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Attributes needed for Japan’s central bank digital currency

Hiroshi FUJIKI

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TOKYO CENTER FOR ECONOMIC RESEARCH
1-7-10-703 Iidabashi, Chiyoda-ku, Tokyo 102-0072, Japan

Abstract

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Hiroshi FUJIKI
TCER
and
Chuo University
Faculty of Commerce
742-1 Higashinakano, Hachioji-shi, Tokyo
192-0393, Japan
fujiki@tamacc.chuo-u.ac.jp

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Hiroshi FUJIKI*

Chuo University

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The issuance of central bank digital currency became a real policy issue after the announcement of Facebook's Libra. Which types of product attributes should a central bank digital currency have to be widely accepted? We answer this question by analyzing the consumers' acceptance of hypothetical payment instruments. We used Japanese data from the 2019 Financial Literacy Survey to estimate a model of consumers' ranking of the frequency of the use of five payment instruments. The estimates of the model showed that the respondents to the survey value payment instruments with shorter transaction times and mobile payment instruments. Based on the estimates of the model, we conducted counterfactual simulations for the introduction of the hypothetical mobile version of noncash payment methods that required a shorter transaction time. We found that these hypothetical products would be the most frequently used payment methods on average; however, respondents with old, low-income, and low-financial asset holdings, who were likely to be heavy cash users, would use them less frequently. The results suggest that if the Bank of Japan wanted to issue a central bank digital currency that would be used almost every day as a replacement for cash, policy tools should be utilized to encourage the use of it by these groups as well.

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* Corresponding author, Faculty of Commerce, Chuo University, 742-1 Higashinakano, Hachioji-shi, Tokyo 192-0393, Japan, Fax: +81-42-674-3651, email: fujiki@tamacc.chuo-u.ac.jp
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1. Introduction

Many central banks, including the Bank of Japan, have begun research on central bank digital currencies (CBDCs) following Facebook's plan in June 2019 to issue a multi-currency coin, which is a digital token linked to a basket of sovereign currencies. For example, the Bank of Japan (2020) pointed out two technical conditions that make the function of CBDC similar to cash: universal access and resilience.[1] To achieve universal access, the terminals for a CBDC should be used by various users. To achieve resilience, a CBDC should have an offline payment function with an upper limit of spending to be resistant to communication and power interruptions given the high frequency of natural disasters in Japan. The Japanese government also said that it would study central bank digital currency in cooperation with other countries in its official economic plan ("Honebuto plan") in July 17, 2020.

One might argue that a CBDC would be widely accepted if these technical issues were resolved. However, consumers and merchants will adopt the means of payment only if they are convenient to them; therefore, the attributes of CBDC must be compared to cash and other privately issued digital means of payment. Consumers may not use central bank digital currency too frequently because it would not provide a consumer discount or reward program, unlike credit cards or debit cards. Shops may be reluctant to invest in a new terminal that accepts a central bank digital currency, as Japanese 2,000 yen bills are rarely in circulation because they can only be withdrawn from a select number of ATMs.

Assuming that shops have the incentive to introduce new terminals with have access to Japanese CBDC, will Japanese CBDC prevail in the market inciting frequent, daily use? A similar question is posed by marketing economists: How can we find a new product that prevails in the market? To answer these questions, marketing

[1] See also Auer and Böhme (2020), Armelius et al (2020), and Shah et al. (2020) for recent examples for technologies for achieving universally accessible CBDC.

economists use characteristics approach, rather than estimate billions of demand functions for new products, possibly considering the substitutions between the products (see Ackerberg et al. [2007] for details). The characteristics approach first classifies new products by their attributes, such as price, fuel cost, top speed, and the number of seats in the case of a car. Then it is used to identify the attributes that attract consumers. Finally, it is used to forecast the best-selling product as having many of these attributes without analyzing the demand functions for billions of new products. We follow the characteristics approach and asks the following question: "Which type of attributes should a central bank digital currency have to be widely accepted?"

In the area of payment economics, two studies investigating the attributes of payment methods related to this question were conducted. First, Borzekowski and Kiser (2008a) considered a structural model to analyze the ranking of the use of four payment methods—debit card, cash, credit cards, and check—that incorporates three product attributes, including the valuation of time, preferences for electronic payment, and the utility of liquid instruments, and consumer demographics, such as age, gender, family structure, and region. They used U.S. data to examine the alternation of the speed of debit card transactions that mimics the introduction of contactless debit cards and found that such innovation of debit cards will increase its market share from 21% to 27%. Second, Kim et al. (2020) considered a structural model to analyze the use of a combination of three payment methods (debit card, cash, and credit cards) for point of sale (POS) payments by the type of transaction (groceries, gasoline, and so forth) that incorporates four product attributes (ease-of-use, affordability of use, security, and transaction costs) together with consumer demographics, such as age, gender, family structure, and region. They used Canadian methods of payment survey data to estimate their model and conducted counterfactual simulations for the adoption of CBDC, which had similar characteristics as cash, debit card, and all of the attractive characteristics of cash and debit card. They found that CBDC could be used at the POS with probabilities ranging between 0.19 and 0.25 and that consumer welfare could improve by 0.60 to 1.63 Canadian dollar per person with a significant variation across demographic groups; however, to the best of the author's knowledge, there is no study on payment methods based on a characteristics approach, such as that used by Borzekowski and Kiser (2008a), and its application to the adoption of CBDC in Japan, as done by Kim et al. (2020).

The present paper presents a case study on the adoption of CBDC in Japan by counterfactual simulations based on a model of ranking the frequency of the use of five payment methods—cash, credit cards, contactless prepaid cards (hereafter referred to as electronic money following the Japanese nickname), branded debit cards, and mobile payments—using smartphone applications (including prepaid or post-paid, QR-code based, or mobile wallets for credit cards, debit cards, or electronic money, hereafter referred to as mobile payments) using the data from the 2019 Financial Literacy Survey (hereafter FLS) that was administered from March 1, 2019 to March 20, 2019 to 25,000 individuals aged 18–79 years in Japan. Following Borzekowski and Kiser (2008a), four product attributes were incorporated: preferences for mobile payments, the utility of credit cards, preference for banknotes, and the valuation of time in addition to consumer demographics, such as income, financial assets holdings, age, gender, educational attainment, occupation, and region. Based on the frequency of the use of five payment methods ("Almost every day," "About once a week," "About once a month," "Scarcely or never," and "Do not adopt it"), a ranking of them from each respondent was obtained. Many indicated using cash "Almost every day" or "About once a week," and hence the top-ranked product is cash, followed by credit cards, electronic money, mobile payments, and debit cards. To investigate the potential adoption of CBDC, the effect of innovative non-cash payment methods, such as contactless electronic money on a mobile phone, was simulated. This began by estimating a rank-ordered logit model to explain the ranking of the five payment methods conditional on the four attributes and demographic variables. The estimates of the model showed that Japanese respondents valued shorter settlement time, mobile payments, and credit cards and banknotes. The counterfactual simulations using the model estimates showed that a hypothetical mobile version of noncash payment methods that required a short transaction time would be highly ranked if they were introduced; however, the adoption of these hypothetical products is not frequent compared with overall samples for a household with zero income, zero amount of financial asset holdings, and an elderly household head, as Borzekowski and Kiser (2008a) and Kim et al. (2020) found. Therefore, if the Bank of Japan wanted to issue a central bank digital currency that would be used almost every day as a replacement for cash, policy tools should be utilized to encourage the use of it by these groups as well. This study contributes to the literature by incorporating the effects of financial literacy and financial behavior as well. For example, it was found that a respondent with better financial literacy tended to use credit cards more frequently and to show a higher adoption rate for these hypothetical products, while a respondent with irrational economic behaviors would adapt to them similarly to the overall average.

This paper relates to the literature on the choice of payment methods in Japan and abroad. First, regarding Japanese studies on the choice of payment methods using the FLS 2019, Fujiki (2020a) estimated the demand for cash conditional on the choice of noncash payment methods, and then Fujiki (2020b) estimated the demand for crypto assets and other payment instruments; however, he did not examine the ranking of the use of payment methods. Fujiki and Tanaka (2018a) and (2018b), Fujiki (2019), and Fujiki (2020c) used the two most favored payment methods for day-to-day transactions and a favored payment method for regularly scheduled payments using data from the Survey of Household Finances. These studies focused on the use of cash, credit cards, electronic money, and automatic withdrawals from bank accounts; however, they did not examine the use of branded debit cards or mobile payments.

Second, recent studies in foreign economies on the choice of payment methods include Esselink and Hernández (2017) for the Eurozone; Trütsch (2020), Hayashi and

Toh (2020), Greene et al. (2017), Koulayev et al. (2016), Schuh and Briglevics (2014), and Borzekowski et al. (2008a,b) for the US; Kim et al. (2020), Henry et al. (2018), Wakamori and Welte (2017), and Chen et al. (2017) for Canada; Brown et al. (2020) for Switzerland, and Jonker et al. (2018) for the Netherlands; however, the literature on the choice of payment methods using the characteristics approach since Hirschman's (1982) study is relatively small except for Borzekowski and Kiser (2008a) and Kim et al. (2020).

While this study is closely related to Borzekowski and Kiser (2008a), there are three limitations due to the availability of data compared with Kim et al. (2020). First, we could not estimate the ranking of the usage of payment methods based on the types and value of transactions conditional on the adoption of the payment methods by merchants because our data only provide the frequency of consumer's use of five payment instruments. Second, we did not examine the use of payment methods conditional on the choice of sets of payment instruments because there were so many combinations of payment methods to be analyzed. Kim et al. (2020) focused on three combinations: cash, cash and debit card, and cash, debit card, and credit card, while Fujiki (2020a) showed that there are eight combinations of the choice of payment methods to be analyzed. Third, the results, which are based on the FLS 2019 conducted in March 2019, could underestimate the use of QR code-based transactions by smartphones due to the anticipation of a government program to subsidize cashless payments from October 1, 2019 to June 30, 2020 for increasing the cashless payment ratio from 20% to 40% by 2025.

Apart from the three limitations of the available data, this paper focuses on the consumers' adoption of CBDC and puts asides other important policy issues related to the issuance of CBDC for merchants and financial service providers. Amamiya (2020) pointed out that while the issuance of CBDC could contribute to interlinking various types of private digital money, it could also present the risk of crowding out the existing private services, such as bank fund transfers, and of suppressing the innovations of private businesses. Moreover, the widespread use of CBDC could also affect banks' funding and the function of financial intermediation, including bank lending and relevant transaction information that flows into the central bank. Pichler et al. (2020) also argue that cash cannot be digitalized without being deprived of its characteristics as an inclusive, crisis-proof, and anonymous means of payment. These important issues are not addressed in this paper.

The remainder of the paper is organized as follows. Section 2 discusses the data and methodology. Section 3 reports the results of the estimation. Section 4 reports the results of the counterfactual simulations. Section 5 concludes the paper.

2. Data and methodology

The data on payment methods, the product attributes of payment instruments, data on financial literacy, financial behavior, and demographic variables, and the statistical models are explained in this section.

2.1. *Use of payment methods*

The FLS 2019 is a web survey that was administered from March 1, 2019 to March 20, 2019 to 25,000 individuals aged 18–79 years in Japan. Variables were constructed on the use of payment methods from Question 45 on the FLS for 25,000 individuals: "How often do you use the following payment methods: credit cards, debit cards, electronic money, mobile payments using smartphones, or cash? Choose only one answer from the following options: Almost every day, About once a week, About once a month, Scarcely or never, Do not adopt it." For this question, mobile payments using smartphones could be prepaid or post-paid, QR-code based, or mobile wallets for credit cards, debit cards, or electronic money. Cash includes checks.

Figure 1 shows the responses of the 25,000 respondents. The proportion of the choice of "Almost every day (white bars)," "About once a week (light gray bars)," "About once a month (white bars with horizontal lines)," "Scarcely or never (dark gray bars)," and "Do not adopt it (black bars)" is shown for five payment instruments. The panel shows that cash is the most frequently used payment instrument among the five choices, followed by credit cards, electronic money, mobile payments, and debit cards.

To quantify the ranking of the use of payment methods, we assigned the value of 5, 4, 3, 2, and 1 for those who replied "Almost every day," "About once a week," "About once a month," "Scarcely or never," and "Do not adopt it," respectively. The second column of Table 1 shows the average use of the five payment methods. As expected, cash is the most frequently used payment instrument based on this measure, followed by credit cards, electronic money, mobile payments, and debit cards. This measure was used to determine the ranking of the frequency of the use of payment methods. For example, if the measures for the cash, credit card, electronic money, mobile payments, and debit card for a respondent are 5, 4, 4, 2, and 1, these five payment methods are ranked as 1, 2, 2, 4, and 5. This ranking is the dependent variable of interest in this research. Note that possibilities of a tie imply that if the average frequency of payment methods are ranked at the top, as the third column of Table 1 labeled as "Unweighted" shows, the sum of the frequency of five payment methods exceeds one. Hence, if a respondent chose W payment instruments ranked at the top, a weight of $(1/W)$ is assigned for his/her response. The results are shown in the fourth column of Table 1 labeled as "Weighted1," which adds up to 1. The fourth column of Table 1shows that the probability of being top-ranked is 65.7%, 17.9%, 11.9%, 2.8%, and 1.7% for cash, credit cards, electronic money, mobile payments, and debit cards, respectively. Note that about 3% of respondents chose "Do not adopt it" for all payment methods; that is, he/she does not adopt any payment instruments. The fifth column of Table 1 labeled "Weighted2" shows the results if these respondents are dropped. The probability of a credit card being chosen as top-ranked increases slightly and the probability of being chosen as top-ranked for the other three payment methods decreases slightly. Similarly, about 4% of respondents choose "Scarcely or never" and/or "Do not adopt it" for all payment instruments. The fifth column of Table 1 labeled "Weighted3" shows the results if these respondents are dropped, which is quite similar to the results for "Weighted2." Because the ranking of the usage of payment instruments is being modeled, people who do not adopt or scarcely use all five payment instruments are not of interest. The respondents who chose "Scarcely or never" and/or "Do not adopt it" for all payment instruments were dropped, and the 23,956 samples of "Weighted3" are discussed hereafter.

2.2. Attributes for payment instruments

Following Borzekowski and Kiser (2008a), the proxies of four product attributes of noncash payment methods were adopted—preferences for mobile payment (*Mobile*), the utility of credit cards (*Credit*), preferences for banknotes, such as wide acceptance including peer to peer transactions and inclusiveness (*Paper*), and the valuation of time (*Times*)—for five payment methods, as shown in Table 2. *Mobile* takes a value of one for mobile payments and otherwise zero. *Credit* takes a value of one for credit cards and otherwise zero. *Paper* takes a value of one for cash and otherwise zero. *Times* takes a value of 12, 8, 17, 12, and 28 (in units of second) for a credit card, electronic money, mobile payments using a smartphone, debit cards, and cash, respectively. These values are results from a survey of the average transaction time conducted by JCB.[2] While the JCB survey did not examine the time for debit cards, it was set equal to that of credit cards, assuming that the branded debit cards would be settled similarly to credit cards.

As Borzekowski and Kiser (2008a) pointed out, up to four product attributes can be used for the choice set containing five elements, and hence the results could include the effects of other attributes correlated with the specified set. For example, *Paper* could also include the attribute of anonymity. Moreover, a dummy variable can be proposed for *Plastics* or *Electronic*, which takes a value of 1 for all the noncash payment methods instead of *Paper*. The dummy variable *Liquid* can also be proposed instead of *Credit*,

[2] The details are available on the website of JCB (accessed April 26, 2020). https://www.global.jcb/ja/press/00000000162855.html

which takes a value of one except for credit cards. The results of the regressions are the same even if *Plastics* and *Liquid* are used instead of *Paper* and *Credit*. Thus, the results can be interpreted in various ways. A brief overview of the background of the use of payment methods in Japan is provided to understand the figures in Table 2.[3]

First, one might wonder why Japanese electronic money transactions are the fastest among the five payment instruments. Major electronic money transactions in Japan use Sony FeliCa contactless IC card technology. It was created for high-speed data transmission of a train ticket, which takes 0.5 seconds to finish a transaction as a passenger goes through the train gate at the train station (Octopus Card in Hong Kong uses this technology as well). Electronic money is now widely accepted in major convenience store chains, taxis, vending machines, and shops nearby train stations. The primary use of electronic money is a quick transaction for a small amount, such as 1,000 Japanese yen (about nine U.S. dollars).

Second, one may wonder if contactless debit cards, such as Visa payWave, would be as fast as electronic money. Note that typical Japanese debit cards provided since 2001 are bank cash withdrawal cards that work only during a bank's business hours and only domestically. Because most terminals that accept electronic money in Japan are based on NFC Sony FeliCa contactless IC card technology, they did not accept branded debit cards and international credit cards based on NFC Type A/B contactless IC card technology, such as Visa payWave, until recently. For example, Orico Card Visa payWave was the first Japanese contactless credit card issued by a Japanese credit card company based on NFC type A/B in 2013; however, its primary use was for overseas shopping.[4] During the last a couple of years, Japanese banks began issuing international branded debit cards because their costs of providing cash through bank branches and

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[3] Interested readers can refer to the Appendix in Fujiki (2019) regarding the use of payment methods in Japan.

[4] See details https://www.orico.co.jp/creditcard/oricocardpaywave/#feat-04.

ATMs were too high under the long and lasting low interest rate environment. Since June 2020, Seven-Eleven Japan accepts VISA, MasterCard, and American Express credit, debit, and prepaid cards based on NFC Type A/B.[5] Therefore, contactless debit cards could be widely used if other shops are willing to accept them.

Third, it was assumed that the majority of smartphone payments are based on QR codes, and thus the results for QR code transactions for mobile payments were used. From the merchants' perspectives, QR code-based transactions require relatively inexpensive terminals and lower merchant fees compared with those of credit cards; however, a QR code-based transaction is slower than contactless payments by electronic money because a QR code-based payment requires time for a consumer to load an application to show the QR code on the smartphone as well as time for a sales clerk to read the QR code with a barcode reader.

Note that following the Japanese government's subsidy for cashless payments from October 2019 to June 2020, the use of QR code-based transactions seems to have increased, reflecting the subsidy to consumers (2% or 5% depending) and the subsidies for merchants to introduce a new terminal that accepts cashless transactions including QR code-based transactions. For example, according to an internet survey on cashless settlements conducted in 2019 to January 2020 with over 48,208 individuals by the Mobile Marketing Data Laboratory, 52% of respondents who use cashless payments at least once a month stated that credit cards are the most frequently used payment instruments, 19.2% stated electronic money, 18.2% stated QR code-based payments, and 5.6% stated smartphone contactless payments.[6]

2.3. Financial literacy, financial behavior, and demographic characteristics[7]

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[5] The link to the press release is https://prtimes.jp/a/?c=6846&r=89&f=d6846-89-pdf-0.pdf (Accessed April 26, 2020).

[6] The details of the two surveys are available upon request from the website of the Mobile Marketing Data Laboratory: https://mmdlabo.jp/company/ (Accessed April 26, 2020).

[7] This section depends heavily on Section 3 of Fujiki (2020b).

Three types of controls were prepared for the following variables: those related to financial literacy, financial behavior, and demographic characteristics from the FLS 2019 as Fujiki (2020b) did, which followed Sekita et al (2018), and Kadoya and Khan (2020).

First, the FLS included true/false questions on financial literacy. We follow Sekita et al. (2018) to use *Objective financial literacy*, defined as the number of correct answers to eleven questions below, which include four questions to construct "Big 3" questions on compound interest, inflation, and stock risk to measure personal financial literacy (see Lusardi and Mitchell [2014]).

First, we use two questions on compound interest rates.

Question 18: "Suppose you put 1 million yen into a savings account with a guaranteed interest rate of 2% per year. If no further deposits or withdrawals are made, how much would be in the account after 1 year, once the interest payment is made? Disregard tax deductions. Answer with a whole number."

Question 19: "Then, how much would be in the account after 5 years? Disregard tax deductions." Choose only one answer from the following options: More than 1.1 million yen, Exactly 1.1 million yen, Less than 1.1 million yen, Impossible to tell from the information given, Do not know.

Second, we use two questions on risk and diversification.

Question 21 (3): "Please indicate whether you think the following statements are true or false. An investment with a high return is likely to be high risk."

Question 21 (4): "Please indicate whether you think the following statements are true or false. Buying a single company's stock usually provides a safer return than a stock mutual fund."

Third, we use two questions on insurance.

Question 25: "Which of the following statements on the basic function of insurance is appropriate? Choose only one answer from the following options: 1, Insurance is effective when a risk occurs with high frequency, causing a large loss, 2.

Insurance is effective when a risk occurs with low frequency, causing a large loss, 3. Insurance is effective when a risk occurs with high frequency, causing a small loss, 4. Insurance is effective when a risk occurs with low frequency, causing a small loss, 5. Don't know."

Question 26: "When a 50-year-old man reviews his life insurance policy (whole life insurance) after his children have become financially independent, which of the following statements is appropriate? Suppose that other circumstances have not changed. Choose only one answer from the following options: 1. He should consider increasing the death benefit, 2. He should consider decreasing the death benefit, 3. There is no need to review the policy, in particular, 4. Don't know."

Fourth, we use four questions on debt.

Question 21 (2): "Please indicate whether you think the following statements are true or false. When compared, a 15-year mortgage typically requires higher monthly payments than a 30-year loan, but the total interest paid over the life of the loan will be less."

Question 30: "Which of the following statements on mortgages is appropriate? Choose only one answer. 1. It is far less costly to continue living in a rented house for your whole life than buying a house with a loan. 2. Mortgages can be repaid by either the equal payment method or the equal principal payment method, but the total repayment is the same for both methods. 3. Mortgages are offered with either a floating interest rate or a fixed interest rate, and those with a fixed interest rate are always more advantageous than those with a floating interest rate. 4. In order to decrease the total mortgage repayment, it is effective to prepare as much down payment as possible and make advanced repayments to the extent possible. 5. Don't know."

Question 31: "Suppose you owe 100,000 yen on a loan and the interest rate you are charged is 20% per year, compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double? Choose only one answer from the following options: Less than 2 years, At least 2 years but less than 5 years, At least 5 years but less than 10 years, At least 10 years, Don't know."

Question 22: "If interest rates rise, what will typically happen to bond prices? Choose only one answer from the following options: They will rise, They will fall, They will stay the same, There is no relationship between bond prices and the interest rate, Don't know."

Fifth, we use two questions on inflation.

Question 20: "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? Choose only one answer from the following options: More than today, Exactly the same, Less than today, Do not know."

Question 21 (1): "Please indicate whether you think the following statement is true or false. High inflation means that the cost of living is increasing rapidly."

Finally, we obtain Objective financial literacy from the number of correct answers on the 11 questions above.

We also use the frequency of obtaining information on financial and economic conditions from newspapers, magazines, television, and the Internet (*News*), dummy variables of the experience of financial education at school or college (*Fin. education school*) or in the household (*Fin. education home*), the experience of financial troubles such as a bank transfer fraud or multiple debts (*Fraud*), debt holdings (*Debt*), and knowledge about credit cards (*Credit card literacy*). *Credit card literacy* takes a value of one for a respondent who chooses option one from the following five options and is otherwise zero: 1. using credit cards in a well-planned manner according to income; 2. any unsettled credit card payment is practically a debt; 3. a credit card fee (interest) is charged for revolving payments but not for installment payments; 4. failure to pay the credit card charge may cause credit card transactions to be declined; and 5. don't know. Note that Kadoya and Khan (2020) used *News* and *Fraud.*

As a proxy of objective financial literacy, dummy variables were also used indicating the source of obtaining information on financial and economic conditions. We constructed dummy variables that take one and otherwise zero for those who responded that they do not know about the sources (*S_do_not_know*), for those who obtain information from financial institutions only (*S_fin*), for those who obtain it from websites only (*S_net*), for those who obtain it from financial experts, financial institutions, and other sources (*S_fin_exp*), for those who obtain it from financial institutions and websites but not financial experts (*S_fin_net*), and for the remainder of respondents (*S_other*). Because these dummy variables are constructed for those who select financial products by themselves, the base case for these dummy variables is for those who do not select financial products by themselves, which is about 38% of respondents.

Second, following Sekita et al. (2018), we use six variables that capture financial behavior from the perspective of behavioral economics (See Beshears et al. [2018] for literature in behavioral household finance) as below. *Myopia* captures the present-biased preferences in which one places extra value on more immediate awards. It is based on the following question: "If I had the choice of (1) receiving 100,000 yen now or (2) receiving 110,000 yen in 1 year, I would choose (1), provided that I can definitely receive the money." *Herding* is a proxy variable that shows whether a person prefers to follow others in making financial decisions. It is based on the following question: "When there are several similar products, I tend to buy what is recommended as the best-selling product rather than what I actually think is a good product." *Self-control* is a proxy of the degree to which a person makes deliberate and thoughtful decisions. It is based on the following question: "Before I buy something, I carefully consider whether I can afford it." *Over-confidence* captures one's over-confidence regarding financial literacy through the difference between one's subjective financial literacy (self-evaluation of one's level of financial literacy in comparison to other people) and *Objective financial literacy*.[8] *Loss*

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[8] Note that *Over-confidence* is not measured using the gap between the self-perceptions of the score of

aversion is a dummy variable that takes a value of 1 for a person who says "no" to the question "If you invested 100,000 yen, you would either get a capital gain of 20,000 yen or a capital loss of 10,000 yen at 50% probability." Finally, Risk aversion is a proxy value for the extent to which a person is reluctant to take a risk on an investment. It is based on the following question: "I am prepared to take a risk when saving or making an investment."

Third, we constructed the following dummy variables for demographic variables. These include a dummy variable indicating household annual pretax income (*Income*) by ranges (units are 10 thousand yen), household total financial asset holdings (*Asset*) by ranges (units are 10 thousand yen), the ages of respondents by ranges, (*Age*, below 25, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 74-79), the gender of respondents (*Male* = 1 for men), the employment status of respondents (*Private* company, *Public* company, *Teacher*, *Self-employed*, *Part-time*, no job, and no schooling, referred as *House*, *Student*), educational attainment (*Senior high*, *Vocational college*, *Junior college*, *University*, and *Graduate*, where the base case is below *Senior high*), and nine areas of residence (base case is the *Kanto* region, which includes Tokyo). The means and standard errors of these variables are reported in Table 3.

2.4. Methodology

This section presents counterfactual simulations for the adoption of CBDCs that are similar to improved versions of existing payment instruments. To perform these simulations, we first estimated the rank-ordered logit model by Beggs et al. (1981) to explain the respondents' ranking of five payment methods conditional on the four attributes and conditioning variables X explained in the previous section: financial literacy, financial behavior, and standard demographic variables.

Specifically, let Y_{ij} be a ranking of respondent i for the frequency of the use of

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Objective financial literacy and the actual score of *Objective financial literacy* done by Anderson et al. (2017).

payment methods j=1, 2, …, and J, where 1 is the best rank, and J is the worst. We assumed that the following model would approximate a household's choice and ranking of five payment methods. Suppose the utility of a respondent i from the use of j-th instruments is V_{ij}, and assume that V_{ij} is the sum of the systematic component μ_{ij} and a random component ϵ_{ij}, which follows an independent and identically distributed extreme value distribution:

$$V_{ij} = \mu_{ij} + \epsilon_{ij}, \tag{1}$$

Under the assumption of equation (1), the probability of a respondent i giving payment method j a better rank than payment method k is:

$$\Pr\left(V_{ij} > V_{ik}\right) = \frac{exp\mu_{ij}}{(exp\,\mu_{ij} + exp\,\mu_{ik})}.$$

Let $R_i\left(r_1, r_2, \ldots, r_J\right)$ be a respondent i's ranking of available choices, where r_h gives the rank of the choice in position h. In this notation, the probability of observing the sequence of ranking is:

$$\Pr(R_i) = \Pr\left(V_{r1} > V_{r2} > \cdots . > V_{rJ}\right) \tag{2}$$

$$= \prod_{h=1}^{J-1} \frac{exp\mu_{ir_h}}{\sum_{m=h}^{J}(exp\,\mu_{ir_m})}.$$

Where V_{ir_h} is the utility received from the option ranked in position h. Following Borzekowski and Kiser (2008a), we assume $V_{ij} = \beta(X_i \otimes Z_j)$, where X_i is a 1×66 vector of 65 explanatory variables listed in Table 3 and a constant term, and Z_j is 1×4 vector of attributes *Mobile*, *Credit*, *Paper*, and *Times* defined in Table 2. Under this assumption, the log-likelihood of observing the sequence of ranking shown in (2) becomes:

$$\mathrm{L}(\beta) = \sum_{i=1}^{N} \log\Pr(R_i) = \sum_{i=1}^{N}\sum_{h=1}^{J-1} \beta(X_i \otimes Z_h) - \sum_{i=1}^{N}\sum_{h=1}^{J-1}\sum_{m=h}^{J} \exp(\beta(X_i \otimes Z_h)), \tag{3}$$

where N is the number of respondents, which is 23,956. We can estimate parameters β by maximum likelihood methods using the Stata 16 command cmrologit. Note that the fifth column of Table 1 labeled "Weighted3" corresponds to the average probabilities of being top-ranked, and we are forecasting based on the estimates of equation (3). Consistent with the weighted ranking, Stata 16 command cmrologit assumes that if a respondent expresses a tie between two or more alternatives, such as he or she uses both cash and credit cards "Almost every day", he or she holds one particular strict preference ordering but with all possibilities of a strict ordering consistent with the expressed weak ordering being equally probable.

3. Results of the estimation of the rank-ordered logit model

The upper panel of Table 4 reports the results of the parameter estimates of the rank-ordered logit model equation (3), assuming that X_i is a 1×1 matrix that contains a constant term only. While we do not report the standard errors of the marginal effects, we do include superscripts *, **, and *** to denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors were adjusted to an intragroup correlation within the clusters formed by gender, age group, and prefectures because the respondents of the FLS were randomly chosen via cluster sampling—based on gender, six age groups, and 47 prefectures (2*6*47 = 564 clusters)—from amongst the people registered with an internet survey company. The upper panel of Table 4 shows that the respondents expressed a negative utility from *Times* and a positive utility from *Mobile*, *Credit,* and *Paper*.

The lower panel of Table 5 reports the results of the parameter estimates of the rank-ordered logit model equation (3) assuming that X_i is a 1×66 vector of a constant term and the individual specific control variables. The baseline case corresponding to the constant term is a respondent who does not select financial products by themselves, who has no experience of financial education at school or home, who has no experience of financial trouble, who does not have debt, who has a lower level of credit card literacy, who is not loss averse, whose *Income* is between 0 and 2.5 million yen, whose *Asset* is between 0 and 2.5 million yen, whose *Age* is below 25 years old, whose gender is female, whose occupation is other occupations, whose educational attainment is below senior high school, and who is living in the Kanto area. The second through fifth columns report the estimates of the cross terms of X_i and *Mobile*, *Credit*, *Paper,* and *Times*. The figures under shade show the statistically significant estimates that have an opposite sign to dampen the results in the upper panel of Table 4, which show striking differences in the utility from the four attributes depending on the situation of a household.

First, the parameter estimates of the cross terms of *Financial education school, Fraud, Myopia, Self-control, Asset_0, Male, Chugoku, Shikoku,* and *Kyusyu*, and *Mobile Credit*, and *Paper* are negative and the parameter estimates of the cross terms of *Financial education school, Fraud, Myopia, Self-control, Asset_0, Male, Chugoku, Shikoku,* and *Kyusyu*, and *Times* were positive. It shows that the respondents with an experience of financial education at school and an experience of financial trouble, myopic, higher degrees of better self-control, zero asset holdings, and male gender living in Chugoku, Shikoku, and Kyusyu areas (Southwest part of Japan) expressed lower utility from mobile payments, credit cards, and cash and higher utility from a slower speed of settlement compared with the baseline respondent.

Second, the parameter estimates of the cross terms of *Age70_74*, *Age75_79, Hokkaido, Tohoku, Hokuriku, Chubu,* and *Kinki* and *Mobile* and *Paper* are negative, and those for *Times* are positive, which means people aged over 69 and people living in these areas feel lower utility from mobile payments and cash and higher utility from slower transaction speeds compared with the baseline respondent.

Third, the parameter estimates of the cross term of *Age70_75* and *Mobile* was negative and those of *Age70_75* and *Times* are positive. The parameter estimate of the cross term of *Income_0* and *Mobile* is negative. The parameter estimate of the cross term of *Students* and *Credit* is negative, which may reflect the strict control of consumer credit depending on the earnings of credit card holders.

Based on the parameter estimates of the model reported in Table 4, the Stata 16 command of predict gave the probability that cash, credit card, electronic money, mobile payments, and debit cards are top-ranked. In Table 5, the second column shows the actual probabilities, the third column shows the forecast based on the results reported in the upper panel of Table 4, and the fourth column shows the forecast based on the results reported in the lower panel of Table 4. The results yield similar forecasts, and the ordering of top-ranked payment instruments is consistent with the data. The model underestimated the probability for cash by about 10 percentage points and overestimated the probabilities for credit cards, electronic money, mobile payments, and debit cards about 1 to 4 percentage points.

Because there are some differences in the signs of parameters across the demographic groups in the lower panel of Table 4, Figure 2 shows the forecast of average probabilities chosen as top-ranked by demographic groups shown in the horizontal axis using the results in the lower panel of Table 4. The thick solid line, the thin solid line, the thick dashed line, the thin dashed line, and the dotted line show the predicted average probabilities chosen as top-ranked for the case of cash, credit card, electronic money, mobile payments, and debit cards, respectively. The results above the label "Benchmark" are the benchmark results in the fourth column of Table 5.

Figure 2 shows that for financially illiterate, elderly, low-income, and low-asset holding groups (*Fraud*, *S_do_not_know*, *Overconfidence, Income_*0, *Asset_*0, *Age75_79*, and *Student* shown with dashed vertical bars), the probabilities that a credit card was top-ranked is lower than the benchmark case. In contrast, for the groups with financial literacy, who seek information on economics and finance from websites, with top income, with top asset holdings, old age, teachers, and those with higher educational attainment, (*Financial education home, S_net, Income_1500_*, *Asset_2000_*, *Teacher,* and *Graduate* shown with solid vertical bars), the probability that a credit card is top-ranked is higher, and it is lower for cash than the benchmark case. These results are consistent with the findings of Fujiki (2020b) on the characteristics of credit card users.

4. Results of counterfactual simulations

Using the parameter estimates reported in the lower panel of Table 4, counterfactual simulations were conducted to introduce better versions of existing noncash instruments to consider the effect of introducing CBDCs, which are similar to the hypothetical payment instruments. Table 4 show that consumers value mobile payments and faster payments. Hence, the focus is hypothetical payment instruments with better attributes of *Mobile* and *Times*.

First, a mobile version of electronic money that sets the value of *Mobile* to 1, as in the top panel of Table 6, is considered. We call this case as "E-mobile" hereafter. While the speed of transactions by electronic money is faster than other payment methods, electronic money transactions are based on plastic cards. Imagine a situation in which an electronic money application for smartphones, such as "Mobile Suica" provided by East Japan Railway Company since 2006, is widely circulated.[9]

Second, we consider a mobile version of a faster contactless debit card that sets the value of *Mobile* to 1 and *Times* to 8, as in the second panel of Table 6. We refer to this case as "D-fast-mobile" hereafter. This simulation corresponds with the widespread use of the branded debit card in an application for smartphones, such as "Sony Bank WALLET" provided by Sony Bank, in shops that accept Visa payWave by Google Pay.[10]

Third, we consider a mobile payment that would have a faster settlement time that sets the value of *Times* to 8, as in the second panel of Table 6. We refer to this case as "M-fast" hereafter. Currently, most mobile payment settlements that are QR code-based are slower than credit card settlements. We consider a shift from a QR code-based transaction to electronic money transactions or debit card transactions using a smartphone as in the cases of "E-mobile" or "D-mobile."

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[9] https://www.jreast.co.jp/e/press/20051101/index.html for the service of mobile Suica as of 2006.

[10] See details about Sony Bank WALLET at https://moneykit.net/en/card/

Finally, we consider a situation in which all four noncash payment methods, including credit cards, become mobile and require shorter times for transactions, and thus we set the value of *Times* to 8 for a credit card, mobile payments, and debit card and set the value of *Mobile* to 1 for a credit card, electronic money, and debit card. This case is based on that of Canada, where both contactless mobile debit cards and contactless mobile credit cards are widely accepted. We refer to this case as "All-fast-mobile" hereafter. Note that we do not consider a faster mobile version of a credit card a model for CBDC because the Bank of Japan Act does not allow provisions of consumer credit for the Bank of Japan. Note also that we do not consider a better version of cash because CBDC is a replacement for cash.

Table 7 shows the benchmark estimates of the average probabilities chosen as top-ranked payment instruments based on the estimates in the lower panel of Table 4 (column labeled "Benchmark") and the average probabilities chosen as top-ranked under four counterfactual simulations and their deviations from the Benchmark results in the parentheses. For the first three simulations, a mobile version of electronic money, a mobile version of a faster debit card, and a faster smartphone will be top-ranked at about 40%, followed by cash at about 36-38% and credit cards at about 11%. In the final All-fast-mobile simulation, a mobile version of a faster credit card would be top-ranked at about 50%, followed by 15% for cash, and the remaining three would be 11%. This case corresponds with the dominance of mobile or contactless credit cards among four noncash payment instruments and a very low share of cash payments.

The figures in the parentheses show that in the first three cases, mobile and/or faster new payment methods would increase their top-ranked probabilities by 30 percentage points at the sacrifice of the remainder of the four payment methods; however, in the final All-fast-mobile simulation, a mobile version of electronic money reduces its average top-ranked probabilities due to the presence of two other similar products.

In summary, a faster and/or mobile payment method and cash would both be top-ranked with their average probabilities at about 40%; however, if similar fast and mobile payment methods show up together, they would be adopted but with smaller average probabilities of being top-ranked, and a faster and mobile credit card would dominate. Note that we do not consider the cost of adopting these newer products for both merchants and consumers in the simulations. For example, the merchants must introduce a new terminal to accept contactless debit cards or contactless credit cards. Consumers may not have the incentive to switch their electronic money cards to the mobile version if they are concerned about the safety of mobile payments (See U.S. experience of slow adoption of contactless debit cards related to its terminal costs to merchants and consumer's concern on security in Akana and Ke [2020]). While a debit card may be helpful for those who are concerned about overspending, for a majority of Japanese credit card users who pay their credit card bills within two months, the contactless debit card payment may not deliver any attractive attributes if they also use electronic money for faster payments. If the costs of adopting one of the new payment methods are sufficiently lower than the remainder of the noncash payment methods, there may be a situation similar to one of the first three cases.

Note that the forecasts of average probabilities chosen as top-ranked by demographic groups in Figure 2 are different for financially illiterate, old, low-income, and low-asset holding groups (*Fraud*, *S_do_not_know*, *Overconfidence*, *Income*_0, *Asset*_0, *Age*75_79, and *Student*) and the groups with financial literacy, who seek information on economics and finance from websites, with top income, top asset holdings, teachers, and higher educational attainment (*Financial education home*, *S_net*, *Income*_1500_, *Asset*_2000_, *Teacher* and *Graduate*). Do these groups yield different results for the counterfactual simulations as well?

To answer this question, three left panels of Figure 3 show the results of the counterfactual simulations for old, low-income, and low-asset holdings groups: *Age*75_79, *Income*_0, and *Asset*_0. White bars, light gray bars, bars with horizontal lines, dark gray bars, and black bars show the results for cash, credit card, electronic money, mobile payments, and debit cards, respectively. The results labeled "Group deviation from the benchmark" correspond with the difference between the forecast of average probabilities to be top-ranked under counterfactual simulations for these groups and the forecast of average probabilities to be top-ranked for these groups under the benchmark. For the four simulation results, the difference is shown between the average forecast probabilities to be top-ranked under the counterfactual simulations and those under the benchmark on average in Table 7 by white circles, light gray circles, black triangles, dark gray circles, and black circles, which correspond to the results for cash, credit card, electronic money, mobile payments, and debit cards, respectively.

Three left panels of Figure 3 show that old, low-income, and low-asset holding groups tend to use cash more frequently and credit cards less frequently compared with the sample average. Under the simulation, they do use fast and/or mobile payment methods; however, the probabilities that these payment methods are top-ranked are relatively lower than the sample average. For example, in the case of *Age75*_79, the results for E-mobile, D-fast-mobile, M-fast, and All-fast-mobile show that respondents in this group increase the probability that electronic money, debit card, mobile payments, and credit cards would be top-ranked by 9% point (Bar with horizontal lines), 12% point (Black bar), 12% point (Gray bar) and 20% point (Light gray bar), while respondents on average increase the probability that electronic money, debit card, mobile payments, and credit cards would be top-ranked by 31% point (Black triangle), by 38% point (Black circle), by 36% point (Dark gray circle) and by 32% point (Light gray circle). These results are similar to the findings by Hayashi and Toh (2020) using the US data that banked households that are lower income, less educated, older, not in the labor force, disabled, unmarried, or in a rural area are significantly more likely to lack a smartphone and home internet access, are less likely to use mobile banking and thus are unlikely to benefit from faster payments. In contrast, three right panels of Figure 3 show that the results of the counterfactual simulations for middle-age, high-income, and high-asset holdings groups: *Age*55_59, *Income*_1500_, and *Asset*_2000_. It shows that the probabilities that these payment methods are top-ranked by the respondents with middle age, high income, and a large amount of asset holdings are relatively higher than the sample average.

We also examined the results for the respondents with high financial literacy, who seek information on economics and finance from websites, teachers, and higher educational attainment (*Financial education home*, *S_net*, *Teacher,* and *Graduate*). The results are similar to those for the high-income and large amounts of asset holding groups. Regarding the results for financially illiterate groups and students (*Fraud*, *S_do_not_know*, *Overconfidence*, and *Student*), students tend to use credit cards less frequently compared with the sample average; however, the remaining groups tend to have similar probabilities to use the five payment instruments. In the simulations, these groups tend to increase the probabilities to be top-ranked for fast and/or mobile payment instruments, similar to the average results.

These results suggest two policy implications. First, the promotion of cashless payments by encouraging mobile payments and faster payments would alter the use of "mobile electronic money," "mobile contactless debit card," or "faster QR codes" differently depending on the demographic characteristics. Respondents with zero income, zero financial asset holdings, and aged between 75 to 79 would adopt these products less frequently compared with the rest of the Japanese people. If the use of CBDC is a provision of a stable unit of accounting for public policy, the Bank of Japan should consider how these groups would welcome the CBDC as banknotes because the central bank financial products should be ubiquitous. Financial inclusion in terms of "unbanked" has never been a policy issue in Japan because both the postal banking system and private banks have provided free bank accounts and ATMs everywhere until recently; however, given the long-lasting low interest rate period, private banks would likely charge transaction fees more extensively and close ATMs. Because old people, low-income people, and low-asset holding people prefer cash transactions for day-to-day payments compared with the rest of the sample, as Fujiki and Tanaka (2018a) observed, if the Bank of Japan wants to issue a CBDC that would be used almost every day as a replacement for cash, policy tools should be utilized to encourage its use for this group.

Second, as the fourth simulation shows, if Japanese consumers value faster and mobile payments, similar services provided by different payment instruments would have a smaller market share if the costs of their adoption are similar. For Japan, the services provided by different noncash payment methods could be similar in such a situation through competition. Japanese electronic money issued by train companies was originally in the form of a prepaid card that must be charged by railway stations. Japanese credit card companies found it could outweigh credit cards, and thus they began so-called reloading services. When the amount of prepaid cash reaches a certain amount, the prepaid card will be charged from the credit card that the holder of the electronic money specifies. Thus, the distinction between a credit card and electronic money is not clear apart from the limit of daily usage for electronic money. Moreover, the cost for shops to accept several payment instruments are not negligible. Given the network effects of noncash payment methods, regulators may wish to focus on a particular product rather than subsidizing all noncash payment methods equally if adequate attention is paid to the adverse effects of the monopoly of payment services by a private company.

5. Conclusion

The present paper presents a case study of Japan on the use of CBDC through counterfactual simulations based on a model ranking the frequency of the use of cash, credit cards, electronic money, branded debit cards, and mobile payments using data from the 2019 FLS in Japan. The parameter estimates of the model show that Japanese respondents value shorter settlement time, mobile instruments, credit cards, and cash. The counterfactual simulations using the model estimates show that hypothetical mobile and/or faster versions of credit cards, electronic money, and debit cards and mobile payments with faster settlement times would be highly ranked if they were introduced. The results also suggest that people with zero income, zero financial asset holdings, and those aged 70–74 would adopt these products less frequently compared with the rest of the Japanese people. If the Bank of Japan wants to issue a CBDC that would be used almost every day as a replacement for cash, policy tools should be utilized to encourage its use by these groups. Note that the results are based on the FLS 2019 administered in March 2019, and thus we could have underestimated the use of mobile payments after the introduction of the subsidization of cashless payments in some registered retail shops from October 1, 2019, to June 30, 2020, to increase the cashless payment ratio to household spending from 20% to 40% by 2025, which may have increased the use of payment methods via smartphone applications. Also, we do analyze the ranking of the frequency of use of five payment methods, however, we cannot analyze the ranking of the value of transactions by these payment methods, and thus our results do not give any guide to the achievement of government's target of 40% cashless payment ratio.

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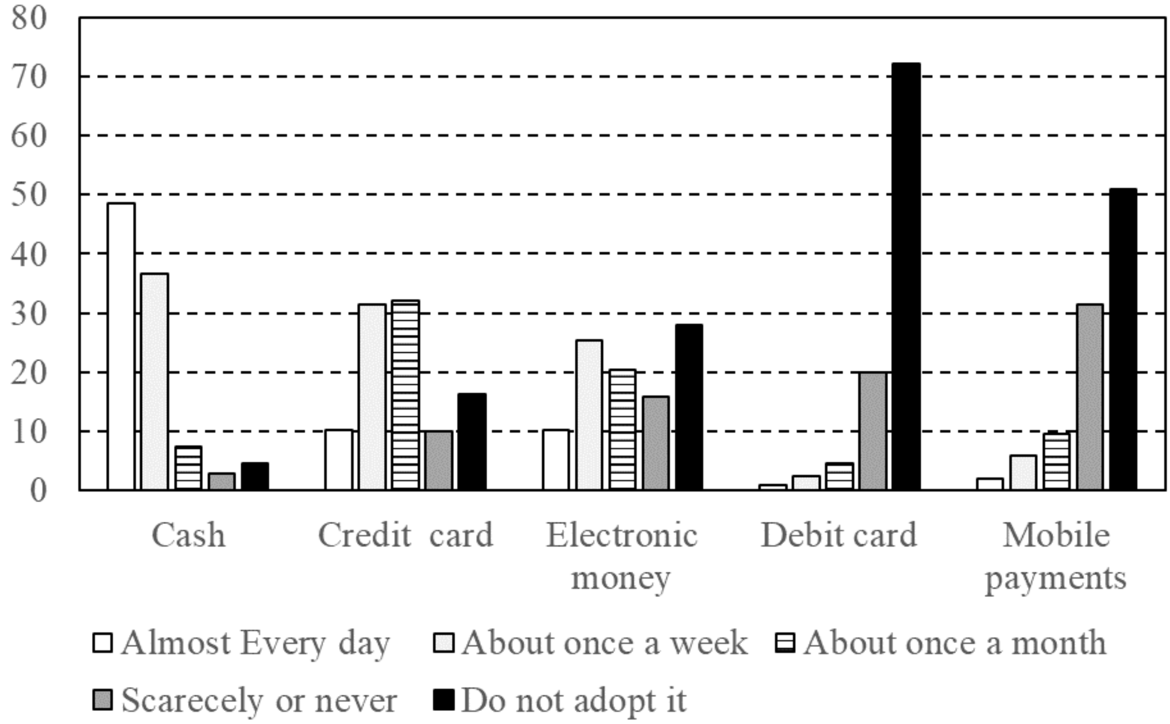
Figure 1 Use of payment methods



Notes: Units are in percentage.

Figure 2 Forecast of ranking by demographic variables

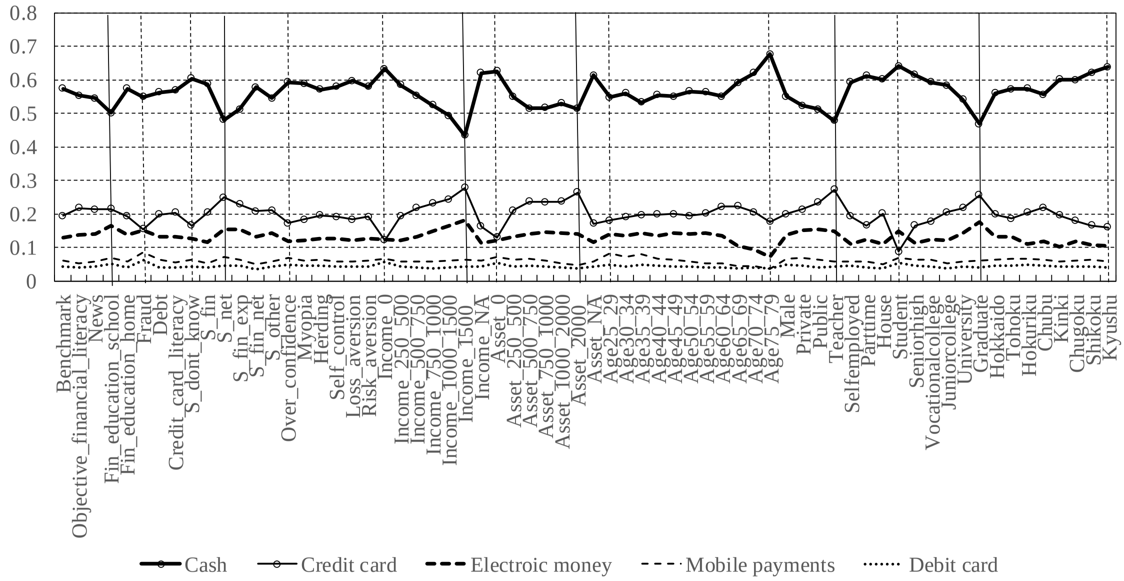


Figure 3 Results of counterfactual simulations by demographic groups

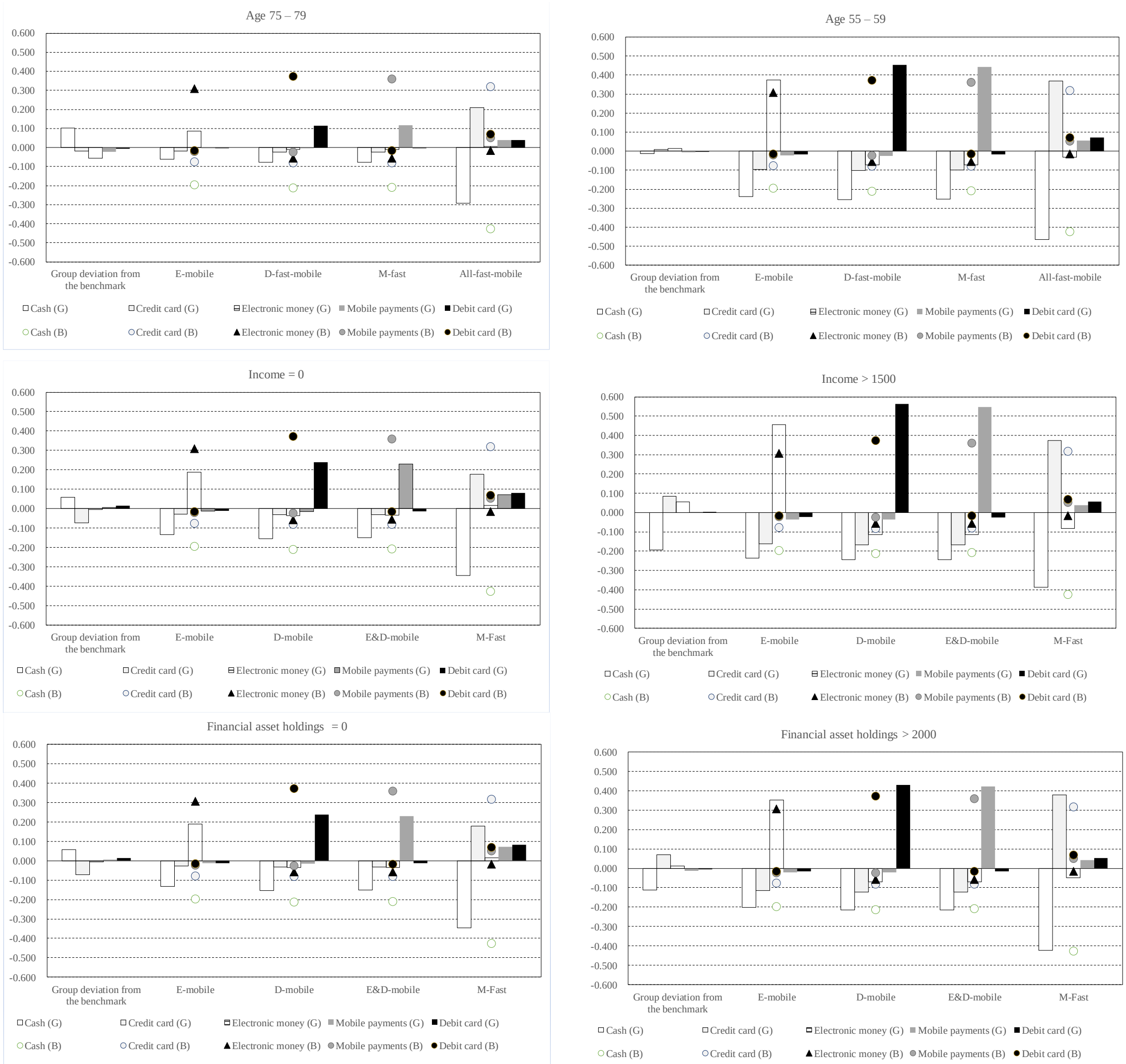


Table 1 Use of payment methods and probabilities to be ranked first

	Average use	Probability to be ranked first			
		Unweighted	Weighted 1	Weighted 2	Weighted 3
Samples	All	All	All	Drop top = 1	Drop top = 1 and/or 2
Cash	4.217	0.844	0.657	0.671	0.674
Credit card	3.095	0.326	0.179	0.178	0.177
Electronic money	2.741	0.260	0.119	0.116	0.116
Mobile payments	1.765	0.085	0.028	0.023	0.021
Debit card	1.400	0.056	0.017	0.012	0.010
Total		1.571	1.000	1.000	1.000
N	25,000	25,000	25,000	24,252	23,956

Note: We assigned the value of 5, 4, 3, 2, and 1 for those who replied “Almost every day,” “About once a week,” “About once a month,” “Scarcely or never,” and “Do not adopt it,” respectively.

Table 2 Characteristics of payment method

	Mobile	Credit	Paper	Times
Cash	0	0	1	28
Credit card	0	1	0	12
Electronic money	0	0	0	8
Mobile payments	1	0	0	17
Debit card	0	0	0	12

Note: The figures in the column labeled "Times" show average transaction time (seconds) of POS estimated by the JCB. Source: https://www.global.jcb/ja/press/00000000162855.html

Table 3 Means and standard deviations (S.E.) of control variables

		Mean	S.E.
Financial literacy	Objective_financial_literacy	6.618	3.524
	News	2.298	1.523
	Fin_education_school	0.074	0.261
	Fin_education_home	0.210	0.407
	Fraud	0.067	0.250
	Debt	0.314	0.464
	Credit_card_literacy	0.510	0.500
Information sources	S_dont_know	0.049	0.217
	S_fin	0.100	0.300
	S_net	0.083	0.275
	S_fin_exp	0.108	0.310
	S_fin_net	0.162	0.368
	S_other	0.138	0.345
Financial behavior	Over_confidence	-5.123	3.304
	Myopia	2.175	1.582
	Herding	1.597	1.053
	Self_control	2.964	0.988
	Loss_aversion	0.767	0.423
	Risk_aversion	0.913	0.282
Pretax income	Income_0	0.028	0.164
	Income_250_500	0.287	0.452
	Income_500_750	0.177	0.382
	Income_750_1000	0.101	0.301
	Income_1000_1500	0.055	0.229
	Income_1500_	0.019	0.138
	Income_NA	0.176	0.381
Financial assets	Asset_0	0.126	0.332
	Asset_250_500	0.097	0.296
	Asset_500_750	0.051	0.219
	Asset_750_1000	0.050	0.217
	Asset_1000_2000	0.068	0.251
	Asset_2000_	0.129	0.335
	Asset_NA	0.322	0.467

		Mean	S.E.
Age	Age25_29	0.074	0.262
	Age30_34	0.075	0.264
	Age35_39	0.084	0.277
	Age40_44	0.086	0.280
	Age45_49	0.105	0.307
	Age50_54	0.082	0.275
	Age55_59	0.081	0.273
	Age60_64	0.108	0.310
	Age65_69	0.088	0.284
	Age70_74	0.105	0.307
	Age75_79	0.041	0.199
Gender	Male	0.493	0.500
Employment status	Private	0.333	0.471
	Public	0.030	0.170
	Teacher	0.012	0.110
	Selfemployed	0.067	0.251
	Parttime	0.155	0.361
	House	0.194	0.396
	Student	0.047	0.211
Education	Seniorhigh	0.322	0.467
	Vocationalcollege	0.111	0.315
	Juniorcollege	0.114	0.318
	University	0.387	0.487
	Graduate	0.039	0.194
Area of residence	Hokkaido	0.043	0.204
	Tohoku	0.070	0.255
	Hokuriku	0.041	0.199
	Chubu	0.141	0.348
	Kinki	0.163	0.370
	Chugoku	0.057	0.233
	Shikoku	0.030	0.169
	Kyushu	0.111	0.314
Number of observations		23,956	

Table 4 Results of regressions

Without demographic variables	Mobile		Credit		Paper		Times	
	1.553	***	1.376	***	6.472	***	-0.250	***

Notes: N = 23,956, Log pseudolikelihood = -90830.2, Wald chi2(3) =21739.73***, BIC = 181700.8

With demographic variables	Mobile		Credit		Paper		Times	
Constant	1.034	***	0.355	***	4.477	***	-0.166	***
Objective_financial_literacy	0.039	**	0.057	***	0.037		-0.007	***
News	0.043	***	0.000		0.116	***	-0.008	***
Fin_education_school	-0.131	**	-0.163	***	-0.529	***	0.017	*
Fin_education_home	0.092	**	0.006		0.314	***	-0.013	**
Fraud	-0.245	***	-0.528	***	-0.993	***	0.039	***
Debt	0.184	***	0.165	***	0.354	***	-0.014	***
Credit_card_literacy	0.126	***	0.106	***	0.403	***	-0.020	***
S_dont_know	0.266	***	0.069		0.737	***	-0.041	***
S_fin	0.076	*	0.090	***	0.315	**	-0.017	**
S_net	0.134	**	0.170	***	0.100		-0.017	*
S_fin_exp	0.182	***	0.059	*	0.430	***	-0.033	***
S_fin_net	0.271	***	0.177	***	0.922	***	-0.049	***
S_other	0.122	***	0.093	***	0.406	***	-0.026	***
Over_confidence	-0.020		0.020	**	-0.169	***	0.004	
Myopia	-0.024	***	-0.034	***	-0.096	***	0.006	***
Herding	-0.021		0.006		-0.112	***	0.005	**
Self_control	-0.045	***	-0.020	**	-0.075	*	0.007	***
Loss_aversion	-0.024		0.016		0.150		0.002	
Risk_aversion	0.089	*	0.047		0.325	**	-0.011	
Income_0	-0.144	*	-0.071		-0.271		0.018	
Income_250_500	0.128	***	0.069	**	0.384	***	-0.014	**
Income_500_750	0.218	***	0.172	***	0.648	***	-0.027	***
Income_750_1000	0.259	***	0.152	***	0.759	***	-0.036	***
Income_1000_1500	0.318	***	0.099	**	0.730	***	-0.038	***
Income_1500_	0.297	**	0.091		0.450		-0.034	*
Income_NA	0.063		-0.029		0.168		-0.004	
Asset_0	-0.160	***	-0.246	***	-0.437	***	0.024	***
Asset_250_500	-0.036		0.064	*	-0.152		0.007	
Asset_500_750	-0.072		0.100	**	-0.318		0.013	
Asset_750_1000	0.054		0.096	**	0.054		-0.010	
Asset_1000_2000	0.044		0.139	***	0.221		-0.015	
Asset_2000_	0.009		0.221	***	0.207		-0.011	
Asset_NA	-0.024		0.013		0.012		0.004	
Age25_29	0.219	**	0.248	***	0.187		-0.019	
Age30_34	0.255	***	0.347	***	0.500	**	-0.031	**
Age35_39	0.146		0.264	***	0.111		-0.016	
Age40_44	0.043		0.328	***	0.226		-0.018	
Age45_49	0.167	*	0.378	***	0.645	***	-0.041	***
Age50_54	0.127		0.378	***	0.704	***	-0.043	***
Age55_59	0.145		0.428	***	0.863	***	-0.050	***
Age60_64	0.033		0.508	***	0.562	**	-0.034	**
Age65_69	-0.106		0.702	***	0.421		-0.012	
Age70_74	-0.406	***	0.562	***	-0.304		0.034	**
Age75_79	-0.716	***	0.515	***	-0.819	***	0.076	***
Male	-0.382	***	-0.313	***	-1.236	***	0.062	***
Private	0.322	***	0.178	***	0.715	***	-0.042	***
Public	0.433	***	0.300	***	1.093	***	-0.060	***
Teacher	0.074		0.229	**	0.153		-0.014	
Selfemployed	-0.018		0.072		-0.110		0.013	
Parttime	0.255	***	0.020		0.704	***	-0.036	***
House	0.085		0.069	*	0.144		-0.008	
Student	0.372	***	-0.240	***	1.339	***	-0.074	***
Seniorhigh	0.123		0.251	***	0.553	***	-0.024	**
Vocationalcollege	0.209	**	0.386	***	0.915	***	-0.042	***
Juniorcollege	0.205	**	0.449	***	0.946	***	-0.046	***
University	0.310	***	0.515	***	1.273	***	-0.067	***
Graduate	0.476	***	0.601	***	1.735	***	-0.099	***
Hokkaido	-0.210	***	-0.016		-0.739	***	0.043	***
Tohoku	-0.166	**	-0.065		-0.700	***	0.042	***
Hokuriku	-0.557	***	-0.070		-1.889	***	0.113	***
Chubu	-0.364	***	0.062	*	-1.250	***	0.077	***
Kinki	-0.580	***	-0.019		-1.659	***	0.109	***
Chugoku	-0.231	***	-0.075	*	-0.839	***	0.059	***
Shikoku	-0.292	***	-0.146	***	-1.092	***	0.079	***
Kyushu	-0.335	***	-0.109	***	-0.957	***	0.073	***

Notes: N = 23,956, Log pseudolikelihood = -88062.86, Wald chi2(198) = 168600.63***, BIC = 18787.9

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Standard Errors are adjusted for clusters formed by gender, age group, and prefectures.

Table 5 Forecast and actual probabilities of being top ranked

	Data	Model	
Cash	0.674	0.566	0.575
Credit card	0.177	0.190	0.194
Electronic money	0.116	0.131	0.128
Mobile payments	0.021	0.065	0.060
Debit card	0.010	0.048	0.043
Demmographic variables		No	Yes

Table 6 Assumptions for counterfactual simulations

Counterfactual 1: "E-mobile," Mobile option for electronic money

	Mobile	Credit	Paper	Times
Cash	0	0	1	28
Credit card	0	1	0	12
Electronic money	0 → 1	0	0	8
Mobile payments	1	0	0	17
Debit card	0	0	0	12

Counterfactual 2: "D-fast-mobile": Mobile option for debit card

	Mobile	Credit	Paper	Times
Cash	0	0	1	28
Credit card	0	1	0	12
Electronic money	0	0	0	8
Mobile payments	1	0	0	17
Debit card	0 → 1	0	0	12→ 8

Counterfactual 4: "M-fast": Faster Mobile payments via smartphone

	Mobile	Credit	Paper	Times
Cash	0	0	1	28
Credit card	0	1	0	12
Electronic money	0	0	0	8
Mobile payments	1	0	0	17 → 8
Debit card	0	0	0	12

Counterfactual 4: "Al-fasl-mobilet" Faster mobile payments

	Mobile	Credit	Paper	Times
Cash	0	0	1	28
Credit card	0 → 1	1	0	12→ 8
Electronic money	0 → 1	0	0	8
Mobile payments	1	0	0	17 → 8
Debit card	0 → 1	0	0	12→ 8

Note: The figures in the column labeled “Times” show average transaction time (seconds) of POS estimated by the JCB. Source: https://www.global.jcb/ja/press/00000000162855.html

Table 7 Results of counterfactual simulations

	Benchmark	E-mobile	D-fast-mobile	M-fast	All-fast-mobile
Cash	0.575	0.379	0.363	0.367	0.149
(Change from the benchmark)		(-0.196)	(-0.211)	(-0.208)	(-0.425)
Credit card	0.194	0.118	0.113	0.114	0.513
(Change from the benchmark)		(-0.076)	(-0.081)	(-0.080)	(0.319)
Electronic money	0.128	0.437	0.071	0.072	0.113
(Change from the benchmark)		(0.308)	(-0.057)	(-0.056)	(-0.016)
Mobile payments	0.060	0.038	0.037	0.420	0.113
(Change from the benchmark)		(-0.022)	(-0.023)	(0.360)	(0.053)
Debit card	0.043	0.028	0.416	0.027	0.113
(Change from the benchmark)		(-0.015)	(0.373)	(-0.016)	(0.069)