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Predicting the Payment Preference for CBDC: A Discrete Choice Experiment*

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Abstract

To overcome the lack of data in predicting the payment preference for central bank digital currency (CBDC), we conducted a discrete choice experiment that varied the attributes of payment methods among over 3,500 participants in Korea. We identified key attributes, such as the discount rate and the issuance form, that shape the demand for payment methods. The predicted usage shares of existing payment methods closely align with their actual usage patterns in Korea, which lends credible support for the external validity of our experimental design. Building on this validation, we further predict that CBDC, when introduced, will be preferred over cash and mobile fast payment but less preferred than credit and debit cards, with its adoption rate as the most preferred payment method ranging 19–27% of respondents.

Keywords: Payment Preference, CBDC, Discrete choice experiment
***JEL* classifica-tion numbers**: E40, E50, C90

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1 Introduction

Many central banks around the world are considering the issuance of retail central bank digital currency (CBDC), a type of digital money issued by the central bank to businesses and households. To study the impact of CBDC, it is important to predict the demand for CBDC when it is introduced as a means of payment. Although there is a growing body of theoretical research that examines the implications of a CBDC for the payment system, financial stability, and monetary policy (e.g., Williamson (2022), Keister and Sanches (2022), Garratt and van Oordt (2021)), the scarcity of data poses a challenge for empirical research.

The purpose of our study is to predict the preference for CBDC as a payment instrument. For this purpose, we characterize CBDC as a new bundle of payment attributes. Using the method of discrete choice experiments, we estimate preferences for these attributes and then use the estimated preferences to predict the preference for CBDC. In a survey of a nationally representative sample in South Korea, respondents are presented with pairs of hypothetical payment methods, each characterized by nine attributes, and asked to indicate their preferred choice in each pair. By randomly assigning attribute values, we examine the preferences of individual respondents for the relevant attributes of the payment methods.

The discrete choice experiment allows us to identify preferences for payment methods that may be difficult to discern from real-world data. In the real world, payment methods exist as a combination of different attributes, making it difficult to identify which attribute plays a significant role in observed usage data of payment methods. For example, even if we can observe that people primarily use credit cards, it is difficult to distinguish between preferences for payment methods issued by private financial institutions and preferences for an instrument in the form of a plastic card. Discrete choice experiments overcome this problem by allowing a researcher to capture most of the relevant attributes of the payment methods and to create situations in which the individual attribute values are exogenously varied for causal interpretation.

Specifically, we consider the following nine attributes found in the literature to be the core characteristics relevant to the choice of available payment instruments, such as cash, credit and debit card, mobile payment: (i) issuer, (ii) form of issuance, (iii) disclosure of information type, (iv) merchant acceptance, (v) risk of loss, (vi) discount rate, (vii) delay in payment, (viii) timing of settlement, and (ix) monthly fee (see, e.g., Jonker, 2007; Rambure and Nacamuli, 2008; Chen et al., 2019; Drehmann et al., 2002). Each of the nine attributes consists of a few values, such as three issuers (central bank, private financial institution, and BigTech company) and three forms of issuance (banknote, plastic card, and smartphone app), as detailed in Table 1. Respondents are presented with pairs of these hypothetical payment methods constructed with nine attribute values and asked to indicate their preferred choice in each pair. This exercise is repeated five times per respondent, with each iteration involving a different pair of hypothetical payment methods characterized by randomly generated attribute values. Because all hypothetical payment methods are randomly generated, each respondent rates a unique set of payment method pairs. This randomization ensures that the attributes are uncorrelated, resulting in unbiased estimates of the parameters.

We then characterize existing payment methods - cash, credit and debit cards, and mobile fast payments - as bundles of these nine attributes. Using the estimated preferences for these attributes from the experiment, we calculate the relative demand for each payment method and compare it to real-world usage data. Finally, we simulate the introduction of CBDC, assuming a benchmark design in which CBDC is characterized by central bank-issued cards or apps, no interest, no fees, transaction times of less than ten seconds, immediate settlement, 1% probability of loss, acceptance by most merchants (80%), and disclosure of both personal identification and transaction information.[1] We examine what the demand for CBDC would be under conditions where existing payment methods continue to coexist. We also examine how the adoption of CBDC would change in response to adjustments in the monthly fees and discount rates of existing payment methods offered by private institutions.

The main findings are as follows. First, the payment method preference is highly sensitive to attributes related to financial incentives. Depending on the monthly fee associated with the use of a payment method, the expected probability that the respondents choose it as their preferred payment method decreases by up to 14 percentage points. Similarly, the availability of a discount for using a payment method to purchase goods increases the expected likelihood of selection by up to 11 percentage points.

Second, non-monetary attributes also have a significant but modest effect on payment choice. The willingness to pay for a non-monetary attribute such as the form of issuance is quite high, close to that for a monetary attribute (e.g., discount rate). In particular, the relatively high willingness to pay for switching from banknotes to smartphone apps is relevant to CBDC in that it is more likely to be provided in the form of smartphone apps.

Third, the estimated preferences for these attributes allow us to predict preferences for existing payment methods - cash, credit and debit cards, and mobile fast payments. The

[1] Risk of loss here is close to the probability of losing the value of one transaction. See Section 2.3 (Attributes of Payment Method) for more details.

predicted usage is relatively close to the actual usage patterns of these payment methods in Korea, which lends credible support for the external validity of our experiment. When CBDC is introduced under different scenarios, we robustly predict that CBDC will be preferred over cash and mobile fast payments, but less preferred than credit and debit cards. In the benchmark scenario with the central bank as the the form of issuance, acceptance by most merchants (80%), 1% loss probability, ten-second payment delay, immediate settlement, no monthly fee, disclosure of both personal identification and transaction information, and zero discount rate, about 19% of respondents would choose CBDC as their most preferred payment method, second only to credit and debit cards.[2] In another scenario, where the discount rate of CBDC is similar to that of credit cards, the adoption rate of CBDC as the most preferred payment method would reach 27%. These results indicate that if CBDC is introduced, it is likely to be used more readily than cash or mobile fast payments. Moreover, the payment preference for CBDC is highly responsive to the level of discount rate, which means that the monetary reward for CBDC is likely to play an important role in the choice of CBDC as the most preferred payment method.

Our paper contributes to the rapidly growing literature on the empirical study of CBDC. There are a few studies that ask directly about people's demand for a hypothetical CBDC. Bijlsma et al. (2021) conducted a survey in the Netherlands to investigate the demand for an account-based CBDC. They found a positive relationship between intended adoption of CBDC and respondents' knowledge of CBDC, trust in the central bank, and monetary incentives. In their survey conducted in Austria, Abramova et al. (2022) found that while only half of the respondents expressed interest in CBDC, the same proportion expected personal benefits from using it. Kantar Public (2022) surveyed all 19 euro area countries and found that universal acceptance was considered the most important feature of CBDC. They also found that ease of use, contactlessness, and security were also considered important. However, the above studies are based on an imaginary CBDC with which the majority of respondents are unfamiliar, raising concerns about the interpretation of the survey results (Chapman et al., 2023).[3]

Other studies use a structural model to estimate consumer preferences for features of existing payment instruments and then use the estimated parameters to predict demand for a CBDC, which is characterized as a new bundle of payment features that consumers value (Huynh et al. (2020), Fujiki (2021), and Li (2023)). Using a structural model, Huynh et al. (2020) predicted that CBDC would be used at the point of sale with probabilities ranging from 19% to 25%. They also identified transaction costs as the primary attribute that

[2] See section 2.3 (Attributes of Payment Method) for more details on each value of these attributes.

[3] According to the Bijlsma et al. (2021), 53% of participants were unaware of CBDCs, and among those who were aware, 33% lacked understanding of what a CBDC entailed.

would make CBDC attractive to consumers. Using a similar structural model, Li (2023) predicted that the demand for CBDC in Canada as a percentage of total household liquid assets would range from 4% to 52%, depending on CBDC-specific effects. Fujiki (2021) used Japanese financial literacy survey data to estimate and simulate CBDC adoption. He found the importance of reducing transaction time in increasing CBDC adoption. Using German survey evidence and a structural model, Bidder et al. (2024) show that CBDC could lead to disintermediation of banks with potential risks and benefits. Li et al. (2025) estimated a structural model using Canadian household survey data and found that the crowding-out effects of a non-interest-bearing CBDC on bank deposits depend critically on whether the CBDC is designed to provide the same complementary products and services that commercial banks currently offer. However, as Chapman et al. (2023) rightly point out, one of the limitations of existing structural approaches is the limited range of payment products available, which makes it difficult to identify consumer preferences across all relevant features. Our paper overcomes this problem by using an experimental methodology that allows for a more precise estimation of preferences.

Our study is also related to the small but growing literature that uses experimental methodology to study CBDC. Using choice experiments, Fairweather et al. (2023) found that privacy design choices play a significant role in people's evaluations of CBDC. Using a randomized survey experiment, Choi et al. (2024) showed that the degree of anonymity and privacy protection in the design of CBDC would significantly affect the willingness to use CBDC. In line with recent experimental approaches in monetary economics that emphasize the essentiality of money, such as those of Duffy and Puzzello (2014) and Bigoni et al. (2020), Camera (2023) used laboratory experiments to investigate how the introduction of CBDC would affect the stability and performance of the currency system. Similarly, Arifovic et al. (2023) used laboratory experiments and found that the network effect is strong and that a lower fixed cost of adopting a new payment method, such as CBDC, plays a significant role in its adoption.

The remainder of this paper is organized as follows. Section 2 describes the online survey and discrete choice experiments on payment method preferences. Section 3 discusses the econometric framework followed by the estimation results about the causal effects of each attribute of payment method on the likelihood of choosing it as a preferred payment method. It also presents the willingness to pay for a given attribute. Section 4 uses the estimated model to predict preferences for payment methods, including CBDC. Section 5 concludes the paper with some remarks. Appendices present additional figures and tables as well as the survey questionnaire.

2 Data Collection and Experimental Design

2.1 Sampling

We conducted an online survey in November 2021 through Hankook Research, a professional survey company, using a nationally representative sample of 3,561 participants born in South Korea and aged 19 and older. Each participant was paid KRW 2,000 (USD 1.57 as of June 13, 2023) upon completion of the survey. Beginning with a module on respondent characteristics, the full survey consists of five modules, including the payment behavior module, in which we conducted a discrete choice experiment to estimate preferences for a wide range of attributes that characterize different payment methods.[4] The full survey questionnaire (the original Korean version as well as its English translation) is available in the online appendix. Table A1 in Appendix A shows that our samples are representative of the South Korean population in terms of gender, age, residence in Seoul, marital status, education, and employment.

2.2 Discrete Choice Experiments

We use discrete choice experiments to understand what factors people consider important when using payment methods. Discrete choice experiments have become a popular method for analyzing multi-attribute preferences in economics and other social sciences (see, e.g., de Bekker-Grob et al., 2010; Hoyos, 2010; D.Clark et al., 2014). In our hypothetical scenario, each payment method is characterized by a combination of nine attribute values. By randomly assigning these attribute values, we construct random profiles of hypothetical payment methods. Each respondent was asked to choose a preferred payment method from a pair of randomly selected hypothetical payment methods. This task was repeated five times for each respondent. To keep the choice scenarios realistic, we excluded pairs in which one payment method dominated the other in all attributes. Figure A1 in Appendix A shows sample screenshots used in the experiment.

A key aspect of our methodology is the random assignment of attribute values across all pairs, ensuring that respondents evaluate the five different choice scenarios that are randomly and independently drawn within and across individual attributes. This randomization ensures that the attributes of each hypothetical payment method are uncorrelated, allowing us to obtain unbiased causal estimates of the parameters of interest. Table A2 shows that the attribute values randomly assigned to each payment method were indeed

[4] Before the payment behavior module, we implemented another randomization module regarding the CBDC and privacy. We report the results of these omitted modules in a companion paper, Choi et al. (2024).

uncorrelated. In addition, Table A3 shows that each value of an attribute appears nearly an identical number of times in the choice scenarios presented to respondents, confirming that the attribute values are well balanced.

One concern with discrete choice experiments is external validity, since preferences are revealed in an artificial survey setting rather than in real-world behavior. Despite this, the literature has shown that well-designed discrete choice experiments are a good reflection of respondents' real-world preferences, as demonstrated by Hainmueller et al. (2015). For example, high correlations have been found between job preferences expressed in discrete choice experiments and actual job choices (Wiswall and Zafar, 2018; Maestas et al., 2023), further supporting the validity of our methodology. In Section 4, we also validate our methodology by verifying that the simulated distribution of payment usage, based on the preferences measured in our experiment, closely resembles actual usage in South Korea.

2.3 Attributes of Payment Method

In the discrete choice experiment, we randomly vary the following nine attributes: issuer, form of issuance, disclosure of information type, merchant acceptance, risk of loss, discount rate, delay in payment, timing of settlement, and monthly fee. Table 1 shows the full list of attribute values. While our list of attributes does not encompass every feature of payment instruments, it does cover a core set of attributes relevant to currently available payment instruments. Below we briefly explain each of the nine attributes we selected, along with the literature that motivated the selection.

Issuer

In addition to the central bank which issues its own money as a means of payment, private financial institutions and large digital platform operators ("BigTech" companies) have emerged as new payment service providers. The preference for a particular issuing institution could directly influence the choice of payment methods. For example, in societies where trust in the government is high, there may be a tendency to use central bank money as the main payment instrument. In the survey experiment, we consider three types of issuers: central bank, private financial institutions, and BigTech companies.[5]

Form of Issuance

Payment methods can be physical or digital, which differ in their ease of use, storage, and

[5] In a related study on platform-based financial services, Croxson et al. (2023) classifies fintechs, big techs, and incumbent financial institutions as three types of digital platforms prevalent in financial services, while our classification of issuers focuses on payment services.

Table 1: Attributes for Payment Methods Profiles

Attributes	**Values**
Issuer	central bank private financial institutions IT or BigTech companies
Form of issuance	banknote plastic card smartphone apps
Disclosure of information type	none personal identification information personal identification & transaction information
Merchant acceptance	always (100%) most (80%) half (50%)
Risk of loss	1% 5% 10%
Discount rate	none 3% 5%
Delay in payment	less than ten seconds about one minute about two minutes
Timing of settlement	immediate specific date after payment installment
Monthly fee	none KRW 3,000 (USD~2) KRW 5,000 (USD~3.5)

ability to cope with uncertainties. This means that the form of issuance can influence the use of payment methods. For example, Rambure and Nacamuli (2008) and Chen et al. (2019) found that despite desirable features of cash for privacy and the absence of fees, people attach a negative value to the inconvenience of having to carry it around. On the other hand, an issuance form such as a smartphone app requires a network connection which is susceptible to technological malfunctions. Card payments require a point-of-sale (POS) terminal or an online interface to enter a card number and potentially a security code. The experiment considers the following three forms of issuance: banknote, plastic card, and smartphone apps.

Disclosure of information type

Drehmann et al. (2002) pointed out that the degree of anonymity in the use of a payment instrument can significantly affect consumers' preference for certain payment methods. In particular, people are reluctant to disclose their purchase records for privacy-sensitive goods or services (e.g., psychiatric services, adult products). Privacy is considered a key feature in the design of CBDC. According to the European Central Bank's recent online survey, the largest majority of respondents (41%) selected privacy as the most important feature to consider when issuing CBDC (European Central Bank, 2021). The Federal Reserve also explored privacy as one of the key issues of CBDC (Board of Governors of the Federal Reserve System, 2022). In the experiment, the disclosure of information type takes one of the following three cases: none of personal identification and transaction information is disclosed, only personal identification information is disclosed, and both personal identification and transaction information are disclosed.[6]

Merchant acceptance

Use of a payment method may be subject to differences in acceptance by merchants. For example, in South Korea, cash is sometimes the only payment method accepted in some small shops, while only cards or smartphone apps can be used to pay for public transportation. Jonker (2007) found that, in the Netherlands, the more merchants or locations accept a payment method, the more consumers view it as a useful means of payment. In the experiment, merchant acceptance is considered by allowing the probability of acceptance to take one of the following three values: 50%, 80%, and 100%.

Risk of loss

[6] Although we use the term *information disclosure* in this paper, the attribute we analyze specifically concerns information recorded when using a payment method. We deliberately adopt the term "disclosure" because, from the user's perspective, merely leaving a trace can be perceived as revealing information, even if it is not actively shared. While we do not explicitly specify in the paper who might access this recorded information, it is natural in our setting to interpret it as potentially being disclosed to the payment method's issuer. Armantier et al. (2021) provides survey evidence on U.S. consumers' trust in various institutions to handle such data.

A payment method carries a risk of loss or theft, which also affects its use as a means of payment. In particular, Jonker (2007) found that a major aversion to cash stems from its lack of security due to the risk of theft or loss. In the experiment, we account for the risk of loss by assigning the probability of loss one of the following three values: 1%, 5%, and 10%.[7]

Discount rate

There are many situations where some discounts are applied when using a certain payment method. For example, financial institutions or BigTech companies offer discounts when their payment services or platforms are used to make purchases at affiliated stores.[8] On the other hand, mom-and-pop stores often offer discounts for cash payments in order to avoid card fees or taxes. Moreover, in the case of debit cards, one can also earn interest on the associated deposit account.[9] These monetary incentives can influence the use of payment methods. In particular, given the possibility of rewarding a CBDC, it is important to understand the extent to which monetary incentives can influence the choice of CBDC as a payment method. In the experiment, we examine the following three discount rate cases: zero, 3%, and 5%.

Delay in payment

Ease of use is an attribute generally considered in the literature on payment method preferences (Koulayev et al., 2016; Wakamori and Welte, 2017). Specifically, Fujiki (2021) found that survey respondents value shorter transaction time as the most important attribute when using a payment method. In this experiment, we focus on the time it takes to process a payment method as an important aspect of convenience of use. A payment method profile is given one of the following three cases with respect to the time it takes to make a payment: less than ten seconds, about one minute, and about two minutes.

Timing of settlement

Some payment methods (e.g., credit cards) not only allow consumers to settle on a specific date rather than at the time of purchase, but also settle in installments if they wish.[10]

[7] In general, risk of loss or theft varies with payment methods. Since the values of an attribute in our experiment were assigned per transaction, 1%, 5% or 10% risk of loss is close to the probability of losing the value of one transaction. There are also differences in the level of insurance or recourse. For instance, credit cards typically can reverse a fraudulent transaction, and have some insurance, while this is not available for cash. We do not specify here differences in recourse and recovery of failed or fraudulent transactions.

[8] For instance, credit cards often offer rewards or points to their users, and some premium cards (especially in the US) offer 2% or 3% cash back on all purchases or certain categories of purchases (restaurants, fuel, etc). Of course, they charge correspondingly high merchant discount rates to make this possible.

[9] Li (2023) found that the deposit-to-cash ratio varies greatly according to the rate of return.

[10] This is all about when the consumer sees the funds leave their account. But there is also a delay in the availability of funds to the merchant. For card payments, this can be a few days, for instance, while for fast payments it is instant.

According to Jonker (2007), people use credit cards to take advantage of settling in installments or making deferred payments. On the other hand, Arango et al. (2011) found that some consumers avoid using credit cards to prevent themselves from overspending. To investigate how the timing of settlement affects the preference for a payment method, we consider the following three cases: immediate, specific date after payment, and installment.

Monthly fee

There are many cases where using a payment method involves some financial cost. For example, there is a membership fee that consumers have to pay for using a credit card, while data usage fees are charged for mobile fast payments. According to Jonker (2007), among those dissatisfied with credit cards, 45% cited high financial costs as a reason for dissatisfaction. In our experiment, we consider the following three monthly fees for using a payment method: none, KRW 3,000 (USD~2), and KRW 5,000 (USD~3.5).

3 Estimating Preferences for Payment Methods

We begin by describing an econometric framework for estimating preferences for attributes of payment methods. We then report estimates of the average marginal effect (AME) of a change in the value of each attribute on the expected probability of choosing a payment method profile with the corresponding attribute. These results are used in the next section to predict preferences for payment methods such as cash, credit and debit cards, mobile payments, and CBDC. We also present the measures of willingness to pay for each attribute using the AME estimates.

3.1 Econometric Framework

In order to estimate preferences for attributes of payment methods, we assume that the underlying choice process can be expressed by an indirect utility function as follows:

$$U_{ijk} = \beta' X_{ijk} + \delta c_{ijk} + \epsilon_{ijk} \tag{3.1}$$

where U_{ijk} denotes an individual i's utility from a payment method scenario j for a choice pair $k = 1, 2, ..., 5$. In (3.1), X_{ijk} is a vector of attributes (except monthly fee) that individual i faces in payment method scenario j for choice pair k, c_{ijk} denotes the monthly fee, i.e., the cost that individual i pays each month to use payment method j for choice pair k, and ϵ_{ijk} denotes an unobserved utility shock. For a given choice pair k, assuming that ϵ_{ijk} is independently and identically distributed with a type I extreme value distribution, the probability that individual i chooses a payment method scenario j with characteristics X_{ijk} and cost c_{ijk} over another payment method scenario $l \neq j$ with characteristics X_{ilk} and cost c_{ilk} is given by

$$P(U_{ijk} > U_{ilk}) = \frac{\exp(\beta' X_{ijk} + \delta c_{ijk})}{\exp(\beta' X_{ijk} + \delta c_{ijk}) + \exp(\beta' X_{ilk} + \delta c_{ilk})} \tag{3.2}$$

We estimate the above equation using a conditional logit model with maximum likelihood.

3.2 Average Marginal Effect Estimates

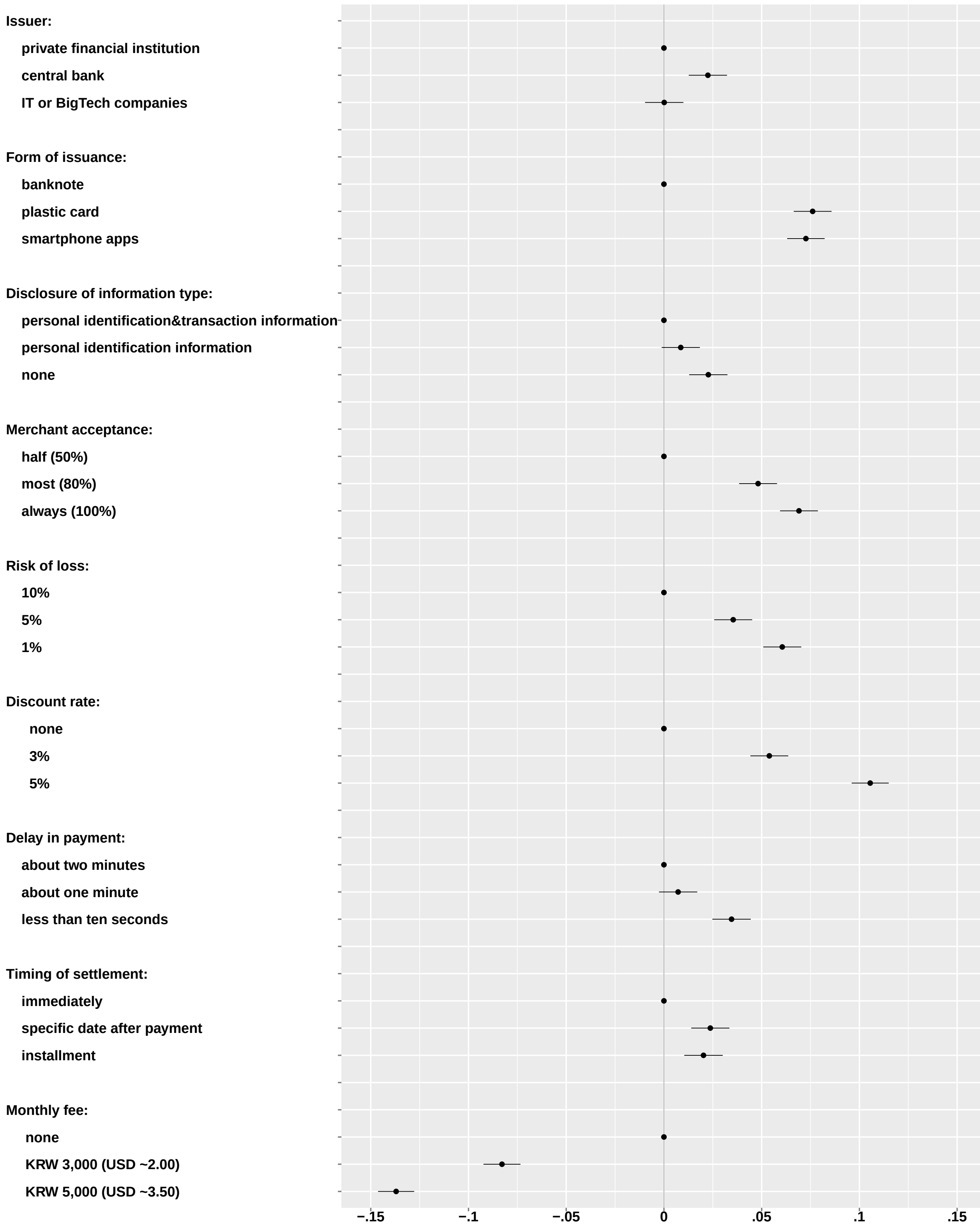
We first present the results of the maximum likelihood estimation of the conditional logit model using (3.2). Most of the coefficient estimates of the parameter vector (β, δ) are highly significant, as reported in Table A4. Figure 1 reports the point estimates of the average marginal effect (AME) of each attribute with 95 percent confidence intervals for all respondents.[11] Using (3.2), this shows how a change in a particular attribute of payment method affects the expected probability of choosing a payment method profile with that attribute. Each estimate is given relative to a particular baseline value for the corresponding attribute. For example, in the case of the issuer attribute which consists of three values (central bank, private financial institutions, and BigTech companies), we take private financial institutions as the baseline value. Therefore, the "central bank" row in Figure 1 indicates that a payment method profile with central bank as the issuer, as opposed to private financial institutions, increases the probability of respondents selecting that payment method profile as their preferred means of payment by an average of 2.2 percentage points.

We find that the choice of payment method is highly responsive to attributes related to monetary incentives. Depending on the monthly fee associated with the use of a payment method, the expected probability that respondents will choose it as their preferred payment method decreases by up to 14 percentage points. Similarly, depending on whether a payment method offers a discount on the purchase of goods, the expected likelihood of selection increases by up to 11 percentage points.

In addition, we find that attributes such as form of issuance, acceptance, and probability of loss also have a significant impact on the choice of payment method. In the case of issuance form, both a plastic card and a smartphone app increase the expected probability of choosing a payment method by about 7.5 percentage points compared to a banknote. And

[11]The average marginal effect (AME) of each attribute is calculated using the associated coefficient estimates of the parameter vector (β, δ) and the values of X_{ijk} and c_{ijk} in (3.2).

Figure 1: Average Marginal Effect (AME) Estimates for Attributes



Notes: The graph plots the average marginal effect (AME) estimates for each attribute value with a 95% confidence interval. Each estimate is specified relative to a baseline value for the corresponding attribute.

a payment method that is accepted with 80% and 100% probability, respectively, increases the expected likelihood of choosing that payment method by 4.8 and 6.8 percentage points compared to one that is accepted with only 50% probability. The probability of losing a payment method also has a significant effect, increasing the expected likelihood of choosing a payment method by 6 percentage points.

For the other attributes, we find significant but modest effects. When the issuer of a payment method is a central bank, the expected probability of choosing that payment method increases by 2.2 percentage points compared to private financial institutions. Having BigTech companies as the issuer of a payment method has no marginal effect on the probability of choosing that payment method compared to the one issued by private financial institutions. And there are only minor effects of the timing of settlement and the delay in payment (i.e. the time it takes to process the payment). In addition, the expected probability of choosing a payment method increases by up to 2.3 percentage points when the personal identification and transaction information associated with the use of the payment method is not disclosed. It is possible that disclosure of information affects choice differently depending on the level of financial incentive, such as a discount. However, the interaction effect between disclosure of information type and discount rate is small and insignificant, meaning that the two dimensions act independently in predicting choice (Table A5).

Finally, given that these are estimated preferences for attributes of payment methods in a general context of consumption, caution is warranted when applying these findings to a specific context. For example, in the case of purchasing privacy-sensitive goods or services, the degree of information disclosure may have a greater effect on the choice of payment method as shown in Choi et al. (2024).

3.3 Willingness-to-Pay for Attributes

While the average marginal effect estimates above are useful for understanding the relative importance of each attribute in the choice of payment method, they do not lead directly to monetary value interpretations. Following the literature as in Hensher et al. (2015), we can use the estimates of the parameter vector (β, δ) to derive the willingness to pay (WTP) for a given attribute r, denoted by WTP_r, as the additional cost that would make an individual indifferent between payment methods with and without the given attribute r. By controlling for the other attributes not to be varied in this exercise, we assume that if a payment method does not have the attribute value r, an individual would simply pay c. On the other hand, if the payment method has the attribute value r, she would be willing to pay $c+WTP_r$ for an increase in utility of β_r associated with the given attribute value r. We try to find the value WTP_r that satisfies the following indifference condition with respect to the "net utility" of the given attribute r:

$$\delta c = \beta_r + \delta(c + WTP_r) \tag{3.3}$$

This implies that an estimate of WTP_r given by:

$$WTP_r = -\frac{\beta_r}{\delta} \tag{3.4}$$

We calculate the WTP_r's for each attribute of the payment method using (3.4) and the parameter estimates in Table A4. Each number in Table 2 represents the willingness to pay for a specific attribute value of the payment method when switching from a base value for the corresponding attribute.

First, with respect to a monetary attribute, the WTP_r's for the 5% and 3% discount rates are KRW 3,821 (USD~3.00) and KRW 1,952 (USD~1.53), respectively. Furthermore, it is worth noting that the WTP_r for a non-monetary attribute such as the form of issuance is quite high relative to a monetary attribute (e.g., discount rate), exceeding USD 2. The relatively high WTP_r for switching from banknotes to smartphone apps is particularly relevant for CBDC, in the sense that it is more likely to be provided in the form of smartphone apps. We also find that the WTP_r's for merchant acceptance and risk of loss are moderately high, exceeding or close to USD 1. Meanwhile, the WTP_r's for the other non-monetary attributes (e.g., issuer, disclosure of information type, delay in payment, and timing of settlement) are relatively modest, below USD 1.

Table 2: Willingness-to-Pay for Attributes

Attributes	WTP (KRW/Month)	WTP (USD/Month)
Issuer		
private financial institutions (base value)		
central bank	814	0.64
IT or BigTech companies	5	0.00
Form of issuance		
banknote (base value)		
plastic card	2,754	2.16
smartphone apps	2,629	2.07
Disclosure of information type		
personal identification & transaction information (base value)		
personal identification information	311	0.24
none	822	0.65
Merchant acceptance		
half (50%) (base value)		
most (80%)	1,744	1.37
always (100%)	2,501	1.96
Risk of loss		
10% (base value)		
5%	1,283	1.01
1%	2,192	1.72
Discount rate		
0% (base value)		
3%	1,952	1.53
5%	3,821	3.00
Delay in payment		
about two minutes (base value)		
about one minutes	262	0.21
less than ten seconds	1,252	0.98
Timing of settlement		
immediate (base value)		
specific date after payment	859	0.67
installment	733	0.58

Notes: The table provides respondents' mean willingness to pay for an attribute value r relative to a baseline value for the corresponding attribute. The 1,273 is the applied exchange rate between USD and KRW (as of June 13, 2023).

4 Predicting the Preference for CBDC

In this section, we perform an exercise to predict the preference for CBDC as a bundle of attributes, based on the estimation results of the conditional logit model shown in Figure 1. To check the plausibility of our prediction analysis, we first predict the preferences for the existing payment methods (not including CBDC) and compare the prediction results with the actual usage of payment methods in South Korea.

We assume that an individual i chooses a payment method from cash, credit and debit card, mobile fast payment, and CBDC. Each payment method can be regarded as consisting of its own unique bundle of attributes. The specific composition of each existing payment method is detailed in Table 3, and that of CBDC in Table 4. For example, in Scenario 1 in Table 4 which is the baseline design, CBDC is assumed to be issued by the central bank, cards or apps as the form of issuance, both personal identification and transaction information disclosed, acceptance by most merchants (80%), zero discount rate, 1% probability of loss, ten-second delay in payment, immediate settlement, and no monthly fee.

Now, with the distributional assumption on ϵ_{ij} as in (3.2), the probability of choosing a payment method $j \in$ {cash, credit/debit card, mobile, CBDC} is expressed as

$$P_{ij} = \frac{\exp(\beta' X_{ij} + \delta c_{ij})}{\sum_l \exp(\beta' X_{il} + \delta c_{il})} \tag{4.1}$$

Preferences for attribute values are reflected in the observed utility $\beta X_{ij} + \delta c_{ij}$. The higher this utility, the greater the probability of choice P_{ij}. Even if the observed utility is higher, the probability of choice could be lower because of an unobserved utility shock $\epsilon_{i,j}$. Therefore, using the estimates of the parameter vector (β, δ) in Figure 1, we can predict the preference for each payment method, including CBDC.

Table 3: Attributes of Existing Payment Methods

	Cash	Credit card	Debit card	Mobile payment
Issuer	central bank	private financial institutions	private financial institutions	IT or BigTech companies
Form of issuance	banknote	plastic card	plastic card	apps
Disclosure of information type	none	personal identification & transaction	personal identification & transaction	personal identification & transaction
Merchant acceptance	most (80%)	most or always (80% ~ 100%)	most or always (80% ~ 100%)	half or most (50% ~ 80%)
Risk of loss	1–5%	1%	1%	1%
Discount rate	0–5%	5%	0%	0%
Delay in payment	thirty seconds	ten seconds	ten seconds	fifteen seconds
Timing of settlement	immediately	specific date or installment	Immediately	Immediately
Monthly fee	none	KRW 500 (USD~0.4)	none	none

Notes: The table shows the attributes of each different payment method: cash, credit card, debit card, and mobile payment. Issuer, form of issuance, disclosure of information type, and timing of settlement each represent fixed inherent values for each payment method. Merchant acceptance is set lower for mobile payment methods to capture the fact that there are many places where they are not used. Risk of loss is set higher for cash by reflecting Jonker (2007). Delay in payment follows results of Fujiki (2021). Thirty seconds of delay in payment using cash reflect its cumbersome usage in the highly digitalized payment system in Korea. Discount rate and monthly fee are set within a range that aligns with the practice of credit card industry in Korea (Bank of Korea (2022a), Bank of Korea (2022b)).

4.1 Preference for Existing Payment Methods

In the discrete choice experiment, we identified the preference for three entities as issuers of payment methods: the central bank, which provides cash; private financial institutions, including commercial banks, which offer widely used payment methods such as debit and credit cards; and IT or BigTech companies, which introduce innovative payment

Table 4: CBDC Attributes under Different Design Scenarios

	Scenario 1 (baseline)	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Issuer	central bank	central bank	central bank	central bank	central bank
Form of issuance	cards or apps	cards or apps	cards or apps	cards or apps	cards or apps
Disclosure of information type	personal identification & transaction	personal identification	none	personal identification & transaction	personal identification & transaction
Merchant acceptance	most (80%)	most (80%)	most (80%)	most (80%)	most (80%)
Risk of loss	1%	1%	1%	1%	1%
Discount rate	0%	0%	0%	3%	5%
Delay in payment	ten seconds	ten seconds	ten seconds	ten seconds	ten seconds
Timing of settlement	immediately	immediately	Immediately	Immediately	Immediately
Monthly fee	none	none	none	none	none

Notes: The table shows the attributes of CBDC under four different design scenarios. Issuer, issuance form, merchant acceptance, risk of loss, payment delay, and timing of settlement are set the same in all scenarios. Disclosure of information type and discount rate varies depending on each scenario. We set scenario 1, where both personal identification and transaction information are disclosed and there is no discount rate, as the benchmark. Then, in scenario 2 and 3, the degree of information disclosure is reduced to only personal identification information and no disclosure, respectively. In scenarios 4 and 5, the discount rate increased to 3% and 5%, respectively. The vendor acceptability value is assigned assuming the steady state, past the initial introduction stage. The results of the counterfactual analysis under complementary scenarios: vendor acceptability evolving from 50% at the point of initial introduction to 80% and eventually 100% is provided in the figure A2.

solutions facilitated by the widespread use of smartphones and thereby emerge as important providers of fast payment services. We categorize existing payment methods into three groups based on the entity responsible for providing the popular payment methods.

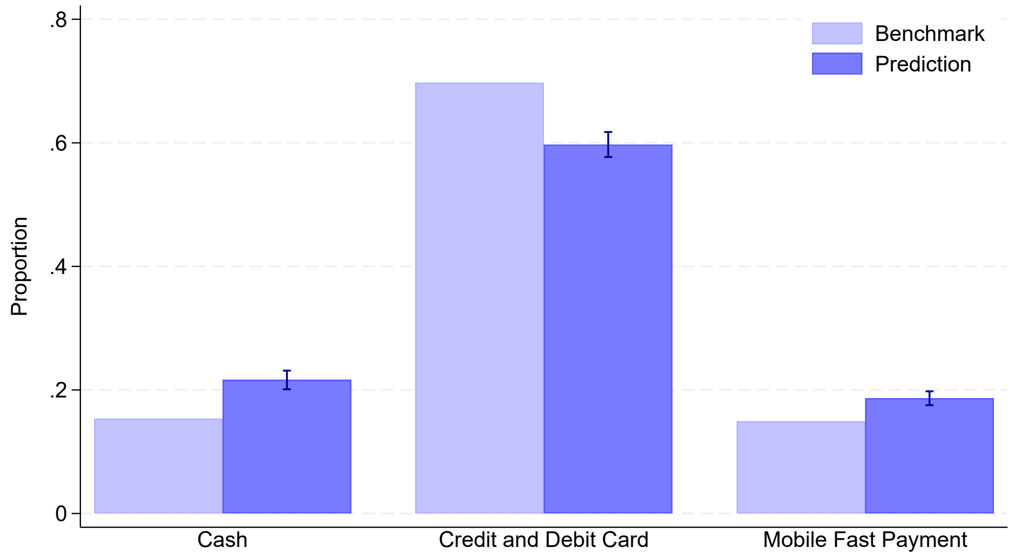
We start by assigning attribute values to existing payment methods such as cash issued by the central bank, credit and debit cards issued by private financial institutions, and mobile payment issued by IT or BigTech companies, as shown in Table 3. The assignment of attribute values to the existing payment methods reflects not only the related studies such as Jonker (2007) on risk of loss and Fujiki (2021) on delay in payment, but also the current situation in South Korea as described in the payment survey by Bank of Korea (2022a) and the report on the average daily usage volumes in Bank of Korea (2022b).[12] Based on the estimation results shown in Figure 1, we then predict the payment preferences for cash, credit and debit cards, and mobile fast payment.

Figure 2 shows the results of our predictions compared with the actual use of payment methods, including data from the Bank of Korea's payment survey.[13] Overall, our predictions for existing payment methods seem to be relatively close to the actual usage patterns of payment methods in South Korea. According to Bank of Korea (2022a) and Bank of Korea (2022b), the use of credit and debit cards is the highest at about 70% of the value of transactions. In our forecast, these payment methods also account for the largest share at 61%. The predicted share of mobile fast payments is about 19%, which is slightly

[12]It is worth noting that a slightly higher credit card discount rate is imposed to account for discounts linked to product purchases and credit card usage. Companies that sell expensive home appliances, electronic products or furniture offer promotions tied to specific credit cards. For example, if a consumer purchases a newly released smartphone and signs a contract with a specific credit card, they can receive a discount based on their credit card usage. Additionally, online marketplaces often offer discounts ranging from 5% to 10% when using specific credit cards. In Korea, this type of sales strategy is common.

[13]The measures are different in that the benchmark is the proportions based on the average daily usage volume as well as BOK payment survey, while the prediction is the share of users who would see this as their dominant means of payment.

Figure 2: Comparison between Bank of Korea's Payment Survey and Prediction Results



Notes: The prediction is made based on the assignment of attribute values in Table 3 and the estimation results reported in Figure 1. We use actual usage data of credit/debit cards and prepaid electronic payment instrument, combined with the 2021 survey of consumer payment choice in South Korea to construct the benchmark. Specifically, according to the 2021 Annual Report on the Payment and Settlement Systems (Bank of Korea (2022b)), the average daily usage volume of credit cards amounted to KRW 23,120 billion, while debit cards registered KRW 5,810 billion in daily usage. Additionally, according to Bank of Korea (2023), the average daily usage of prepaid electronic payment instruments provided by payment service providers was KRW 6,184 billion in 2021. Finally, the daily usage amount of cash is estimated using both the data aforementioned and the proportional distribution data of cash, credit cards, debit cards, and prepaid electronic payment instruments (Bank of Korea (2022a)). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

higher than the actual share of 15% in the payment survey. However, the use of mobile fast payments is growing rapidly in South Korea, doubling every year in recent years (Bank of Korea, 2022a). Overall, these provide plausible ground for the external validity of our experimental design.

4.2 Preference for CBDC

We now introduce CBDC into the prediction exercise as an additional means of payment. Many central banks around the world are researching and developing CBDCs as well as considering different design features, to assess their benefits and risks. Given that most of the features of CBDCs have yet to be determined by central banks, we conduct simulations under different CBDC design scenarios. The following attribute values are commonly assigned to all design scenarios: central bank as issuer, cards or apps as issuance form, acceptance by most merchants (80%), 1% probability of loss, ten-second delay in payment, immediate settlement, and no monthly fee. These attribute values are considered to be mostly inherent features of CBDC as an electronic form of central bank money. On the other hand, there are features of CBDC design that can be chosen by the central bank, such as the disclosure of information type when using CBDC as a means of payment and the remuneration rate for CBDC which is provided in the form of a discount rate applied to purchases using CBDC.

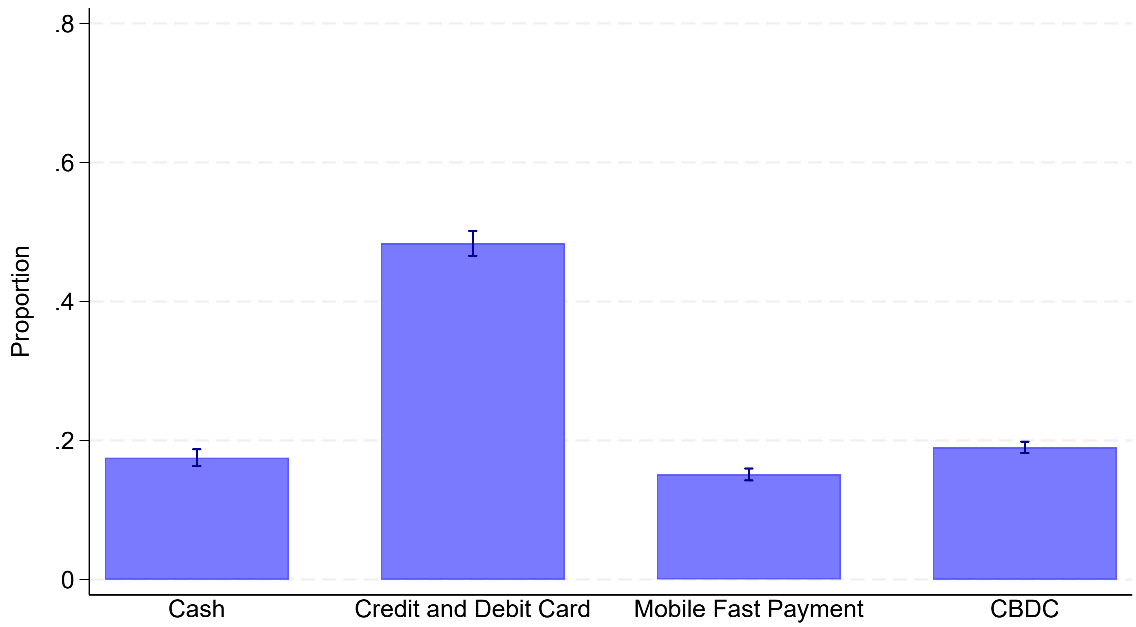
Table 4 shows the compositions of attribute values assigned to four different design scenarios of CBDC that we use in simulations. In each scenario, we vary the attribute values for the disclosure of information type and the discount rate to examine their effect on the payment preference for CBDC. Scenario 1 is the benchmark, in which both personal identification and transaction information are disclosed and there is a zero discount rate when using CBDC. In Scenario 2, only personal identification information is disclosed, while the discount rate increases to 3% and 5% in Scenarios 3 and 4, respectively.

First, Figure 3 shows the predictions of payment preferences with the introduction of CBDC using the benchmark design of Scenario 1. In this benchmark analysis, the proportion of CBDC being chosen as the most preferred means of payment is about 19% of respondents, ranking second only to credit and debit cards. These results suggest that if CBDC is introduced, it is likely to be used more frequently than cash or mobile fast payment.

Second, we examine how the preference for CBDC changes in response to variations in the disclosure of information type and the discount rate as in Scenarios 2 through 5. Figure 4 shows that in the case of Scenario 2, where only personal identification information is disclosed, there is a slight increase, by about 0.6 percentage points (pp), in the preference for CBDC relative to the benchmark Scenario 1. When neither personal identification nor transaction information is disclosed (Scenario 3), there is an increase, by about 1.6 pp, in the preference for CBDC relative to the benchmark Scenario 1. This appears to be consistent with our earlier findings in Section 3, which show the relatively modest average marginal effect (AME) of the disclosure of information type on the expected probability of choosing a payment method where neither personal identification nor transaction information is disclosed. On the other hand, as the discount rate increases in Scenarios 4 and 5, the preference for CBDC increases by about 4–8% pp, which amounts to an increase of 21–44% relative to the baseline Scenario 1. This implies that the monetary reward for using CBDC is likely to play an important role in the choice of CBDC as the most preferred payment method.

Finally, we investigate the situations in which private financial institutions and BigTech companies proactively respond to the introduction of CBDC by adjusting the attributes of

Figure 3: Prediction of Payment Preference with CBDC



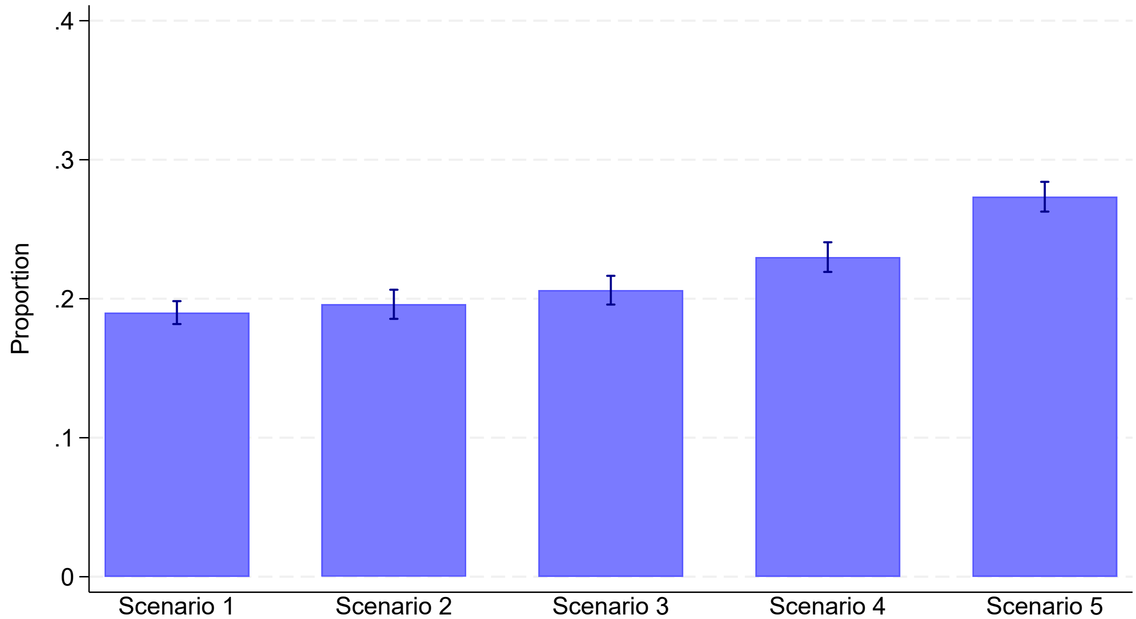
Notes: The prediction is made based on the assignment of attribute values in Table 3 and Table 4 with Scenario 1(baseline) design of CBDC, and the estimation results reported in Figure 1. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

credit cards and mobile payments to maintain their competitiveness. They may respond by providing financial incentives in the form of lower monthly fees and higher discount rates. Figure 5 shows that if the monthly fee for credit card decreases to zero and the discount rate for mobile payment increases to 3%, the preference for CBDC decreases by 1.1 %p, which is a decrease by 6% compared to the baseline scenario. This result implies that the choice of CBDC as a payment method is likely to decrease if private financial institutions and BigTech companies compete with CBDC by lowering their monthly fees or increasing their discount rates.

4.3 Predictions with Nested Logit Model

We present alternative predictions of payment preferences using a nested logit framework to test the robustness of the predictions using a conditional logit model. The combined share of credit and debit card usage, which we used as a benchmark in the previous section, may not accurately capture the fact that the Korean payment market is dominated by credit cards, where the share of credit card usage is over 50%. In addition, it may overestimate the substitution effect on credit card usage when CBDC is introduced. Therefore,

Figure 4: Prediction of Payment Preference for CBDC under Different Design Scenarios



Notes: The prediction is made based on the assignment of attribute values in Table 3 and Table 4 with Scenario design of CBDC, and the estimation results reported in Figure 1. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

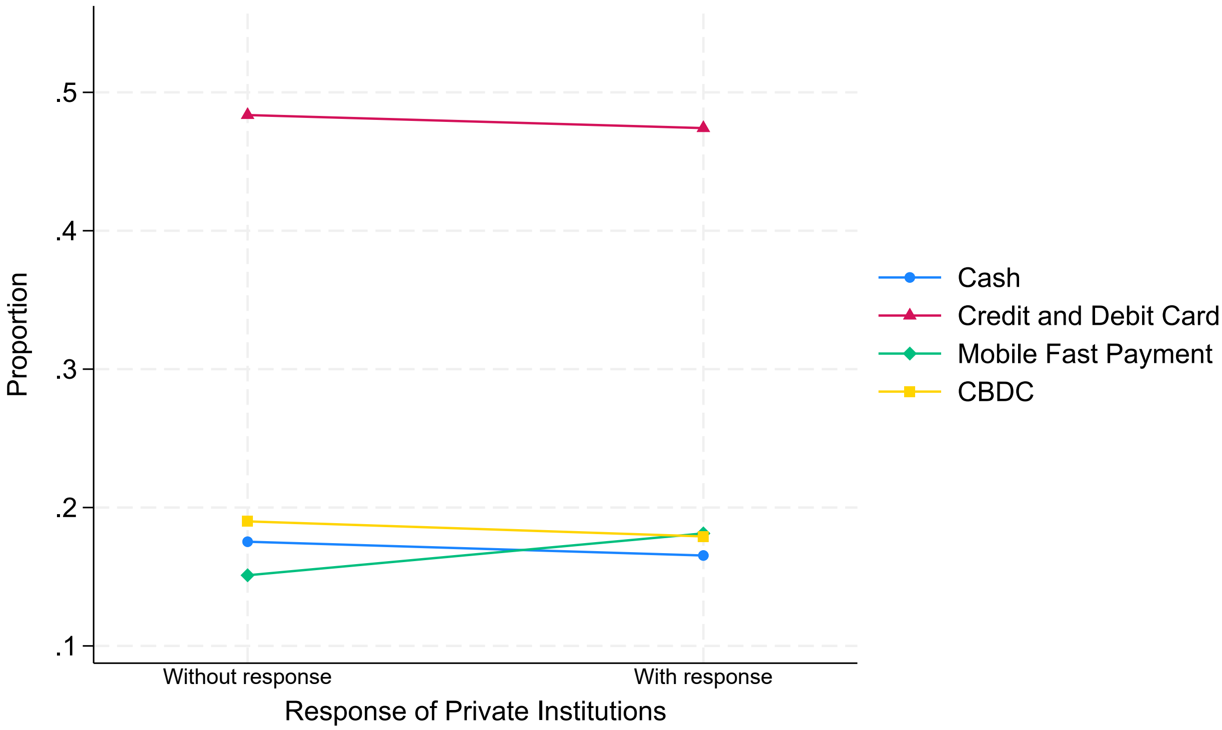
we use the nested logit model to find the nested combinations of cash, credit cards, debit cards, and mobile payments that fit well with actual usage and present the predictions of payment preference for each payment method when CBDC is introduced.[14]

The choice decision in the nested logit framework can be decomposed into two stages: (1) the choice between nests and (2) the choice between alternatives within the chosen nest (Train, 2009). The probability that an individual i chooses a payment alternative j in a particular nest $B(j) \in \{B_m | m = 1, 2, ..., M\}$ with characteristics X_{ij} and cost c_{ij} is, with the distributional assumption on ϵ_{ij} as in (3.2), expressed as follows:

$$P_{i,j} = \frac{\exp((\beta' X_{ij} + \delta c_{ij})/\tau_j)}{\Sigma_{n \in B(j)} \exp((\beta' X_{in} + \delta c_{in})/\tau_j)} \frac{(\Sigma_{n \in B(j)} \exp((\beta' X_{in} + \delta c_{in})/\tau_j))^{\tau_j}}{\Sigma_{m=1}^{M} (\Sigma_{n \in B_m} \exp((\beta' X_{in} + \delta c_{in})/\tau_m))^{\tau_m}} \tag{4.2}$$

[14] An independently and identically distributed error term ϵ_{ijk} in (3.1), or the idiosyncratic unobserved utility shock is one of the crucial assumptions of the conditional logit framework, which at the same time involves a limitation. Under the i.i.d. error terms assumption, whenever the share of one of the alternatives in the choice set increases, each of the other alternatives decreases in proportion to its initial share. Practically, it neither assumes nor reflects substitute-complement relationship between alternatives. On the contrary, the nested logit framework allows for interrelated error terms for the alternatives in the same nest. Under such construction, whenever any one of the alternatives in the given nest increases in share due to the enhancement of attributes or when a new alternative is introduced to the nest, it substitutes more than proportionally from the alternatives included in the same nest.

Figure 5: Predicted Preference for CBDC with the Private Institutions' Response



Notes: Without response refers to the baseline scenario (scenario 1) in Tables 3 and 4. With response refers to the case where the monthly fees for credit cards decrease to zero and the discount rate for mobile payment methods increase to 3%.

Note that $\tau_m \equiv \sqrt{1-\rho_m} \in (0,1]$ refers to the dissimilarity parameter, which can also be interpreted as an inverse measure of the correlation, $\rho_m \in (0,1]$, between the idiosyncratic unobserved utilities of the alternatives within the nest B_m.

By applying the nested logit framework, the model can incorporate the effects of attributes not captured by the experimental design, thereby better accounting for substitution and complementarity effects between alternatives. When a particular alternative is placed in a nest consisting of only one option, it may imply the presence of a significant unobserved factor that makes it more difficult to substitute with other alternatives.[15] Specifically, for those who experience immediate liquidity shortage after credit card charges are repaid — an attribute not explicitly considered in our experimental design, it may be difficult for them to switch to other payment methods, including CBDC. This reflects an intertemporal liquidity smoothing mechanism inherent in credit card use, whereby con-

[15] In principle, once the nest structure is defined, the dissimilarity parameter τ is estimated from the data. However, since our data is based on the binary choice experiment, estimation of the substitution effect is infeasible. This is why we have conducted simulation over all the possible range of τ to find the parameter that best fits the real world, or the "preferred τ" to exogenously plug it in for the counterfactual analysis, and thus the caution is required for interpretation of the result.

sumers benefit from a delay between purchase and actual fund withdrawal. The absence of this feature in our choice experiment design may result in overestimating the substitutability of CBDC for credit cards.

We heuristically compare the predictions across different specifications of nest structures by visually inspecting and identifying patterns that match the benchmark. As a result, we have defined two preferred nests and the corresponding values of τ. Figure A8 shows our prediction results using the nested logit model along with the actual usage of payment methods (benchmark). The nest structure that assigns all alternatives except credit card to the same single nest with dissimilarity parameter $\tau = 0.6$ cardinally best describes the benchmark. The nest structure that assigns cash and debit card to the same nest with $\tau = 0.5$ and assigns credit card and mobile payment to their own respective nests so that each nest consists of only one alternative, matches the ordinal preference among alternatives in the benchmark.

In addition, Table A7 shows the predicted payment preferences for the introduction of CBDC using the benchmark design of Scenario 1. The results include the cases where CBDC is assigned to: (1) the largest nest (Table A7 (a), (c)), (2) its own nest consisting only of CBDC (Table A7 (b), (d)), or (3) the same nest with mobile payment (Table A7 (e)). The proportion that CBDC is chosen as the most preferred payment method ranges from 15% to 23%, which covers the predictions in the previous section. When the alternative CBDC designs of Scenarios 2 through 5 are simulated, this proportion varies between 16% and 33% (Tables A8-A11).

4.4 Heterogeneous Effects

We report the heterogeneous analysis across subgroups to understand the differences in predicted demand for CBDC. We focus on four social and demographic factors: gender, age, education, and income. The subgroup models in this section are also estimated using conditional logit models.

First, we estimate separately by gender and present the average marginal effect (AME) results in Figure A3. Overall, there are no differences in preference for attributes between men and women, except that women are slightly more responsive to the level of merchant acceptance. These attribute preferences also do not lead to differences in preference for CBDC, as shown in Table A6. Similarly, we find no significant differences in preferences for attributes and preferences for CBDC between education groups and income groups (Figures A6-A7, Table A6).

In the case of age, we find significant differences in preferences for attributes between the younger age group (19-39) and the older age group (40-70) (Figure A4). The most notable difference is in the evaluation of the issuer. For the older age group, the expected probability of choosing a payment method increases by 3.0 percentage points when the issuer is the central bank, but there is no significant effect for the younger age group. On the other hand, when the issuer is IT or BigTech company, the probability of choosing a payment method increases by 3.2 percentage points for the younger age group, but decreases by 1.5 percentage points for the older age group. We also find different preferences between age groups for the form of issuance. For the younger age group, the probability of choosing a payment method increases by 8.6 percentage points when the form of issuance is a smartphone app and 7.9 percentage points when the issuance form is a plastic card. Thus, a smartphone app is the most preferred form of issuance. On the other hand, for the older age group, there is an increase of 6.6 percentage points for a smartphone app and by 7.5 percentage points for a plastic card, indicating that the plastic card is the most preferred form of issuance. Table A6 shows that the different attribute preferences by age lead to different preferences for payment methods. For the younger age group, the preference for CBDC is similar to that for mobile payment. However, for the older age group, CBDC is significantly preferred over mobile payment. When the older age group is narrowed down to the 60-70 group, the above pattern becomes even more pronounced (Figure A5, Table A6). Previous studies have emphasized that age is a key demographic characteristic that influences payment choices.[16] Our results show that CBDC is also likely to be adopted differently by age, which is in line with evidence presented in Armantier et al. (2024) and Carlin et al. (2017).

5 Concluding Remarks

In this paper, we have attempted to predict the demand for CBDC as a means of payment using the method of a discrete choice experiment. First, we found that the propensity to choose a payment method strongly depends on attributes associated with financial incentives. The likelihood of respondents selecting a payment method as their preferred option decreases by up to 14 percentage points in the presence of a monthly fee associated with its usage. Similarly, the availability of a discount for purchasing goods with a particular payment method increases the expected probability of selecting it by up to 11 percentage points. Second, non-monetary attributes also have a significant but relatively modest impact on payment choice. The willingness to pay for non-monetary attributes such as

[16] It is reported that older consumers use significantly more cash and credit cards, while using significantly fewer debit cards, ATM cards, and electronic payment methods (Borzekowski et al., 2007, Borzekowski and Kiser, 2008, von Kalckreuth et al., 2014, Yang and Ching, 2014).

the form of issuance is relatively high, comparable to that for monetary attributes like a discount. In particular, the significant willingness to pay for the switch from banknotes to smartphone apps is relevant for CBDC, as it is more likely to be provided through smartphone apps. In addition, privacy preservation—captured by the type of information disclosure in our experiment—enhances the preference for CBDC as a means of payment, and its effects may extend beyond any one jurisdiction.

By characterizing a payment method as bundles of these attributes, we predict the relative demand for existing payment methods - cash, credit and debit cards, and mobile fast payment - and compare them to real-world usage data. We find that the predictions align well with actual usage patterns. In addition, the predictions show that if CBDC were introduced as an additional payment option following a benchmark design, about 20% of respondents would select CBDC as their most preferred payment method, ranking it second only to credit and debit cards. These results suggest that CBDC, once introduced, would likely be more readily adopted than cash or mobile fast payments. In addition, the payment preference for CBDC is highly sensitive to the discount rate, suggesting that the financial rewards associated with CBDC are likely to play a critical role in its selection as a preferred payment method.

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Appendices

A Figures and Tables

Figure A1: Screenshot of Hypothetical Payment Method Pair Evaluated by a Respondent

F1-1. When making a purchase at a physical store, which payment method would you prefer between A and B?

Attributes	Payment method A	Payment method B
Issuer	Central Bank	Private financial institutions
Form of issuance	Smartphone apps	Plastic card
Disclosure of information type	None	Personal identification information
Merchant acceptance	Half (50%)	Always (100%)
Risk of loss	5%	1%
Discount rate	3%	5%
Delay in payment	About two minutes	About one minutes
Timing of settlement	Installment	Immediately
Monthly fee	Three thousands won	Five thousands won

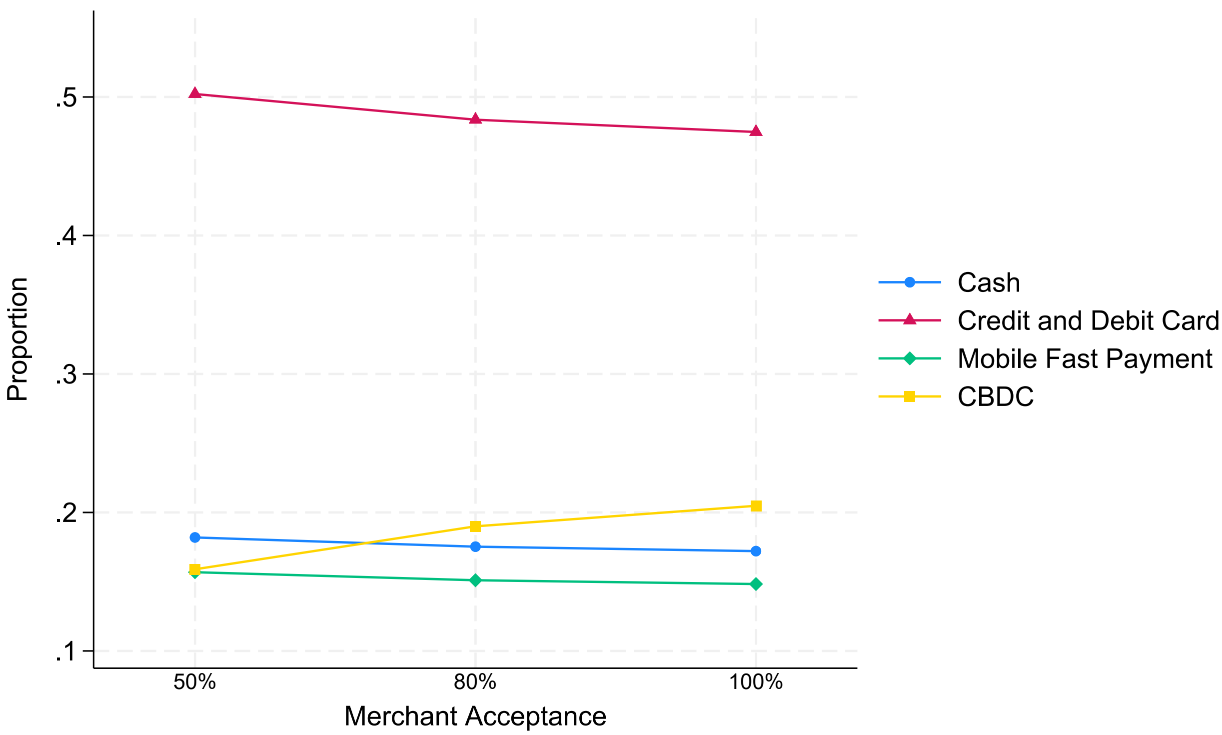
1. I will pay with A
2. I will pay with B

F1-2. When making a purchase at a physical store, which payment method would you prefer between A and B?

Attributes	Payment method A	Payment method B
Issuer	IT or BigTech companies	Central Bank
Form of issuance	Plastic card	Banknote
Disclosure of information type	Personal identification information	None
Merchant acceptance	Half (50%)	Most (80%)
Risk of loss	10%	1%
Discount rate	5%	None
Delay in payment	About one minute	less than ten seconds
Timing of settlement	Immediately	Specific date after payment
Monthly fee	Three thousands won	None

1. I will pay with A
2. I will pay with B

Figure A2: Predicted Preference for CBDC with Evolving Merchant Acceptance over Time



Notes: The above bar means the predicted demand for CBDC in each scenario. The scenarios vary solely on the vendor acceptability and all the other attribute values follows the baseline scenario (scenario 1) in Tables 3 and 4.

Figure A3: Average Marginal Effect (AME) Estimates for Attributes by Gender

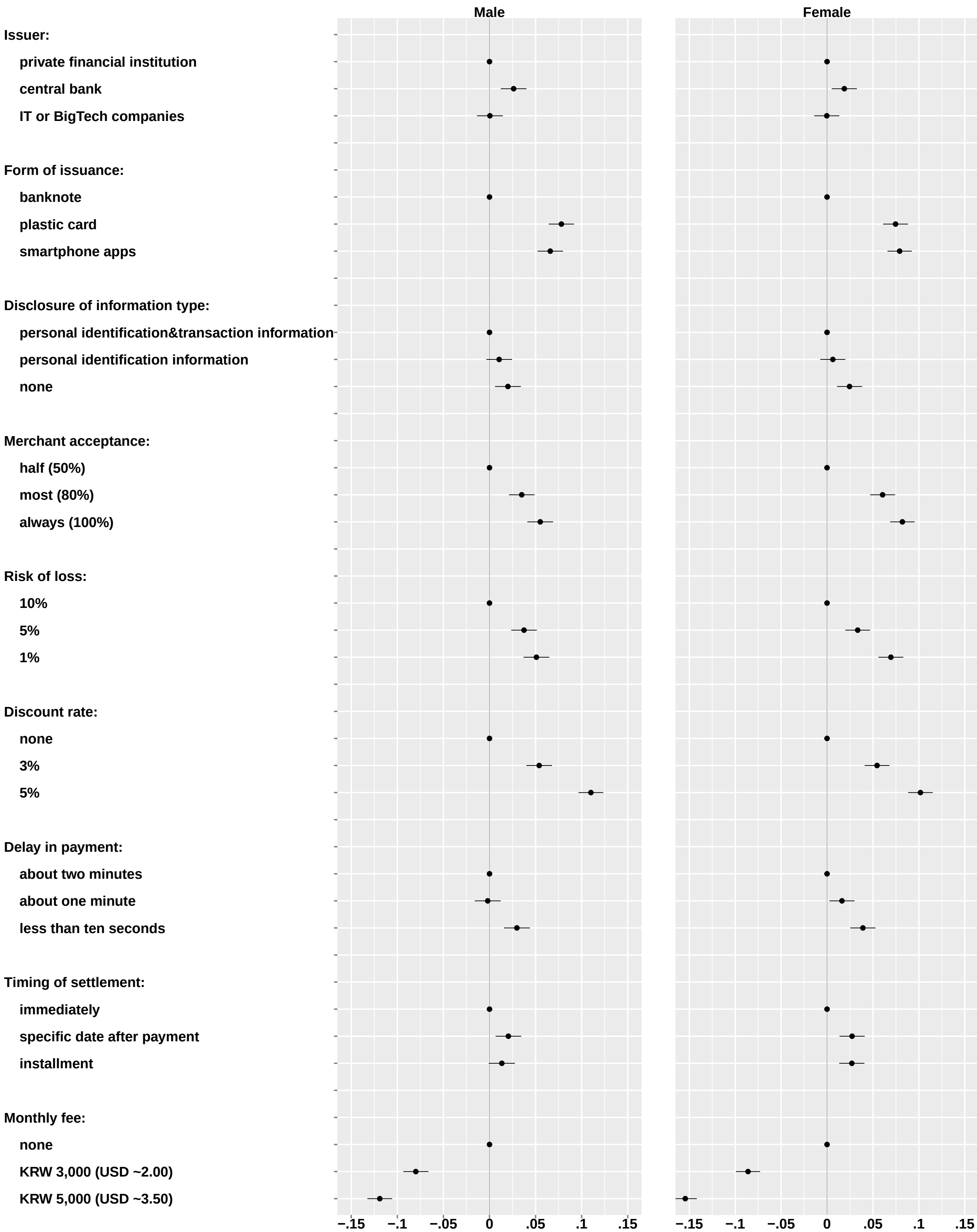


Figure A4: Average Marginal Effect (AME) Estimates for Attributes by Age

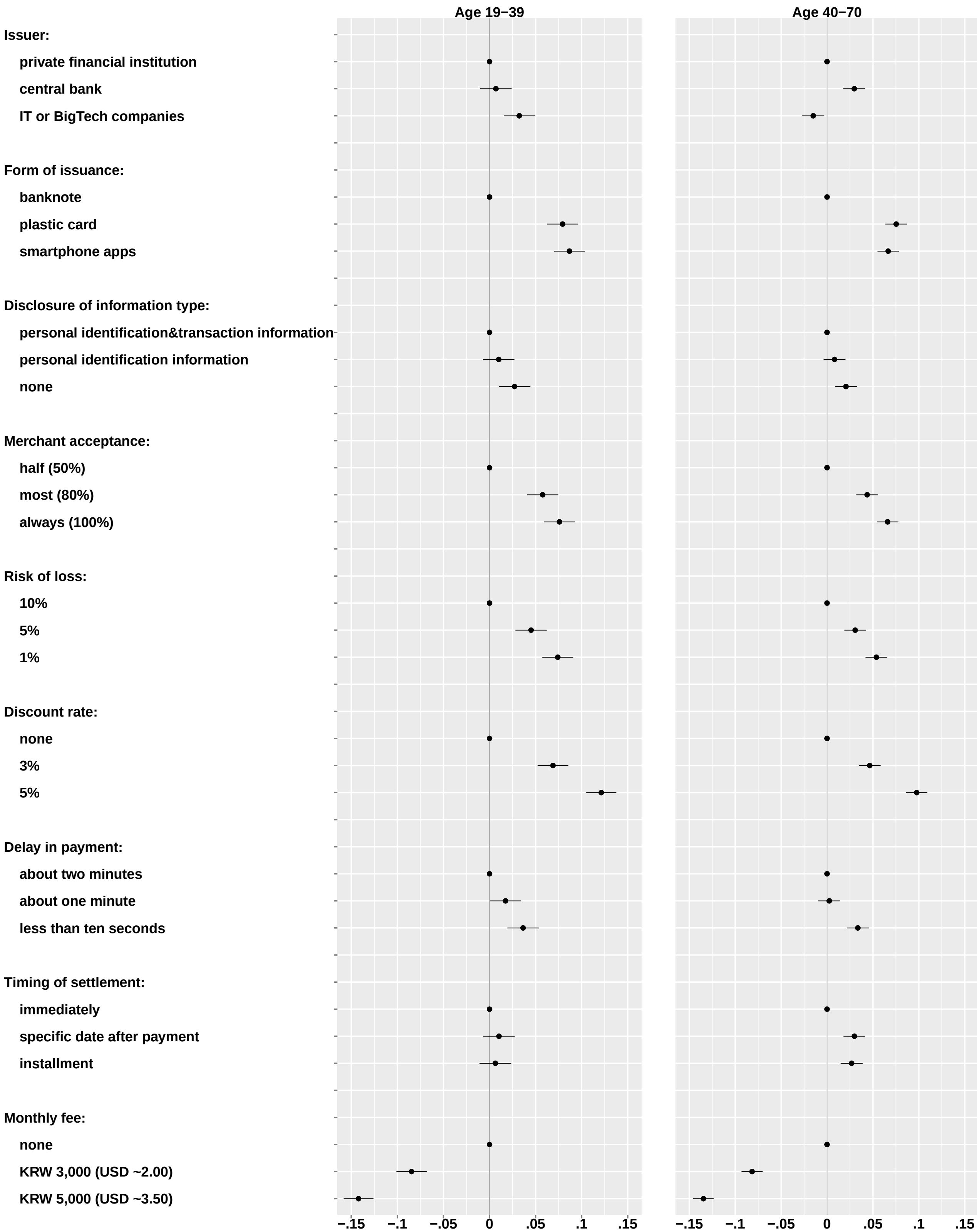


Figure A5: Average Marginal Effect (AME) Estimates for Attributes by Age

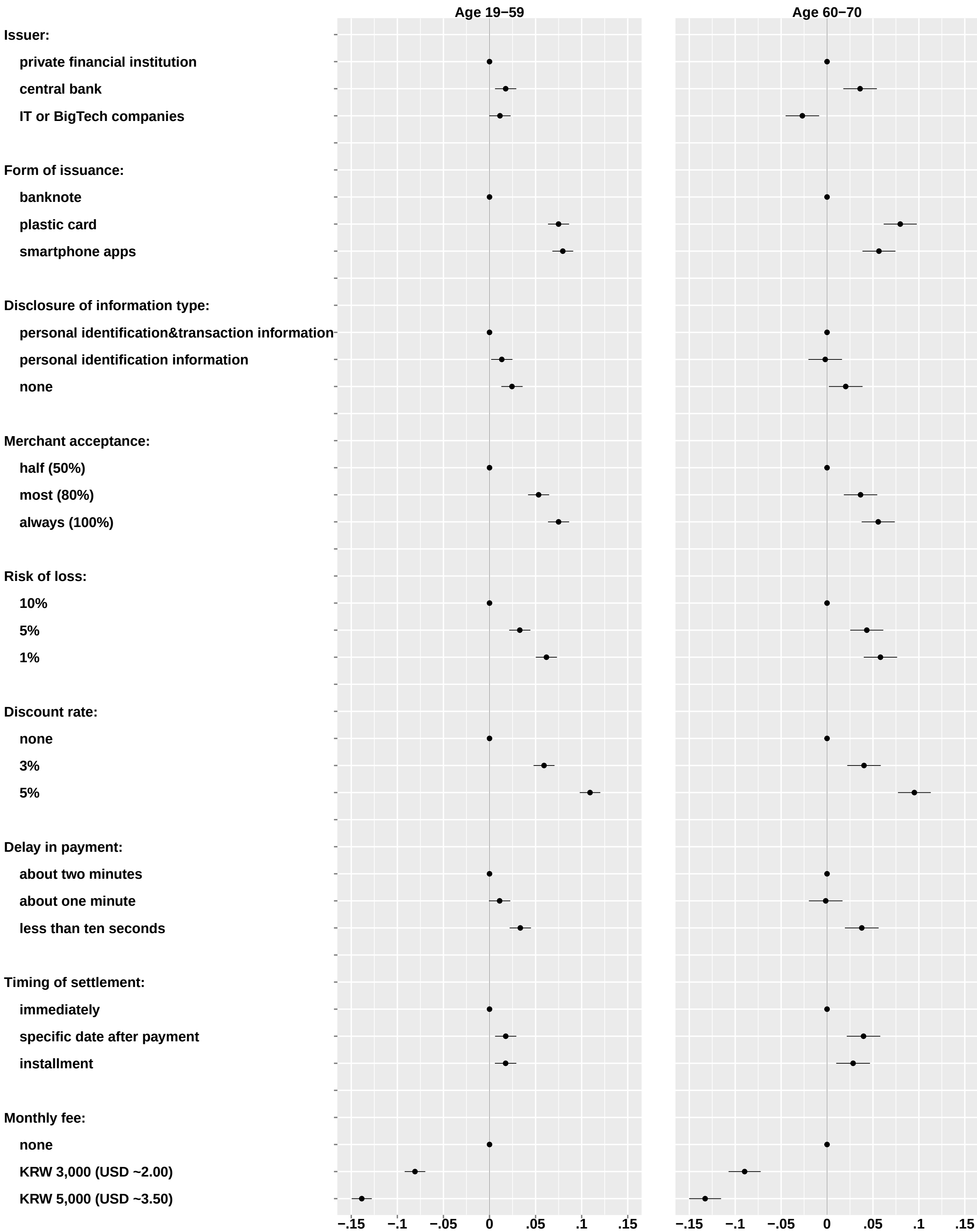


Figure A6: Average Marginal Effect (AME) Estimates for Attributes by Education

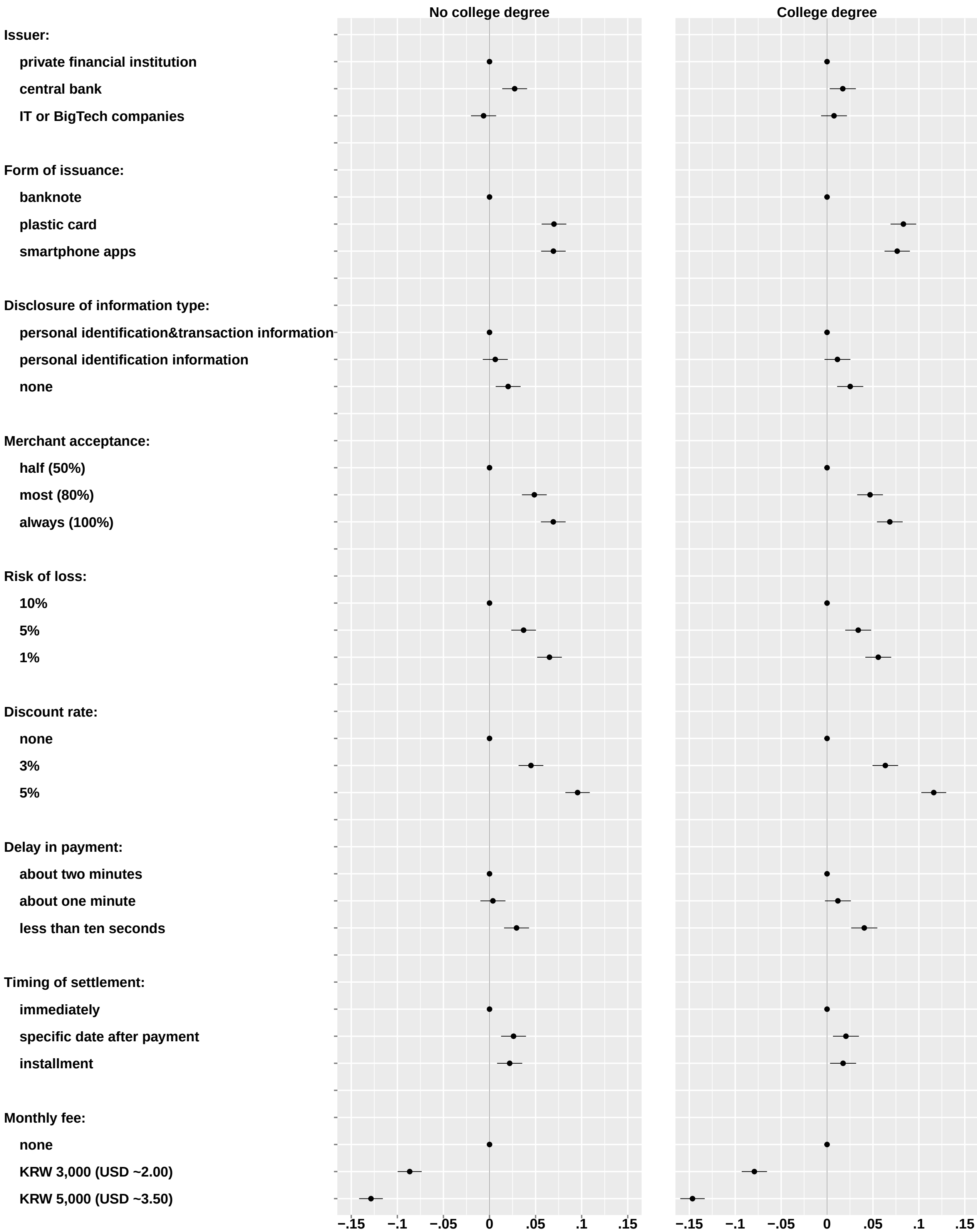


Figure A7: Average Marginal Effect (AME) Estimates for Attributes by Income

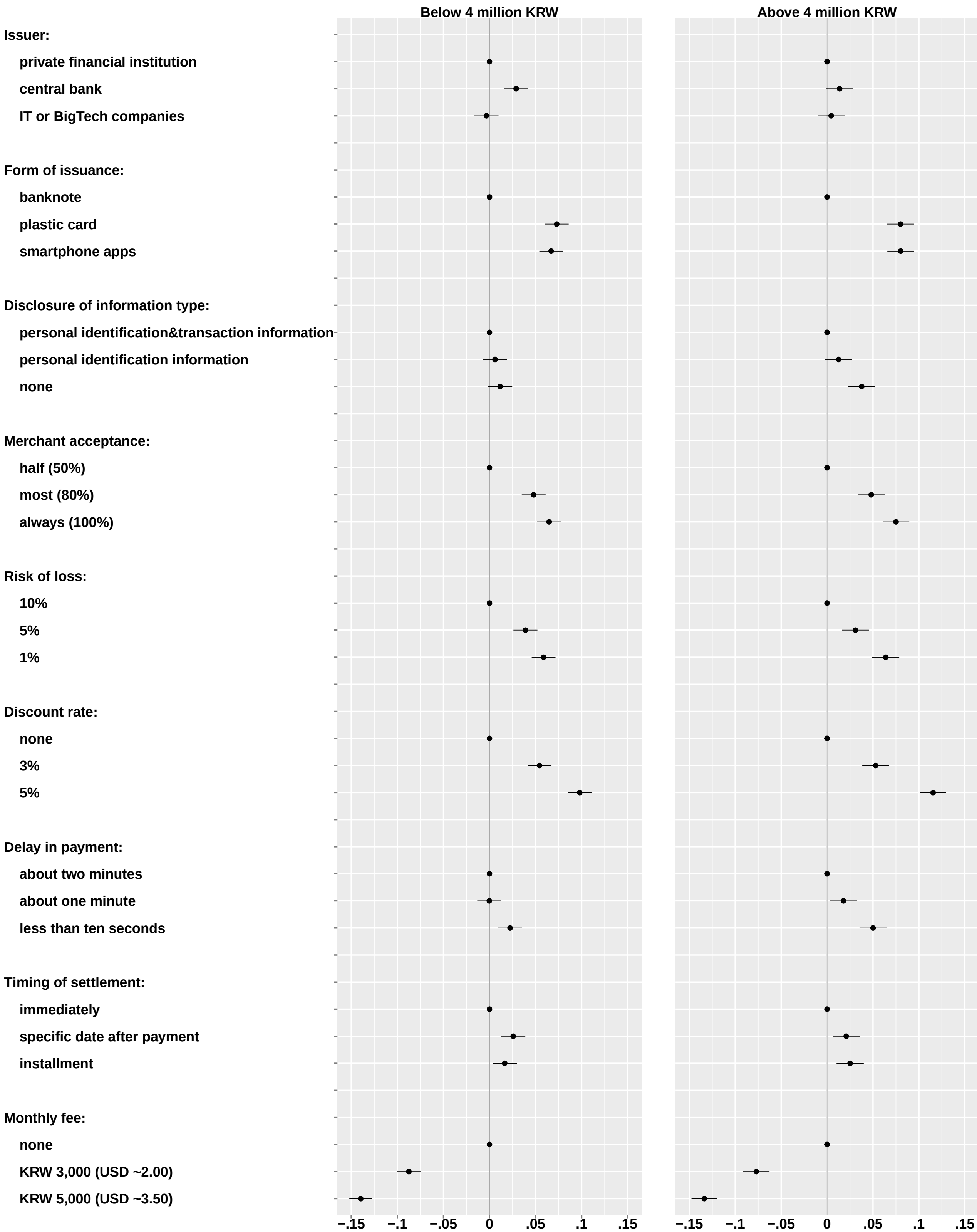
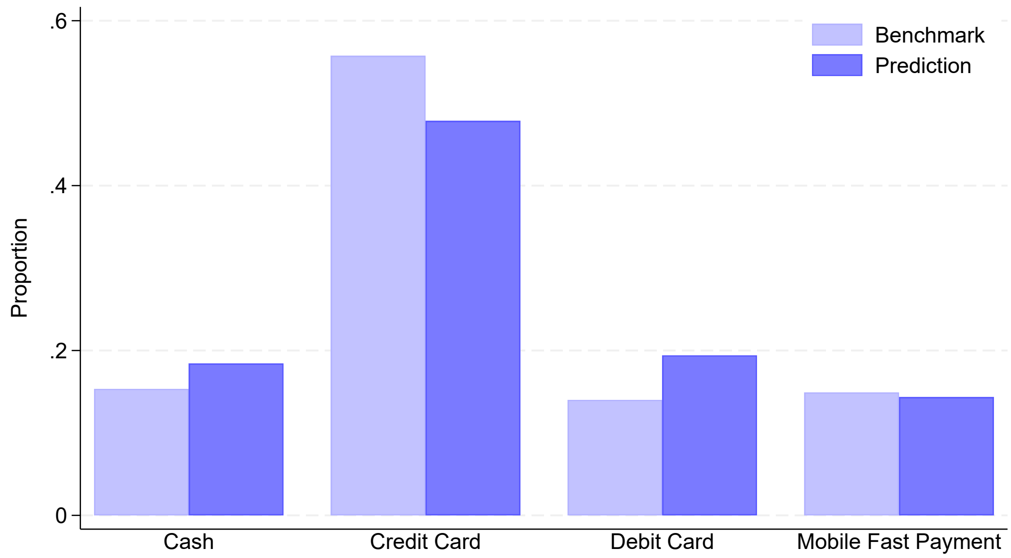


Figure A8: Comparison between Bank of Korea's Payment Survey and Simulation Results under Nested Logit Framework

(a) Nest: Cash & Debit Card & Mobile Payment(τ=0.6) | Credit Card



(b) Nest: Cash & Debit Card(τ=0.5) | Mobile Payment | Credit Card

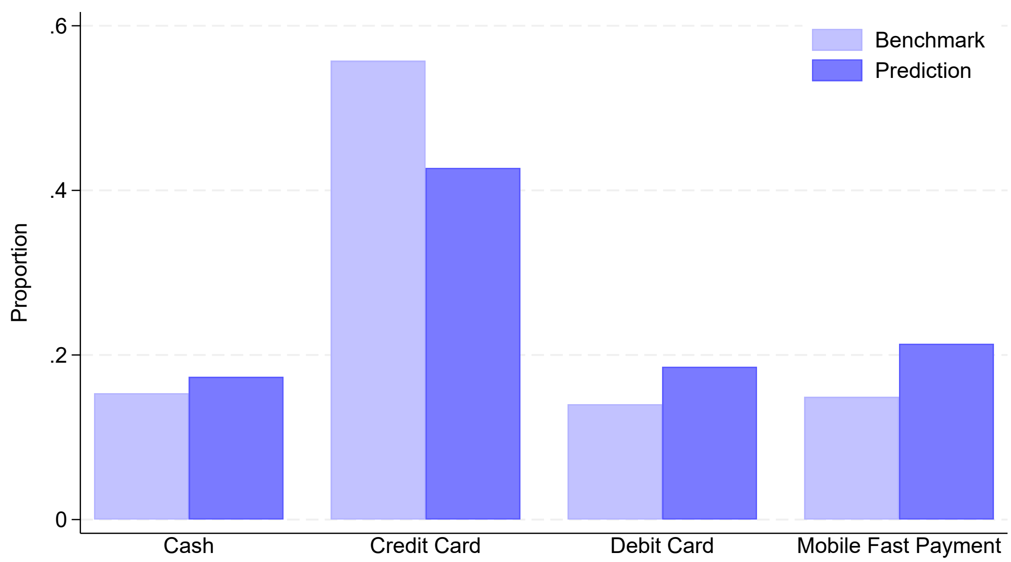


Table A1: Sample Characteristics

	This Survey	South Korea population
Female	0.51	0.50
Age		
19~29	0.16	0.15
30~45	0.26	0.25
46~59	0.29	0.30
Above 60	0.29	0.30
Living in Seoul	0.18	0.18
Married	0.62	0.60
Education		
Above College degree	0.47	0.47
Employment		
Employed	0.50	0.40
Self-employed	0.10	0.15
Not-employed	0.40	0.45

Notes: This table displays statistics for the overall South Korea population and compares it to the characteristics of the sample of surveys. National statics on gender, age, place of residence are from the South Korea Demographic Statistics December 2021. Marriage, education are from the South Korea Population Census 2015, and Employment is from the 2019 Korea Labor Income Panel Study(KLIPS).

Table A2: Correlations between attributes

	Issuer			Issuance form			Disclosure of information type			Vendor acceptability		
	central bank	private financial institutions	It or BigTech Companies	banknote	plastic card	smartphone apps	none	personal Inf	personal Inf & transaction Inf	1%	5%	10%
Issuance form												
banknote	-0.00	0.00	0.00									
plastic card	0.01	0.00	-0.01									
smartphone apps	-0.00	-0.01	0.01									
Disclosure of information type												
none	-0.01	-0.00	0.01	-0.00	-0.01	0.01						
personal Inf	-0.01	0.01	0.00	-0.01	0.01	-0.00						
personal & transaction Inf	0.01	-0.00	-0.01	0.01	-0.00	-0.00						
Vendor acceptability												
always (100%)	-0.01	-0.00	0.01	-0.00	0.01	-0.00	-0.01	0.01	-0.01			
most (80%)	0.01	-0.00	-0.01	-0.00	-0.00	0.01	-0.00	-0.00	0.01			
half (50%)	0.00	0.01	-0.01	0.01	-0.00	-0.00	0.01	-0.01	0.00			
Risk of loss												
1%	-0.01	-0.00	0.01	0.01	-0.00	-0.00	0.00	0.00	-0.01	0.01	-0.01	0.00
5%	0.00	0.00	-0.01	-0.00	0.00	-0.00	-0.00	-0.00	-0.01	0.00	-0.00	-0.00
10%	0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.00	-0.01	0.01	0.00
Discount rate												
none	-0.01	0.00	0.00	0.01	0.00	-0.01	0.00	0.00	-0.00	0.01	-0.01	-0.00
3%	-0.01	0.00	0.00	-0.01	0.00	0.01	0.00	-0.00	0.00	-0.01	0.01	0.00
5%	0.01	-0.01	-0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	-0.00	0.00
Payment delay												
less than ten seconds	0.01	-0.01	-0.00	0.00	0.00	-0.01	-0.00	-0.00	0.00	0.01	-0.01	0.00
about one minute	0.00	0.01	-0.01	-0.01	-0.00	0.01	0.01	-0.01	-0.00	-0.00	0.01	-0.00
about two minutes	-0.01	0.00	0.01	0.00	-0.00	-0.00	-0.00	0.01	-0.00	-0.00	-0.00	0.01
Timing of settlement												
immediately	-0.00	-0.00	0.01	0.00	0.00	-0.00	0.00	0.00	-0.00	-0.01	0.01	-0.00
specific date after payment	-0.00	0.01	-0.01	-0.01	-0.00	0.01	-0.00	0.00	0.00	-0.00	0.01	-0.00
installment	0.01	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.1	-0.01	-0.01
Monthly fee												
none	0.00	0.00	-0.00	-0.01	0.00	0.00	-0.00	0.01	-0.00	0.00	-0.01	-0.01
KRW 3,000	-0.01	0.01	0.00	0.01	-0.01	-.00	0.00	-0.00	0.00	0.01	-0.01	-0.01
KRW 5,000	0.01	-0.01	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.01	0.00	0.01

	Risk of loss			Discount rate			Payment delay			Timing of settlement		
	none	3%	5%	none	3%	5%	less than ten seconds	about one minutes	about two minutes	immediately	specific date after payment	installment
Discount rate												
none	-0.00	0.00	-0.00									
3%	-0.00	0.00	0.00									
5%	0.00	0.0	-0.01									
Payment delay												
less than ten seconds	-0.00	0.01	-0.00	-0.00	0.00	-0.00						
about one minute	-0.01	-0.00	0.01	0.01	0.01	-0.01						
about two minutes	0.01	-0.00	-0.00	-0.01	0.00	0.01						
Timing of settlement												
immediately	-0.00	-0.00	0.01	-0.00	-0.00	0.00	0.00	-0.01	0.00			
specific date after payment	-0.00	0.01	-0.00	0.01	-0.00	-0.01	-0.00	-0.00	0.00			
installment	0.01	-0.00	-0.00	-0.01	0.01	0.00	-0.00	0.01	-0.01			
Monthly fee												
none	0.00	-0.00	-0.00	-0.00	-0.00	0.01	-0.00	0.00	-0.00	0.00	-0.01	0.01
KRW 3,000	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.01	0.01	-0.01	0.01	0.00
KRW 5,000	-0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	-0.01	0.01	-0.00	-0.01

Table A3: Number of Observations in Attributes

		Observations
Issuer	central bank	11,838
	private financial institutions	11,851
	IT or BigTech companies	11,921
Issuance form	banknote	11,877
	plastic card	11,803
	smartphone apps	11,930
Disclosure of information type	none	11,906
	personal indentification information	11,846
	personal identification & transaction information	11,858
Merchant Acceptance	always (100%)	11,870
	most (80%)	11,835
	half (50%)	11,905
Risk of loss	1%	11,803
	5%	11,883
	10%	11,924
Discount rate	none	11,853
	3%	11,766
	5%	11,991
Payment delay	less than ten seconds	11,881
	about one minute	11,940
	about two minutes	11,789
Timing of settlement	immediately	11,835
	specific date after payment	11,921
	installment	11,854
Monthly fee	none	11,914
	KRW 3,000	11,879
	KRW 5,000	11,817

Table A4: Estimation Results from Conditional Logit Models

	Coefficient	SE
Issuer		
central bank	0.101***	0.022
IT or BigTech companie	0.001	0.022
Issuance form		
plastic card	0.341***	0.023
smartphone apps	0.325***	0.022
Disclosure of information type		
personal identification information	0.039*	0.023
none	0.102***	0.022
Merchant acceptance		
most(80%)	0.216***	0.022
always(100%)	0.310***	0.023
Risk of loss		
5%	0.159***	0.022
1%	0.271***	0.022
Discount rate		
3%	0.241***	0.022
5%	0.473***	0.022
Payment delay		
about one minutes	0.032	0.022
less than ten seconds	0.155***	0.022
Timing of settlement		
specific date after payment	0.106***	0.022
installment	0.091***	0.022
Monthly fee		
three thousands won	-0.371***	0.022
five thousands won	-0.614***	0.023
Number of observations	35,610	
Number of individuals	3,561	
Log-likelihood	-11,344	

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For issuer, the base value is private financial institutions. For issuance form, the base value is banknote. For disclosure of information type, the base value is transaction & personal identification information. For merchant acceptance, the base value is half (50%). Forrisk of loss, the base value is 10%. For discount rate, the base value is 0%. For payment delay, the base value is about two minutes. For timing of settlement, the base value is immediately. For monthly fee attribute, the base value is none.

Table A5: Estimation Results from Conditional Logit Models with Interaction Term

	Coefficient	SE
Issuer		
central bank	0.101***	0.022
IT or BigTech companie	0.000	0.022
Issuance form		
plastic card	0.341***	0.023
smartphone apps	0.326***	0.022
Disclosure of information type		
personal identification information	0.008	0.051
none	0.120***	0.050
Merchant acceptance		
most(80%)	0.216***	0.022
always(100%)	0.310***	0.023
Risk of loss		
5%	0.159***	0.022
1%	0.272***	0.023
Discount rate		
3%	0.230***	0.050
5%	0.472***	0.050
Payment delay		
about one minutes	0.032	0.022
less than ten seconds	0.155***	0.023
Timing of settlement		
specific date after payment	0.106***	0.022
installment	0.090***	0.023
Monthly fee		
three thousands won	-0.371***	0.022
five thousands won	-0.614***	0.023
Interaction term		
personal identification information × 3%	0.086	0.078
personal identification information × 5%	0.005	0.078
none × 3%	-0.050	0.078
none × 5%	-0.002	0.078
Number of observations	35,610	
Number of individuals	3,561	
Log-likelihood	-11,342	

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For issuer, the base value is private financial institutions. For issuance form, the base value is banknote. For disclosure of information type, the base value is transaction & personal identification information. For merchant acceptance, the base value is half (50%). For risk of loss, the base value is 10%. For discount rate, the base value is 0%. For payment delay, the base value is about two minutes. For timing of settlement, the base value is immediately. For monthly fee, the base value is none.

Table A6: Prediction of Payment Preference by Group

	Cash	Credit and Debit Card	Mobile Fast Payment	CBDC
Gender				
Male	0.179	0.481	0.150	0.190
Female	0.171	0.487	0.152	0.190
Age				
19-39	0.170	0.476	0.177	0.178
40-70	0.177	0.487	0.140	0.196
19-59	0.174	0.478	0.161	0.187
60-70	0.179	0.496	0.127	0.198
Education				
No college degree	0.178	0.473	0.150	0.197
College degree	0.172	0.493	0.152	0.182
Income				
Below 4 million KRW	0.178	0.475	0.150	0.197
Above 4 million KRW	0.172	0.493	0.152	0.182

Notes: The prediction is made based on the assignment of attribute values in Table 3 and Table 4 with Scenario 1(baseline) design of CBDC, and the estimation results reported in Figure 1.

Table A7: Prediction of Payment Preference under Nested Logit Framework: Scenario 1

	Cash	Credit Card	Debit Card	Mobile Fast Payment	CBDC
(a) Nest: Cash & Debit Card & Mobile Payment & CBDC					
	0.145	0.428	0.152	0.112	0.163
(b) Nest: Cash & Debit Card & Mobile Payment					
	0.142	0.368	0.149	0.110	0.231
(c) Nest: Cash & Debit Card & CBDC					
	0.129	0.392	0.135	0.196	0.148
(d) Nest: Cash & Debit Card					
	0.137	0.337	0.146	0.168	0.212
(e) Nest: Cash & Debit Card | Mobile Payment & CBDC					
	0.154	0.378	0.164	0.118	0.186

Notes: In (a), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment & CBDC is defined as 0.6. In (b), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment is defined as 0.6. In (c), the dissimilarity parameter τ for the nest Cash & Debit Card & CBDC is defined as 0.5. In (d), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5. In (e), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5 and the same value of the dissimilarity parameter is assumed as a representative example for the nest Mobile Payment & CBDC. The simulation is conducted based on attribute values in Table 3 and Table 4 with the Scenario 1 (Benchmark) design of CBDC.

Table A8: Prediction of Payment Preference under Nested Logit Framework: Scenario 2

	Cash	Credit Card	Debit Card	Mobile Fast Payment	CBDC
(a) Nest: Cash & Debit Card & Mobile Payment & CBDC					
	0.143	0.425	0.149	0.110	0.172
(b) Nest: Cash & Debit Card & Mobile Payment					
	0.141	0.364	0.148	0.109	0.238
(c) Nest: Cash & Debit Card & CBDC					
	0.126	0.390	0.133	0.195	0.157
(d) Nest: Cash & Debit Card					
	0.136	0.334	0.145	0.167	0.218
(e) Nest: Cash & Debit Card | Mobile Payment & CBDC					
	0.152	0.375	0.163	0.115	0.195

Notes: In (a), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment & CBDC is defined as 0.6. In (b), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment is defined as 0.6. In (c), the dissimilarity parameter τ for the nest Cash & Debit Card & CBDC is defined as 0.5. In (d), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5. In (e), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5 and the same value of the dissimilarity parameter is assumed as a representative example for the nest Mobile Payment & CBDC. The simulation is conducted based on attribute values in Table 3 and Table 4 with the Scenario 2 design of CBDC.

Table A9: Prediction of Payment Preference under Nested Logit Framework: Scenario 3

	Cash	Credit Card	Debit Card	Mobile Fast Payment	CBDC
(a) Nest: Cash & Debit Card & Mobile Payment & CBDC					
	0.139	0.421	0.146	0.108	0.186
(b) Nest: Cash & Debit Card & Mobile Payment					
	0.138	0.359	0.146	0.107	0.250
(c) Nest: Cash & Debit Card & CBDC					
	0.122	0.386	0.128	0.193	0.172
(d) Nest: Cash & Debit Card					
	0.134	0.329	0.143	0.165	0.229
(e) Nest: Cash & Debit Card | Mobile Payment & CBDC					
	0.150	0.370	0.161	0.109	0.210

Notes: In (a), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment & CBDC is defined as 0.6. In (b), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment is defined as 0.6. In (c), the dissimilarity parameter τ for the nest Cash & Debit Card & CBDC is defined as 0.5. In (d), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5. In (e), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5 and the same value of the dissimilarity parameter is assumed as a representative example for the nest Mobile Payment & CBDC. The simulation is conducted based on attribute values in Table 3 and Table 4 with the Scenario 3 design of CBDC.

Table A10: Prediction of Payment Preference under Nested Logit Framework: Scenario 4

	Cash	Credit Card	Debit Card	Mobile Fast Payment	CBDC
(a) Nest: Cash & Debit Card & Mobile Payment & CBDC	0.131	0.409	0.137	0.101	0.221
(b) Nest: Cash & Debit Card & Mobile Payment	0.133	0.346	0.140	0.104	0.277
(c) Nest: Cash & Debit Card & CBDC	0.112	0.376	0.117	0.188	0.208
(d) Nest: Cash & Debit Card	0.129	0.318	0.138	0.159	0.255
(e) Nest: Cash & Debit Card | Mobile Payment & CBDC	0.146	0.359	0.156	0.096	0.244

Notes: In (a), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment & CBDC is defined as 0.6. In (b), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment is defined as 0.6. In (c), the dissimilarity parameter τ for the nest Cash & Debit Card & CBDC is defined as 0.5. In (d), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5. In (e), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5 and the same value of the dissimilarity parameter is assumed as a representative example for the nest Mobile Payment & CBDC. The simulation is conducted based on attribute values in Table 3 and Table 4 with the Scenario 4 design of CBDC.

Table A11: Prediction of Payment Preference under Nested Logit Framework: Scenario 5

	Cash	Credit Card	Debit Card	Mobile Fast Payment	CBDC
(a) Nest: Cash & Debit Card & Mobile Payment & CBDC					
	0.116	0.386	0.121	0.090	0.287
(b) Nest: Cash & Debit Card & Mobile Payment					
	0.125	0.323	0.131	0.097	0.326
(c) Nest: Cash & Debit Card & CBDC					
	0.094	0.355	0.098	0.178	0.275
(d) Nest: Cash & Debit Card					
	0.121	0.298	0.130	0.149	0.301
(e) Nest: Cash & Debit Card | Mobile Payment & CBDC					
	0.137	0.337	0.146	0.075	0.304

Notes: In (a), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment & CBDC is defined as 0.6. In (b), the dissimilarity parameter τ for the nest Cash & Debit Card & Mobile Payment is defined as 0.6. In (c), the dissimilarity parameter τ for the nest Cash & Debit Card & CBDC is defined as 0.5. In (d), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5. In (e), the dissimilarity parameter τ for the nest Cash & Debit Card is defined as 0.5 and the same value of the dissimilarity parameter is assumed as a representative example for the nest Mobile Payment & CBDC. The simulation is conducted based on attribute values in Table 3 and Table 4 with the Scenario 5 design of CBDC.

B Questionnaire

B.1 Korean Version

The original survey questionnaire in Korean is available in the following link:

Questionnaire-Korean Version

B.2 English Version

The translated survey questionnaire in English is available in the following link:

Questionnaire-English Version

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