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Demand for Payment Services and Consumer Welfare: The Introduction of a Central Bank Digital Currency

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Abstract

In recent years, there have been rapid technological innovations in retail payments. Such dramatic changes in the economics of payment systems have led to questions regarding whether there is consumer demand for cash. The entry of these new products and services has resulted in significant improvements in the characteristics of existing methods of payment, such as tap-and-go technology or contactless credit and debit cards. In addition, the introduction of decentralized digital currencies has raised questions about whether there is a need for a central bank digital currency (CBDC) and, if so, what its essential characteristics should be. To address these questions, we develop and estimate a structural model of demand for payment instruments. Our model allows for rich heterogeneity in consumer preferences. Identification of the distribution of consumer heterogeneity relies on observing individual-level consumer decisions at the point of sale. Using parameter estimates, we conduct a counterfactual experiment of an introduction of CBDC and simulate post-introduction consumer adoption and usage decisions. We also provide insights into the potential welfare implications of the introduction of new payment instruments.

Bank topics: Bank notes; Digital currencies and fintech; Financial services
JEL codes: C51, E42, L14, L52

1 Introduction

In recent years, the rapid development of new technologies in the payment industry has attracted a lot of attention from central banks around the world. It is clear that at least some of the demand for new payment methods, including decentralized digital currencies, may be generated by early adopters experimenting with new technologies and speculators seeking returns in a highly volatile environment. However, the new technologies also carry many new features that are valued by consumers due to their enhanced convenience, privacy, or security. Therefore, it may be socially desirable to facilitate adoption of these new technologies.

In this paper, we assess the effect of introducing a digital currency issued by the central bank, as defined in Engert et al. (2018), on the demand for existing means of payment such as cash, debit cards and credit cards. In order to do so, we estimate a structural characteristics-based discrete-choice model of consumer demand for payment instruments. The model represents a consumer decision as a two-stage process. In the first stage, consumers make decisions about adopting various combinations of payment instruments. In the second stage, consumers and merchants are randomly matched at the point of sale for each transaction, and consumers choose which method of payment, modelled as a bundle of characteristics, to use given that it is accepted by the merchant. From survey data on usage and adoption of existing methods by consumers, we recover the different—perceived and actual—contributions of the product characteristics to the utility of different consumers for different transactions. This characteristics-based approach allows us to model the consumers' choice among bundles of characteristics rather than simply among unique discrete alternatives. Rich consumer heterogeneity allows us to estimate substitution patterns implied by an introduction of new products. In this paper, we do not model merchant acceptance decisions explicitly but rather hold them fixed at the observed values.[1] The model is estimated using simulated maximum likelihood based on transaction-level data.

Our estimation results show that consumers' utility is affected mostly by the transaction cost, followed by ease-of-use, affordability, and security perceptions, in order of decreasing importance. We find it is important to include consumer demographics and transaction-type variables because they can control for the unobserved quality of credit and debit cards as well as for consumer participation in various reward programs (to the extent that these are based on observable demographic characteristics). Using parameter estimates, we then conduct counterfactual simulations and welfare analysis of a newly introduced product.

As an example of a new product, we consider central bank digital currencies (CBDCs) with various levels of observed and unobserved product characteristics. We consider a uniform adoption and acceptance scenario and a scenario where consumers endogenously choose what to adopt and what

[1] An equilibrium analysis with endogenous merchant acceptance and consumer adoption decisions can be found in a companion paper, Huynh et al. (2019).

to use given the acceptance rate by merchants. By conducting these counterfactual simulations, we illustrate changes of usage frequency, adoption probability, and consumer welfare within a partial equilibrium analysis. The analysis is partial because we do not allow merchants, network providers, or card issuers and acquirers to change their decision when the new means of payment is introduced. Therefore, our welfare analysis is focused on the consumer side of the market. Estimating the cost of developing and introducing the new product is also beyond the scope of this paper, but obviously the estimated benefits should be balanced against these costs.

Our counterfactual simulations suggest that a new payment method can be used at the point of sale (POS) with probabilities ranging between 0.19 and 0.25. We find that high level of CBDC adoption does not necessarily imply high usage probabilities, i.e., consumers may choose to have a payment instrument but not use it. Consistently with the parameter estimates, transaction cost is the main characteristic that can make a new payment instrument attractive for consumers. The introduction of a new product can improve consumer welfare on average by 0.60 CAD to 1.63 CAD per month, depending on its characteristics and the assumptions about merchant acceptance decisions. We illustrate the overall change in consumer welfare as well as the change in welfare of particular demographic groups defined by income, age, and education. Overall, our conclusion is that a CBDC that combines only the existing features of cash and debit would have to be significantly better in terms of consumer perceptions and the transaction cost to completely replace existing payment methods, even with full consumer adoption and merchant acceptance. Even though most Canadians already have access to banking services, the CBDC would have a small but significant welfare benefit. These benefits have to be compared with the costs of development and introduction and other potential macroeconomic consequences.

This paper is related to a small but growing literature on consumer payment choice. Wakamori and Welte (2017) explore the reasons for shoppers to use cash at the payment register and found that even if all merchants are forced to accept cards, cash use would decrease by only 8 percentage points, indicating that many other characteristics explain cash use at the point of sale. Schuh and Stavins (2010) use a reduced-form control function approach to pick out the determinants of cheque decline in the U.S. Koulayev et al. (2016) develop a rich structural model of the two-step payment choice and use it to determine the response of consumers to a change in payment card fees. Shy (2019) analyzes the effect of eliminating cash on welfare by estimating a discrete-choice model on payment method usage with U.S. data. Network effects and merchant payment choice are discussed in the literature on platform competition and equilibrium fees (see, for example, Rochet and Tirole 2003). An important empirical work on network effects in payments is Rysman (2007), which establishes a feedback loop between consumer usage and merchant acceptance, a necessary condition for the two-sidedness of a market. Bounie et al. (2016) provide a summary of empirical research involving network effects in a merchant payment choice context.[2] Finally, this research is

[2] See Loke (2007), Arango and Taylor (2008), Jonker (2011), Carbo-Valverde et al. (2012).

related to the literature on new product introduction. Ackerberg et al. (2007) survey the literature on the use of characteristics-based demand systems to analyze the effect of either price changes or new products on consumer welfare. In the method of payments context, Borzekowski and Kiser (2008) estimate a characteristics-based demand system for U.S. data and predict the usage market share of new contactless payment methods designed to replace debit cards. This paper estimates a characteristics-based discrete-choice model of both adoption and usage of existing payment methods with random coefficients to better capture consumer tastes and use the estimates to analyze the effect of introducing a new payment method in Canada.

The rest of the paper is organized as follows. Section 2 describes the institutional environment in the Canadian payment industry and available data. It also provides summary statistics for the key variables used in our empirical analysis. In Section 3, we develop a structural model of consumer demand for payment methods, representing it as a two-stage decision process. Section 4 summarizes the estimation results. Counterfactual simulations and welfare analysis are summarized in Section 5. Section 6 concludes.

2 Survey Data and Market Structure

For this study, we use the Bank of Canada's Methods-of-Payment Survey, collected in 2009, 2013 and 2017; see Arango and Welte (2012), Henry et al. (2015), Henry et al. (2018). These surveys are nationally representative. Besides demographics, and perceived and actual attributes of payment methods, they also track shopping in three-day diaries at the individual level; see Henry et al. (2018). Each participant's diary contains multiple transactions that are different in terms of shopping types, transaction values, and the type of product purchased. The data include POS transactions only (i.e., no online or peer-to-peer transactions). For each survey year we observe data from a survey questionnaire (SQ) containing information on consumer adoption decisions and perceptions regarding various product attributes. The SQ also provides rich consumer demographics, such as age, gender, income, education, and marital status. In the 2009 survey, we also observe realized merchant acceptance decisions at the POS for each transaction. For 2013 and 2017, we observe only whether the merchant is a cash-only business. Therefore, we use average merchant acceptance probabilities by transaction type (to integrate over possible realizations) for each payment method unless the merchant is cash-only or if the transaction was made by credit card (assuming that those merchants who accept credit cards at the POS accept debit cards as well). Each of the SQs is supplemented by a diary, where consumers record their POS transactions over a three-day period. In our sample, more than 90 percent of transactions were conducted using one of cash, debit cards, or credit cards. Since our focus is on the POS transactions, we do not consider other payment instruments such as cheques and various online transfers.

Summary statistics for the key variables used in estimation are provided in Tables 1 and 2. Table 3 reports consumer demographics. Table 4 reports transaction types. Note that our data are not a panel but rather a repeated cross-section, where in 2009, 2013, and 2017, we observe a three-day diary and an SQ per respondent. The respondents are not the same across years.

Table 1: Summary statistics for transaction and payment instruments

Variable	Mean	Median	Min	Max	Std. Dev.
Transactions recorded over three days					
number of transactions	6.56	6.00	1.00	35.00	3.42
transaction price	31.80	18.00	0.10	300.00	40.85
Cash attributes (categorical)					
ease-of-use (↑ easier)	4.60	5.00	1.00	5.00	0.82
affordability-of-use (↑ cheaper)	4.49	5.00	1.00	5.00	0.93
security (↑ safer)	4.06	4.00	1.00	5.00	1.11
transaction cost (↑ costlier)	2.13	1.70	1.23	17.40	1.36
Debit card attributes (categorical)					
ease-of-use (↑ easier)	4.50	5.00	1.00	5.00	0.80
affordability-of-use (↑ cheaper)	3.73	4.00	1.00	5.00	1.13
security (↑ safer)	3.75	4.00	1.00	5.00	1.03
transaction cost (↑ costlier)	5.40	5.39	5.37	5.58	0.03
Credit card attributes (categorical)					
ease-of-use (↑ easier)	4.51	5.00	1.00	5.00	0.80
affordability-of-use (↑ cheaper)	3.19	3.00	1.00	5.00	1.36
security (↑ safer)	3.59	4.00	1.00	5.00	1.09
transaction cost (↑ costlier)	0.59	0.59	0.59	0.60	0.00

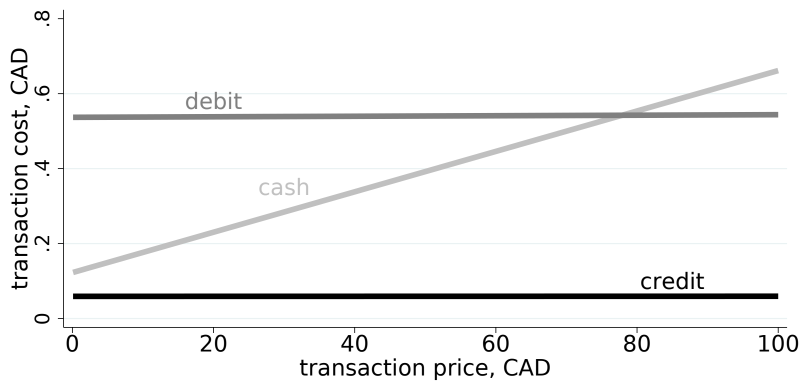
Notes: In estimation, we standardize perception variables. The transaction cost variable is calculated for each transaction as $c_{j,m}(p_j) = c_{0,m} + c_{1,m}p_j$, where p_j is transaction value, and $(c_{0,m},\ c_{1,m})$ are per-transaction and per-value costs estimated using survey data on costs of payment methods. For all but the transaction cost variable, we expect positive marginal effects.

The variables in Table 1 will be included in the set of explanatory variables denoted with X_{bmj}. Note that all but the transaction cost variables are categorical. Perceived ease-of-use, affordability-of-use and security are measured on a five-point scale, with larger values implying easier, less costly, and more secure usage of a given payment instrument, respectively. On average, cash is easier to use than credit, which is easier to use than debit. The affordability-of-use variable measures how affordable it is to use a given payment method. For example, larger values for cash (4.49) than for credit (3.19) or debit (3.73) imply that on average, respondents believe transacting in cash is cheaper. The transaction cost variable is the only monetary variable in our estimation. It is calculated for each transaction of every consumer as a linear function of the transaction price,

$$\text{Transaction Cost}_{b,j,m} = c_{0,m} + c_{1,m} p_{b,j}, \tag{1}$$

where $(c_{0,m}, c_{1,m}),\ m \in \{ca, dc, cc\}$ are the estimates of per-transaction and per-value costs for each payment instrument including cash, debit and credit cards.[3] Figure 1 illustrates consumer transaction costs as functions of transaction price. Note that credit on average appears to be the cheapest means of payment for consumers.

Figure 1: Consumer cost functions for each payment method



In estimation, we use the relative perception variables to make comparing the marginal effects easier. Similar to Arango and Taylor (2008)[4] approach, we normalize all perception variables by the sum of the individual's perception levels across payment methods.

At the POS, we restrict consumer choice to the set of payment instruments that are both adopted by this consumer in the first stage and accepted by the merchant. By integrating over the likely realizations of a random-matching process, we allow consumers to form expectations and subsequent valuation of alternative combinations of payment instruments. These valuations are then translated into consumer adoption decisions.

Summary statistics in Table 2 suggest that most consumers (89 percent in 2017) adopt all three means of payment. In our sample, we observe about 14 percent of cash-only merchants in 2009 and 12 and 11 percent in 2013 and 2017, respectively. There is a small and declining fraction of merchants accepting cash and debit cards only (less than 5 percent). In 2009, about 81 percent of businesses report accepting all three payment instruments. In 2013 and 2017, the number of such merchants increases to 85 and 86 percent, respectively. Over time, the frequency of cash usage has declined from 53 to 34 percent. Usage of debit cards remained relatively stable. Over the same period, we observe a significant increase in credit card usage.

[3]Details of the estimation can be found in Kosse et al. (2017).

[4]We normalize by the formula $X_{ca,normalized} = \frac{X_{ca}}{X_{ca}+X_{dc}+X_{cc}}$.

Table 3 summarizes the demographic variables used in our empirical analysis. Table 4 summarizes the usage of payment methods by year and by transaction types. The share of cash payments decreases over time in every transaction type, but from different starting points. In 2017, consumers' use of cash is the lowest for gasoline (13 percent), personal attire (20 percent), durable goods (22 percent), and health care (24 percent). Cash has the highest share in travel/parking (47 percent), but we also observe the biggest drop of cash share in this type of transaction (from 84 percent share in 2009). Professional and personal services and entertainment and meals transactions also have a relatively high cash share, but each has dropped significantly (from 56 to 45 percent and from 69 to 43 percent, respectively, from 2009 to 2017).

Table 2: Average adoption, acceptance and usage decisions by year

Variable	2009	2013	2017
Consumer adoption decisions, $\mathcal{M}_b \in \{0,1\}$			
cash only	0.01	0.03	0.01
cash and debit	0.14	0.10	0.10
cash, debit, and credit	0.85	0.86	0.89
Merchant acceptance decisions, $\mathcal{M}_s \in \{0,1\}$			
cash only	0.14	0.12	0.11
cash and debit	0.05	0.03	0.03
cash, debit, and credit	0.81	0.85	0.86
Observed usage decisions, $d_{b,m,j} \in \{0,1\}$			
use cash	0.53	0.44	0.34
use debit	0.25	0.23	0.25
use credit	0.21	0.33	0.41

Notes: All variables but merchant acceptance are discrete and take value 1 if adoption or usage decision is positive, and 0 otherwise. For merchant acceptance, we observe exact choice for 2009. For 2013 and 2017, we observe only whether a merchant is cash only. In cases where the transaction is made by credit card, we assume that the merchant accepts all cards. In cases where the transaction is made by debit card, we use the average probability of accepting cash, debit, and credit card by transaction type in 2009.

Table 3: Summary statistics for demographic variables in 2009, 2013, 2017

Variable	Mean	Median	Min	Max	Std. Dev.
Age	46.71	47.00	18.00	99.00	16.10
Income	64,899.47	55,000.00	0.00	225,000.00	49,131.61
Credit score	746.42	766.53	310.00	881.67	110.71
Education	3.54	3.00	1.00	6.00	1.40
Urban	0.82	—	—	—	0.38
Female	0.52	—	—	—	0.50
Employed	0.45	—	—	—	0.50
Married	0.55	—	—	—	0.50
Smartphone	0.42	—	—	—	0.49

Notes: Urban, Female, Employed, Married and Smartphone ownership are categorical; therefore, we omit the minimum, maximum, and median statistics.

Table 4: Shares of payment method usage by transaction type

Transaction Type	2009			2013			2017		
	cash	debit	credit	cash	debit	credit	cash	debit	credit
Groceries/Drugs	47	32	21	39	26	34	30	28	42
Gasoline	29	30	40	20	29	51	13	27	60
Personal Attire	28	33	39	25	29	46	20	23	58
Health Care	37	27	36	35	27	38	24	24	52
Hobby/Sporting Goods	45	28	26	41	19	40	37	21	42
Professional/Personal Services	56	21	23	45	16	39	45	14	42
Travel/Parking	84	6	10	61	10	29	47	10	42
Entertainment/Meals	69	19	12	59	18	23	43	24	33
Durable Goods	32	28	40	30	26	45	22	20	58
Other	69	18	14	55	20	25	47	21	32

Source: Bank of Canada, Methods-of-Payment Surveys DSI 2009, 2013, 2017

3 Discrete-Choice Demand Model

Drawing from Huynh et al. (2019), we consider a market populated by consumers, $b = 1, \dots, N_b$, who differ with respect to their observable demographic characteristics such as age, gender, income, and education. Each consumer is endowed with a set of transactions to complete, $\mathcal{J}_b$, where the transactions vary by type (e.g., grocery, electronics, personal service providers) and value (price).

We assume $\mathcal{J}_b$ is given exogenously and that consumers have inelastic demand for transactions, i.e., all of them must be completed.

Every period, consumers make decisions about adoption and usage, which are made sequentially in the first and second stages, respectively. It is clear that adoption and usage decisions are interrelated because a consumer is more likely to choose a payment instrument that is expected to be used more often. We begin our discussion with the second (usage) stage, which provides the necessary ingredients for the first stage of adoption.

Second (usage) stage. In the second stage, we model consumer usage decisions. Our unit of observation is a transaction $j \in \mathcal{J}_b$ conducted at the POS by a consumer b. Each transaction can be conducted by one of the means of payment, including cash, debit card, and credit card. Let $\mathcal{M} \in \big\{\{ca\}, \{ca, dc\}, \{ca, dc, cc\}\big\}$ denote a set of all combinations of payment instruments potentially available to consumers, $\mathcal{M}_b$, and merchants, $\mathcal{M}_s$. We use subscript $m \in \mathcal{M}$ to index individual methods of payment and assume a consumer b's indirect utility function for a transaction j executed with method m has the following form:

$$\begin{aligned} U(X_{bmj}, Z_{bj}; \theta) &= X_{bmj}\beta + Z_{bj}\alpha_m + \varepsilon_{bmj} \\ &= \delta_{bmj} + \varepsilon_{bmj}, \end{aligned} \tag{2}$$

where $\theta = (\beta, \alpha_m)$, $X_{bmj} \in \mathbb{R}^k$ denote observable method-specific characteristics of transaction $j \in \mathcal{J}_b$, Z_{bj} are consumer-transaction-specific characteristics such as demographics and transaction type, and $\varepsilon_{bmj} \overset{iid}{\sim} F_\varepsilon$ are random innovations to the consumer utility at the POS. We make the following distributional assumption.

Assumption 1: *Random innovations to consumer utility function at the POS are independent, identically distributed innovations from standard Gumbel distribution with density*

$$f(\varepsilon_{bmj}) = \exp(-\varepsilon_{bmj}) \times \exp(-\exp(-\varepsilon_{bmj})).$$

In the second stage, consumers are randomly matched with merchants for each transaction, and consumers maximize utility by choosing a payment instrument from the set $\mathcal{M}_b \cap \mathcal{M}_s$. Let $P_{\mathcal{M}_s}$ denote the probability that a merchant accepts combination $\mathcal{M}_s$. Then, the second-stage consumer problem for transaction j can be written as:

$$
\begin{aligned}
\mathbb{E}[U_{bj}|\mathcal{M}_b] &= \sum_{\mathcal{M}_s} P_{\mathcal{M}_s} \times \mathbb{E} \max_{m' \in \mathcal{M}_b \cap \mathcal{M}_s} \{\delta_{bm'j} + \varepsilon_{bm'j}\} \\
&= \sum_{\mathcal{M}_s} P_{\mathcal{M}_s} \times \ln \left(\sum_{m' \in \mathcal{M}_b \cap \mathcal{M}_s} \exp(\delta_{bm'j}) \right),
\end{aligned} \tag{3}
$$

where the last equality follows from the properties of the Gumbel distribution. We assume that consumers have rational expectations and their beliefs about merchant acceptance decisions are consistent with the realizations of these decisions. In the notes for Table 2, we discuss data limitations, where we do not observe the exact merchant acceptance decision (unless the merchant is cash only) for 2013 and 2017.

Given δ_{bmj}, we can compute the expected probability that a transaction is executed using payment instrument m as a function of the consumer first-stage adoption choice. Define:

$$
\Lambda_{m2}\big(\delta_{bmj}, \delta_{bkj}\big) \equiv \frac{\exp(\delta_{bmj})}{\exp(\delta_{bmj}) + \exp(\delta_{bkj})}
$$

to represent the probability that method m is chosen by the consumer out of a two-instrument set, $\mathcal{M}_b \cap \mathcal{M}_s$.[5] Consider the conditional probability that cash is used if the first-stage consumer choice is $\mathcal{M}_b = \{ca, dc\}$,

$$
\Pr\big(j, ca | \mathcal{M}_b = \{ca, dc\}\big) = \Pr(\mathcal{M}_s = ca) + \begin{bmatrix} \Pr(\mathcal{M}_s = \{ca, dc\}) + \\ \Pr(\mathcal{M}_s = \{ca, dc, cc\}) \end{bmatrix} \times \Lambda_{ca,2}\big(\delta_{b,ca,j}, \delta_{b,dc,j}\big), \tag{4}
$$

while the probability that debit card is used instead becomes

$$
\Pr\big(j, dc | \mathcal{M}_b = \{ca, dc\}\big) = \begin{bmatrix} \Pr(\mathcal{M}_s = \{ca, dc\}) + \\ \Pr(\mathcal{M}_s = \{ca, dc, cc\}) \end{bmatrix} \times \Lambda_{dc,2}\big(\delta_{b,dc,j}, \delta_{b,ca,j}\big). \tag{5}
$$

Probabilities for other cases are calculated similarly. Note that in the case when both a consumer and a merchant in the first stage choose to have all three payment instruments, i.e., when $\mathcal{M}_b \cap \mathcal{M}_s = \{ca, dc, cc\}$, calculations would involve the probability of choosing m out of three alternatives, i.e., $\Lambda_{m3}(\delta_{bmj}, \delta_{blj}, \delta_{bhj})$.

Using these probabilities, we construct the second (usage) stage likelihood function conditional on the first-stage consumer adoption decision as follows:

[5] Note that if a merchant is a cash-only business, the only way to complete a transaction is cash, and the probability of using it is 1.

$$\mathcal{L}(\beta) = \prod_{b=1}^{N_b} \prod_{j \in \mathcal{J}_b} \Pr(j, ca|\mathcal{M}_b)^{d_{b,ca,j}} \times \Pr(j, dc|\mathcal{M}_b)^{d_{b,dc,j}} \times \Pr(j, cc|\mathcal{M}_b)^{d_{b,cc,j}}, \tag{6}$$

where $d_{b,m,j} = 1$ if m is used and 0 otherwise. Since consumers can choose only one means of payment for each transaction, it must be the case that $\sum_{m' \in \mathcal{M}_b} d_{b,m,j} = 1$. We use data from consumer diary surveys for 2009, 2013, and 2017 to estimate parameters of the usage stage.

First (adoption) stage. Equation (3) defines the expected maximum utility a consumer can derive from each transaction in the case of the first-stage adoption choice $\mathcal{M}_b$. Consumers in our data are heterogeneous with respect to the set of transactions, $\mathcal{J}_b$. Let J_b denote cardinality of this set and consider maximum gross utility for a consumer b, defined as:

$$EU_b(\mathcal{M}_b) = \sum_{j=1}^{J_b} \mathbb{E}[U_{bj}|\mathcal{M}_b]. \tag{7}$$

We assume that adoption decisions are costly. Let $F_{b,\mathcal{M}_b}$ denote the cost of adoption for combination $\mathcal{M}_b$. By allowing for bundle-specific costs of adoption, we account for possible economies of scope, e.g., when banks offer bundles of debit and credit cards. We make the following simplifying assumption.

Assumption 2: *Adoption costs $F_{b,\mathcal{M}_b}$ are given by*

$$F_{b,\mathcal{M}_b} = \begin{cases} \bar{F}_{\mathcal{M}_b} - \epsilon_{b,\mathcal{M}_b}, & \textit{if } \mathcal{M}_b = \{ca, dc\} \textit{ or } \mathcal{M}_b = \{ca, dc, cc\} \\ -\epsilon_{b,0}, & \textit{if } \mathcal{M}_b = \{ca\}, \end{cases}$$

where $\epsilon_{b,\mathcal{M}_b}$ are iid draws from standard Gumbel distribution.

Therefore, total consumer utility if bundle $\mathcal{M}_b$ is chosen in the first stage is given by

$$EU_{1b}(\mathcal{M}_b) = EU_b(\mathcal{M}_b) - F_{\mathcal{M}_b} + \epsilon_{b,\mathcal{M}_b}, \tag{8}$$

where $EU_b(\mathcal{M}_b)$ is defined in equation (7).

To estimate parameters of the adoption cost distribution, we construct the following first-stage likelihood function:

$$
\begin{aligned}
\mathcal{L}(\bar{F}) = \prod_{b=1}^{N_b} \Pr\Big(ca = \underset{\mathcal{M}'_b \in \mathcal{M}}{\arg\max}\{EU_b(\mathcal{M}'_b)] - F_{\mathcal{M}'_b}\}\Big)^{D_{b,\{ca\}}} \\
\times \Pr\left(\{ca, dc\} = \underset{\mathcal{M}'_b \in \mathcal{M}}{\arg\max}\{EU_b(\mathcal{M}'_b)] - F_{\mathcal{M}'_b}\}\right)^{D_{b,\{ca,dc\}}} \\
\times \Pr\left(\{ca, dc, cc\} = \underset{\mathcal{M}'_b \in \mathcal{M}}{\arg\max}\{EU_b(\mathcal{M}'_b)] - F_{\mathcal{M}'_b}\}\right)^{D_{b,\{ca,dc,cc\}}},
\end{aligned}
\tag{9}
$$

where $EU_b(\mathcal{M}_b)$ is defined in equation (7) and $D_{b,\mathcal{M}_b}$ is the observed adoption decision. Since we allow consumers to consider all feasible combinations of payment instruments, it must be the case that $\sum_{\mathcal{M}'_b \in \mathcal{M}} D_{b,\mathcal{M}'_b,j} = 1$. In estimation, we use data from consumer SQs for 2009, 2013, and 2017.

It is worth noting that parameter values in the second stage of the model affect the first-stage likelihood function. Hence, there are efficiency gains in estimating structural parameters in both stages jointly. Consistent with assumptions 1 and 2, the joint likelihood function is just a product of stage-specific likelihood functions (6) and (9).

3.1 Empirical specifications

In the second stage, our goal is to estimate consumer preference parameters $\theta = (\beta, \alpha_m)$. In the data, we observe stated consumer preferences regarding ease-of-use, perceived affordability-of-use, security and estimated monetary cost of transacting for each payment instrument. In addition, we also observe whether a consumer reports participation in a credit card reward program as a dummy variable.[6] These variables are included in vector X_{bmj}.

While we control for the participation in a credit card reward program by including a corresponding dummy variable, we do not observe the "quality" of such programs. For example, cash-back rewards may have different returns depending on the type of transaction (e.g., grocery versus gasoline purchase). It is conceivable that consumers with different levels of income or employment status have debit and credit cards with alternative structures of fees and reward levels, explored further in Arango et al. (2015). For example, per-transaction fees for debit and credit cards may vary with the type of card. To control for these factors, which we did not observe but which are factors important for consumer usage choice, we include a vector of demographic and transaction-specific variables, Z_{bj}. In particular, Z_{bj} includes education, employment status, income, gender, marital status, and transaction type and year dummy variables.

Our baseline specification estimates marginal utilities for observable product characteristics, β, a vector of method-specific coefficients on buyer and transaction-specific variables, α_m, and two adoption cost parameters, $(F_{ca,dc}, F_{ca,dc,cc})$. Below, we extend the model along two dimensions by

[6] We assume that for cash and debit cards, the reward program dummy takes a value of 0.

introducing random marginal utilities and including an observable consumer credit score variable into the first specification for adoption costs. We discuss these extensions next.

Random coefficients. Random coefficients are often used in demand estimation to allow for more realistic substitution patterns, when a consumer tends to substitute between products with similar characteristics. To introduce this additional flexibility into substitution patterns of individual consumers, we allow for random marginal utilities for each of the k observed characteristics. In particular, we make the following parametric restriction on the vector of marginal utilities.

Assumption 3: *The vector of marginal utilities, β_b, is given by iid draws from the joint normal distribution with a vector of means and a diagonal covariance matrix to estimate, i.e.,*

$$\beta_b \overset{iid}{\sim} N \begin{pmatrix} \beta_1 & \sigma_1^2 & \dots & 0 \\ \vdots\,, & & \ddots & \\ \beta_k & 0 & \dots & \sigma_k^2 \end{pmatrix} \; s.t. \; \beta_b \perp X_{bmj}.$$

To estimate the random coefficients version of the model, we update the conditional choice probabilities defined in equations (4) and (5) as well as the expected maximum in equation (7) by integrating over a set of simulated consumers represented by random draws from the joint normal distribution.[7]

Credit score. Credit score and adoption probability are likely to be related. For example, a consumer with a lower credit score may have a lower chance of being approved for a credit card and/or receive less attractive terms for debit and credit cards (e.g., fees or limit on the number of free debit card transactions, or a smaller credit line). We assume a linear effect of the credit score and allow for different coefficients for two adoption combinations. In other words, we update assumption 2 by assuming that $F_{b,\mathcal{M}_b}$ becomes

$$F_{b,\mathcal{M}_b} = \begin{cases} \bar{F}_{\mathcal{M}_b} + \gamma_{\mathcal{M}_b} CS_b - \epsilon_{b,\mathcal{M}_b}, & \text{if } \mathcal{M}_b = \{ca, dc\} \text{ or } \mathcal{M}_b = \{ca, dc, cc\}, \\ -\epsilon_{b,0}, & \text{if } \mathcal{M}_b = \{ca\}. \end{cases}$$

While we don't observe credit scores for each consumer in the survey, we use a nearest neighbour estimator (based on the reported banking information and demographics) to impute their credit scores using the TransUnion credit registry.

[7]In practice, we use a pure frequency simulator with 500 random draws.

4 Estimation Results

Table 5 summarizes results from three specifications. Specification (1) assumes homogeneous preferences for ease-of-use, affordability, security, and transaction cost characteristics of payment instruments. Credit card reward is also assumed to have a homogeneous effect on the utility from usage. First-stage parameters include average bundle costs for each bundle of payment methods, $\bar{F}_{ca,dc}$ and $\bar{F}_{ca,dc,cc}$. Specification (2) introduces heterogeneity in consumer preferences by adding random coefficients on the key characteristics of payment methods. In particular, we allow consumer preferences for affordability, security, and transaction cost to be normally distributed as per assumption 3.[8] Finally, specification (3) extends the first-stage of specification (2) by allowing first-stage adoption costs/benefits to be functions of the consumer credit score. All specifications include a vector of demographic and transaction-specific variables, Z_{bj}.

Estimation results suggest that accounting for consumer heterogeneity is important. Our estimates suggest consumers receive net benefits when choosing to bundle cash with debit and credit cards. These benefits are independent of the number of transactions and may represent the ability to conduct online purchases and the ability to make/receive other electronic payments, which is not accounted for in the second stage of the model.[9] Consumers who adopt a credit card in addition to cash and debit receive larger fixed benefits. Our intuition is that in addition to online transactions, credit cards also provide lines of credit and the ability to borrow, which is beneficial for many consumers.

Allowing first-stage adoption costs/benefits to depend on the consumer credit score improves model fit, and the parameter estimates suggest that a higher credit score reduces adoption cost (increases adoption benefit) for consumers choosing all three payment methods. This is consistent with the intuition that consumers with higher credit scores are more likely to get approval for credit cards or get a better card on average. At the same time, having a higher credit score, when choosing cash and debit combination only, reduces adoption benefits, but only slightly. This finding is a bit counterintuitive. One possible explanation is that consumers who (despite their high credit score and hence better chances of receiving a decent credit card) choose not to have a credit card tend to have lower benefits from electronic payment methods in general. For example, these consumers may have stronger preference for using cash or cheques (i.e., conduct more transactions using these alternative payment methods), perhaps due to anonymity, privacy, or security concerns.

[8] We also experimented with adding random coefficients on the ease-of-use and the reward status variables. The estimates of standard deviations for these variables turn out to be not statistically different from 0, suggesting homogeneous preferences along these dimensions.

[9] While there is no theoretical difficulty of including online transactions in the second stage, available data contain only POS transactions.

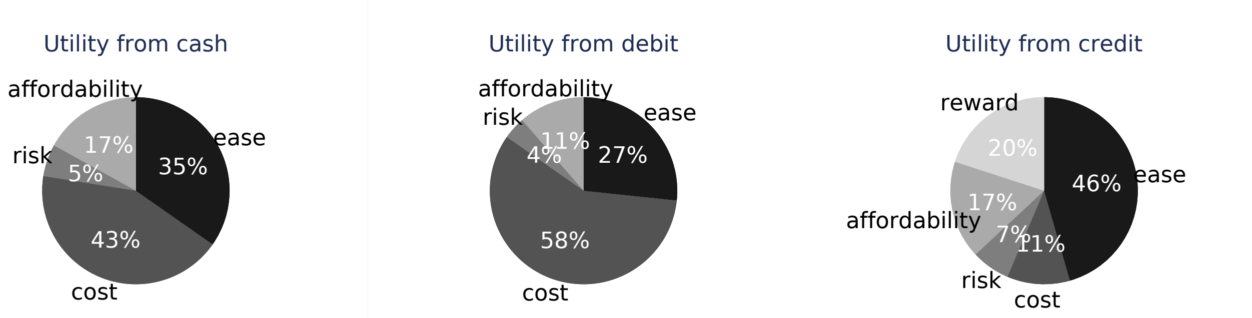
Table 5: Estimation results

Variable	Conditional logit	Mixed logit			
	(1)	(2)		(3)	
	coef.	coef.	s.d	coef.	s.d.
Ease-of-use (↑ easier)	6.380	7.144	—	7.078	—
(s.e.)	(0.219)	(0.243)	—	(0.242)	—
Affordability (↑ cheaper)	2.459	3.058	2.672	3.041	2.590
(s.e.)	(0.096)	(0.118)	(1.556)	(0.117)	(1.161)
Security (↑ safer)	0.845	1.059	2.615	1.040	2.497
(s.e.)	(0.107)	(0.130)	(1.191)	(0.129)	(1.251)
Reward	1.117	1.384	—	1.323	—
(s.e.)	(0.025)	(0.030)	—	(0.029)	—
Transaction cost	-0.878	-0.964	0.302	-0.959	0.296
(s.e.)	(0.004)	(0.005)	(0.022)	(0.005)	(0.022)
$\bar{F}_{ca,dc}$ (cash & debit)	-1.309	-1.326	—	-1.685	—
(s.e.)	(0.135)	(0.135)	—	(0.134)	—
$\bar{F}_{ca,dc,cc}$ (all)	-2.249	-2.147	—	1.450	—
(s.e.)	(0.130)	(0.130)	—	(0.130)	—
$\gamma_{ca,dc}$ credit score ('00)	—	—	—	0.065	—
(s.e.)	—	—	—	(0.019)	—
$\gamma_{ca,dc,cc}$ credit score ('00)	—	—	—	-0.495	—
(s.e.)	—	—	—	(0.018)	—
Demo & trans. controls, Z_{bj}	yes	yes		yes	
NLL	28,649.06	28,602.62		28,420.03	
AIC	57,416.12	57,333.24		56,972.06	
BIC	57,915.72	57,875.18		57,530.94	

Notes: We report the estimates from both stages of the adoption equation. Estimates of only second stage are available in a technical appendix. Each specification includes a large vector of demographic- and transaction-specific variables. We report parameter estimates for these variables in Appendix A. A negative estimate of the fixed cost parameter implies benefit of adoption. Specification 1 is based on conditional logit and does not use random coefficients, while specifications 2 and 3 include random coefficients.

Figure 2 illustrates the average contribution of five key variables to the consumer utility function. For transactions made with cash and debit card, actual transaction costs and perceived ease-of-use are the most important factors. For transactions made with credit card, the contribution of the ease-of-use is followed by the contribution of reward programs, with the actual transaction costs being the fourth important factor.

Figure 2: Contributions of various factors to consumer utility



Notes: Each pie chart illustrates average relative contributions of ease-of-use, perceived affordability, security, transaction cost, and reward variables to consumer utility function. The contributions are averaged across all consumers and transactions made by a given payment method and are calculated as $\mathbb{E}[\beta_x X_{bj}]$.

Table 6 summarizes elasticity of usage and adoption probabilities with respect to the variables measuring key perception and monetary characteristics. The first three rows, labelled "CA", "DC", and "CC", report own and cross-variable elasticity measures for usage probability, while the last three rows report elasticity of adoption combinations with respect to the variables of interest.

Table 6: Elasticity of usage and adoption probabilities

	Ease			Affordability			Risk			Transaction cost		
	CA	DC	CC	CA	DC	CC	CA	DC	CC	CA	DC	CC
CA	1.25	-0.51	-0.78	0.65	-0.23	-0.31	0.20	-0.07	-0.10	-1.40	0.86	0.18
DC	-0.54	1.32	-0.86	-0.27	0.56	-0.31	-0.08	0.19	-0.12	0.36	-2.51	0.17
CC	-0.50	-0.44	0.91	-0.23	-0.18	0.32	-0.07	-0.06	0.13	0.42	0.89	-0.23
$\mathcal{M}_s = ca$	7.38	-2.78	-4.93	3.51	-1.20	-1.85	1.07	-0.40	-0.70	-9.69	4.85	1.26
$\mathcal{M}_s = ca, dc$	2.00	2.81	-4.93	0.95	1.11	-1.85	0.30	0.41	-0.70	-2.69	-6.42	1.26
$\mathcal{M}_s = ca, dc, cc$	-0.07	-0.06	0.12	-0.03	-0.02	0.04	-0.01	-0.01	0.02	0.07	0.15	-0.04

To provide the monetary equivalent of the adoption costs, we use the parameter estimate on the variable measured in dollars. Since our transaction cost variable directly measures the responses of buyers to monetary cost, the coefficient on this variable can be used to translate between utility values and monetary values. To calculate the monetary value of the first-stage adoption costs, we divide them by the coefficient estimate on the transaction cost variable and summarize the results in Table 7.

Table 7: Estimates of first-stage consumer monthly adoption benefits over cash only, CAD 2017

	(1)	(2)	(3)
Debit	1.49	1.38	$1.76 - 0.07CS/100$
Debit and credit	2.56	2.23	$-1.51 + 0.52CS/100$

Notes: Monetary values of monthly adoption costs are obtained by dividing the adoption cost parameter estimate by the coefficient on transaction cost variable. Specification 5 bundle adoption benefit is a function of each consumer's credit score.

To provide some intuition for how credit score affects adoption benefits, consider consumers with a credit score of as low as 360 or as high as 780. For a consumer with a low credit score, adopting a cash and debit combination would bring about CAD 1.51 per month, while a consumer with a high credit score would receive CAD 1.21 by adopting the same combination. Note that the high-score consumer receives lower benefits from adopting a cash and debit combination than a low-score consumer. This pattern is reversed for a combination of cash, debit, and credit. In particular, a low-score consumer would get only about CAD 0.36, while a high-score consumer would enjoy CAD 2.55 in benefits if adopting all means of payments.

5 Counterfactual Simulations

In the counterfactual simulations, we introduce a new payment method, CBDC, with known characteristics $X_{b,cbdc,j}$ and demographic control parameters β_{cbdc}. We consider two counterfactual scenarios: (1) universal adoption/acceptance and (2) non-universal adoption/acceptance. Under the universal adoption/acceptance scenario, CBDC becomes a part of every consumer adoption combination and every merchant acceptance bundle. In other words, the set of all possible combinations of payment instruments becomes $\tilde{\mathcal{M}} = \{\{ca, cbdc\}, \{ca, dc, cbdc\}, \{ca, dc, cc, cbdc\}\}$.

In the case of non-universal adoption/acceptance of the new payment instrument, we allow consumers to adopt one of six possible combinations given by $\mathcal{M} \cup \tilde{\mathcal{M}}$; i.e., in addition to three factual combinations of payment instruments, $\mathcal{M}$, we included three choices given by $\tilde{\mathcal{M}}$. Since we do not model merchant acceptance decisions explicitly, we make an assumption that merchants accept the new payment instrument with probability $r \in (0, 1)$. In particular, we assume that out of six possible choices in $\mathcal{M} \cup \tilde{\mathcal{M}}$, merchants choose to accept $\mathcal{M}_s \in \mathcal{M}$ with probability $(1 - r) \times P_{\mathcal{M}_s}$ and choose to accept $\mathcal{M}_s \cup cbdc$ with probability $r \times P_{\mathcal{M}_s}$, where $P_{\mathcal{M}_s}$ is the factual probability observed in our data. Then, by varying the hypothetical CBDC penetration rate for merchants r, we evaluate consumer response in terms of the adoption and usage probabilities.

To construct a hypothetical new product, we explore three alternative forms of CBDC. First, we assume the new instrument is identical to cash in every dimension. This case serves as an approximation to a token-based coin with decentralized clearing and usage patterns similar to cash. Second, we simulate introduction of an account-based CBDC that has characteristics of a debit card. Third, we simulate the most optimistic scenario, when the new payment instrument combines the best features of cash and debit cards. It is worth noting that the last scenario should at best be considered as an upper bound on the outcomes that can be achieved by introducing CBDC. In each of the counterfactual simulations, our focus is on the new adoption and usage probabilities and the resulting change in consumer welfare. We measure consumer welfare as the expected consumer surplus, where the expectation is taken over random innovations at the POS and the likely merchant acceptance decisions.

Consumer surplus. In the first stage, consumer utility is given by equation (8). Then, the expected consumer surplus in the two-stage model can be calculated as follows:

$$\begin{aligned} E_u(CS_b) &= \mathbb{E}_\epsilon \left[\max_{\mathcal{M}'_b} \left\{ EU_b(\mathcal{M}'_b) - F_{\mathcal{M}'_b} + \epsilon_{\mathcal{M}'_b} \right\} \right] \\ &= \ln \left[\sum_{\mathcal{M}'_b} \exp \left(EU_b(\mathcal{M}'_b) - F_{\mathcal{M}'_b} \right) \right], \end{aligned} \tag{10}$$

which is expressed in utils. To express consumer surplus in monetary values, we divide the expression in equation (10) by the coefficient on the transaction cost variable, β_{tc}, i.e.,

$$E(CS_b) = \frac{1}{\beta_{tc}} \ln \left[\sum_{\mathcal{M}'_b} \exp \left(EU_b(\mathcal{M}'_b) - F_{\mathcal{M}'_b} \right) \right]. \tag{11}$$

Finally, to calculate total consumer surplus, we aggregate consumer utility by summing over consumer types:

$$E[CS] = \sum_{b=1}^{N} E(CS_b). \tag{12}$$

Comparison of consumer surplus. It is worth noting that our universal and non-universal CBDC adoption/acceptance scenarios differ significantly in the underlying assumptions, which makes direct welfare comparison across these simulations more complicated. Under universal adoption/acceptance, we assume that all consumers have CBDC in their wallets and all merchants can accept CBDC at the POS. In other words, no new payment combination is introduced in the first stage. We also do not account for the potential adoption and acceptance costs of implementing this scenario. Note that in the second stage of our counterfactual simulations, some consumers may face larger (than the factual) choice set, which includes a new payment instrument. This would unambiguously increase consumer welfare due to the increased variety. While we think that the product characteristics of the new payment method are important for consumer welfare, increasing variety of the instruments by itself should make consumers happier.

In the case of non-universal acceptance/adoption, in the first stage consumers face six products, i.e., three original combinations of payment methods and three additional combinations, each including CBDC. Due to the well-known property of models with additively separable random tastes for products, comparing a factual three-bundle to a counterfactual six-bundle choice combination may result in a mechanical increase in the welfare simply due to the larger number of products. Therefore, in case of non-uniform adoption/acceptance, we compare consumer welfare after CBDC introduction to a modified factual also containing six products, where each of the original products has an identical copy. The intuition is simple—we compare a situation where CBDC is so bad that it is never used (modified factual with identical copies of the original bundles) to a situation where its usage is optimal given observable characteristics and estimated consumer preferences. This way, consumer welfare does not increase simply due to a larger choice set. Different from our uniform acceptance/adoption scenario, adoption occurs endogenously and depends on the estimated distribution of consumer adoption costs.[10]

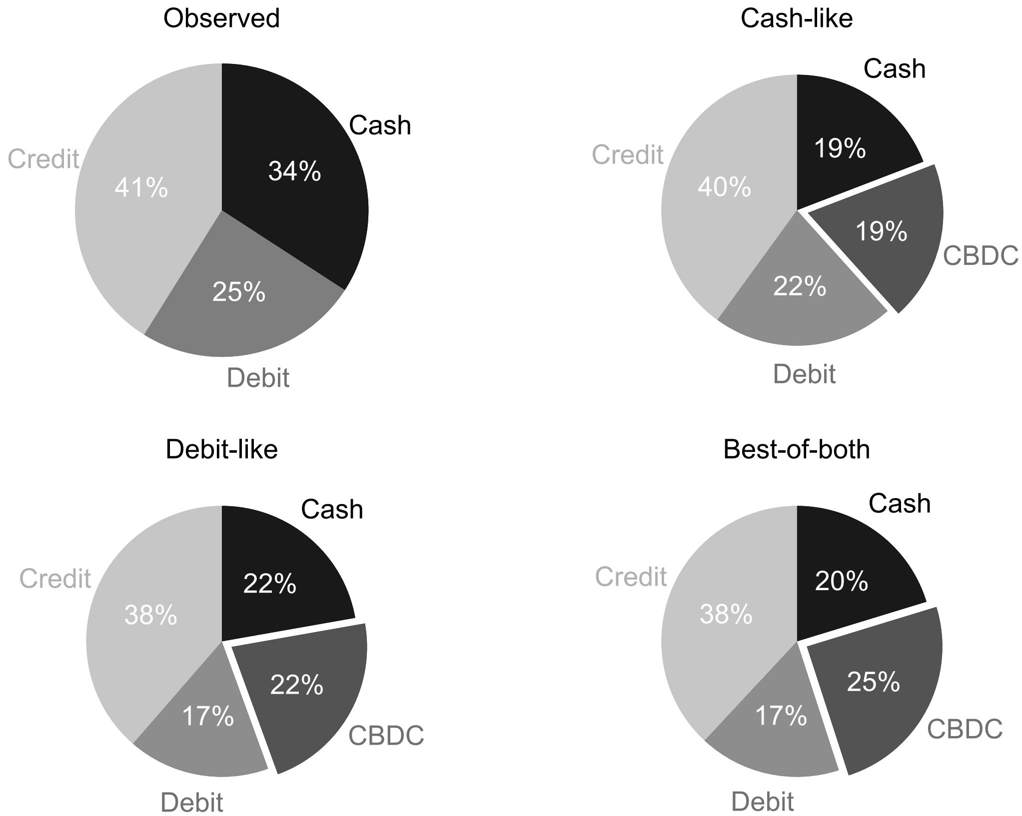
Given that we look only at the demand side, the predictions of these experiments do not consider either the responses of merchants (we take their acceptance probabilities as given) or the responses of the banks (which may lower the adoption and usage costs of debit and credit cards or increase their benefits). Furthermore, as we look at only POS transactions, our predictions also cannot consider the increasing level of online sales, where cash cannot be used. Finally, our predictions are based on the characteristics of existing payment methods, and as a result they cannot account for new applications of our new hypothetical payment method (for example, smart contracts, programmable money).

5.1 Universal adoption and acceptance of CBDC

Figure 3 illustrates one factual and three counterfactual expected usage probabilities. Not surprisingly, cash-like CBDC would replace cash in transactions mostly done in cash. Only a small percentage of transactions previously made with debit and credit cards are affected.

[10]Recall that merchant acceptance rate is not modelled in this paper, and in simulations we simply assume various levels of acceptance.

Figure 3: Observed and counterfactual usage probabilities, universal adoption/acceptance



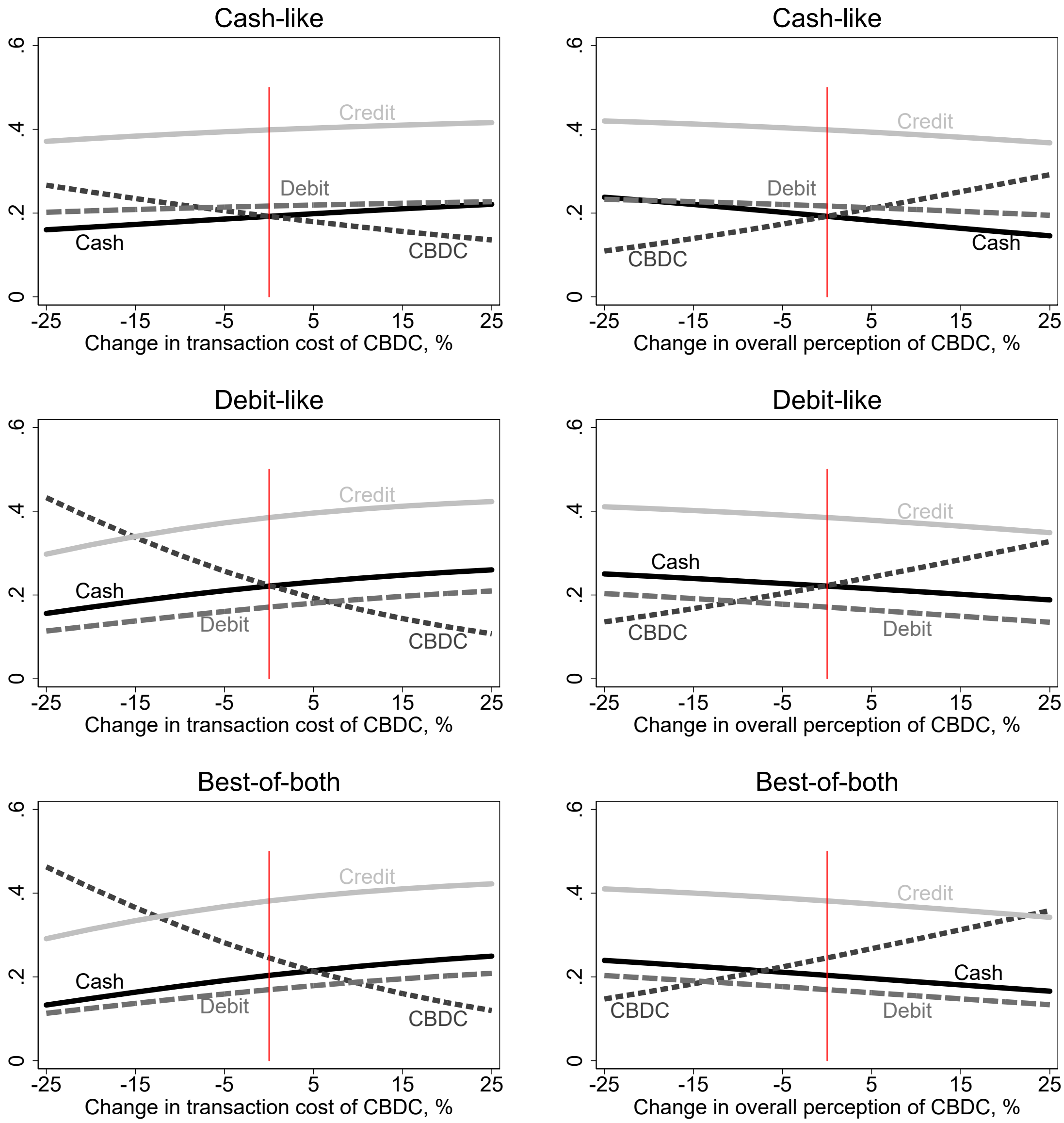
Notes: In this simulation we assume all merchants and consumers adopt CBDC as a payment method in all possible choice sets. Cash-like CBDC inherits characteristics of cash; debit-like CBDC has the same characteristics as debit cards. The best-of-both scenario takes the best of characteristics of cash and debit.

If CBDC has characteristics similar to debit cards, it will have a more significant impact on debit (8 percent of consumers would switch away). In this case, cash and credit would lose 12 and 3 percent of users, respectively. Even when CBDC is assigned the best features of both cash and debit cards, its usage probability reaches only about 25 percent of all transactions. The results suggest that a new payment instrument must have significantly better characteristics than either cash or debit card. To investigate various scenarios of introducing CBDC, we simulated several sequences of consumer choices when hypothetical characteristics of a new payment instrument are increased or decreased relative to their factual levels.

In particular, to explore the implications of potentially lower transaction costs (e.g., due to the non-profit motive of a central bank) and potentially different consumer perceptions of the new payment method, we changed these characteristics of CBDC by varying them by 50 percent around the factual values. The resulting purchase probabilities are described in Figure 4.

Figure 4 suggests that usage probability of a new payment instrument can reach and exceed 0.4 if some of its characteristics improve. This can be achieved, for example, by either reducing transaction costs or improving the overall perception of other characteristics. Interestingly, a reduction in transaction costs has a much weaker effect on usage probability of the cash-like version of CBDC than its other versions (debit-like and combining best features of cash and debit).

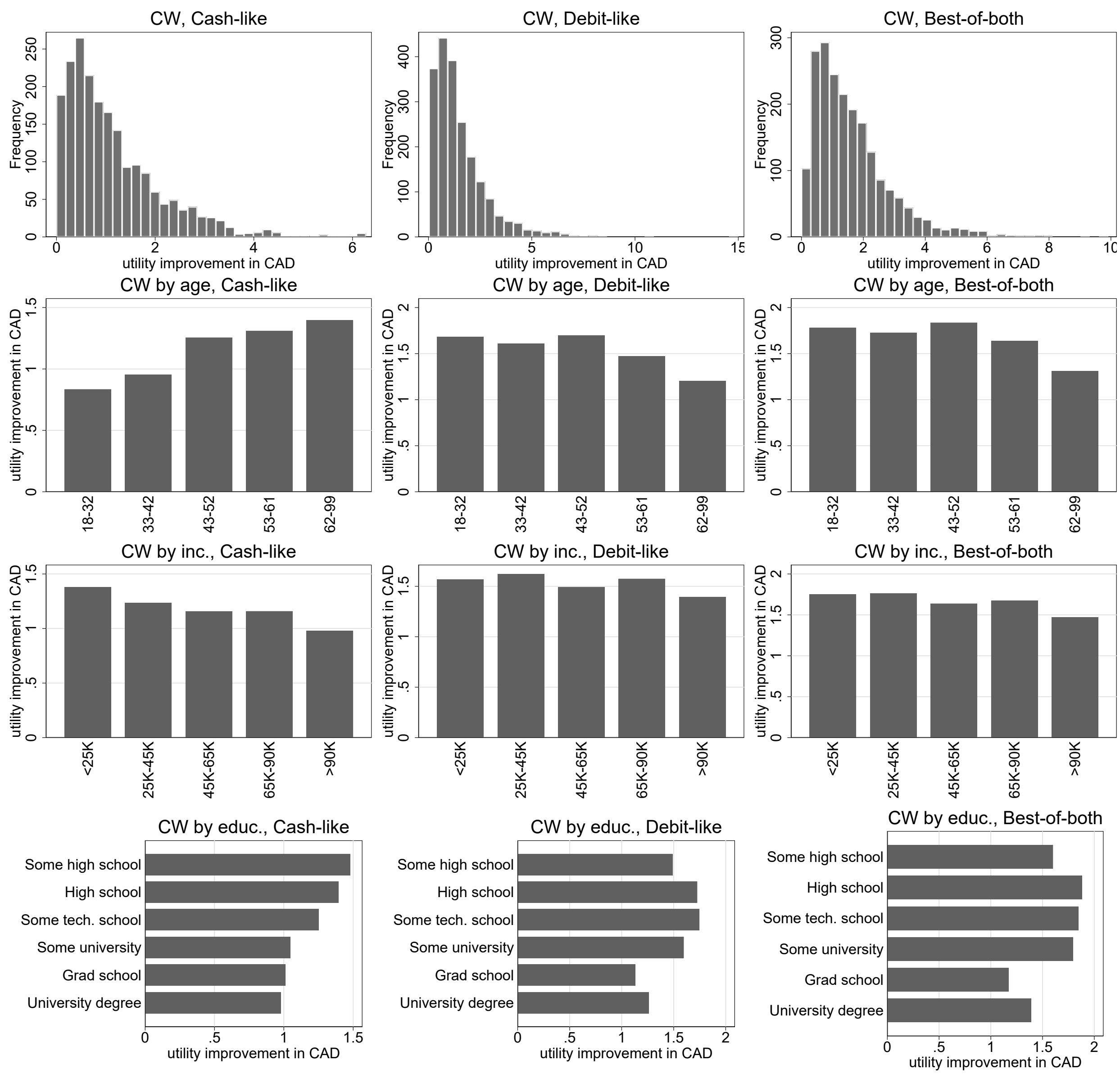
Figure 4: Determinants of usage probabilities, universal adoption/acceptance



Notes: Central vertical line is at factual. Left panels illustrate change in consumer usage behaviour due to variation in the transaction cost of the new payment instrument. Right panels show change in the usage pattern due to the overall increase in consumer perceptions of ease, affordability, and security of the new payment instrument.

Finally in Figure 5, we illustrate the overall increase in consumer welfare as well as the breakdown of welfare improvements for various demographic groups. When introduced, cash-like CBDC would increase consumer welfare on average by CAD 1.15 (median CAD 0.87), debit-like CBDC by CAD 1.51 (median CAD 1.13), and best of cash and debit CBDC by CAD 1.63 (median CAD 1.32). Cash-like features of the new product would mostly benefit older people and people with lower income and education. A debit-like version of CBDC as well as the product combining the best features of cash and debit could have a non-monotone welfare improvement effect on people of various ages and varying degrees of education and income.

Figure 5: Increase in consumer welfare (CW) due to CBDC, universal adoption/acceptance



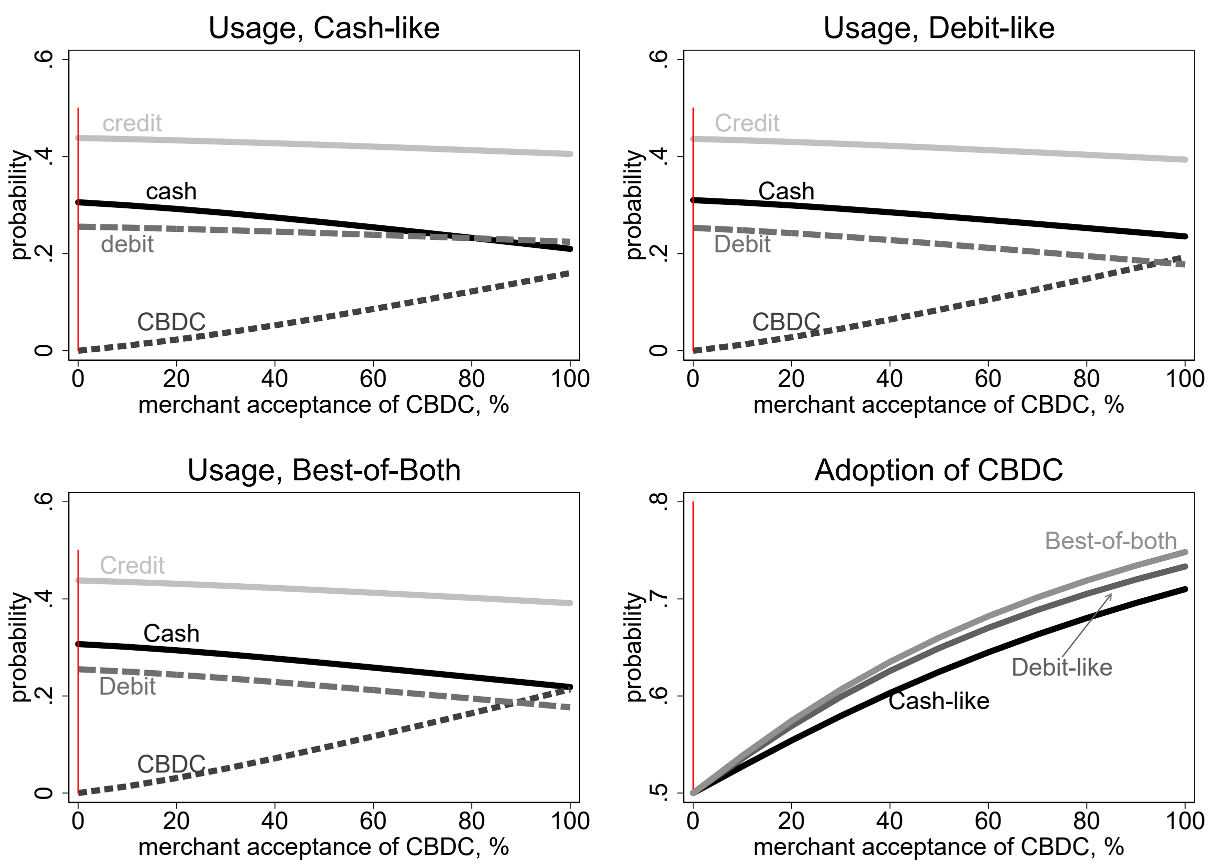
It is worth noting that the welfare analysis provided above does not account for potential costs of making adoption and acceptance of the new payment instrument universal. In the model, consumers have adoption costs associated with every feasible combination of payment instruments. If universal adoption/acceptance is enforced, somebody has to subsidize these costs for every consumer and merchant. To provide an alternative analysis of consumer welfare, we relax the universal adoption/acceptance assumption by allowing consumers to choose out of six combinations. The first three combinations represent the initial (pre-CBDC) set of options, with three additional bundles given by {cash, CBDC}, {cash, debit, CBDC}, and {cash, debit, credit, CBDC}. By making assumptions about the merchant acceptance rate for the new payment method, we can compute the optimal consumer adoption choice. This choice will take into account fixed adoption costs for each payment combination. We assume that adding CBDC to a bundle does not increase the adoption cost of this bundle.

5.2 Non-universal adoption and acceptance of CBDC

Under non-universal adoption and acceptance of CBDC, we fix merchant acceptance rate r at a given level and simulate optimal consumer adoption and usage decisions as a function of r. Consumer adoption is not universal due to the random distribution of fixed adoption costs, as discussed in assumption 2.

Figure 6 describes expected usage probabilities and consumer adoption probability as a function of the merchant acceptance rate $r \in (0, 1)$. The simulation results suggest that merchant acceptance is the key to a successful introduction of a new payment instrument. With a low merchant acceptance rate, a CBDC that combines best characteristics of cash and debit cards would be used for less than 20 percent of transactions.

Figure 6: Usage probabilities and CBDC adoption (bottom right) given merchant acceptance rate



Another interesting observation is that a high adoption rate of a new payment instrument does not necessarily imply its high usage probability.[11]

We also compute welfare improvements for all consumer types. To obtain these measures, we assume a 75 percent merchant acceptance rate of CBDC. In the first stage, we allow consumers to choose out of six adoption combinations. To make a comparison of consumer welfare meaningful when computing pre-introduction welfare, we allow consumers to choose from six adoption combinations with three original and three exact copies of the original adoption combinations. This way we compare the pre-introduction situation with six products to the post-introduction situation with six products, where in the first case the CBDC that "enters" half of the bundles is never used.

Figure 7 summarizes consumer welfare gains from three alternative types of CBDC, assuming a merchant acceptance rate of 75 percent.[12]

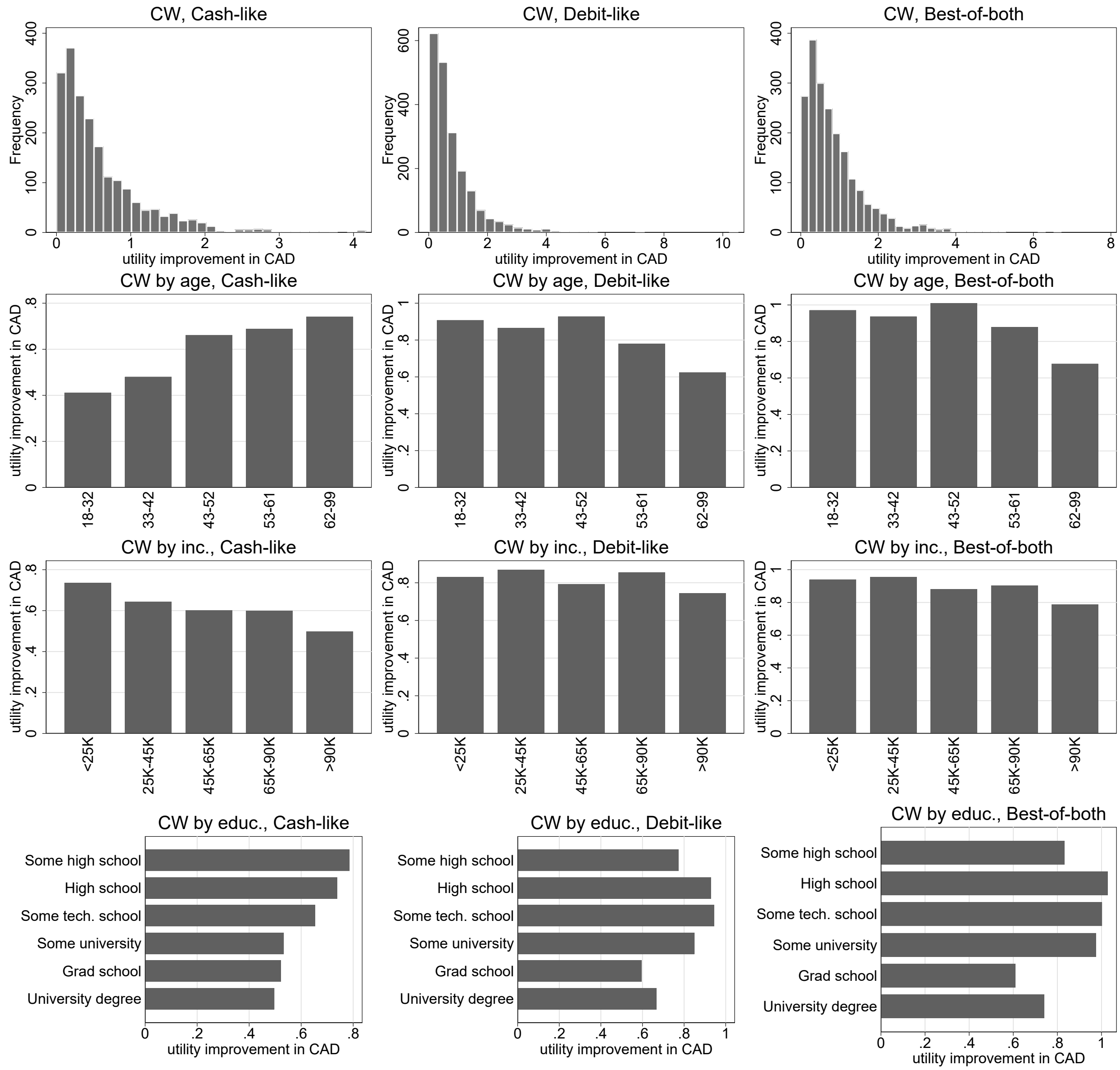
Similar to the universal adoption case, cash-like CBDC tends to generate more utility for older, less educated people with lower income. Change in welfare becomes non-monotone with age, income, and education for a debit-like version of CBDC and for CBDC combining the best features of cash and debit cards.

Last but not least, a brief discussion of the welfare contribution by different channels may be needed. Recall that in our paper, welfare measure is based on the expected maximum utility a consumer can receive from both stages of the game. CBDC affects consumer welfare through several channels. First, it increases the product variety facing a consumer. Mathematically, this is represented by another additive random taste that would be taken into account when computing utility from the second stage. Second, for some consumer-transaction-merchant combinations, CBDC may provide higher utility than cash, debit, or credit. The lower the transaction cost and the higher the other characteristics of the new product, the higher its impact on consumer welfare. When adoption/acceptance is not uniform, higher merchant acceptance affects both the extensive and intensive margins on the consumer side as more consumers decide to adopt a bundle with CBDC, and those who adopted it previously would increase its usage at the POS.

[11]Note that the result of 50 percent adoption probability, when none of the merchants accept a new payment method (bottom-right panel), can be viewed as consumers randomizing between adopting or not a payment instrument that is free to have but is also useless at the POS.

[12]Other scenarios available upon request.

Figure 7: Increase in consumer welfare (CW) at 75% merchant acceptance of CBDC



6 Conclusions

Rapid innovations and technological developments in the payment industry quickly change its landscape, when new products such as digital currencies and e-transfers significantly reduce usage of more traditional payment instruments such as cheques and cash. The social welfare effects of these changes are of major interest to central banks. It is conceivable that policy interventions in the form of issuing a CBDC may increase social welfare by providing additional features currently missing in the decentralized digital currencies, such as legal tender status and enhanced security.

To simulate counterfactual experiments of the introduction of new payment methods, we first develop and estimate a two-stage model of consumer adoption and usage decisions for the three most widely used payment instruments: cash, debit cards, and credit cards. Our estimation results reveal heterogeneity in consumer preferences for characteristics of payment instruments. We also find it important to control for the unobserved quality of the payment cards by including consumer demographics and transaction type variables.

Using parameter estimates from the structural model, we simulate several counterfactual experiments by allowing for a fourth major payment instrument that is assumed to possess various combinations and levels of product attributes. We consider two scenarios with uniform and non-uniform adoption and acceptance of the new payment instrument. In the latter case, we simulate optimal consumer adoption and usage decisions for various levels of merchant acceptance.

Our simulation results suggest that a new payment method can be used on average for every fourth or fifth transaction. Consumer welfare can improve by 0.60 to 1.63 CAD per person, with significant variation across demographic groups. A hypothetical CBDC that combines the best features of debit cards and cash (both in terms of perceived ease, cost and risk of use and estimated transaction cost) would still leave significant, non-zero market shares for both debit and cash as a form of payment method and could compete with only the non-reward-paying credit cards. The CBDC would have to be significantly better in terms of the perceived ease-of-use, cost, and security of the payment method and the actual transaction cost as well to completely replace these payment methods even with full consumer adoption and merchant acceptance. We also find that merchant acceptance is important for a successful launch of a new payment instrument. In all scenarios, the predicted usage rate does not reach 10 percent until at least 60 percent of the merchants accept the new payment method. Even though most Canadians already have access to banking services, the CBDC would have a small but significant welfare benefit. These benefits have to be compared with the costs of development and introductions and other potential macroeconomic consequences.

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Appendix A Model Estimates

Table 8 recaps the first- and second-stage estimates. Table 9 reports parameter estimates and standard errors for a vector of demographic and transaction-specific variables, Z_{bj}, included in each specification. A recap of model equations:

$$\delta_{bmj} = X_{bmj}\beta + Z_{bj}\alpha_m$$

$$F_{b,\mathcal{M}_b} = \bar{F}_{\mathcal{M}_b} + \gamma_{\mathcal{M}_b} CS_b - \epsilon_{b,\mathcal{M}_b}$$

where specification 2, 3 uses random coefficients in the second stage and specification 3 uses credit score in the first stage.

Table 8: Estimation results

Variable	Conditional logit	Mixed logit			
	(1)	(2)		(3)	
	coef.	coef.	s.d	coef.	s.d.
Ease-of-use (↑ easier)	6.380	7.144	—	7.078	—
(s.e.)	(0.219)	(0.243)	—	(0.242)	—
Affordability (↑ cheaper)	2.459	3.058	2.672	3.041	2.590
(s.e.)	(0.096)	(0.118)	(1.556)	(0.117)	(1.161)
Security (↑ safer)	0.845	1.059	2.615	1.040	2.497
(s.e.)	(0.107)	(0.130)	(1.191)	(0.129)	(1.251)
Reward	1.117	1.384	—	1.323	—
(s.e.)	(0.025)	(0.030)	—	(0.029)	—
Transaction cost	-0.878	-0.964	0.302	-0.959	0.296
(s.e.)	(0.004)	(0.005)	(0.022)	(0.005)	(0.022)
$\bar{F}_{ca,dc}$ (cash & debit)	-1.309	-1.326	—	-1.685	—
(s.e.)	(0.135)	(0.135)	—	(0.134)	—
$\bar{F}_{ca,dc,cc}$ (all)	-2.249	-2.147	—	1.450	—
(s.e.)	(0.130)	(0.130)	—	(0.130)	—
$\gamma_{ca,dc}$ credit score ('00)	—	—	—	0.065	—
(s.e.)	—	—	—	(0.019)	—
$\gamma_{ca,dc,cc}$ credit score ('00)	—	—	—	-0.495	—
(s.e.)	—	—	—	(0.018)	—
Demo & trans. controls, Z_{bj}	yes	yes		yes	
NLL	28,649.06	28,602.62		28,420.03	
AIC	57,416.12	57,333.24		56,972.06	
BIC	57,915.72	57,875.18		57,530.94	

Table 9: Parameter estimates for demographic- and transaction-specific variables

	Conditional logit		Mixed logit			
	(1) Debit	(1) Credit	(2) Debit	(2) Credit	(3) Debit	(3) Credit
Employed	0.113	-0.066	0.143	-0.072	0.143	-0.086
(s.e.)	(0.032)	(0.036)	(0.039)	(0.044)	(0.039)	(0.044)
Married	0.222	0.046	0.26	0.036	0.258	0.035
(s.e.)	(0.032)	(0.036)	(0.04)	(0.043)	(0.04)	(0.043)
Age	-0.02	-0.015	-0.022	-0.016	-0.022	-0.017
(s.e.)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Income (10000)	-0.013	0.013	-0.017	0.016	-0.017	0.015
(s.e.)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Male	-0.155	0.049	-0.203	0.068	-0.201	0.071
(s.e.)	(0.029)	(0.032)	(0.036)	(0.039)	(0.036)	(0.038)
Urban	0.183	0.353	0.188	0.408	0.187	0.408
(s.e.)	(0.039)	(0.044)	(0.048)	(0.053)	(0.048)	(0.053)
Homeowner	-0.09	0.394	-0.161	0.462	-0.158	0.449
(s.e.)	(0.035)	(0.04)	(0.043)	(0.048)	(0.043)	(0.048)
Canadian-born	0.084	-0.403	0.154	-0.457	0.15	-0.454
(s.e.)	(0.046)	(0.047)	(0.056)	(0.056)	(0.056)	(0.056)
Smartphone owner	0.252	0.023	0.306	0.012	0.303	0.008
(s.e.)	(0.034)	(0.038)	(0.042)	(0.046)	(0.041)	(0.045)
High school	0.274	0.549	0.3	0.63	0.297	0.626
(s.e.)	(0.069)	(0.093)	(0.083)	(0.111)	(0.083)	(0.111)
Technical school	0.369	0.775	0.38	0.88	0.379	0.875
(s.e.)	(0.065)	(0.088)	(0.078)	(0.105)	(0.077)	(0.105)
Some university	0.512	1.112	0.532	1.257	0.529	1.244
(s.e.)	(0.073)	(0.095)	(0.088)	(0.115)	(0.088)	(0.114)
University	0.236	1.229	0.176	1.427	0.176	1.415
(s.e.)	(0.069)	(0.089)	(0.083)	(0.107)	(0.083)	(0.107)
Grad school	0.13	1.311	0.054	1.531	0.055	1.522
(s.e.)	(0.082)	(0.097)	(0.099)	(0.116)	(0.099)	(0.116)
Durable goods	-0.029	0.504	-0.105	0.572	-0.102	0.572
(s.e.)	(0.069)	(0.069)	(0.084)	(0.086)	(0.084)	(0.085)
Entertainment	-0.299	-0.32	-0.357	-0.347	-0.355	-0.35
(s.e.)	(0.039)	(0.044)	(0.048)	(0.052)	(0.048)	(0.051)

Gasoline	0.105	0.603	0.089	0.68	0.087	0.681
(s.e.)	(0.052)	(0.055)	(0.065)	(0.07)	(0.065)	(0.069)
Healthcare	0.064	0.39	0.033	0.417	0.032	0.413
(s.e.)	(0.101)	(0.107)	(0.127)	(0.134)	(0.127)	(0.133)
Hobby goods	-0.141	0.276	-0.183	0.292	-0.181	0.291
(s.e.)	(0.079)	(0.085)	(0.097)	(0.103)	(0.096)	(0.102)
Personal attire	-0.04	0.401	-0.074	0.456	-0.074	0.456
(s.e.)	(0.065)	(0.069)	(0.08)	(0.086)	(0.08)	(0.086)
Personal services	-0.487	0.018	-0.573	0.055	-0.568	0.048
(s.e.)	(0.119)	(0.121)	(0.146)	(0.151)	(0.145)	(0.151)
Travel/parking	-0.454	0.793	-0.595	0.977	-0.592	0.97
(s.e.)	(0.163)	(0.155)	(0.196)	(0.178)	(0.195)	(0.177)
Other	-0.352	-0.235	-0.389	-0.26	-0.388	-0.257
(s.e.)	(0.047)	(0.053)	(0.057)	(0.064)	(0.057)	(0.064)
2013	0.216	1.331	0.187	1.577	0.183	1.561
(s.e.)	(0.035)	(0.039)	(0.043)	(0.046)	(0.043)	(0.046)
2017	0.713	1.441	0.713	1.604	0.714	1.653
(s.e.)	(0.041)	(0.045)	(0.05)	(0.055)	(0.05)	(0.055)
Constant	2.768	-3.295	2.944	-3.948	2.94	-3.842
(s.e.)	(0.103)	(0.126)	(0.126)	(0.152)	(0.126)	(0.152)