Attributes needed for Japan’s central bank digital currency

Conference on Payments and Market Infrastructures in Emerging Economies

Hiroshi FUJIKI
Chuo University
June 16, 2021

Source: https://diamond-rm.net/ec-epayment/40787/

Source: https://www.smbc-card.com/nyukai/index.jsp
Question

“Which type of attributes should a central bank digital currency have to be widely accepted?”

Four product attributes were incorporated: preferences for mobile payments, the utility of credit cards, preference for banknotes, and the valuation of time, following Borzekowski and Kiser (2008a).

We also pay attention to the heterogeneity by demographic groups.
Results

Survey respondents valued shorter settlement time, mobile payments, and credit cards and banknotes in ranking payment instruments.

Our counterfactual simulations showed that a hypothetical mobile version of noncash payment methods that required a short transaction time would be highly ranked if they were introduced.

Compared with overall samples, the adoption of these hypothetical products is not frequent for respondents who are elderly and with small financial asset holdings as Borzekowski and Kiser (2008a) and Kim et al. (2020) found.
Policy implication

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, a mobile version of noncash payment methods that required a short transaction time would be highly ranked by Japanese households.

Policy tools should be utilized to encourage the use of it by a consumer with zero amount of financial asset holdings and an elderly household head as well for the sake of universal access.
Why study CBDC in Japan?

Facebook announced a new cryptocurrency, the Libra, in June 2019.

Before the Libra, the volatile price formation of crypto assets suggested that they were not useful for day-to-day transactions. At best, they were useful as a store of value. (El Salvador makes Botcpoint legal tender!)

However, as a means of day-to-day payments, people in emerging market economies might adopt stable Libra coins instead of using their unstable sovereign currencies.

The Japanese government said that it would study central bank digital currency in cooperation with other countries in its official economic plan in July 17, 2020.

Methodology (1)

Use the Financial Literacy Survey (FLS) 2019 in Japan.

Get the data on the frequency of the use of five payment instruments: 1. cash, 2. credit cards, 3. contactless prepaid cards (electronic money), 4. branded debit cards, and 5. mobile payments using smartphone applications (including prepaid or post-paid, QR-code based, or mobile wallets for credit cards, debit cards, or electronic money).

Frequency of use: “Almost every day,” “About once a week,” “About once a month,” “Scarcely or never,” and “Do not adopt it”.

Compute a ranking of the frequency of the use of five payment methods.

The top-ranked product is cash, followed by credit cards, electronic money, mobile payments, and debit cards.
Methodology (2)

Estimate a rank-ordered logit model to explain the ranking of use of the five payment methods conditional on the four attributes (preferences for mobile payments, the utility of credit cards, preference for banknotes, and the valuation of time).

The estimates of the model showed that survey 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 by the Japanese consumers if they were introduced.

The Bank of Japan might wish to issue a CBDC with these attributes.
Choice of payment methods using the characteristics approach
Hirschman’s (1982), Borzekowski and Kiser (2008a), and Kim et al. (2020).
Closely related to Borzekowski and Kiser (2008a).
There are limitations due to the availability of data compared with Kim et al. (2020); No analysis on the usage of payment methods based on the types and value of transactions. No analysis conditional on the choice of sets of payment instruments.
This paper focuses on the consumers’ adoption of CBDC and puts aside other important policy issues related to the issuance of CBDC for merchants and financial service providers.
The FLS 2019

The FLS is a web survey that was administered from March 1 to March 20, 2019.

It covers 25,000 individuals aged 18–79 years in Japan.

The survey asks questions choice of payment methods.

It also asks true/false questions on financial knowledge and financial decision-making skills, along with behavioral and attitudinal questions.
Use of payment methods

- Use of payment methods:
  - Cash: Almost Every day, About once a week, About once a month, Scarcely or never, Do not adopt it
  - Credit card: Almost Every day, About once a week, About once a month, Scarcely or never, Do not adopt it
  - Electronic money: Almost Every day, About once a week, About once a month, Scarcely or never, Do not adopt it
  - Debit card: Almost Every day, About once a week, About once a month, Scarcely or never, Do not adopt it
  - Mobile payments: Almost Every day, About once a week, About once a month, Scarcely or never, Do not adopt it
# Use of payment methods

<table>
<thead>
<tr>
<th>Observations used for analysis</th>
<th>All observations</th>
<th>Drop observations with top actual rank = 1</th>
<th>Drop observations with top actual rank &lt;= 2</th>
<th>Drop observations with partial rank = 33333</th>
</tr>
</thead>
<tbody>
<tr>
<td>Names of samples</td>
<td>Sample 0</td>
<td>Sample 1</td>
<td>Sample 2</td>
<td>Sample 3</td>
</tr>
<tr>
<td>Number of observations</td>
<td>25,000</td>
<td>24,252</td>
<td>23,956</td>
<td>24,148</td>
</tr>
<tr>
<td>Types of rankings</td>
<td>Actual</td>
<td>Partial</td>
<td>Actual</td>
<td>Partial</td>
</tr>
<tr>
<td>Number of ranks</td>
<td>1,454</td>
<td>361</td>
<td>1,453</td>
<td>361</td>
</tr>
<tr>
<td>Average use</td>
<td>4.217</td>
<td>0.844</td>
<td>0.657</td>
<td>0.840</td>
</tr>
<tr>
<td>Cash</td>
<td>3.095</td>
<td>0.326</td>
<td>0.179</td>
<td>0.305</td>
</tr>
<tr>
<td>Credit card</td>
<td>2.741</td>
<td>0.260</td>
<td>0.119</td>
<td>0.237</td>
</tr>
<tr>
<td>Electronic money</td>
<td>1.765</td>
<td>0.085</td>
<td>0.028</td>
<td>0.057</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1.400</td>
<td>0.056</td>
<td>0.017</td>
<td>0.026</td>
</tr>
<tr>
<td>Total</td>
<td>1.571</td>
<td>1.000</td>
<td>1.465</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note: We assigned the value of 5, 4, 3, 2, and 1 for those who replied “Almost every day,” “About once a week,” “Scarcely or never,” and “Do not adopt it,” respectively. We call this ranking actual rank. To deal with the possibilities of ties, we define partial rank. For example, if the actual rank is 5, 4, 4, 2, and 1, we define its corresponding partial rank for cash, credit cards, electronic money, mobile payments, and debit cards as 5, 3.5, 3.5, 2, and 1.
Attributes

<table>
<thead>
<tr>
<th></th>
<th>Mobile</th>
<th>Credit</th>
<th>Paper</th>
<th>Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>Credit card</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Electronic money</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Debit card</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>12</td>
</tr>
</tbody>
</table>

Notes: *Times* follows the results from a survey of the average transaction time conducted by JCB. While the JCB survey did not examine *times* 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. The time for mobile payments was set equal to that of QR code-based transaction.
Rank-ordered logit model

\[ U_{ij} = V_{ij} + \epsilon_{ij}. \]

- \( U_{ij} \): the utility of a respondent \( i \) from the use of \( j \)-th instruments
- \( V_{ij} \): the systematic component
- \( \epsilon_{ij} \): a random component which follows an independent and identically distributed extreme value distribution

\[ r_{i} = (r_{i1}, r_{i2}, \ldots, r_{ij})' \]: the response of respondent \( I \) where \( r_{ij} \) denotes the item number that received rank \( j \) by respondent \( i \)

The probability of observing this respondent’s ranking

\[ \pi(r_{i}) = \Pr \left( U_{ir_{i1}} > U_{ir_{i2}} > \cdots > U_{ir_{ij}} \right) = \prod_{j=1}^{J-1} \frac{\exp V_{ir_{ij}}}{\sum_{l=j}^{J} \exp V_{ir_{il}}} \]
Forecasts by rank-ordered logit model

Assume \( V_{ij} = \beta(X_i \otimes Z_j) \), where \( X_i \) is a vector of explanatory variables and \( Z_j \) is \( 1 \times 4 \) vector of attributes Mobile, Credit, Paper, and Times. The log-likelihood of observing the sequence of ranking is

\[
L(\beta) = \sum_{i=1}^{N} \log \pi(r_i) = \sum_{i=1}^{N} \sum_{h=1}^{J} \beta(X_i \otimes Z_{r_{ih}}) - \sum_{i=1}^{N} \sum_{h=1}^{J} \sum_{m=h}^{J} \log \sum_{m=h}^{J} \beta(X_i \otimes Z_{r_{im}}).
\]

Use the parameter estimates from the above equation to forecast the probability that the five payment methods are top-ranked.
TR and LCL models

The parameter estimates from an ROL model could be biased if the researchers paid insufficient attention to the ranking ability of the respondents (Fok et al. (2012)).

**TR model:** An ROL model that used decision weights based on the most preferred alternatives only. TR models use the partial ranking that assigns 1 for the top rank choices and 0 for the other choices. Payment choice can vary with demographic variables.

**LCL model:** A latent class conditional logit model (Fok et al. (2012)). Allows latent class segments to identify ranking capabilities endogenously (Stata package by Yoo (2020)). Probabilities belonging to latent classes are determined by demographics. Payment choice depends only on attributes. Dropping 852 observations that rank all choices as the best choice to use this package (Use Sample 3).
LCL model

Assume that the joint likelihood of a respondent $i$ choosing the $j$-th payment method, $P_i(\gamma)$, is:

$$P_i(\gamma) = \prod_{j=1}^{J-1} \left( \frac{\exp(Z_j \gamma)}{\sum_{h=1}^J \exp(Z_h \gamma)} \right)^{b_{ij}},$$

where $b_{ij}$ denotes a binary indicator that equals 1 if the respondent’s choice is the $j$-th payment method $j$, $Z_j$ is a $1 \times 4$ vector of the attributes, and $\gamma$ is a column vector of four attributes for the $j$-th payment method.

$C = 1, 2, \ldots, C$ classes of respondents with unobserved preference heterogeneity related to ranking capabilities. The respondent in class $c$ has utility coefficient vector $\gamma_c$ with the conditional logit model above.
LCL model

Then, the probability that the respondent $i$ belongs to class $c$ is:

$$
\pi_{ic}(\theta) = \frac{\exp(X_i\theta_c)}{1 + \sum_{l=1}^{C-1} \exp(X_i\theta_l)}
$$

$X_i$ is a $1 \times 62$ vector of 61 control variables and a constant term, and $\theta_c$ is a parameter of the model that determines the membership to class $c$. $\theta_c$ is normalized to be zero for identification, and $\theta$ is a collection of the identified membership coefficients, $\theta = (\theta_1, \theta_2, ..., \theta_{C-1})$.

The joint likelihood of the LCL model becomes:

$$
\sum_{c=1}^{C} \pi_{ic}(\theta)P_i(y_c).
$$

Use Yoo (2020) to estimate the parameters $\theta$ and $y_c$ by maximizing the sample log-likelihood function using an expectation-maximization (EM) algorithm. $C = 2$ chosen by the minimum BIC.
### Control variables

<table>
<thead>
<tr>
<th>Financial literacy</th>
<th>Objective financial literacy</th>
<th>0.642</th>
<th>0.637**</th>
<th>0.661**</th>
<th>0.658***</th>
<th>0.552**</th>
<th>0.981**</th>
<th>0.946**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fin. education</td>
<td>0.072</td>
<td>0.073</td>
<td>0.074</td>
<td>0.073</td>
<td>0.074</td>
<td>0.026**</td>
<td>0.004**</td>
<td>0.041**</td>
</tr>
<tr>
<td>Fin. education</td>
<td>0.203</td>
<td>0.208</td>
<td>0.21*</td>
<td>0.208</td>
<td>0.21*</td>
<td>0.026**</td>
<td>0.004**</td>
<td>0.041**</td>
</tr>
<tr>
<td>Fraud</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
<td>0.014**</td>
<td>0.005*</td>
<td>0.054*</td>
</tr>
<tr>
<td>Debt</td>
<td>0.307</td>
<td>0.313</td>
<td>0.314</td>
<td>0.312</td>
<td>0.313</td>
<td>0.139**</td>
<td>0.158**</td>
<td>0.167**</td>
</tr>
<tr>
<td>Credit card literacy</td>
<td>0.499</td>
<td>0.506**</td>
<td>0.51**</td>
<td>0.507**</td>
<td>0.511**</td>
<td>0.155**</td>
<td>0.147**</td>
<td>0.126**</td>
</tr>
<tr>
<td>Information sources</td>
<td>News</td>
<td>2.253</td>
<td>2.288**</td>
<td>2.298**</td>
<td>2.27**</td>
<td>1.14**</td>
<td>1.21**</td>
<td>1.284**</td>
</tr>
<tr>
<td>S_door know</td>
<td>0.049</td>
<td>0.05</td>
<td>0.049</td>
<td>0.05</td>
<td>0.049</td>
<td>0.019**</td>
<td>0.034**</td>
<td>0.022**</td>
</tr>
<tr>
<td>S_fin inst</td>
<td>0.376</td>
<td>0.386**</td>
<td>0.388**</td>
<td>0.385**</td>
<td>0.39**</td>
<td>0.091**</td>
<td>0.102**</td>
<td></td>
</tr>
<tr>
<td>S_exclude_fin inst</td>
<td>0.196</td>
<td>0.201</td>
<td>0.202*</td>
<td>0.201</td>
<td>0.203**</td>
<td>0.035**</td>
<td>0.027**</td>
<td>0.062**</td>
</tr>
<tr>
<td>S_door_choose</td>
<td>0.379</td>
<td>0.364**</td>
<td>0.366**</td>
<td>0.364**</td>
<td>0.369**</td>
<td>0.089**</td>
<td>0.085**</td>
<td>0.082**</td>
</tr>
<tr>
<td>Financial behavior</td>
<td>Overconfidence</td>
<td>-4.946</td>
<td>-5.085**</td>
<td>-5.123**</td>
<td>-5.094**</td>
<td>-0.441**</td>
<td>-0.885**</td>
<td>-0.746**</td>
</tr>
<tr>
<td>Impatience</td>
<td>2.177</td>
<td>2.176</td>
<td>2.175</td>
<td>2.176</td>
<td>2.179**</td>
<td>1.773**</td>
<td>0.842**</td>
<td></td>
</tr>
<tr>
<td>Reputation</td>
<td>1.604</td>
<td>1.598</td>
<td>1.597</td>
<td>1.596</td>
<td>1.799**</td>
<td>1.773**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-control</td>
<td>2.950</td>
<td>2.963</td>
<td>2.964</td>
<td>2.964</td>
<td>2.535**</td>
<td>2.626**</td>
<td>2.559**</td>
<td></td>
</tr>
<tr>
<td>Risk aversion 1</td>
<td>0.773</td>
<td>0.769</td>
<td>0.767</td>
<td>0.77</td>
<td>0.912**</td>
<td>0.905**</td>
<td>0.865**</td>
<td></td>
</tr>
<tr>
<td>Risk aversion 2</td>
<td>0.914</td>
<td>0.913</td>
<td>0.913</td>
<td>0.913</td>
<td>0.951**</td>
<td>0.941**</td>
<td>0.938**</td>
<td></td>
</tr>
<tr>
<td>Pretax income</td>
<td>Income_0</td>
<td>0.032</td>
<td>0.029**</td>
<td>0.028**</td>
<td>0.028**</td>
<td>0.138**</td>
<td>0.128**</td>
<td>0.129**</td>
</tr>
<tr>
<td>Income_250</td>
<td>0.157</td>
<td>0.156</td>
<td>0.156</td>
<td>0.156</td>
<td>0.166</td>
<td>0.165</td>
<td>0.163</td>
<td></td>
</tr>
<tr>
<td>Income_250</td>
<td>0.283</td>
<td>0.286</td>
<td>0.287</td>
<td>0.286</td>
<td>0.189**</td>
<td>0.206**</td>
<td>0.195**</td>
<td></td>
</tr>
<tr>
<td>Income_500, 750</td>
<td>0.173</td>
<td>0.176</td>
<td>0.177</td>
<td>0.176</td>
<td>0.079**</td>
<td>0.088**</td>
<td>0.085**</td>
<td></td>
</tr>
<tr>
<td>Income_750, 1000</td>
<td>0.098</td>
<td>0.1</td>
<td>0.101</td>
<td>0.1</td>
<td>0.041**</td>
<td>0.041**</td>
<td>0.052**</td>
<td></td>
</tr>
<tr>
<td>Income_1000, 1500</td>
<td>0.054</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055</td>
<td>0.055**</td>
<td>0.028**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income_1500</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
<td>0.019</td>
<td>0.013</td>
<td>0.011**</td>
<td>0.022</td>
<td></td>
</tr>
<tr>
<td>Income_NA</td>
<td>0.184</td>
<td>0.178</td>
<td>0.176**</td>
<td>0.179</td>
<td>0.354**</td>
<td>0.35**</td>
<td>0.327**</td>
<td></td>
</tr>
<tr>
<td>Financial assets</td>
<td>Asset_0</td>
<td>0.133</td>
<td>0.128*</td>
<td>0.126**</td>
<td>0.128*</td>
<td>0.309**</td>
<td>0.298**</td>
<td>0.295**</td>
</tr>
<tr>
<td>Asset_250</td>
<td>0.155</td>
<td>0.157</td>
<td>0.157</td>
<td>0.157</td>
<td>0.088**</td>
<td>0.091**</td>
<td>0.064**</td>
<td></td>
</tr>
<tr>
<td>Asset_250</td>
<td>0.095</td>
<td>0.097</td>
<td>0.097</td>
<td>0.097</td>
<td>0.048**</td>
<td>0.055**</td>
<td>0.054**</td>
<td></td>
</tr>
<tr>
<td>Asset_500, 750</td>
<td>0.050</td>
<td>0.051</td>
<td>0.051</td>
<td>0.05</td>
<td>0.029**</td>
<td>0.033**</td>
<td>0.038*</td>
<td></td>
</tr>
<tr>
<td>Asset_750, 1000</td>
<td>0.048</td>
<td>0.049</td>
<td>0.05</td>
<td>0.049</td>
<td>0.017**</td>
<td>0.013**</td>
<td>0.026**</td>
<td></td>
</tr>
<tr>
<td>Asset_1000, 2000</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
<td>0.023**</td>
<td>0.038**</td>
<td>0.042**</td>
<td></td>
</tr>
<tr>
<td>Asset_2000</td>
<td>0.125</td>
<td>0.128</td>
<td>0.129</td>
<td>0.128</td>
<td>0.029**</td>
<td>0.025**</td>
<td>0.042**</td>
<td></td>
</tr>
<tr>
<td>Asset_NA</td>
<td>0.328</td>
<td>0.324</td>
<td>0.322</td>
<td>0.325</td>
<td>0.456**</td>
<td>0.466**</td>
<td>0.426**</td>
<td></td>
</tr>
</tbody>
</table>

**Table 1.** Financial literacy, Education, Employment status, Pretax income, Financial behavior, and Pretax income. The table shows the sample means and standard deviations for each variable. The table also includes the number of observations for each sample.
**Parameter estimates of the ROL (Sample 0)**

<table>
<thead>
<tr>
<th>Control variables</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile</td>
<td>1.482***</td>
<td>0.925***</td>
</tr>
<tr>
<td>Credit</td>
<td>1.302***</td>
<td>0.389***</td>
</tr>
<tr>
<td>Time</td>
<td>-0.238***</td>
<td>-0.151***</td>
</tr>
<tr>
<td>Paper</td>
<td>6.087***</td>
<td>3.713***</td>
</tr>
<tr>
<td>N</td>
<td>25,000</td>
<td>25,000</td>
</tr>
<tr>
<td>pseudo Rsq</td>
<td>0.186</td>
<td>0.211</td>
</tr>
<tr>
<td>chi2</td>
<td>17727.616</td>
<td>153000</td>
</tr>
<tr>
<td>p-value</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Type of model test statistics</td>
<td>Wald</td>
<td>Wald</td>
</tr>
</tbody>
</table>

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard Errors are adjusted for clusters. Ties are handled by the Efron option of Stata 16.
Counterfactual simulations

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

<table>
<thead>
<tr>
<th></th>
<th>Mobile</th>
<th>Credit</th>
<th>Paper</th>
<th>Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>Credit card</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Electronic money</td>
<td>0 $\rightarrow$ 1</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Debit card</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>12</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Mobile</th>
<th>Credit</th>
<th>Paper</th>
<th>Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>Credit card</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Electronic money</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Debit card</td>
<td>0 $\rightarrow$ 1</td>
<td>0</td>
<td>0</td>
<td>12 $\rightarrow$ 8</td>
</tr>
</tbody>
</table>

### Counterfactual 3: "M-fast": Faster Mobile payments via smartphone

<table>
<thead>
<tr>
<th></th>
<th>Mobile</th>
<th>Credit</th>
<th>Paper</th>
<th>Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>Credit card</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Electronic money</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>17 $\rightarrow$ 8</td>
</tr>
<tr>
<td>Debit card</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>12</td>
</tr>
</tbody>
</table>

### Counterfactual 4: "All-fast-mobile" Faster mobile payments

<table>
<thead>
<tr>
<th></th>
<th>Mobile</th>
<th>Credit</th>
<th>Paper</th>
<th>Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>28</td>
</tr>
<tr>
<td>Credit card</td>
<td>0 $\rightarrow$ 1</td>
<td>1</td>
<td>0</td>
<td>12 $\rightarrow$ 8</td>
</tr>
<tr>
<td>Electronic money</td>
<td>0 $\rightarrow$ 1</td>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Mobile payments</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>17 $\rightarrow$ 8</td>
</tr>
<tr>
<td>Debit card</td>
<td>0 $\rightarrow$ 1</td>
<td>0</td>
<td>0</td>
<td>12 $\rightarrow$ 8</td>
</tr>
</tbody>
</table>
Counterfactual simulations by the ROL (Sample 0, with demographic variables)
# Counterfactual simulations by the ROL (Sample 0, by demographic groups)

<table>
<thead>
<tr>
<th>Samples 0</th>
<th>Benchmark</th>
<th>E-mobile</th>
<th>D-fast-mobile</th>
<th>M-fast</th>
<th>All-fast-mobile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Median</td>
<td>P</td>
<td>Average</td>
<td>Median</td>
</tr>
<tr>
<td>Average</td>
<td>Cash</td>
<td>0.538</td>
<td>0.542</td>
<td>0.551</td>
<td>0.349</td>
</tr>
<tr>
<td></td>
<td>Credit card</td>
<td>0.203</td>
<td>0.201</td>
<td>0.127</td>
<td>0.123</td>
</tr>
<tr>
<td></td>
<td>Electronic money</td>
<td>0.138</td>
<td>0.134</td>
<td>0.440</td>
<td>0.436</td>
</tr>
<tr>
<td></td>
<td>Mobile payments</td>
<td>0.069</td>
<td>0.064</td>
<td>0.046</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>Debit card</td>
<td>0.051</td>
<td>0.046</td>
<td>0.035</td>
<td>0.029</td>
</tr>
<tr>
<td>Age75_79</td>
<td>Cash</td>
<td>0.634</td>
<td>0.637 ***</td>
<td>0.571</td>
<td>0.573</td>
</tr>
<tr>
<td></td>
<td>Credit card</td>
<td>0.192</td>
<td>0.190 ***</td>
<td>0.172</td>
<td>0.169</td>
</tr>
<tr>
<td></td>
<td>Electronic money</td>
<td>0.082</td>
<td>0.080 ***</td>
<td>0.172</td>
<td>0.160</td>
</tr>
<tr>
<td></td>
<td>Mobile payments</td>
<td>0.045</td>
<td>0.042 ***</td>
<td>0.041</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>Debit card</td>
<td>0.046</td>
<td>0.043 ***</td>
<td>0.042</td>
<td>0.038</td>
</tr>
<tr>
<td>Asset_0</td>
<td>Cash</td>
<td>0.541</td>
<td>0.545</td>
<td>0.399</td>
<td>0.396</td>
</tr>
<tr>
<td></td>
<td>Credit card</td>
<td>0.153</td>
<td>0.152 ***</td>
<td>0.112</td>
<td>0.109</td>
</tr>
<tr>
<td></td>
<td>Electronic money</td>
<td>0.144</td>
<td>0.141 ***</td>
<td>0.365</td>
<td>0.353</td>
</tr>
<tr>
<td></td>
<td>Mobile payments</td>
<td>0.092</td>
<td>0.088 ***</td>
<td>0.069</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>Debit card</td>
<td>0.071</td>
<td>0.067 ***</td>
<td>0.055</td>
<td>0.050</td>
</tr>
</tbody>
</table>

Note: Benchmark shows the difference from the average benchmark estimates. E-mobile, D-fast-mobile, M-fast, and All-fast-mobile shows the difference between the deviation from benchmark and counterfactual simulations for average results and those for Age7_79 or those for Asset_0. A rank sum test for the equality of the median of the projected forecast probabilities that each payment methods are top ranked between Age75_79 = 1 vs 0 and Asset_0 = 1 or 0 are conducted. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
The Hausman test favors the TR model over the ROL model. However, the TR model yields qualitatively similar results to our counterfactual simulations. Quantitatively, on average, the TR model tends to predict a higher probability of hypothetical mobile and/or faster versions of credit cards, electronic money, debit cards, and mobile payments with faster settlement times being top-ranked compared with the ROL model.
Counterfactual simulations
(Sample 3 <Drop Partial rank = 33333>,
ROL and TR with demographic variables)

The probabilities of being top-ranked for the hypothetical fast and/or mobile payment methods based on the LCL model are about 0.8 on average.
These results mainly reflect the preference of the respondents in class 1 in the LCL (about 90% of the sample) because the respondents in class 2 (about 10% of the sample) rank cash as top at 70–90% in the counterfactual simulations.
Key takeaways

Survey respondents valued shorter settlement time, mobile payments, and credit cards and banknotes in ranking payment instruments.

Our counterfactual simulations showed that a hypothetical mobile version of noncash payment methods that required a short transaction time would be highly ranked if they were introduced.

Compared with overall samples, the adoption of these hypothetical products is not frequent for a consumer with zero amount of financial asset holdings and an elderly household head as Borzekowski and Kiser (2008a) and Kim et al. (2020) found.
Policy implication

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, a mobile version of noncash payment methods that required a short transaction time would be highly ranked by Japanese consumers. Policy tools should be utilized to encourage the use of it by a consumer with zero amount of financial asset holdings and an elderly household head as well.

https://iphone-mania.jp/news-258207/

“Mobile Suica” by East Japan Rail