability of adopting electronic money.

Because credit cards are a payment alternative to cash and electronic money, we also examine the effect of their usage in the decision on electronic money adoption. While the coefficient for the credit card usage dummy is positive, the dummy for the use for payments under 1,000 yen is negative. Thus, the credit card user is more likely to adopt electronic money in general, while those who use credit cards for small value transactions are less likely to do so. However, the credit card usage dummy for payments less than 1,000 is insignificant.[28] Finally, as expected, we can

statistically significant effect of income.

[27]This is consistent with the results obtained in studies of the adoption of debit cards. For example, using data on Austrian households, Stix (2004) concludes that transaction value is positively correlated with debit card adoption.

[28]One may wonder whether the use of credit cards may be endogenous, and thus the dummy variable for credit cards is endogenous. In the analysis thus far, we do not have good instrumental variables to cope with this problem. However, as we discuss in the following subsection, we do not find evidence for selection bias for the demand for

see the significant effect of the financial technology variables. The coefficient for the density of electronic money terminals is positive and significant, indicating that households in areas where there are more terminals—and thus the net benefit of electronic money is higher–are more likely to adopt electronic money. Indeed, the marginal increase in the number of electronic money terminals increases the likelihood of electronic money adoption by about 2.2 percent. Based on this estimate, we confirm the positive network externality of electronic money, which is typical in a two-sided market as previously noted.[29] Passenger-kilometers, the measure of the ease of access to the railroad transportation system, also displays a significant and positive sign. Therefore, a household more likely to commute by railroad has a greater probability of using electronic money.

Given the results obtained in this section, we select the technology availability variables and the household head tertiary education dummy as instruments for the estimation of the average treatment effect of electronic money adoption in the demand function for currency. One may still worry about the validity of instruments despite the fact that the test of each coefficient suggests the relevance. We also compare the measure of the fit, for the model with these variables to one without and confirm that they significantly improve it: for instance pseudo $R^2$ is 0.118 for the model with the three variables and is 0.069 for the model without them. Thus, we find these variables satisfy the relevance criteria of instrument validity. The exogeneity of these variables in equation (4) will be discussed in the next subsection.

### 4.2 Estimates of the Currency Demand Function

We estimate the demand functions for currency conditional on electronic money adoption status. As explanatory variables, we include the disposable income and asset variables, household composition and employment status, and some controls for regional effects.[30] Following Attanasio, Guiso, and Jappelli (2002), the income and asset variables are used as proxies for nondurable consumption expenditure. Given that the ages of the household heads in our sample vary between 20 and 80

currency regarding choice of credit card.

[29]Rysman (2004) finds a similar effect, referred to as a "positive feedback loop," in the choice of consumer credit card in the U.S.

[30]Another variable of interest in the literature is the interest rate. However, as we only have cross-sectional data, and given that in 2007 there is little regional variation in interest rates, we cannot identify the interest rate elasticity for currency demand.

years, income alone may not be a good measure of the consumption level as the consumption of retired households is not likely to be proportionate to their current flow income (such as from pension payments) but rather likely a function of asset holdings. We include the squared terms of the consumption proxies to capture potential nonlinearity. Five city-size dummies (not reported) are also included to control for regional variation in the ease of access to bank branches and ATMs. All variables measuring monetary values are in natural logarithms, including the dependent variable.

Table 9 reports the regression results for both (A) OLS and (B) IV regression. Similar coefficient estimates are obtained in both models except for the value of $\alpha$.

Both the log of disposable income and the log of total financial assets are negative, while both squared terms have a positive sign. This indicates that cash demand decreases with consumption size at a certain threshold (i.e., 108,000 yen for disposable income and 33,200 yen for total assets). In our sample, less than 1 percent of households are below the threshold for disposable income and less than 20 percent for total financial assets. In addition, annual debt payments are negative and significant.

Employment status does not appear to affect cash management, except for self-employment, where self-employed households hold 1,500 yen more than those who are not self-employed. This is in line with anecdotal evidence that the self-employed tend to hold more cash for their business as a precautionary motive.

Identification of $\alpha$, the average difference in currency demand under electronic money adoption and no adoption, is achieved using the fitted value of the adoption model discussed in the previous section. Note that for this estimation, we include all variables in $X_i$ as regressors in probit estimation of model (1) and (2). As it turns out, IV estimate of $\alpha$ is positive and significant at 10 percent. It implies that households increase cash holding on average 4.9 times by the adoption of electronic money.

Note that OLS estimate of $\alpha$ is positive but not statistically significant. These results suggest the endogeneity of electronic money adoption in the currency demand function. The test based on C-statistics rejects the hypothesis that electronic money adoption is exogenous in equation (4) at the 2 percent level of significance. The direction of bias of the OLS estimate implies that electronic money adoption decision is negatively correlated with unobservable component in the demand equation. In other words, households who tend to hold less cash are more likely to adopt the electronic money, controlling for all observable factors.

Because this model is just identified, we cannot perform formal test for overidentifying restriction. However, our basis of IV estimates is the exclusion of three variables–electronic money terminal density, passenger-kilometers, and tertiary education dummy variable for household head–from the conditional money demand function, mentioned in the previous section. Therefore, we estimate 2SLS using these variables as excluded instruments instead of fitted value of adoption probability, and perform the test for overidentifying restriction. The value of J statistics, which follows $\chi^2$ distribution with 2 degrees of freedom under the null, is 4.54, indicating that it cannot reject the null hypothesis and providing the support for the validity of our instruments.

The result that $\alpha$ is positive is counterintuitive and at odds with theory of transaction demand for money; that is, the adoption of electronic money decreases household cash holdings after controlling for other factors. We offer two kinds of explanation for this somewhat counterintuitive result. We attribute the first explanation to the prepaid nature of electronic money described in Section 2. Most noncontact IC form of electronic money requires the deposit of cash at a deposit terminal.[31] For instance, the Bank of Japan (2008) argues that users are inclined to minimize their balances held on electronic money cards partly because under current legislation, any balance is not guaranteed for loss. As there are an increasing number of retail stores and transportation systems favoring electronic money transactions over cash, usage substitution from cash to electronic money takes place. However, as consumers use electronic money as a value storage device to a limited extent, adoption does not change cash holdings greatly. Moreover, there is minimum amount, typically 1,000 yen, that consumer can deposit at each occasion at most terminals. Consequently, some households may increase holding of 1,000 yen bills, in case of the balance on electronic money reaching zero. While this possibility does not apply to the adoption of debit cards, the increase of cash due to adoption of new payment medium appears to be largely driven by prepaid noncontact IC form. Nevertheless, the magnitude of increase inferred from our estimate looks larger than a reasonable level.

Next, we offer three technical possibilities for obtaining these counterintuitive results. These relate to the measurement of cash in our data, the sample size of users, and the nonnormality of the

[31]Some services offer the option of an auto-deposit from a bank account or credit card or an online transfer. However, we believe that the users of these services do not represent a major share of our sample.

data on cash. We explain each in turn. First, the 2007 SHF truncates average cash balances below 10,000 yen. If one believes that the adoption of electronic money decreases the holding of coins and bills in low denominations, say 1,000 yen bills, the data do not capture the changes in balances due to the adoption of electronic money. Furthermore, the SHF survey does not distinguish between cash holdings held for transaction purposes or for store-of-value purposes, while we take the SHF data as a proxy for cash holdings for transaction purposes. Given that the SHF specifically asks for cash holdings, excluding balances held in checking accounts, this deviation should not be as large as the discrepancy between aggregate currency in circulation and that held for transaction purposes.[32] However, Fujiki and Shioji (2006) and the references therein report the tendency for Japanese households to hold cash as part of their portfolios. They also find the evidence for the increased preference for cash to other interest-bearing assets in the 1990s given low interest rates and growing concerns about the health of financial institutions. Thus, this discrepancy due to the difference in the purpose of cash holding may not be negligible. For these reasons, it is natural not to find the substitution of cash with electronic money when using the SHF data. Finally, the SHF data are cross-sectional and thus do not capture changes in a particular person's cash balances over time. For example, the data cannot detect the possibility that the adoption of electronic money may not reduce the average amount of cash held in one's wallet but may reduce the frequency of withdrawing money from a bank account.

Second, we have a small sample problem in the adoption of the electronic money that may reduce the reliability of our estimates. There are less than 100 observations of user households in our sample. Note that we also obtain positive estimate of $\alpha$ using single household sample, which contains more than 600 user observations as shown in appendix. We also find the evidence of endogeneity of the electronic money adoption in equation (4) and positive estimate of $\alpha$, though in much smaller magnitude. From this analysis, we suspect that our family sample overestimates the effect but yields correct estimates in terms of sign, although single household sample has other issues as discussed in section 2.4.

Third, we observe that the empirical distribution of average cash balances (in logs) is skewed to the left with a long tail on the right. The current data set does not provide additional explanatory variables that account for this distribution, especially at the higher end, even though we do our

[32]Moreover, currency in circulation consists of currency held by household sector as well as business and government sectors.

best by adding the square terms of the logs of disposable income and financial assets. Thus, our econometric model may not be able to capture the true effect of electronic money.

In order to deal with the first and third technical issues, we believe it is promising to estimate a demand for currency equation with an electronic money adoption indicator using a quantile regression. By estimating the model at different quantiles, we then will be able to identify the effect of electronic money on the entire distribution of cash balances. This may be a particularly useful exercise, as households who mainly hold cash for transaction purposes and those who hold it for saving purposes may respond to electronic money adoption very differently, presuming that the former tend to have lower cash balances, as pointed out earlier. To cope with the endogeneity of electronic money adoption in this equation, we employ the Instrumental Quantile Regression from Chernozhukov and Hansen (2005, 2006), the details of which are provided in the next section.

### 4.3 Instrumental Quantile Regression

In this subsection, we estimate the quantile of money demand, conditional on electronic money adoption status as in the previous specification. The linear quantile version of the model is described as follows:

$$\log(m) = D\alpha(U) + X'\beta(U), \tag{5}$$

$$U|X,Z \sim \text{Uniform}(0,1) \tag{6}$$

$$D = \delta(X,Z,V), \tag{7}$$

where $m$ is the cash balance and $D$ is technology adoption status. $X$ contains other explanatory variables for cash holdings. $U$ is a scalar random variable that aggregates all of the unobserved factors affecting the structural outcome equation; in this case, the currency demand function conditional on the observable factors $X$ and the electronic money adoption status $D$. A function $\delta$ is unknown and defines the adoption decision. $Z$ includes some explanatory variables that account for electronic money adoption $D$ but does not correlate with cash holdings and $U$. $V$ is an unobserved factor for the adoption of electronic money and is dependent on $U$. Because of this dependence, the adoption decision $D$ is endogenous in equation (5), and the ordinary quantile regression yields biased estimates of the structural parameters, $\alpha(U)$ and $\beta(U)$.

The parameter of interest is $\alpha(U)$, which captures the effect of electronic money adoption on the cash demand given the ranking of the cash balance, $U$. Values in lower case letters $(d, x, z)$

denote potential values that the corresponding upper case random variables $(D, X, Z)$ may take. The structural quantile function of the above model is given by:

$$S_{\log(m)}(\tau|d,x) = d'\alpha(\tau) + x'\beta(\tau),$$

which defines the $\tau$th quantile of potential outcome $\log(m)$ conditional on the adoption status $d$ and other controls $x$. This differs from the ordinary quantile function in that it expresses the quantile of the latent outcome $\log(m_d) = d\alpha(\tau) + x'\beta(\tau)$.

If the model satisfies the regularity conditions as in Chernozhukov and Hansen (2005), the model equations (5),(6) and (7) imply as follows, by the conditional moment condition:

$$P[\log(m) \leq S_{\log(m)}(\tau|D,X)|Z,X] = \tau,$$

using instrument $Z$. Furthermore Chernozhukov and Hansen (2006) propose a feasible estimation procedure by using the quantile analogue (inverse) of the instrument relevance test statistics.

Because of the specification above, we uncover the impact of the change in technological adoption status on the demand for cash.

Table 10 summarizes the estimation results for the 0.15, 0.25, 0.50, 0.75 and 0.85 quantiles. We use the same sets of variables used in the IV estimation in Table 9. The estimated values of $\alpha(\tau)$, measuring the effect of electronic money adoption on currency demand, take values between 0.30 and 3.92 (or 13,000 yen to 504,000 yen) and are positive across quantiles. This set of results confirms that households tend to increase cash holdings because of the new payment technology. Nevertheless, $\alpha(\tau)$ is not statistically significant; thus, the result is suggestive but not conclusive. The impact of electronic money adoption on the cash balance varies substantially from quantile to quantile. As for the remaining explanatory variables, the effect varies with quantiles, though the qualitative effects are similar to the IV results.

One caveat, however, is that the Instrumental Quantile Regression suffers from another data problem; that is, truncation. As the data are truncated below 10,000 yen, 12.39 percent of the sample are assigned cash balances of less than 10,000 yen. By ignoring truncation, this approach is then likely to yield biased estimates at the lower quantiles of our data. We hope to deal with this issue in the future.

## 5 Conclusion

We estimate the currency demand functions conditional on electronic money adoption to investigate how the diffusion of a new payment technology influences the household demand for currency. Using unique household-level survey data from Japan, we estimate the currency demand functions with IV regression and instrumental quantile regression. To the best of our knowledge, this is the first paper to investigate this issue using a micro-level data set.

Based on our estimates, we obtain the following results. First, the probit estimates of electronic money adoption model indicate that a household is more likely to adopt electronic money if it has more members in their thirties, has a self-employed head with a tertiary education, and has greater exposure to the new payment technology. Second, the IV estimation of currency demand indicates that average cash balances increase with the adoption of electronic money. Third, households at the lower quantiles of the cash balance distribution tend to hold more cash after adopting electronic money. This is at odds with the predictions obtained from the Baumol–Tobin model of the transaction theory of the demand for money. However, the results are consistent with available Japanese evidence based on aggregate statistics, which do not find the significant substitution of cash holding for electronic money, despite the rapid diffusion of electronic money among Japanese households.

We would like to conclude this paper with an agenda for future research. First, the biases in the instrumental quantile regression estimates from the truncation of the data set need to be addressed. As our intuition suggests that households with low average cash balances are more likely to behave according to a Baumol–Tobin model of transaction money demand, it is important to check whether the current findings are maintained following any correction. Second, our estimation procedure does not correct the possible endogeneity of electronic money availability in the electronic money adoption decision. For instance, merchants are more likely to adopt electronic money if more of their customers adopt and are ready to use it. This endogeneity must be corrected with appropriate instruments. Third, our analysis is cross-sectional and not suitable for forecasts. Thus, we would like to extend the model to accommodate the dynamics once data of future years are made available.

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# Appendix

## A Results for Single-person Households

In this appendix, we present the results of the same analysis on the single-person household sample as that on the family sample reported in the main body of the text.

The single-person sample is not collected using random sampling: the responses are chosen from a pool of individuals who registered with a survey company with a sampling probability assigned based on the latest census, by age, gender, and region. Moreover, the responses are collected through the Internet. Thus, the sample is self-selected, and respondents tend to be more accustomed to adopting new technology, like the Internet, than the average single-person household. For example, the summary statistics in Table 4 indicate that they are accustomed to the use of credit cards (54 percent of family households and 74 percent of single-person households) and electronic money (4 percent of family households and 26 percent of single-person households).

Nonetheless, analysis of the single-person household data set has a few advantages if we are careful about the possible bias in the sample. First, the respondent is the same person who makes the decision on the adoption of electronic money and cash holdings. Therefore, there are fewer measurement errors in this sample than in the family household sample. Second, the single-person household data set has a greater incidence of electronic money adoption. Thus, the small sample problem discussed in Section 4.2 is believed to be less serious. To see the second point, let us examine the average cash balance by the choice of payment type in Table 12 and the choice of payment type by transaction amount in Table 11. The tables show that the single-person household data set has a greater incidence of electronic money adoption and that the average balance of households using electronic money increases as the transaction amount decreases, contrary to the findings for the family households. We do not know to what extent these characteristics depend on the sample design. With these reservations, let us consider the estimation results for the single-person households.

### A.1 Electronic Money Adoption

Table 13 provides the probit estimation results for electronic money adoption using the single-person household data. Regarding the financial status variables, unlike the family sample results, disposable income is not significant, but the financial asset balance is positive and significant. Thus, for a single person, the net benefit of adopting electronic money positively depends on the level of financial assets.

Regarding the household characteristic variables, males are 8.6 percent more likely to adopt electronic money than females after controlling for other relevant characteristics. Tertiary education and self-employment dummies are both insignificant in adoption model, unlike the results from family sample. Age dummies are significant if the age is above 45 years. Above 45 years, the estimates imply that the likelihood of adoption decreases monotonically with age. Age dummies below 45 years are not significant; thus, at earlier ages, there is no distinction in electronic money adoption behavior relative to those of the age group below 25 years old after controlling for other conditions. This finding confirms that the age of the respondent predicts adoption above a certain age, comparable to the family sample results.

The credit card usage dummy is positive and significant, though the dummy for the usage of credit cards for a transaction amount below 1,000 yen is negative and significant, and the magnitude is larger. This suggests that individuals who use credit cards for transactions in small amounts are about 6.4 percent less likely to adopt electronic money, but those who use credit cards for payments of larger amounts are about 11.8 percent more likely to adopt electronic money compared with those who do not use credit cards at all. These results may mean that, for individuals using credit cards, the cost of adopting electronic money is lower than for those who do not. However, the benefit of adopting electronic money may be low for individuals who make payments of small amounts by credit cards, as they already substitute cash payments for credit.

Unfortunately, the SHF does not provide city size data for this sample, and we cannot match the financial technology variable as precisely as for the family sample. Nevertheless, consistent with the family sample results, the number of electronic money terminals per square kilometer is positive and significant.

## A.2 Estimates of Currency Demand Function

Given the results in Table 13, we specify the number of electronic money terminals per square kilometer in the area and the credit card usage dummy for small transactions as exogenous instruments when estimating model (4). Comparison of R-squared measures shows significant improvement by including these two variables and gives support for their relevance. Note that the log of passenger-kilometers is not included as it is highly correlated with the number of electronic money terminals once they are aggregated to the regional level.

The results shown in Table 14 are similar to those from the family sample. The demand for cash is positively correlated with proxies for consumption such as disposable income and financial assets. Self-employed individuals tend to hold significantly more cash than others do. Individuals over 60 years of age hold significantly more cash than those below 25 years old.

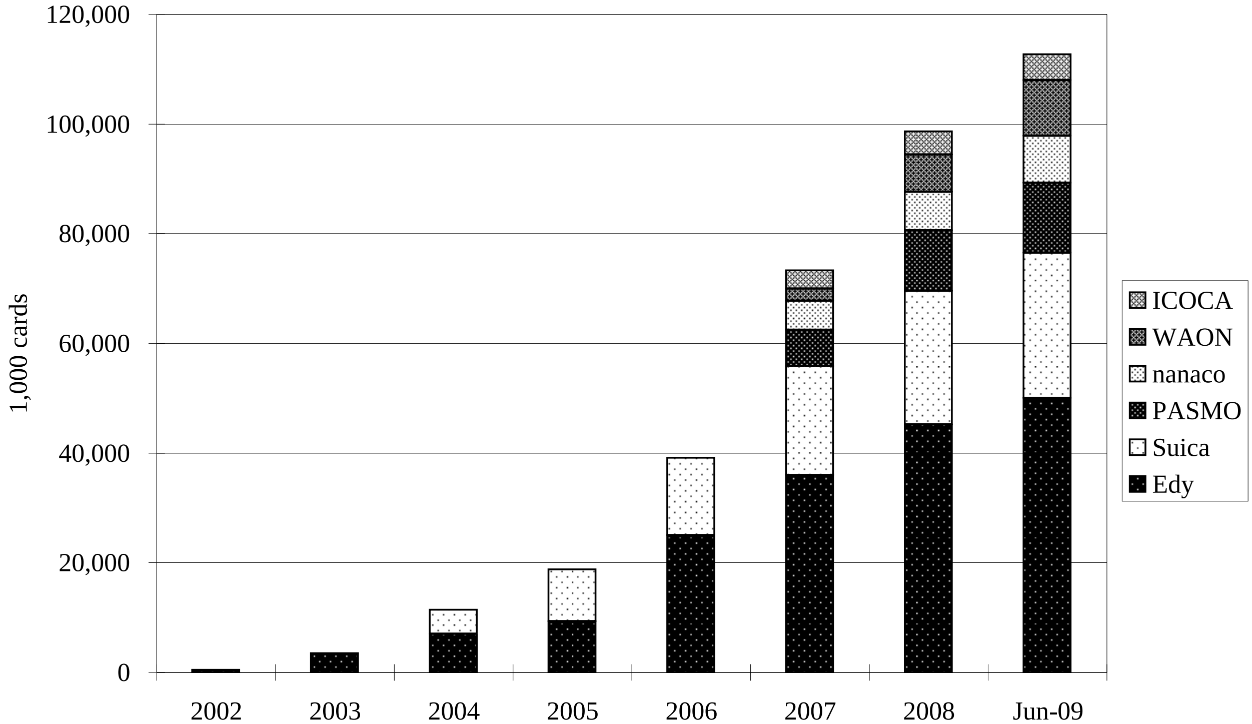
However, the main variable of interest, electronic money adoption status, is negative with OLS and positive with IV and only IV estimate is statistically significant at 10 percent. Similar to the results using family household sample, the difference in OLS and IV estimates indicates that OLS is negatively biased. It implies that the unobserved heterogeneity of cash holdings negatively correlated with adoption of electronic money. The magnitude of the effect is about 50 percent increase based on IV, which is substantially smaller than the estimate using family sample.

Note that the test based on C-statistics rejects the hypothesis that electronic money adoption is exogenous in money demand equation. Moreover, the test of overidentifying restrictions does not reject the hypothesis that orthogonality conditions are satisfied and lends credence to the validity of the instruments assuming specification of money demand is correct.

To check the robustness of these results further, the instrumental quantile regressions are also estimated. Table 15 indicates that electronic money adoption has a significantly positive effect on cash holdings for individuals whose cash holding is at or less than the median. These results from instrumental quantile regressions are in line with those using family household sample. However they show statistically significant yet smaller effect in magnitude.

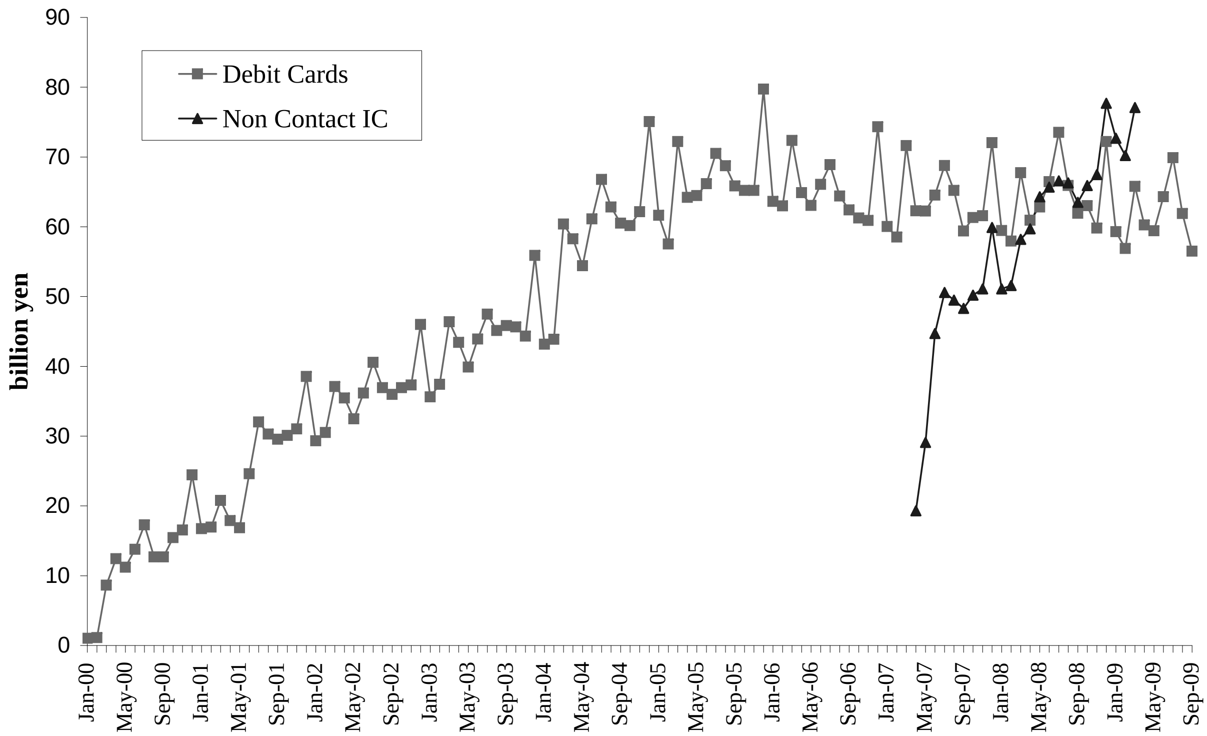
# B Figures and Tables

Figure 1: DIFFUSION OF ELECTRONIC MONEY – NUMBER OF PREPAID NONCONTACT IC FORMS




Note: Compiled by authors with the information obtained from some issues of Nikkei Marketing Journal and websites of bitWallet.Inc. and East Japan Railway Company.

Figure 2: DIFFUSION OF ELECTRONIC MONEY - TRANSACTION VOLUME IN YEN FOR DEBIT CARDS AND PREPAID NONCONTACT IC CARDS)




Note: Compiled by authors based on the information obtaind from Bank of Japan (2009) and the website of the Japan Debit Card Promotion Association.

Figure 3: RATIO OF CURRENCY IN CIRCULATION TO NOMINAL GNP (%)

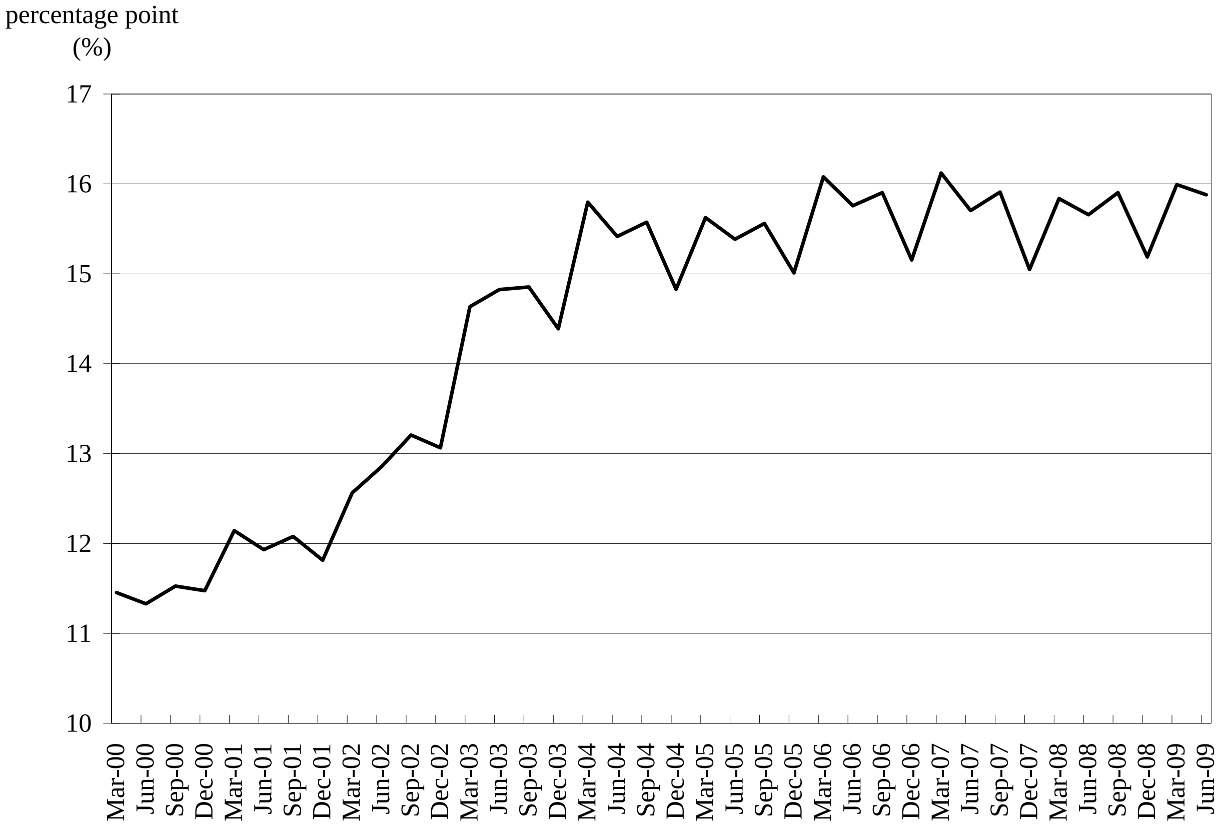


Figure 4: BANKNOTES AND COINS IN CIRCULATION

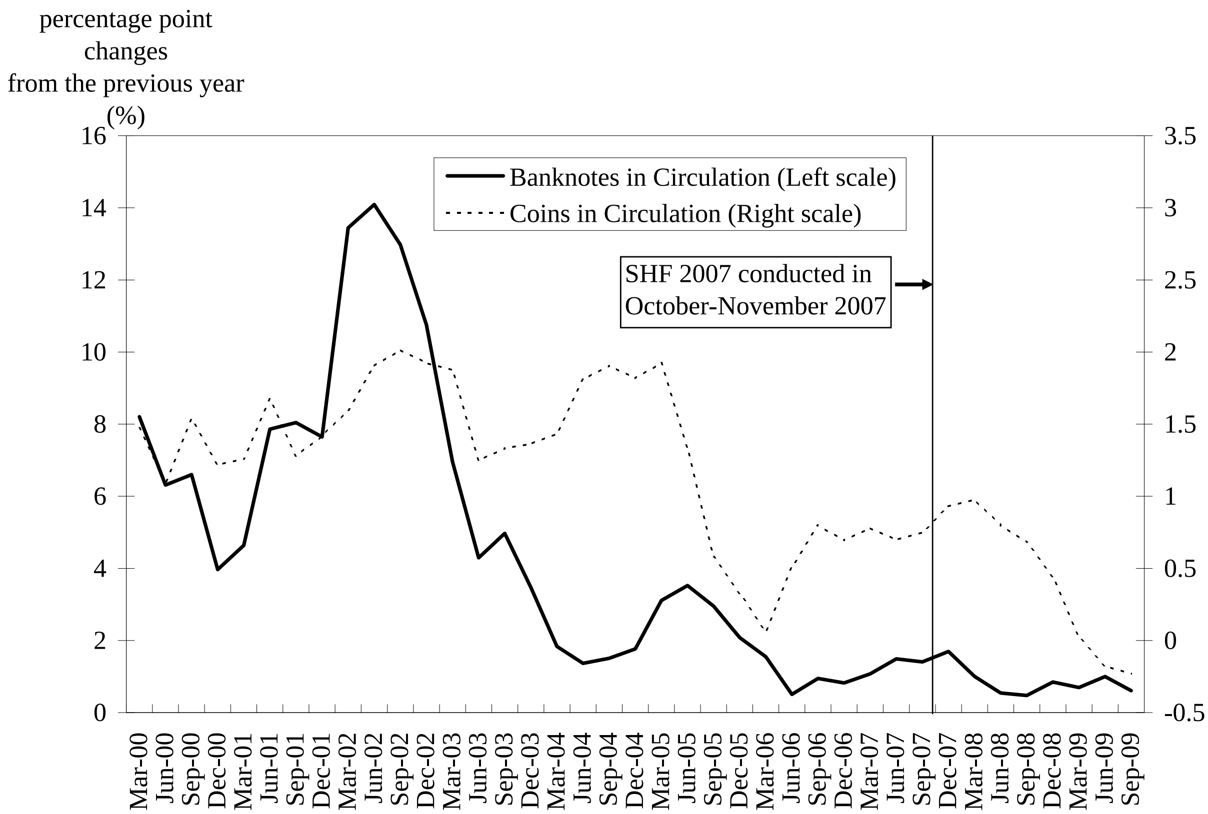


Table 1: PROPERTIES OF PAYMENT INSTRUMENTS

| | Paper | Plastic | | | Direct Transfer |
|---|---|---|---|---|---|
| | | Electronic Money | | | |
| | Cash | Debit | Noncontact IC | Credit | |
| Acceptance | all | limited[a] | limited | limited | - |
| Adoption Cost(Payer) | 0 | $> 0$ | $\approx 0$ | $> 0$ | - |
| Usage Charge(Payer) | 0 | $0^b$ | $0^b$ | $0^b$ | $> 0$ |
| Usage Charge (Payee) (% of transaction balance) | 0 | 2 % | 2-3% | 3-5% | 0 |
| Transaction Speed (seconds) [c] | 10-30 | 10 | 1 | 30 | NA |
| Float | 0 | 0 | 0 | 15–45 days | 1–2 days |
| Need for the Transfer of Balance | yes | no | yes[d] | no | no |
| Anonymity | yes | no | yes[e] | no | no |

Notes:[a] Available during ATM operating hours with some exceptions. [b] Some card issuers offers cash rebates and royalty points programs. Thus, this cost may be negative. [c] From articles in Realtime Retail, October 2004, Nikkei Business Publication Inc. and Business Media Sei, June 2006, ITmedia Inc.[d] With some exceptions. [e] Some cards may not be anonymous, such as one combined with a commuter pass.

Table 2: AVERAGE TRANSACTION VALUES BY WITHDRAWAL AND PAYMENT INSTRUMENTS, AS OF 2007 IN USD[a]

| | ATM Withdrawal[b] | Credit | Debit | E-Money |
|---|---|---|---|---|
| Japan | 454 | 68[c] | 597[c] | 6 |
| U.S.A. | 99[c] | 89 | 39 | - |
| France | 91 | 64 | 65 | 24 |
| U.K. | 132 | 126 | 92 | - |

Notes:[a] Authors' calculation from Bank for International Settlements (2009). These figures include currency circulated outside the country and need to reflect actual circulation within the country. Europe includes Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Slovenia. All values are the average transaction value in the given year. [b] Excludes cash withdrawals from "own ATMs" of financial institutions. [c] The data are as at 2006.

Table 3: SUMMARY STATISTICS: FAMILY HOUSEHOLD SAMPLE

| | Overall | | Electronic money adoption | | | |
|---|---|---|---|---|---|---|
| | | | user | | nonuser | |
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| Cash balance | 14.50 | 41.89 | 15.70 | 33.44 | 14.46 | 42.17 |
| Disposable income | 518 | 348 | 661 | 338 | 513 | 347 |
| Financial assets | 1,322 | 2,586 | 1,202 | 1,332 | 1,327 | 2,621 |
| Home ownership | 0.73 | 0.45 | 0.66 | 0.48 | 0.73 | 0.44 |
| Holding of risky assets | 0.02 | 0.14 | 0.06 | 0.25 | 0.02 | 0.14 |
| Age of household head | 54.88 | 13.96 | 49.62 | 12.11 | 55.07 | 13.98 |
| Household size | 3.43 | 1.34 | 3.50 | 1.27 | 3.43 | 1.34 |
| Presence of children | 0.32 | 0.46 | 0.39 | 0.49 | 0.31 | 0.46 |
| Self-employment | 0.11 | 0.31 | 0.15 | 0.36 | 0.11 | 0.31 |
| Unemployment | 0.16 | 0.37 | 0.07 | 0.26 | 0.17 | 0.37 |
| Credit card usage | 0.54 | 0.50 | 0.74 | 0.44 | 0.53 | 0.50 |
| Electronic money usage | 0.04 | – | 1.00 | – | 0 | – |
| Education above high school | 0.41 | 0.49 | 0.68 | 0.47 | 0.40 | 0.49 |
| Observations | 2,663 | | 94 | | 2,569 | |

Table 4: SUMMARY STATISTICS: SINGLE-PERSON HOUSEHOLD SAMPLE

| | Overall | | Electronic money adoption | | | |
|---|---|---|---|---|---|---|
| | | | user | | nonuser | |
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| Cash balance | 15.91 | 59.70 | 13.39 | 45.63 | 16.78 | 63.80 |
| Disposable income | 312 | 686 | 374 | 1,194 | 291 | 376 |
| Financial assets | 723 | 3,801 | 574 | 1,283 | 774 | 4,339 |
| Home ownership | 0.06 | 0.24 | 0.05 | 0.21 | 0.07 | 0.25 |
| Holding of risky assets | 0.02 | 0.16 | 0.03 | 0.17 | 0.02 | 0.15 |
| Age of household head | 39.78 | 14.58 | 36.14 | 12.26 | 41.02 | 15.10 |
| Self-employment | 0.04 | 0.21 | 0.03 | 0.18 | 0.05 | 0.21 |
| Unemployment | 0.16 | 0.36 | 0.10 | 0.30 | 0.18 | 0.38 |
| Credit card usage | 0.74 | 0.44 | 0.84 | 0.37 | 0.70 | 0.46 |
| Electronic money usage | 0.26 | – | 1.00 | – | 0 | – |
| Education above high school | 0.63 | 0.48 | 0.67 | 0.47 | 0.61 | 0.49 |
| Observations | 2,500 | | 638 | | 1,862 | |

Table 5: CHOICE OF PAYMENT TYPE BY PAYMENT AMOUNT: FAMILY HOUSEHOLDS (%)

| | Payment amount | Cash | Credit card | Electronic money | Others |
|---|---|---|---|---|---|
| (1) | Less than ¥1,000 | 86.59 | 2.75 | 2.39 | 0.5 |
| (2) | ¥1,000 – ¥5,000 | 84.12 | 12.02 | 1.27 | 0.6 |
| (3) | ¥5,000 – ¥10,000 | 78.20 | 20.77 | 0.69 | 0.9 |
| (4) | ¥10,000 – ¥50,000 | 63.98 | 39.22 | 0.63 | 1.7 |
| (5) | Greater than ¥50,000 | 52.26 | 45.65 | 0.69 | 4.5 |
| | All | 97.04 | 51.18 | 3.59 | |

| Recurring Payment | Cash | Credit card | Electronic money | Bank transfer |
|---|---|---|---|---|
| | 33.82 | 14.43 | 0.30 | 86.00 |

Note: Each household was asked to name up to two means of payment for each range of payment amount.

Table 6: AVERAGE CASH BALANCE BY PAYMENT CHOICE: FAMILY HOUSEHOLD (1,000 yen)

| | Payment amount | Cash | Credit card | Electronic money | Overall mean |
|---|---|---|---|---|---|
| (1) | Less than ¥1,000 | 132.66 | 62.70 | 165.97 | 138.32 |
| (2) | ¥1,000 – ¥5,000 | 134.59 | 111.74 | 150.71 | 138.32 |
| (3) | ¥5,000 – ¥10,000 | 135.28 | 102.29 | 98.26 | 138.32 |
| (4) | ¥10,000 – ¥50,000 | 138.85 | 114.57 | 106.19 | 138.32 |
| (5) | Greater than ¥50,000 | 154.99 | 114.28 | 66.52 | 138.32 |
| | All | 137.54 | 115.54 | 141.79 | 138.32 |

Table 7: NUMBER OF EDY TERMINALS PER SQUARE KILOMETER BY CITY SIZE

| Region | Big Cities | To 40,000 households | 20,000–40,000 households | 10,000–20,000 households | below 10,000 households | villages |
|---|---|---|---|---|---|---|
| Hokkaido | 0.49 | 0.05 | 0.05 | 0.01 | 0.00 | 0.00 |
| Tohoku | 0.21 | 0.04 | 0.02 | 0.01 | 0.01 | 0.01 |
| Kanto | 1.87 | 0.22 | 0.04 | 0.02 | 0.00 | 0.01 |
| Hokuriku | 0.08 | 0.05 | 0.02 | 0.01 | 0.01 | 0.01 |
| Chubu | 0.30 | 0.08 | 0.03 | 0.02 | 0.00 | 0.01 |
| Kinki | 0.66 | 0.27 | 0.04 | 0.01 | 0.01 | 0.01 |
| Chugoku | 0.18 | 0.05 | 0.01 | 0.00 | – | 0.00 |
| Shikoku | – | 0.20 | 0.04 | 0.02 | 0.01 | 0.01 |
| Kyushu | 0.80 | 0.21 | 0.09 | 0.04 | 0.01 | 0.03 |

Table 8: ELECTRONIC MONEY TECHNOLOGY ADOPTION DECISION: PROBIT ESTIMATION: FAMILY HOUSEHOLDS

| | Estimates[a] | Marginal Effect |
|---|---|---|
| log(Disposable Income) | 0.201** | 0.01** |
| | (0.099) | (0.005) |
| log(Financial Asset) | -0.003 | 0 |
| | (0.018) | (0.001) |
| log(Annual Debt Payment) | 0.033* | 0.002 |
| | (0.020) | (0.001) |
| Self-employed[b] | 0.332** | 0.023* |
| | (0.147) | (0.012) |
| Tertiary Education[b] | 0.388*** | 0.022*** |
| | (0.106) | (0.007) |
| Credit Card usage[b] | 0.157 | 0.008 |
| | (0.117) | (0.006) |
| Ratio of age group: | | |
| 30s | 0.753*** | 0.039*** |
| | (0.270) | (0.014) |
| 40s | 0.256 | 0.013 |
| | (0.335) | (0.017) |
| 50s | 0.093 | 0.005 |
| | (0.287) | (0.015) |
| 60s | 0.198 | 0.01 |
| | (0.236) | (0.012) |
| 70 and above | -0.366 | -0.019 |
| | (0.322) | (0.016) |
| Ratio of male members | -0.227 | -0.012 |
| | (0.310) | (0.016) |
| Density of electronic money terminals[c] | 0.431*** | 0.022*** |
| | (0.161) | (0.009) |
| log(Passenger kilometers) | 0.073* | 0.004* |
| | (0.040) | (0.002) |
| Constant | -5.246*** | |
| | (0.902) | |
| Observation | 2,663 | 2,663 |
| Log likelihood | -358.546 | -358.546 |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [a] Five city size dummy variables are included. [b] Dummy variables. [c] It is measured by the number of the terminals per square kilometer.

Table 9: CONDITIONAL CURRENCY DEMAND FUNCTION : FAMILY HOUSEHOLDS

| | (A) | (B) |
|---|---|---|
| | OLS[a] | IV[a] |
| Electronic Money Adoption | 0.07 | 1.77* |
| ($\alpha$) | (0.119) | (0.949) |
| log(Disposable Income) | -0.179** | -0.162* |
| | (0.088) | (0.094) |
| (log(Disposable Income))$^2$ | 0.042*** | 0.038*** |
| | (0.010) | (0.011) |
| log(Financial Asset) | -0.051** | -0.048* |
| | (0.025) | (0.026) |
| (log(Financial Asset))$^2$ | 0.024*** | 0.024*** |
| | (0.003) | (0.003) |
| Self-employed[b] | 0.447*** | 0.416*** |
| | (0.074) | (0.081) |
| log(Annual Debt Payment) | -0.027*** | -0.034*** |
| | (0.011) | (0.011) |
| Credit card usage [b] | -0.076 | -0.099* |
| | (0.052) | (0.053) |
| Ratio of male members | 0.383*** | 0.381** |
| | (0.148) | (0.152) |
| Ratio of age group: | | |
| 30s | 0.31** | 0.188 |
| | (0.135) | (0.161) |
| 40s | 0.204 | 0.151 |
| | (0.154) | (0.161) |
| 50s | 0.334*** | 0.328*** |
| | (0.126) | (0.128) |
| 60s | 0.564*** | 0.54*** |
| | (0.116) | (0.124) |
| 70 and above | 0.737*** | 0.744*** |
| | (0.111) | (0.116) |
| Constant | 0.217 | 0.232 |
| | (0.263) | (0.264) |
| Observations | 2,663 | 2,663 |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [aa] Five city size dummy variables are included. [b] Dummy variables.

Table 10: INSTRUMENTAL QUANTILE REGRESSION: FAMILY HOUSEHOLDS[a]

| | 0.15 | 0.25 | 0.5 | 0.75 | 0.85 |
|---|---|---|---|---|---|
| | coef. | coef. | coef. | coef. | coef. |
| Electronic Money Adoption | 0.296 | 3.924 | 3.391 | 2.154 | 1.376 |
| ($\alpha$) | (0.994) | (5.187) | (4.675) | (6.370) | (3.617) |
| log(Disposable Income) | -0.030 | 0.029 | -0.095 | -0.090 | -0.282 |
| | (0.051) | (0.064) | (0.055) | (0.093) | (0.087) |
| (log(Disposable Income))$^2$ | 0.020 | 0.015 | 0.032 | 0.032 | 0.053 |
| | (0.010) | (0.011) | (0.008) | (0.010) | (0.010) |
| log(Financial Asset) | 0.012 | 0.111 | -0.015 | -0.102 | -0.148 |
| | (0.038) | (0.036) | (0.032) | (0.038) | (0.034) |
| (log(Financial Asset))$^2$ | 0.028* | 0.013* | 0.019* | 0.026* | 0.031* |
| | (0.005) | (0.005) | (0.004) | (0.005) | (0.005) |
| log(Annual Debt Payment) | 0.008 | -0.070 | -0.162 | -0.110 | -0.055 |
| | (0.070) | (0.077) | (0.067) | (0.052) | (0.050) |
| (log(Annual Debt Payment))$^2$ | -0.009 | 0.002 | 0.031 | 0.024 | 0.010 |
| | (0.018) | (0.020) | (0.016) | (0.012) | (0.011) |
| Credit Card Usage [b] | 0.064*** | -0.016*** | -0.104*** | -0.202*** | -0.236*** |
| (any amount) | (0.075) | (0.077) | (0.063) | (0.067) | (0.073) |
| Self-employment[b] | 0.444*** | 0.364*** | 0.377*** | 0.518*** | 0.546*** |
| | (0.109) | (0.110) | (0.099) | (0.156) | (0.107) |
| Ratio of Male Members | 0.287 | 0.216 | 0.447 | 0.111 | 0.190 |
| | (0.236) | (0.240) | (0.206) | (0.277) | (0.197) |
| Ratio of age group: | | | | | |
| 30s | 0.321 | 0.193 | -0.009 | 0.107 | 0.168 |
| | (0.266) | (0.242) | (0.167) | (0.215) | (0.176) |
| 40s | -0.012 | -0.011 | 0.075 | 0.134 | 0.349 |
| | (0.241) | (0.241) | (0.188) | (0.224) | (0.251) |
| 50s | 0.293 | 0.366 | 0.261 | 0.285 | 0.232 |
| | (0.168) | (0.175) | (0.158) | (0.154) | (0.163) |
| 60s | 0.268*** | 0.434*** | 0.373*** | 0.529*** | 0.541*** |
| | (0.172) | (0.165) | (0.129) | (0.161) | (0.166) |
| 70 and above | 0.655 | 0.759 | 0.717 | 0.652 | 0.661 |
| | (0.166) | (0.159) | (0.127) | (0.138) | (0.160) |
| Constant | -1.408*** | -1.235*** | 0.068*** | 1.088*** | 1.840*** |
| | (0.418) | (0.383) | (0.348) | (0.466) | (0.472) |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [a] Five city size dummy variables are included. [b] Dummy variables

Table 11: CHOICE OF PAYMENT TYPE BY PAYMENT AMOUNT: SINGLE PERSON HOUSEHOLDS (%)

| | Payment amount | Cash | Credit card | Electronic money | Others |
|---|---|---|---|---|---|
| (1) | Less than ¥1,000 | 92.44 | 12.16 | 21.08 | 1.4 |
| (2) | ¥1,000 – ¥5,000 | 81.60 | 36.36 | 11.36 | 1.5 |
| (3) | ¥5,000 – ¥10,000 | 69.84 | 51.32 | 6.00 | 1.6 |
| (4) | ¥10,000 – ¥50,000 | 50.32 | 67.44 | 4.40 | 2.1 |
| (5) | Greater than ¥50,000 | 39.60 | 69.48 | 3.48 | 4.3 |
| | All | 95.20 | 94.92 | 25.52 | |

| | Recurring Payment | Cash | Credit card | Electronic money | Bank transfer |
|---|---|---|---|---|---|
| | | 30.12 | 45.40 | 3.16 | 68.40 |

Note: Each household was asked to name up to two means of payment for each range of payment amount.

Table 12: AVERAGE CASH BALANCE BY PAYMENT CHOICE: SINGLE-PERSON HOUSEHOLDS (1,000 yen)

| | Payment amount | Cash | Credit card | Electronic money | Overall mean |
|---|---|---|---|---|---|
| (1) | Less than ¥1,000 | 156.85 | 165.00 | 114.48 | 159.13 |
| (2) | ¥1,000 – ¥5,000 | 143.18 | 156.35 | 107.32 | 159.13 |
| (3) | ¥5,000 – ¥10,000 | 144.14 | 156.05 | 135.00 | 159.13 |
| (4) | ¥10,000 – ¥50,000 | 143.28 | 150.04 | 249.55 | 159.13 |
| (5) | Greater than ¥50,000 | 153.88 | 151.38 | 203.45 | 159.13 |
| | All | 160.36 | 157.39 | 133.87 | 159.13 |

Table 13: ELECTRONIC MONEY TECHNOLOGY ADOPTION DECISION: PROBIT ESTIMATION: SINGLE HOUSEHOLDS

| | Estimates | Marginal Effect |
|---|---|---|
| log(Disposable Income) | 0.003 | 0.001 |
| | (0.021) | (0.006) |
| log(Financial Asset) | 0.054*** | 0.016*** |
| | (0.010) | (0.003) |
| log(Annual Debt Payment) | 0.01 | 0.003 |
| | (0.015) | (0.005) |
| Male[a] | 0.292*** | 0.086*** |
| | (0.061) | (0.017) |
| Self-employed[a] | -0.006 | -0.002 |
| | (0.150) | (0.045) |
| Credit card usage[a] | 0.422*** | 0.118*** |
| (below ¥1000) | (0.073) | (0.019) |
| Credit card usage [a] | -0.779*** | -0.182*** |
| (any amount) | (0.100) | (0.017) |
| Age Dummies: [a] | | |
| age 25–29 | 0.068 | 0.021 |
| | (0.101) | (0.031) |
| age 30–34 | 0.118 | 0.037 |
| | (0.112) | (0.036) |
| age 35–39 | 0.149 | 0.047 |
| | (0.122) | (0.040) |
| age 40–44 | 0.099 | 0.031 |
| | (0.130) | (0.042) |
| age 45–49 | -0.246 | -0.068* |
| | (0.165) | (0.041) |
| age 50–54 | -0.305** | -0.083*** |
| | (0.131) | (0.032) |
| age 55–59 | -0.411*** | -0.107*** |
| | (0.150) | (0.032) |
| age 60–64 | -0.584*** | -0.145*** |
| | (0.128) | (0.025) |
| age 65 and above | -0.968*** | -0.196*** |
| | (0.193) | (0.022) |
| Density of electronic | 3.466*** | 1.049*** |
| money terminals[b] | (0.466) | (0.141) |
| Constant | -1.581*** | |
| | (0.132) | |
| Observation | 2,500 | |
| Log likelihood | -1,271 | |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [a]Dummy variables. [b] It is measured by the number of the terminals per square kilometer.

Table 14: CONDITIONAL CURRENCY DEMAND FUNCTION: SINGLE HOUSEHOLDS

| | (A) OLS | (B) IV |
|---|---|---|
| Electronic Money Adoption | -0.079 | 0.402* |
| ($\alpha$) | (0.062) | (0.244) |
| log(Disposable Income) | 0.095*** | 0.094*** |
| | (0.019) | (0.020) |
| log(Financial Asset) | 0.142*** | 0.136*** |
| | (0.010) | (0.010) |
| log(Annual Debt Payment) | -0.07*** | -0.072*** |
| | (0.014) | (0.014) |
| Male[a] | 0.219*** | 0.18*** |
| | (0.054) | (0.058) |
| Self-employed[a] | 0.432*** | 0.438*** |
| | (0.148) | (0.148) |
| Credit card usage[a] | -0.045 | -0.091 |
| (any amount) | (0.066) | (0.071) |
| Age Dummies: [a] | | |
| age 25–29 | -0.126 | -0.138 |
| | (0.092) | (0.093) |
| age 30–34 | -0.068 | -0.088 |
| | (0.103) | (0.105) |
| age 35–39 | -0.184* | -0.207* |
| | (0.111) | (0.113) |
| age 40–44 | -0.147 | -0.16 |
| | (0.130) | (0.133) |
| age 45–49 | -0.014 | 0.023 |
| | (0.160) | (0.160) |
| age 50–54 | 0.199 | 0.242* |
| | (0.121) | (0.125) |
| age 55–59 | 0.164 | 0.222 |
| | (0.133) | (0.138) |
| age 60–64 | 0.307*** | 0.381*** |
| | (0.116) | (0.123) |
| age 65 and above | 0.322** | 0.424*** |
| | (0.144) | (0.153) |
| Constant | 0.269** | 0.223** |
| | (0.105) | (0.107) |
| Observations | 2,500 | 2,500 |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [a] Dummy variables.

Table 15: INSTRUMENTAL QUANTILE REGRESSION: SINGLE HOUSEHOLDS

| | 0.15 | 0.25 | 0.5 | 0.75 | 0.85 |
|---|---|---|---|---|---|
| | coef. | coef. | coef. | coef. | coef. |
| Electronic Money Adoption | 0.435* | 0.583** | 0.512** | 0.432 | 0.688 |
| ($\alpha$) | (0.254) | (0.275) | (0.256) | (0.426) | (0.901) |
| log(Disposable Income) | 0.000 | 0.004 | 0.053*** | 0.077*** | 0.095*** |
| | (0.011) | (0.012) | (0.017) | (0.020) | (0.024) |
| log(Financial Asset) | 0.171 | 0.202 | 0.122 | 0.100*** | 0.121*** |
| | (0.014) | (0.014) | (0.011) | (0.013) | (0.020) |
| log(Annual Debt Payment) | -0.022* | -0.012 | -0.059*** | -0.089*** | -0.068** |
| | (0.013) | (0.013) | (0.016) | (0.021) | (0.030) |
| Male[a] | 0.032 | 0.027 | 0.086 | 0.268*** | 0.313** |
| | (0.062) | (0.066) | (0.063) | (0.080) | (0.128) |
| Self-employment[a] | 0.070 | 0.274* | 0.288** | 0.635*** | 0.426 |
| | (0.136) | (0.156) | (0.149) | (0.214) | (0.262) |
| Credit Card Usage[a] | 0.000 | 0.000 | -0.005 | -0.178* | -0.245* |
| | (0.065) | (0.070) | (0.084) | (0.106) | (0.140) |
| Age dummies:[a] | | | | | |
| age 45–49 | 0.032 | 0.011 | 0.102 | 0.263 | 0.054 |
| | (0.140) | (0.125) | (0.182) | (0.193) | (0.297) |
| age 50–54 | 0.032 | 0.058 | 0.254** | 0.456** | 0.738*** |
| | (0.096) | (0.092) | (0.106) | (0.182) | (0.277) |
| age 55–59 | 0.103 | 0.079 | 0.285** | 0.386** | 0.541* |
| | (0.122) | (0.118) | (0.134) | (0.187) | (0.294) |
| age 60–64 | 0.071 | 0.345*** | 0.638*** | 0.573*** | 0.412* |
| | (0.112) | (0.129) | (0.105) | (0.141) | (0.237) |
| age 65 and above | 0.367** | 0.447*** | 0.533*** | 0.555*** | 0.483 |
| | (0.152) | (0.165) | (0.142) | (0.188) | (0.309) |
| Constant | -0.622*** | -0.578*** | 0.163 | 1.016*** | 1.418*** |
| | (0.076) | (0.083) | (0.123) | (0.150) | (0.178) |

Notes: Standard errors are in parentheses. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level. [a] Dummy variables.