Attributes needed for Japan’s central bank digital currency

Conference on Payments and Market Infrastructures in Emerging Economies

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

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

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 Botcpoin 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.

The Bank of Japan released "The Bank of Japan's Approach to Central Bank Digital Currency“ in October 2020. It planned three phases of Proof of Concept (PoC) and the first phase began in April 2021.

Methodology (1)

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

Get the data on the of 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.

Literature

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 asides other important policy issues related to the issuance of CBDC for merchants and financial service providers.

The FLS 2019

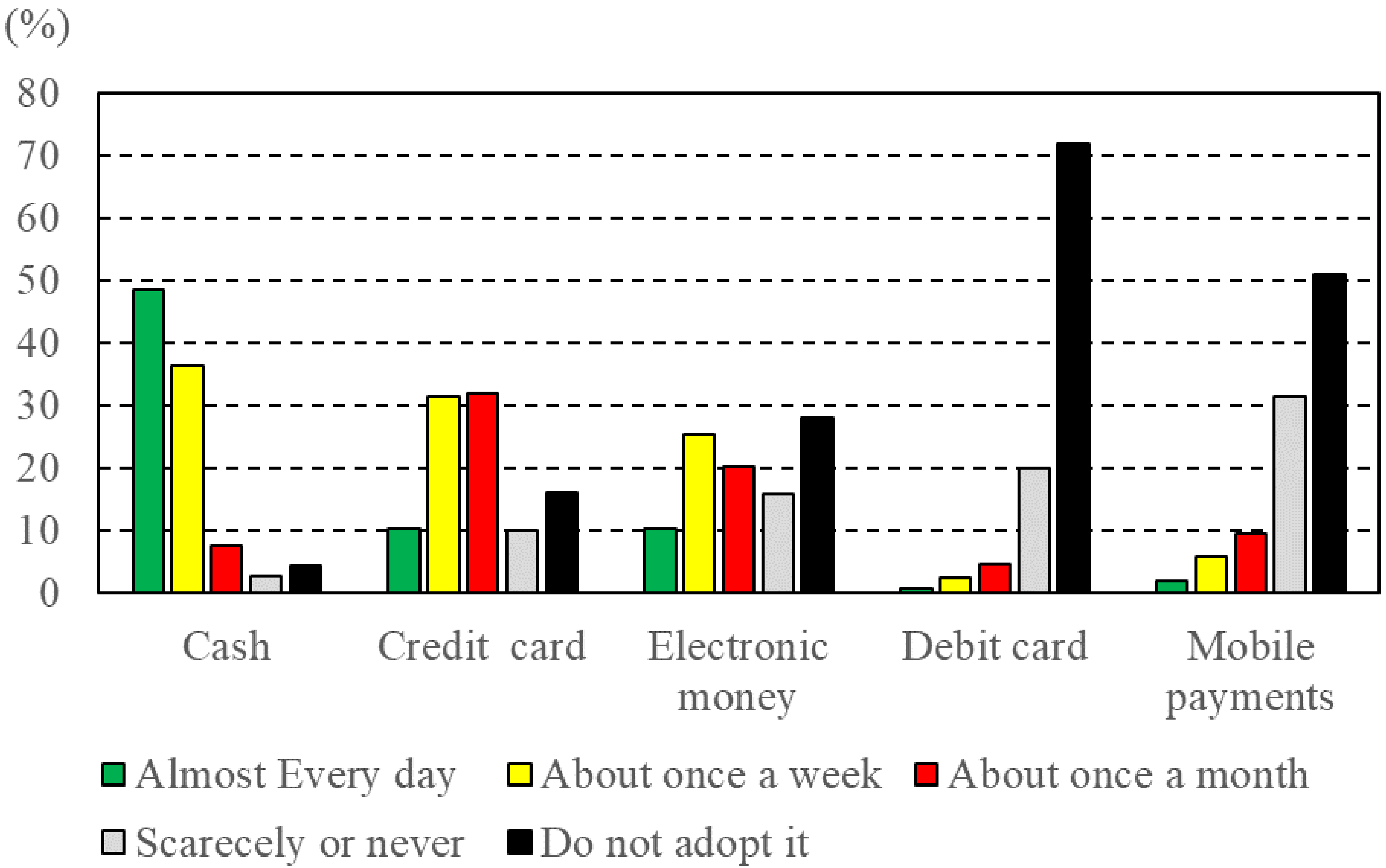
The FLS is a web survey that was administered from March 1 to March 20, 2019.

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

Observations used for analysis		All observations		Drop observations with top actual rank = 1		Drop observations with top actual rank <= 2		Drop observations with patial rank = 33333	
Names of samples		Sample 0		Sample 1		Sample 2		Sample 3	
Number of observations		25,000		24,252		23,956		24,148	
Types of rankings		Actual	Partial	Actual	Partial	Actual	Partial	Actual	Partial
Number of ranks		1,454	361	1,453	361	1,424	361	1,449	360
	Average use	Frequency of payment methods being ranked first							
Cash	4.217	0.844	0.657	0.840	0.671	0.842	0.674	0.839	0.673
Credit card	3.095	0.326	0.179	0.305	0.178	0.302	0.177	0.302	0.178
Electronic money	2.741	0.260	0.119	0.237	0.116	0.235	0.116	0.234	0.116
Mobile payments	1.765	0.085	0.028	0.057	0.023	0.053	0.021	0.053	0.022
Debit card	1.400	0.056	0.017	0.026	0.012	0.023	0.010	0.022	0.011
Total		1.571	1.000	1.465	1.000	1.456	1.000	1.450	1.000
τ_α 95% confidence interval upper bound			0.617		0.636		0.641		0.637
τ_α 95% confidence interval lower bound			0.608		0.630		0.635		0.631

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, 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

	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

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
ϵ_{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

$$\pi(r_i) = \Pr\left(U_{ir_{i1}} > U_{ir_{i2}} > \cdots > U_{ir_{iJ}}\right) = \prod_{j=1}^{J-1} \frac{expV_{ir_{ij}}}{\sum_{l=j}^{J} expV_{ir_{il}}}$$

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 1×4 vector of attributes *Mobile*, *Credit*, *Paper*, and *Times.* The log-likelihood of observing the sequence of ranking is

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

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 1×4 vector of the attributes, and *γ* is a column vector of four attributes for the *j*-th payment method.

C = 1, 2, …, C classes of respondents with unobserved preference heterogeneity related to ranking capabilities. The respondent in class *c* has utility coefficient vector γ_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 1×62 vector of 61 control variables and a constant term, and θ_c is a parameter of the model that determines the membership to class *c*. θ_C is normalized to be zero for identification, and θ is a collection of the identified membership coefficients, $\theta = (\theta_1, \theta_2, \ldots, \theta_{C-1})$.

The joint likelihood of the LCL model becomes:

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

Use Yoo (2020) to estimate the parameters θ and γ_c by maximizing the sample log-likelihood function using an expectation-maximization (EM) algorithm. C = 2 chosen by the minimum BIC.

Control variables

		Sample 0	Sample 1	Sample 2	Sample 3	Top actual rank = 1	Top actual rank <= 2	Drop Partial rank = 33333
Financial literacy	Objective financial literacy	6.424	6.574***	6.618***	6.582***	1.552***	1.981***	1.946***
	Fin. education school	0.072	0.073	0.074	0.073	0.02***	0.026***	0.041***
	Fin. education home	0.203	0.208	0.21*	0.208	0.033***	0.047***	0.062***
	Fraud	0.067	0.067	0.067	0.067	0.041***	0.055*	0.054*
	Debt	0.307	0.313	0.314	0.312	0.139***	0.158***	0.167***
	Credit card literacy	0.495	0.506**	0.51***	0.508***	0.134***	0.155***	0.147***
Information sources	News	2.253	2.288**	2.298***	2.287**	1.114***	1.21***	1.284***
	S_dont_know	0.049	0.05	0.049	0.05	0.019***	0.034***	0.022***
	S_fin_inst	0.376	0.386**	0.388***	0.385**	0.056***	0.091***	0.102***
	S_exclude_fin_inst	0.196	0.201	0.202*	0.201	0.035***	0.057***	0.052***
	S_dont_choose	0.379	0.364***	0.36***	0.364***	0.89***	0.819***	0.824***
Financial behavior	Overconfidence	-4.946	-5.085***	-5.123***	-5.094***	-0.441***	-0.885***	-0.746***
	Impatience	2.177	2.176	2.175	2.176	2.219	2.229	2.229
	Reputation	1.604	1.598	1.597	1.596	1.798***	1.773***	1.842***
	Self-control	2.950	2.963	2.964	2.964	2.535***	2.628***	2.559***
	Risk aversion 1	0.773	0.769	0.767	0.77	0.912***	0.905***	0.865***
	Risk aversion 2	0.914	0.913	0.913	0.913	0.951***	0.941***	0.938***
Pretax income	Income_0	0.032	0.029**	0.028***	0.028**	0.138***	0.128***	0.129***
	Income_250	0.157	0.156	0.156	0.157	0.166	0.165	0.163
	Income_250_500	0.283	0.286	0.287	0.286	0.189***	0.206***	0.195***
	Income_500_750	0.173	0.176	0.177	0.176	0.079***	0.08***	0.085***
	Income_750_1000	0.098	0.1	0.101	0.1	0.041***	0.041***	0.052***
	Income_1000_1500	0.054	0.055	0.055	0.055	0.02***	0.018***	0.027***
	Income_1500_	0.019	0.019	0.019	0.019	0.013	0.011**	0.022
	Income_NA	0.184	0.178	0.176**	0.179	0.354***	0.35***	0.327***
Financial assets	Asset_0	0.133	0.128*	0.126**	0.128*	0.309***	0.298***	0.295***
	Asset_250	0.155	0.157	0.157	0.157	0.088***	0.093***	0.094***
	Asset_250_500	0.095	0.097	0.097	0.097	0.048***	0.055***	0.054***
	Asset_500_750	0.050	0.051	0.051	0.05	0.029***	0.033***	0.038*
	Asset_750_1000	0.048	0.049	0.05	0.049	0.017***	0.013***	0.026***
	Asset_1000_2000	0.066	0.067	0.068	0.067	0.023***	0.018***	0.026***
	Asset_2000_	0.125	0.128	0.129	0.128	0.029***	0.025***	0.042***
	Asset_NA	0.328	0.324	0.322	0.325	0.456***	0.466***	0.426***

		Sample 0	Sample 1	Sample 2	Sample 3	Top actual rank = 1	Top actual rank <= 2	Drop Partial rank = 33333
Age	Age_25	0.073	0.07	0.069*	0.07	0.175***	0.166***	0.171***
	Age25_29	0.077	0.075	0.074	0.075	0.14***	0.141***	0.143***
	Age30_34	0.076	0.075	0.075	0.075	0.1**	0.098**	0.095*
	Age35_39	0.084	0.084	0.084	0.084	0.098	0.094	0.1
	Age40_44	0.086	0.086	0.086	0.085	0.091	0.089	0.097
	Age45_49	0.105	0.105	0.105	0.105	0.108	0.099	0.109
	Age50_54	0.081	0.082	0.082	0.082	0.061**	0.061***	0.061**
	Age55_59	0.080	0.081	0.081	0.081	0.045***	0.05***	0.043***
	Age60_64	0.106	0.107	0.108	0.107	0.057***	0.058***	0.06***
	Age65_69	0.087	0.088	0.088	0.088	0.04***	0.046***	0.038***
	Age70_74	0.104	0.105	0.105	0.106	0.055***	0.065***	0.055***
	Age75_79	0.041	0.041	0.041	0.041	0.028**	0.034	0.027**
Gender	Male	0.494	0.493	0.493	0.492	0.544***	0.535***	0.562***
Employment status	Private	0.332	0.332	0.333	0.332	0.332	0.311	0.349
	Public	0.030	0.03	0.03	0.029	0.032	0.025	0.036
	Teacher	0.012	0.012	0.012	0.012	0.008	0.008	0.007*
	Self-employed	0.067	0.067	0.067	0.067	0.075	0.068	0.076
	Part-time	0.154	0.154	0.155	0.155	0.139	0.14	0.131**
	House	0.193	0.194	0.194	0.195	0.152***	0.162***	0.146***
	Student	0.049	0.047	0.047	0.047	0.108***	0.102***	0.108***
	No job	0.146	0.146	0.145	0.146	0.151	0.181***	0.144
	Other job	0.017	0.017	0.017	0.017	0.003***	0.004***	0.002***
Education	Senior and Jounior high, Other	0.353	0.35	0.348	0.35	0.439***	0.462***	0.435***
	Vocational college	0.112	0.112	0.111	0.112	0.13	0.136**	0.126
	Junior college	0.113	0.114	0.114	0.114	0.092**	0.087***	0.085***
	University	0.382	0.385	0.387	0.385	0.287***	0.273***	0.299***
	Graduate	0.039	0.039	0.039	0.039	0.052	0.042	0.055**
Area of residence	Hokkaido	0.044	0.043	0.043	0.043	0.049	0.047	0.046
	Tohoku	0.070	0.07	0.07	0.07	0.076	0.077	0.083
	Kanto	0.344	0.342	0.343	0.342	0.382**	0.357	0.378**
	Hokuriku	0.041	0.042	0.041	0.042	0.035	0.042	0.039
	Chubu	0.140	0.141	0.141	0.141	0.111**	0.117**	0.114**
	Kinki	0.163	0.163	0.163	0.163	0.14*	0.144*	0.144
	Chugoku	0.057	0.057	0.057	0.058	0.053	0.057	0.049
	Shikoku	0.030	0.03	0.03	0.03	0.029	0.031	0.028
	Kyushu	0.111	0.111	0.111	0.111	0.123	0.128*	0.119
Number of observations		25,000	24,252	23,956	24,148	748	1,044	852

Parameter estimates of the ROL (Sample 0)

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

*, **, 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

	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

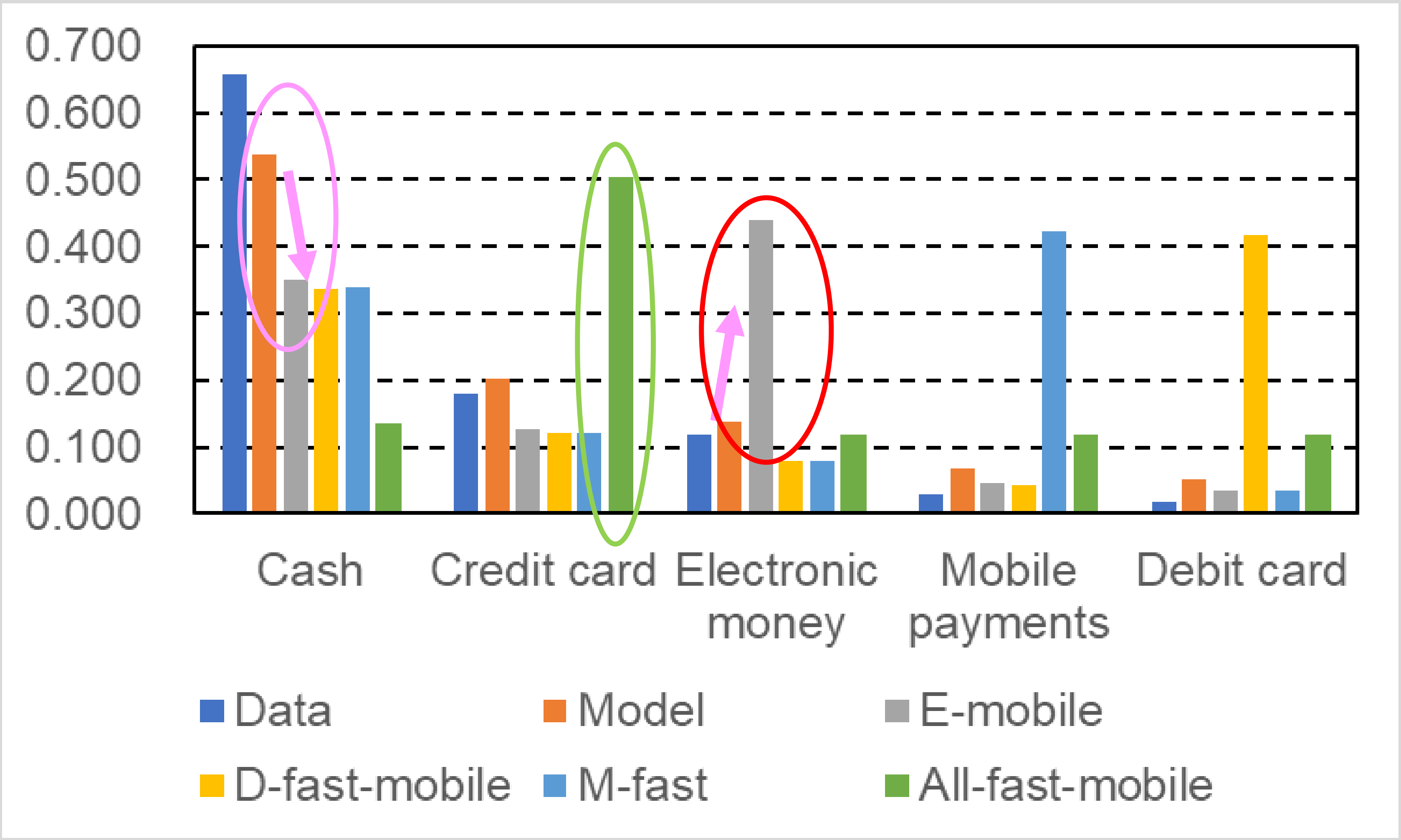
Counterfactual 3: "M-fast": Faster Mobile payments via smartphone

	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: "All-fast-mobile" 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

Counterfactual simulations by the ROL (Sample 0, with demographic variables)

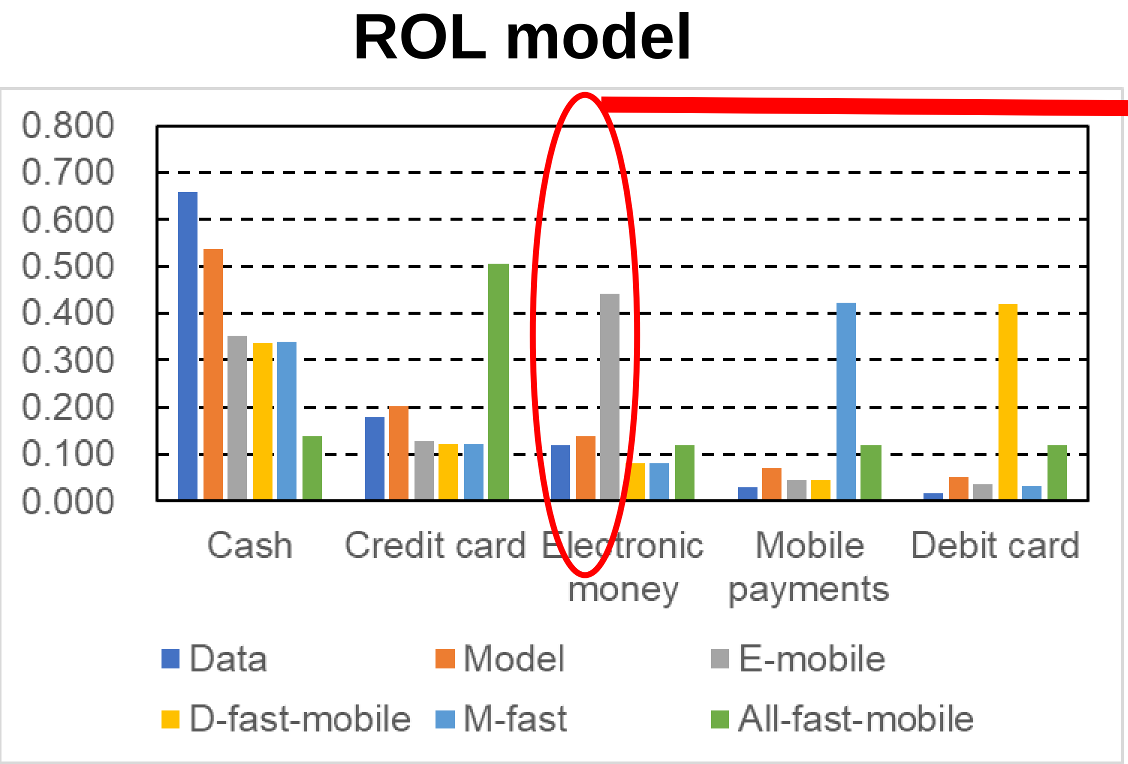


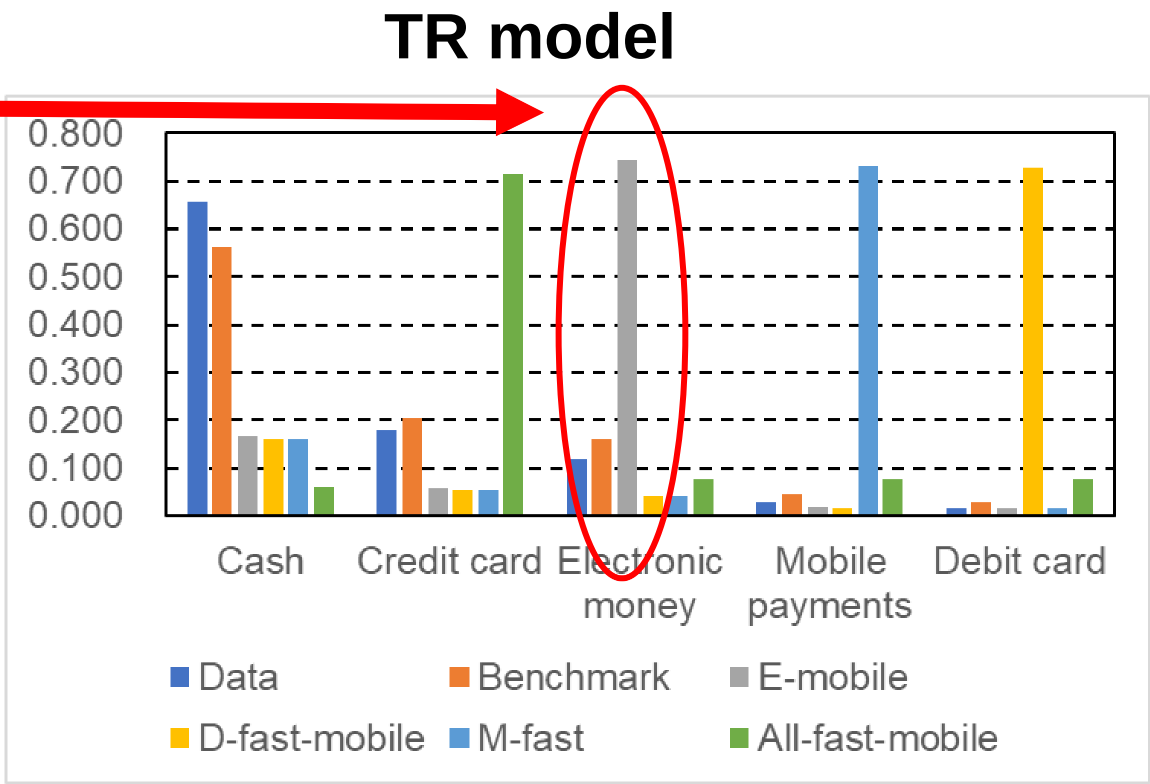
Counterfactual simulations by the ROL (Sample 0, by demographic groups)

Samples 0		Benchmark			E-mobile			D-fast-mobile			M-fast			All-fast-mobile		
		Average	Median	P	Average	Median	P	Average	Median	P	Average	Median	P	Average	Median	P
Average	Cash	0.538	0.542		0.351	0.349		0.336	0.331		0.340	0.336		0.137	0.102	
	Credit card	0.203	0.201		0.127	0.123		0.121	0.117		0.122	0.119		0.505	0.522	
	Electronic money	0.138	0.134		0.440	0.436		0.080	0.077		0.081	0.078		0.119	0.116	
	Mobile payments	0.069	0.064		0.046	0.039		0.044	0.037		0.423	0.418		0.119	0.116	
	Debit card	0.051	0.046		0.035	0.029		0.419	0.413		0.034	0.028		0.119	0.116	
Age75_79	Cash	0.634	0.637	***	0.571	0.573	***	0.555	0.558	***	0.554	0.558	***	0.349	0.328	***
	Credit card	0.192	0.190	***	0.172	0.169	***	0.167	0.164	***	0.166	0.163	***	0.395	0.398	***
	Electronic money	0.082	0.080	***	0.174	0.160	***	0.071	0.070	***	0.071	0.070	***	0.085	0.085	***
	Mobile payments	0.045	0.042	***	0.041	0.038		0.040	0.037		0.168	0.155	***	0.085	0.085	***
	Debit card	0.046	0.043	***	0.042	0.038	***	0.168	0.155	***	0.041	0.037	***	0.085	0.085	***
Asset_0	Cash	0.541	0.545		0.399	0.396	***	0.382	0.378	***	0.387	0.384	***	0.207	0.177	***
	Credit card	0.153	0.152	***	0.112	0.109	***	0.107	0.104	***	0.109	0.106	***	0.349	0.340	***
	Electronic money	0.144	0.141	***	0.365	0.353	***	0.098	0.096	***	0.100	0.097	***	0.148	0.149	***
	Mobile payments	0.092	0.088	***	0.069	0.065	***	0.066	0.061	***	0.351	0.340	***	0.148	0.149	***
	Debit card	0.071	0.067	***	0.055	0.050	***	0.346	0.335	***	0.053	0.048	***	0.148	0.149	***

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.

Counterfactual simulations: ROL vs TR (Sample 0, with demographic variables)

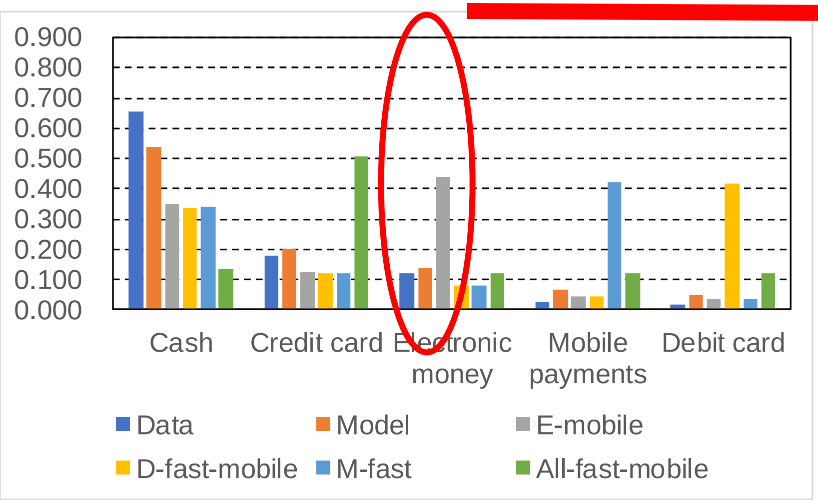




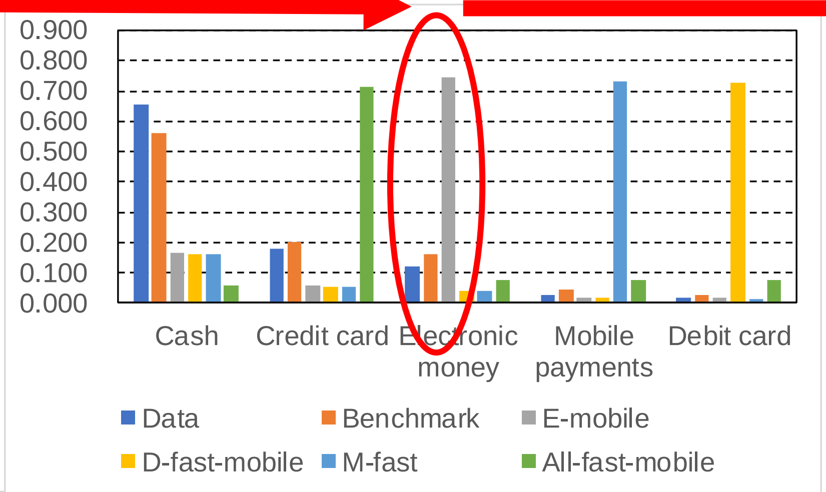
The Hausman test favors the TR model over the ROL model. However, the TR model yields qualitatively similar results to our counterfactual simulations. Quantitatively, on average, the TR model tends to predict a higher probability of hypothetical mobile and/or faster versions of credit cards, electronic 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)

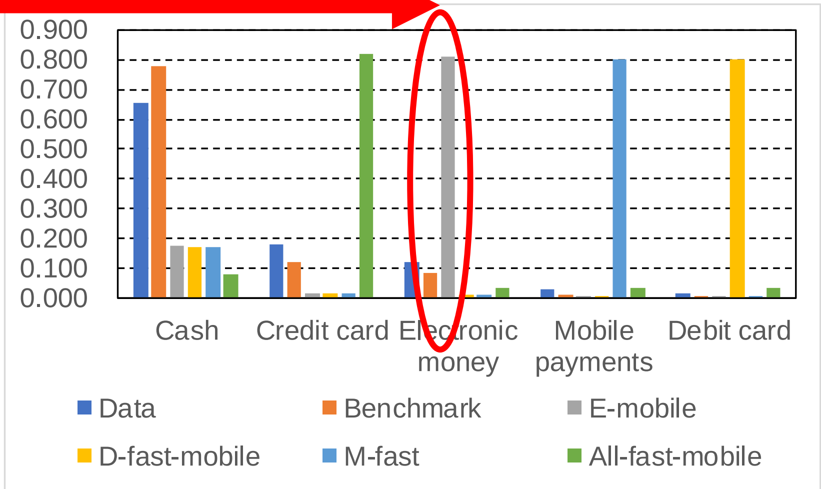
ROL model



TR model



LCL model



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