BANK OF CANADA
BANQUE DU CANADA

Staff Working Paper/Document de travail du personnel—2022-15

Last updated: March 22, 2022

Equilibrium in Two-Sided Markets for Payments: Consumer Awareness and the Welfare Cost of the Interchange Fee

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DOI: https://doi.org/10.34989/swp-2022-15 | **ISSN** 1701-9397

Acknowledgements
We would like to thank Jason Allen, Victor Aguirregabiria, Özlem Bedre-Defolie, Chun-Yu Ho, Charles Kahn, Sergei Koulayev, William Roberds, Marc Rysman, Warren Weber, and participants of various seminars and presentations. We acknowledge the use of the Bank of Canada's High Performance Cluster EDITH2. This paper supersedes one titled "Explaining the Interplay Between Merchant Acceptance and Consumer Adoption in Two-Sided Markets for Payment Methods"; see Huynh et al. (2019). Maren Hansen provided excellent editorial assistance. The views expressed in this paper are those of the authors. No responsibility for them should be attributed to the Bank of Canada. All remaining errors are the responsibility of the authors.

Abstract

The market for payments is an important two-sided one, where consumers benefit from increased merchant acceptance of payment cards and vice versa. The dependence between the decisions that are made on each side of the market results in various network externalities that are often discussed but rarely quantified. We construct and estimate a structural two-stage model of equilibrium in a market for payments in order to quantify the network externalities and identify the main determinants of consumer and merchant decisions. The estimation results suggest significant heterogeneity in consumer adoption costs and benefits. We discuss the critical characteristics that determine which payment instrument is used at the point of sale. Our counterfactual simulation measures the degree of excessive intermediation by credit card providers.

Topics: Bank notes; Digital currencies and fintech; Econometric and statistical methods; Financial services
JEL codes: C51, D12, E42, L14

Résumé

Le marché des paiements est un marché biface important, où les consommateurs tirent parti de l'acceptation accrue des cartes de paiement par les commerçants et vice versa. La dépendance entre les décisions prises de part et d'autre du marché entraîne des externalités de réseau qui sont souvent analysées, mais rarement quantifiées. Nous élaborons et estimons un modèle structurel d'équilibre à deux volets dans un marché des paiements afin de quantifier les externalités de réseau et de répertorier les principaux déterminants des décisions des consommateurs et des commerçants. Les résultats des estimations semblent indiquer une grande hétérogénéité des coûts et des avantages de l'adoption des consommateurs. Nous analysons les caractéristiques essentielles qui déterminent le choix de l'instrument de paiement au point de vente. Notre simulation contrefactuelle mesure le degré de l'intermédiation excessive des fournisseurs de cartes de crédit.

Sujets : Billets de banque, Méthodes économétriques et statistiques, Monnaies numériques et technologies financières, Services financiers
Codes JEL : C51, D12, E42, L14

1 Introduction

When consumers undertake a transaction with a merchant, the payment method finalizes the exchange. Cash has traditionally been the primary payment method, although the introduction of debit and credit cards, in recent history, has provided newer options for consumers and merchants. Due to these innovations, consumers have a choice of payment method. However, consumer choice is dependent on the form of payment merchants accept. Likewise, merchant acceptance of payment options depends on consumer choice. The feedback loop between these decisions is known as a network externality in a two-sided market (see Rochet and Tirole 2003). Quantifying this network externality is key to understanding the adoption/acceptance and usage decisions of consumers and merchants.

This paper explains consumer adoption, merchant acceptance, and the equilibrium usage of payment instruments such as cash and debit and credit cards at the point of sale (POS). To understand these complex interactions, we develop a structural model of a two-sided market for payment methods and estimate the model by using rich micro-level data on both sides of the market. Our main contribution is in the structural interpretation of the network effects within an equilibrium model of a two-sided market. We use parameter estimates to relate the credit card interchange fee and social welfare in the Canadian market for payments in 2014.

Much of the early work on two-sided markets focuses on theoretical modelling of platform competition (see Rochet and Tirole 2002; Schmalensee 2002; Rochet 2003; Wright 2003, 2004; Rochet and Tirole 2011). These theoretical models highlight the role of network externalities. Early examples of empirical work on payments include Gowrisankaran and Stavins (2004), who study network externalities in electronic payment markets, and Rysman (2007), who establishes a feedback loop between consumer usage and merchant acceptance, a necessary condition for the two-sidedness of a market.[1] A survey article by Rysman (2009) highlights the importance of quantifying two-sided markets in order to understand economic exchange.

Quantitative models by Li et al. (2019) articulate that there are two types of network externalities: (1) an adoption externality and (2) a usage externality. In the first case, for a payment system to work, consumers require that merchants accept payment cards and merchants need consumers to have a payment card. In the second case, consumers' usage of payment cards will have implications for merchants' costs (fees) of accepting cards versus cash. Using a calibrated model and aggregate data from US payments networks, they find that the market power of electronic payment networks in the United States plays

[1]Carbó-Valverde et al. (2016) and Bounie et al. (2016) estimate empirical models based on survey data from both consumers and merchants in Spain and France, respectively. These empirical models utilize simultaneous equations with instrumental variables to estimate the cross-partial elasticities of consumer adoption and merchant acceptance. However, these methodologies are unable to quantify or identify the equilibrium source of network externalities.

an essential role in explaining the slow adoption of payment technology. Li et al. (2019) recommend further research on consumer adoption costs and merchant behaviour in retail marketing. Bedre-Defolie et al. (2018) use an empirical structural model to study the market for debit card services in Norway. To estimate the parameters of the model, the authors combine banking data with information on consumer transactions and payment behaviour at the point of sale. The parameter estimates are then used in counterfactual simulations to determine the socially optimal interchange fee regulation.

The application of our model to assess the potential for excessive intermediation by credit card platforms is motivated by recent theoretical work of Bedre-Defolie and Calvano (2013) and Edelman and Wright (2015), who suggest that a profit-maximizing fee set by a platform may induce an inefficient pricing structure where merchants are overtaxed and card usage is oversubsidized. Bedre-Defolie and Calvano (2013) find that the above distortion is driven by the asymmetry between consumers and merchants' decisions, where consumers make both membership and usage decisions, while merchants only decide on membership. Similarly, Edelman and Wright (2015) emphasize the role of price coherence in inflated retail prices, the excessive adoption of the intermediary service and overinvestment in consumer benefits. This reduces consumer welfare in equilibrium, making them worse off compared to the case without any intermediation. Importantly, it is shown that competition between intermediaries increases the magnitude of the effects.

The paper most closely related to ours is Koulayev et al. (2016), where the authors estimate a structural model of the adoption and use of payment instruments by US consumers. Similar to the authors, we distinguish between the adoption and usage stages on the consumer side of the market, where the decisions are separately identified by both the model structure and the variables that satisfy the exclusion restrictions. We also control for consumer perceptions of various characteristics of payment instruments such as ease of use, affordability, security, and perceived merchant acceptance. Differently, we are able to control for the transaction price as an important determinant of the payment choice. We also control for the unobserved match values between consumers, transaction types, and payment methods by means of a rich set of fixed effects. These fixed effects capture the variation in the unobserved service quality and reward programs across consumers with different types of debit and credit cards.[2] More importantly, while Koulayev et al. (2016) focus on the demand side of a two-sided market for payments, our equilibrium model predicts optimal merchant responses in terms of acceptance decisions. By modelling the choices on both sides of the market, we account for the network effects when consumer incentives to adopt electronic means of payment are increasing in merchant acceptance and vice versa. Incorporating merchant decisions into the model allows us to quantify the benefits and costs of accepting electronic payment methods that depend on the degree of

[2]In a reduced-form way, the match values between consumer demographics and credit cards can also capture an essential credit card element that allows consumers to borrow.

consumer awareness about merchant choices.

Our model distinguishes between the behaviour of first-time customers who have limited foreknowledge about what a merchant accepts and repeat customers who are likely to know from experience a merchant's acceptance decisions. It is this latter group of consumers that incentivizes merchants to accept a wider set of payment instruments. The role of the first-time customer is similar to that of the "tourist" in the tourist test of Rochet and Tirole (2011), though in our case a consumer may be both a first-time and repeat customer, depending on the transaction. Throughout the paper we refer to transactions made by first-time customers as "uninformed" transactions and those made by repeat customers as "informed" transactions. We show that the proportion of the transactions conducted by the informed consumer has implications for consumer and merchant incentives to adopt and accept various means of payment and for the strength of the network externalities between the two sides of the market.

Interactions between consumers and merchants in a market for payment methods is represented as a two-stage game that is played every period. In the first stage, consumers and merchants simultaneously and independently make adoption and acceptance decisions about which payment methods will be available for use in the following stage. In the second stage, consumers and merchants are either randomly matched to conduct uninformed transactions or consumers can direct their purchases towards merchants who are accepting consumers' favourite payment methods for the informed transactions.

We estimate the model by using the Bank of Canada's 2013 Methods-of-Payment (MOP) Survey, which provides rich microdata on consumers (see Henry et al. 2015). For merchants, we use the Bank of Canada 2015 Retailer Survey on the Cost of Payment Methods (RSCPM) (see Kosse et al. 2017). The 2013 MOP contains data on consumer adoption and usage of payment instruments, while the 2015 RSCPM contains detailed data on the costs and merchant acceptance of payment methods. Using our parameter estimates, we simulate a sequence of market equilibria for a range of hypothetical levels of the interchange fee to illustrate the evolution of market outcomes under alternative assumptions about the fee pass-through rate from one side of the market to the other. We also show the importance of accounting for informational frictions by relating the equilibrium in the market to the level of consumer awareness.

We find that, in equilibrium, some merchants choose to accept all means of payment to attract more customers. Merchants' incentives to do so depend on the degree of consumer awareness. We estimate a merchant profit margin of 5.2 percent, which shrinks to 3.4 percent after deducting operating expenses and banking fees. Consumers adopting debit and credit cards have heterogeneous adoption costs. Some consumers enjoy reward benefits, while others incur adoption costs. These costs and benefits rarely exceed five Canadian dollars per month. Parameter estimates for the usage stage reveal that transaction cost is the most important determinant of consumer payment choice at the POS. We show that it is essential to account for consumer perceptions of the characteristics of payment instruments such as ease of use, security, and affordability as they affect usage decisions. Our results suggest that consumer awareness is critical for the wide adoption, acceptance and use of electronic payment instruments. Consistent with the findings of platforms' excessive intermediation in the theoretical literature, we confirm that in 2014 the average level of the interchange fee was indeed higher than was socially optimal.

It is worth noting that we do not model competition between networks. Jain and Townsend (2020) build a theoretical model to illustrate the importance of this competition. Belleflamme and Peitz (2019) consider the welfare implications of two alternative market structures by comparing a situation where the users of competing two-sided platforms are singlehoming on both sides of the market versus a situation where the users of one of the sides can multihome. Anderson and Peitz (2020) determine the conditions under which a surplus seesaw effect arises; that is, when a change in the market structure (e.g., platform entry) leads to an increase in the surplus on one side and a decrease in the surplus on the other. We also abstract away from many payment instruments such as cheques, money orders, bank transfers, etc., and focus only on POS transactions. Similarly, we do not model consumer demand for real products and, instead, assume that the observed consumption pattern does not change in response to variation in the adoption, acceptance and usage of alternative payment instruments at the POS.[3]

The rest of the paper is organized as follows. Section 2 provides institutional details and describes our data. We describe our theoretical model in Section 3. The empirical specifications and details of the estimation algorithm are provided in Section 4. Section 5 contains a discussion of the results, including an analysis of the determinants of adoption, acceptance and usage decisions. Section 6 discusses a counterfactual simulation relating the interchange fee to the market equilibrium and social welfare. Finally, Section 7 concludes. All monetary values reported in this paper are in Canadian dollars.

2 Consumer and Merchant Payment Data

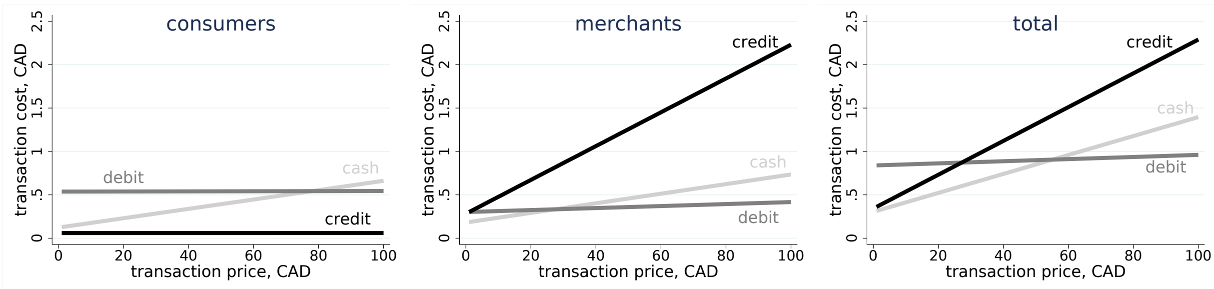
This study makes use of both consumer- and merchant-side surveys developed by the Bank of Canada. The consumer survey is the 2013 MOP Survey, which includes two components. The first component is the survey questionnaire, which contains information on individuals' demographics and payment card ownership. The second component is a diary survey instrument, which asked respondents to report the transactions they made over a three-day period, along with questions on many key characteristics, including the methods used to complete the transactions, the value of each transaction, and the types

[3]Apart from the ability to borrow on a credit card, which is captured by fixed effects in our model, the variation in the costs and benefits of using one payment instrument instead of the other appears to be too small to generate significant income effects.

of stores in which the transactions were made. The merchant-side survey used is the 2015 RSCPM, which includes questions about perceptions of payment method costs and benefits, payment method acceptance, and revenue and fees broken down by payment method.

Usage cost functions. Our data analysis suggests that consumers and merchants view payment methods very differently in terms of their usage costs. Figure 1, which is based on results from Kosse et al. (2017), can be used to rank consumers and merchants' usage costs for a given transaction size. Most noteworthy, for all price points, consumers find credit cards the least costly, while merchants find them the most costly. Further, both consumers and merchants find cash cheaper than debit for smaller transactions, but more costly for larger transactions. The total cost for both sides of the market is obtained by

Figure 1: Transaction costs: consumer (left), merchant (middle), and total (right), 2014



Notes: Transaction costs are defined as linear functions of prices, with the intercepts and slopes for each payment instrument estimated in Kosse et al. (2017) (Figure 13 on p.38). Merchant cost functions vary by province. Consumer cost functions are constant for all consumers.

adding the consumer and merchant cost functions for each price. The right-hand panel of Figure 1 shows that, in 2014, credit cards were never the cheapest payment option. For relatively low transaction values, cash was the cheapest choice, and for prices above 60 dollars, debit cards had the lowest total cost.[4]

Adoption and acceptance decisions. For profit-maximizing merchants, accepting more-expensive payment instruments clearly reduces per-transaction profits. However, extra sales to new consumers who are attracted by such an acceptance choice may generate profits that are larger than the costs incurred. With this we proceed to the discussion of consumer adoption and merchant acceptance choices. Summary statistics for various combinations of payment instruments for each side of the market are reported in Table 1. Consumers almost always (98 percent of consumers) have a payment card of some kind, with 83 percent owning both a debit and a credit card. On the other side, about a fifth (22 percent) of merchants accept only cash, while 70 percent accept both types of

[4]We admit there has been significant technological progress in the payment industry in recent years. Cost structures may have changed, and this should be kept in mind when applying the results to policy analysis.

Table 1: Summary of consumer adoption and merchant acceptance decisions.

Variable	Consumers		Merchants	
	frequency	percent	frequency	percent
Cash only	48	1.98	162	22.10
Cash and debit	239	9.84	31	4.23
Cash and credit	128	5.27	24	3.27
All methods	2,014	82.91	516	70.40
Total	2,429	100.00	733	100.00

Notes: In estimation, we do not allow for the cash-and-credit-only combination, for reasons discussed later, and this combination is re-coded as if consumers (merchants) adopt (accept) all instruments.

cards. This suggests that while merchants can almost always expect consumers to carry a payment card, a consumer may not always be able to use the payment cards they have at their disposal.

Consumer demographics and perceptions. In the data, we observe consumers' demographics variables, their banking information, and a set of transactions they completed over a three-day period. Consumer-level data is summarized in Table 2. These variables are used in the empirical model to control for heterogeneity in consumer preferences for the adoption and usage of various payment instruments at the POS.

Table 2: Summary statistics for consumer-level variables

Variable	Mean	Median	Min	Max	SD
Age	48.24	49.00	18.00	93.00	15.71
Income	68,111	55,000	12,500	202,500	48,628
Education	3.61	3.00	1.00	6.00	1.41
Credit score	768.10	772.39	429.50	875.67	49.98
Urban	0.85	1.00	0.00	1.00	0.36
Female	0.52	1.00	0.00	1.00	0.50
Married	0.51	1.00	0.00	1.00	0.50
Number of transactions	6.68	6.00	1.00	18.00	3.28
Transaction price	32.90	18.04	0.10	300.00	41.64

Notes: Credit scores are imputed by using a nearest neighbour estimator (based on the reported banking information and demographics) and the TransUnion credit registry; there are six levels for education, ranging from some public school (level 1) to a completed graduate degree (level 6); transactions are measured by number within a three-day diary period.

In addition to the demographics variables, we also observe consumers reporting their perceptions, such as ease of use, security, affordability (expected cost of use), and the likely merchant acceptance decisions at the POS. These variables are measured on either a 4- or 5-point Likert scale and are reported in Table 3. The higher values are associated with larger or better characteristics. Note that electronic payment methods, such as debit and credit cards, are typically ranked lower than cash, along any dimension. When comparing debit and credit cards, we find that on average consumers rate debit cards slightly higher than credit cards.

Table 3: Summary statistics for perception variables

Characteristic	Method	Mean	Median	Min	Max	SD
	cash	4.70	5.00	1.00	5.00	0.64
Ease of use	debit	4.48	5.00	1.00	5.00	0.72
	credit	4.48	5.00	1.00	5.00	0.73
	cash	4.58	5.00	1.00	5.00	0.78
Affordability	debit	3.74	4.00	1.00	5.00	1.10
	credit	2.97	3.00	1.00	5.00	1.34
	cash	4.25	5.00	1.00	5.00	1.01
Security	debit	3.76	4.00	1.00	5.00	0.91
	credit	3.64	4.00	1.00	5.00	0.95
	cash	3.92	4.00	1.00	4.00	0.36
Acceptance	debit	3.66	4.00	1.00	4.00	0.64
	credit	3.59	4.00	1.00	4.00	0.61

Notes: In estimation, we normalize all perception variables using the formula: $X_m = \hat{X}_m / \left(\hat{X}_{ca} + \hat{X}_{dc} + \hat{X}_{cc}\right)$*, where* $\hat{X}_m$ *denotes the consumer rating on a 4- or 5-point Likert scale, with the larger values denoting higher characteristics.*

Transaction-level data. In the data, within a three-day period, consumers recorded every transaction, including its price, type, and the realized payment usage decision at the POS (e.g., cash, debit, or credit). The transactions could be of various types, and Table 4 reports the frequency of use for every instrument by transaction type. On average, cash was the most common method of payment (44 percent of transactions), followed by credit cards (33 percent) and debit cards (23 percent).

Table 4: Summary statistics for the POS transaction types and prices

Transaction type	Frequency of use			Prices		
	Cash	Debit	Credit	Mean	Median	SD
Groceries/drugs	0.39	0.26	0.34	34.34	20.00	41.43
Gasoline	0.20	0.29	0.51	45.32	41.00	24.23
Personal attire	0.25	0.29	0.46	53.59	34.00	51.95
Health care	0.35	0.27	0.38	50.75	32.50	55.46
Hobby/sporting goods	0.41	0.19	0.40	37.70	20.00	47.55
Professional/personal services	0.45	0.16	0.39	55.88	32.00	57.71
Travel/parking	0.61	0.10	0.29	23.46	10.00	37.55
Entertainment/meals	0.59	0.18	0.23	17.43	9.00	26.21
Durable goods	0.30	0.26	0.45	49.27	30.00	57.78
Other	0.55	0.20	0.24	31.77	15.00	45.31
Average	0.44	0.23	0.33	32.95	18.50	41.66

Notes: The number of observations is 12,029. Our sample includes transactions completed at the POS only and, hence, may represent the lower tail of the distribution of consumer expenditures.

Consumer awareness. An important feature of our framework allows for consumer uncertainty about the individual merchant's acceptance decisions. Relative shares of repeat customers versus consumers making one-time purchases (i.e., *"tourists"* in the terminology of Rochet and Tirole (2003)), in the overall population of consumers, affects merchants' incentives to accept alternative combinations of payment instruments. To distinguish between purchases made by tourists from purchases made by repeat customers, we supplement our data with consumer diary information for 2017.

Table 5: Consumer awareness, probability of repeated visits, 2017

Transaction type	Age, years		Income, '000		Gender		University		Price, CAD	
	≤ 25	> 25	< 65	≥ 65	male	female	No	Yes	< 100	≥ 100
Groceries/drugs	0.96	0.98	0.97	0.98	0.98	0.97	0.98	0.97	0.98	0.97
Gasoline	0.96	0.96	0.98	0.94	0.95	0.97	0.96	0.96	0.96	0.90
Personal attire	0.91	0.92	0.94	0.90	0.91	0.92	0.92	0.92	0.91	0.94
Health care	0.79	0.92	0.92	0.89	0.87	0.94	0.92	0.89	0.92	0.85
Hobby/sporting goods	0.90	0.91	0.88	0.93	0.86	0.93	0.91	0.90	0.91	0.82
Professional/personal services	0.79	0.84	0.81	0.85	0.84	0.83	0.87	0.81	0.82	0.86
Travel/parking	0.92	0.88	0.90	0.87	0.84	0.94	0.86	0.90	0.89	0.88
Entertainment/meals	0.90	0.92	0.94	0.90	0.93	0.91	0.94	0.90	0.92	0.76
Durable goods	0.96	0.94	0.94	0.95	0.95	0.94	0.95	0.94	0.97	0.87
Other	0.87	0.93	0.94	0.91	0.93	0.92	0.94	0.91	0.93	0.89

Notes: The numbers represent frequencies of consumers' reported return visits to stores by transaction type, age, income, gender, education level and transaction price. These data will be used to impute the probabilities of being aware about combinations of merchant payment acceptances in 2013.

To match this information to our 2013 data, we estimate a logit model of awareness on a vector of demographics variables, transaction values, debit card ownership, number of registers at the POS, time of day, and transaction type. Assuming the distribution of informed transactions was the same in 2017 (conditional on the observed explanatory variables), we use the estimated model to predict the probability of observing an informed transaction in 2013.

Merchant-side data. On the merchant side, we observe revenue, acceptance, and cost information for 733 merchants. The vast majority of these businesses are small enterprises with fewer than 50 employees. The distribution of merchants by size is summarized in Table 6.

Table 6: Distribution of merchant by revenue

	Revenue, thousands of CAD							Total
	50	175	375	625	875	3,000	7,500	
Number	149	114	124	72	58	182	34	733
Percent	20.33	15.55	16.92	9.82	7.91	24.83	4.64	100
Cumulative	20.33	35.88	52.8	62.62	70.53	95.36	100	

Notes: The data description can be found in Kosse et al. (2017)

Usage cost data for merchants is collected from Kosse et al. (2017). Average costs are reported in Figure 1. In the estimation, we allow merchant usage costs to vary by province. Hence, the merchants in our model differ with respect to their size and usage costs. This two-dimensional heterogeneity facilitates identification of the parameters of the merchant acceptance cost distribution and the profit margins.

3 Model

Consider a market populated by merchants, s, who sell various products, and consumers, b, who purchase these products. Let N_s denote the number of merchants and N_b denote the number of consumers in the market. These consumers and merchants interact with each other for the purpose of completing day-to-day transactions. These transactions can be made using one of three means of payment: (1) cash, ca, (2) a debit card, dc, or (3) a credit card, cc.[5] Let $\mathcal{M} = \big(\{ca\}, \{ca, dc\}, \{ca, cc\}, \{ca, dc, cc\}\big)$ denote the set of all possible adoption/acceptance decisions available to consumers and merchants. Let $\mathcal{M}_b \in \mathcal{M}$ and $\mathcal{M}_s \in \mathcal{M}$ denote the set of payment methods adopted by consumer b and accepted by merchant s, respectively. We assume that every merchant and consumer can use cash due to its legal tender status; i.e., $ca \in \mathcal{M}_b$ and $ca \in \mathcal{M}_s$ $\forall b, s$.

Consumers and merchants represent two sides of a market where they interact in a two-stage game. In the first stage, consumers and merchants simultaneously and independently choose which combination of payment methods to adopt or accept. In the second stage, consumers complete a series of transactions at the POS. Transactions can occur in two ways. First, consumers may have prior knowledge regarding merchant acceptance and so

[5]We assume away other means of payment, such as cheques, money orders, and e-transfers because they are more likely to be used for bill payments rather than for day-to-day transactions at the POS.

choose to transact with a merchant whom they know accepts their preferred method of payment. We refer to this type of transaction as *informed*. The remaining transactions are *uninformed*–that is, the consumer has no prior knowledge regarding merchant acceptance. Instead, consumers are randomly matched with a merchant with whom to complete their purchase, in which case they choose their preferred method of payment from the subset of options that is also accepted by the merchant.

In real terms, informed transactions could be thought of as planned or repeat trips, while uninformed transactions could be thought of as random or one-time purchases. Whether or not a transaction is informed is key for the decisions made by consumers and merchants. To illustrate, consider two extremes. If all transactions are informed, then consumers may choose any method of payment they wish and merchants will lose revenue if they do not accept this method. If all transactions are uninformed, then consumers must use the method that is accepted by the merchant they are matched with. In cases of this type of transaction, merchants are guaranteed these sales.[6]

3.1 Consumers

Consumers in our model differ with respect to income, age, gender, education level, marital and urbanization status, credit score, perceptions of various characteristics of payment instruments, and a transaction endowment. We use D_b to denote a vector of demographics variables for consumer b. At the beginning of every period, each consumer is endowed with a set of transactions, $\mathcal{J}_b$, to complete. Each transaction is characterized by a tuple, (p_{bj}, I_{bj}, T_{bj}), where $p_{bj} > 0$ is the transaction price, $I_{bj} \in \{0, 1\}$ is the consumer awareness status for the transaction, and $T_{bj} \in \mathbb{Z}_+$ is the transaction type. We assume inelastic demand for transactions, which is summarized in the following assumption.[7]

Assumption 1: *Every consumer, b, is endowed with a set of transactions, $\mathcal{J}_b$, all of which must be completed. The number of transactions (cardinality of $\mathcal{J}_b$), transaction prices, p_{bj}, and consumer awareness, I_{bj}, are exogenously given.*

In the first stage, each consumer chooses a bundle of payment instruments, $\mathcal{M}_b \in \mathcal{M}$, to adopt. This decision depends on their expectations about the future utility from using these payment methods in the second stage.

[6] This also implies that lower consumer awareness about merchant choices reduces merchant incentives to accept new payment instruments.

[7] The inelastic demand for transactions appears to be a reasonable assumption for the variation in the consumer usage costs we observe in the data, making it unlikely that the level of consumption depends on the payment instrument used to purchase the product.

Second-stage decisions. Let U_{bjm} denote the utility consumer b receives from transaction j for choosing to pay with $m \in \mathcal{M}_b$. We assume that the usage utility depends on one's demographics, D_b, the type of transaction, T_{bj}, and the perceptions, X_{bm}, transaction costs, $C_{bm}(p_{bj})$, and usage innovation, ϵ_{bjm}, in the following way:

$$U_{bjm} = X_{bm}\beta + \alpha\, C_{bm}(p_{bj}) + \xi_m(D_b, T_{bj}) + \epsilon_{bjm}, \tag{1}$$

where β is a vector of the marginal utilities of the perceptions, α is the marginal (dis)utility from the transaction costs, $\xi_m(D_b, T_{bj})$ is a method-specific fixed effect that is related to the demographics and the transaction type, and ϵ_{bjm} is a usage innovation that is realized at the POS. We discuss each element of the utility function (1) below.

The perception variables, X_{bm}, refer to the consumer's rating of the ease of the use, security, and affordability of each method of payment, m. These variables vary across consumers and payment instruments but are constant across the transactions of the same consumer.

When completing their transactions at the POS, consumers incur transaction costs. These costs depend on both the number of transactions and their prices. In particular, we assume that the cost of conducting transaction j by consumer b using method m is

$$C_{bm}(p_{bj}) = c_{0bm} + c_{1bm}p_{bj}, \tag{2}$$

where c_{0bm} and c_{1bm} are, respectively, the per-transaction and per-value costs estimated from Kosse et al. (2017); see Figure 1.

It is conceivable that in addition to the observed consumer perceptions and transaction costs, there are other factors that determine consumer usage of payment instruments at the POS. For example, consumers with generous reward programs are likely to use their credit cards more frequently. Similarly, a debit account with a limited number of free transactions can reduce consumer incentives to use debit for daily purchases. To account for these factors, we include a set of method-specific fixed effects as a function of consumer demographics and transaction type, $\xi_m(D_b, T_{bj})$. For example, if a credit card that is issued to a high-income consumer provides generous cash backs for gas purchases, the consumer has more incentive to use this card when buying gas. The dummy variables can be interpreted as a "match value" between a consumer, a payment method, and a transaction type, which increases or decreases consumer utility and, hence, the incentives to use alternative payment instruments. We discuss the distributional assumption on the random innovation, ϵ_{bjm}, in Section 4.

Consumers choose method m for transaction j by maximizing (1) over a set of available payment methods, $\tilde{\mathcal{M}}$. Let the probability of doing so be denoted as

$$\mathcal{P}^*_{bjm}(\tilde{\mathcal{M}}) = \Pr\left(m = \arg\max_{m' \in \tilde{\mathcal{M}}} U_{bjm'}\right), \tag{3}$$

where the choice set, $\tilde{\mathcal{M}}$ that is realized at the POS depends on the information status of the transaction. Variable I_{bj} defines whether a transaction is informed. If $I_{bj} = 1$, then the consumer can always find a merchant who accepts a given payment instrument for this transaction, in which case they simply choose the best instrument out of $\tilde{\mathcal{M}} = \mathcal{M}_b$. If $I_{bj} = 0$, the consumer is matched randomly with a merchant. In this case, they know only the average probability that a merchant will accept $\mathcal{M}_s$, denoted by $\bar{P}_{\mathcal{M}_s}$,[8] and the consumer chooses their preferred method from the intersection $\tilde{\mathcal{M}} = \mathcal{M}_b \cap \mathcal{M}_s$. The probability that a consumer uses method m, given they choose to adopt $\mathcal{M}_b$, is therefore

$$P_{bjm}(\mathcal{M}_b) = I_{bj}\mathcal{P}^*_{bjm}(\mathcal{M}_b) + (1 - I_{bj}) \sum_{\mathcal{M}_s \in \mathcal{M}} \bar{P}_{\mathcal{M}_s} \times \mathcal{P}^*_{bjm}(\mathcal{M}_b \cap \mathcal{M}_s). \tag{4}$$

First-stage decision. In the first stage, consumers do not yet know their stage-two usage innovations, ϵ_{bjm}. They therefore form expectations of their utility from each transaction, which depends on their adoption choice, $\mathcal{M}_b$. It follows that the total utility a consumer expects in the second stage, given adoption choice $\mathcal{M}_b$, is the sum of the per-transaction expected utilities over all of the transactions in the set, $\mathcal{J}_b$; i.e.,

$$EU_b(\mathcal{M}_b) = \sum_{j \in \mathcal{J}_b} \mathbb{E}_\epsilon \left[I_{bj} \max_{m \in \mathcal{M}_b} U_{bjm} + (1 - I_{bj}) \sum_{\mathcal{M}_s \in \mathcal{M}} \bar{P}_{\mathcal{M}_s} \max_{m \in \mathcal{M}_b \cap \mathcal{M}_s} U_{bjm} \right]. \tag{5}$$

Let $F_{b,\mathcal{M}_b}$ denote the fixed cost for adopting payment combination $\mathcal{M}_b$.[9] We specify the fixed costs to have the form $F_{b,\mathcal{M}_b} = Z_b\, f^b_{\mathcal{M}_b} + \varepsilon_{b,\mathcal{M}_b}$, where Z_b is a vector of the explanatory variables, $\varepsilon_{b,\mathcal{M}_b}$ is a cost innovation that is realized at the time of adoption, and $f^b_{\mathcal{M}_b}$ is a parameter. Consumers choose the bundle $\mathcal{M}_b$ such that the total utility minus the fixed cost is maximized. The probability that bundle $\mathcal{M}_b$ is adopted is

$$P_{b,\mathcal{M}_b} = \Pr\left(\mathcal{M}_b = \arg\max_{\mathcal{M}'_b \in \mathcal{M}} \left\{ EU_b(\mathcal{M}'_b) - F_{b,\mathcal{M}'_b} \right\}\right). \tag{6}$$

[8]We also estimated the model under the alternative assumptions that the consumer knows the probability distribution of the merchant's acceptance decision and the probability of being matched to a merchant is proportional to the merchant's size. The estimation results are very similar to the ones reported in this paper and are available upon request.

[9]While we refer to $F_{b,\mathcal{M}_b}$ as a "cost," we do not impose any non-negativity constraint and thus allow for potential benefits from adoption.

3.2 Merchants

In the second stage, the decisions are entirely made by consumers. Therefore, it is only during the first stage that profit-maximizing merchants, s, make a single decision about accepting a set of payment instruments, $\mathcal{M}_s$. We first describe the decisions made by a merchant who is facing a market size that is exactly equal to our consumer sample. Then we show how to account for the variation in the market size of merchants who are reporting different revenue levels.

Merchants incur costs $C_{sm}(p_{bj})$ if method m is used to complete transaction (b, j). Similar to consumers, costs are decomposed into a per-transaction cost, c_{0sm}, and a per-value cost, c_{1sm}. Specifically,

$$C_{sm}(p_{bj}) = c_{0sm} + c_{1sm}p_{bj}. \tag{7}$$

Note that a mean-zero random innovation (realized at the POS) can be added to equation 7 such that it would not affect merchant's acceptance choice. This is because the linear merchant usage cost function, $C_{sm}(p_{bj})$, enters the profit function in expectation.

Let mc_{sbj} denote the marginal cost to seller s of producing the good purchased in transaction j, excluding the cost of the transaction itself, C_{sm}. In the data, we do not observe the production costs and proceed under the following simplifying assumption.

Assumption 2: *Every merchant earns a constant profit margin,* $\gamma_{sbj} \equiv \dfrac{p_{bj} - mc_{sbj}}{p_{bj}}$, *such that* $\gamma_{sbj} = \gamma$ *for all* s, b, j.

Assumption 2 allows us to express every merchant's profit as a function of a single parameter, γ, and a set of prices that are paid to this merchant.

Recall from equation (3) that the probability consumer b uses method m for transaction j is $\mathcal{P}^*_{bjm}(\tilde{\mathcal{M}})$ and that this choice set depends on whether the transaction is informed or uninformed. In the uninformed case consumers are randomly matched to merchants, while in the informed case consumers always choose a merchant that accepts their preferred method of payment. As a result, these merchants' expected profits depend on the informedness of the transactions.

Let $E\pi^u_{sbj}(\mathcal{M}_s)$ and $E\pi^i_{sbj}(\mathcal{M}_s)$ denote the expected profit from transaction j if merchant s accepts $\mathcal{M}_s$ and is matched with uninformed and informed consumers, respectively. The expected profit from an informed transaction is

$$E\pi^i_{sbj}(\mathcal{M}_s) = \sum_{\mathcal{M}_b \in \mathcal{M}} P_{b,\mathcal{M}_b} \times \sum_{m \in \mathcal{M}_s} \mathcal{P}^*_{bjm}(\mathcal{M}_b)\big[\gamma p_{bj} - C_{bm}(p_{bj})\big], \tag{8}$$

while the expected profit from an uninformed transaction is

$$E\pi^u_{sbj}(\mathcal{M}_s) = \sum_{\mathcal{M}_b \in \mathcal{M}} P_{b,\mathcal{M}_b} \times \sum_{m \in \mathcal{M}_s} \mathcal{P}^*_{bjm}(\mathcal{M}_b \cap \mathcal{M}_s)\big[\gamma p_{bj} - C_{bm}(p_{bj})\big]. \tag{9}$$

These equations differ only in the choice set over which consumers make their payment usage decision in $\mathcal{P}^*_{bjm}(\cdot)$. Note that for any $m \in \mathcal{M}_b \cap \mathcal{M}_s$, $\mathcal{P}^*_{bjm}(\mathcal{M}_b) \leq \mathcal{P}^*_{bjm}(\mathcal{M}_b \cap \mathcal{M}_s)$. Therefore, the expected profit from an informed transaction is weakly smaller than the expected profit from an equivalent uninformed transaction, $E\pi^i_{sbj}(\mathcal{M}_s) \leq E\pi^u_{sbj}(\mathcal{M}_s)$. This is because in the informed case there is a chance that a consumer wants to use a method of payment that is not accepted by the merchant and this results in a lost sale. For example, for a cash-only merchant, $\mathcal{M}_s = \{ca\}$, an uninformed transaction generates an expected profit of

$$E\pi^u\left(\{ca\}\right) = \big[P_{b,\{ca\}} + P_{b,\{ca,dc\}} + P_{b,\{ca,dc,cc\}}\big] \times \big(\gamma p_{bj} - C_{s,ca}(p_{bj})\big),$$

while an identical transaction conducted by the informed consumer provides

$$E\pi^i\left(\{ca\}\right) = \begin{bmatrix} P_{b,\{ca\}} + \\ P_{b,\{ca,dc\}}\mathcal{P}^*_{bj,ca}(\{ca, dc\}) + \\ P_{b,\{ca,dc,cc\}}\mathcal{P}^*_{bj,ca}(\{ca, dc, cc\}) \end{bmatrix} \times \big(\gamma p_{bj} - C_{s,ca}(p_{bj})\big).$$

Given equations (8) and (9) and awareness status I_{bj}, the merchant's expected aggregate profits can be computed using

$$\mathrm{E}\Pi_s(\mathcal{M}_s) = S_s \times \sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} I_{bj} E\pi^i_{sbj}(\mathcal{M}_s) + (1 - I_{bj}) E\pi^u_{sbj}(\mathcal{M}_s), \tag{10}$$

where S_s is the market size facing a merchant, which is discussed next.

Market size. Before we define the merchant profit maximization problem, we have to discuss the market structure facing a merchant. In our data, merchants are heterogeneous with respect to their revenue and location. Since our merchants are small and geographically disperse from each other, we do not model strategic interactions.[10] In other words, every merchant solves a single-agent profit maximization problem and one merchant's acceptance choice does not affect the payoffs of the other merchants in our sample.

Note that equation (10) defines merchants' profits in terms of our consumer sample size. Assuming our consumer data are representative of every merchant's market, we

[10] We admit that there might be competitive effects at the local level, when one merchant's acceptance decision may affect the choices the local competitors make. That being said, without imposing an additional structure it is hard to see how these can be identified, given the available data.

determine the market size for each merchant by using the observed merchants' revenues and pricing data from our consumer sample. Let $\hat{R}_{s,\mathcal{M}_s}$ denote the revenue of the merchant with acceptance combination $\mathcal{M}_s$ who is facing a market size that is exactly equal to our consumer sample and let $m^*_{bj} \in \{ca, dc, cc\}$ denote the (observed) realizations of the consumer usage decisions at the POS. Then, we can write

$$\hat{R}_{s,\mathcal{M}_s} = \sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} \left[(1 - I_{bj}) + I_{bj} \times \sum_{m \in \mathcal{M}_s} \mathbb{1}\{m^*_{bj} = m\} \right] \times p_{bj}, \tag{11}$$

which predicts the revenues generated by all the consumers in our sample as a function of acceptance combination $\mathcal{M}_s$. In the data, we observe merchants' revenues and acceptance decisions. Let $R_{s,\mathcal{M}_s}$ denote merchants' revenues for a combination, $\mathcal{M}_s$, observed in the data and define the market size facing a merchant as

$$S_s = \frac{R_{s,\mathcal{M}_s}}{\hat{R}_{s,\mathcal{M}_s}}. \tag{12}$$

Equation (12) relates the sum of the prices paid by the consumers in our sample to the merchants' revenue and acceptance decisions. For example, a merchant whose revenues are twice as large as the revenue generated by our sample of consumers (i.e., $R_{s,\mathcal{M}_s} = 2 \times \hat{R}_{s,\mathcal{M}_s}$) would sell to a market of size $S_s = 2$.

Note that, while the market size is defined at the realized acceptance choice, equation (11) can be used to predict the counterfactual merchant revenues for all feasible choices of $\mathcal{M}_s \in \mathcal{M}$. In other words, we define S_s according to the factual and use this estimate in the calculation of the counterfactual merchant choices in the same market; i.e.,

$$R_{s,\tilde{\mathcal{M}}_s} = S_s \times \hat{R}_{s,\tilde{\mathcal{M}}_s}$$

for any $\tilde{\mathcal{M}}_s \in \mathcal{M}$.

Analogous to the consumers, the acceptance of $\mathcal{M}_s$ comes with fixed cost $F_{s,\mathcal{M}_s} = Z_s f^s_{\mathcal{M}_s} + \omega_{s,\mathcal{M}_s}$ where Z_s is a vector of the explanatory variables, $\omega_{s,\mathcal{M}_s}$ is a cost innovation that is realized at the time of acceptance, and $f^s_{\mathcal{M}_s}$ is a parameter vector. Merchants choose bundle $\mathcal{M}_s$, which maximizes profits. The probability this occurs is given by

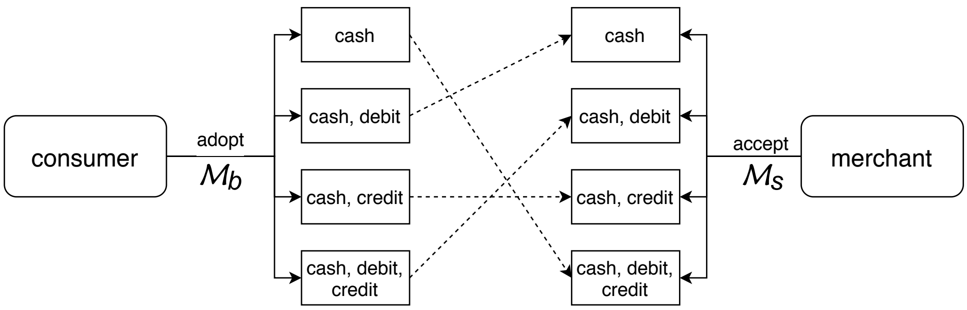
$$P_{s,\mathcal{M}_s} = \Pr\left(\mathcal{M}_s = \operatorname*{arg\,max}_{\mathcal{M}'_s \in \mathcal{M}} \left\{ \mathrm{E}\Pi_s(\mathcal{M}'_s) - F_{s,\mathcal{M}'_s} \right\} \right). \tag{13}$$

3.3 Equilibrium

Figure 2 provides a graphical illustration of the two-stage game played every period. At the beginning of every period, consumers and merchants simultaneously and independently make adoption and acceptance decisions. After all decisions are made, the usage stage begins and consumers are matched with merchants for every transaction until all transactions of all consumers are completed. The matching process depends on consumer awareness being exogenously attached to every transaction. In particular, consumers who are conducting informed transactions visit only those merchants who accept the payment instruments these consumers prefer. Hence, to maximize the utility from the informed transactions, consumers can choose any payment instrument provided it is in $\mathcal{M}_b$. For the uninformed transactions, consumers are randomly matched with merchants. Random matching does not guarantee that a merchant will always accept the payment method chosen by a consumer (unless it is cash). Therefore, to maximize the utility from the uninformed transactions, consumers choose from $\mathcal{M}_b \cap \mathcal{M}_s$, where $\mathcal{M}_s$ is the acceptance combination of the randomly matched merchant.

Figure 2: Two-stage model of interactions between merchants and consumers

STAGE 1



STAGE 2 (informed)

$$\max_{m' \in \mathcal{M}_b} U_{bjm}$$

STAGE 2 (uninformed)

$$\max_{m' \in \mathcal{M}_b \cap \mathcal{M}_s} U_{bjm}$$

Our equilibrium concept is a subgame perfect Nash equilibrium. In what follows, we assume that the set of transactions, $\mathcal{J}_b$, the parameters of the consumers' transaction cost function (2), (c_{0bm}, c_{1bm}), and the distribution parameters of the consumers' adoption costs, $F_{b,\mathcal{M}'_b}$, for all consumer types, $b = 1, \ldots, N_b$, all payment instruments, $m \in \{ca, dc, cc\}$, and all adoption combinations, $\mathcal{M}_b \in \mathcal{M}$, are common knowledge. Similarly, the parameters of the merchant-transaction cost function (7), (c_{0sm}, c_{1sm}), $m \in \{ca, dc, cc\}$, the market size, S_s, and the parameters of the distribution of acceptance cost, $F_{s,\mathcal{M}_s}$, for all $s, \mathcal{M}_s \in \mathcal{M}$, are also common knowledge.

At the beginning of each period, consumers observe private realizations of random innovations to their adoption cost and then choose $\mathcal{M}_b$. Simultaneously, merchants observe realizations of acceptance cost innovations (also private information) and then choose $\mathcal{M}_s$. In the first stage, neither consumers nor merchants observe realizations of the second-stage (usage) innovations to the consumer utility function (1). Therefore, both sides form expectations with respect to ϵ_{bjm}, for which the distribution is known up to a parameter vector.

To make the optimal adoption decision, consumers form expectations about the merchant acceptance probabilities,

$$\bar{P}_{\mathcal{M}_s} = \frac{1}{N_s} \sum_{s=1}^{N_s} P_{s,\mathcal{M}_s}, \ \forall \quad \mathcal{M}_s \in \mathcal{M}, \tag{14}$$

which are then used to calculate the total expected utility (5) for each possible combination of payment instruments, $\mathcal{M}_b \in \mathcal{M}$. A solution to the first-stage consumer utility maximization problem is given by a vector of adoption probabilities $\mathbb{P}_b = \left(P_{b,\{ca\}}, P_{b,\{ca,dc\}}, P_{b,\{ca,dc,cc\}}\right)$ with the elements that are defined in equation (6). We denote the mapping from the distribution of the merchant acceptance probabilities to the optimal consumer adoption probability as the following best response function,

$$\mathbb{P}_b = BR_b \left(\{\mathbb{P}_s\}_{s=1}^{N_s} \right), \ \forall \quad b, \tag{15}$$

where $\mathbb{P}_s = \left(P_{s,\{ca\}}, P_{s,\{ca,dc\}}, P_{s,\{ca,dc,cc\}}\right)$ are the merchants' acceptance probabilities.

Since merchants know the parameters of the consumer utility function, they can evaluate the consumer optimal choice, as in equation (3), the per-transaction expected profits for informed and uninformed consumers, as in equations (8) and (9), and the expected profits for every acceptance combination, which are provided in equation (10). The optimal merchant acceptance probabilities are then defined by equation (13). Let us denote the mapping from the distribution of the consumer adoption probabilities to the optimal merchant acceptance decisions, $\mathbb{P}_s$, as the best response function

$$\mathbb{P}_s = BR_s \left(\{\mathbb{P}_b\}_{b=1}^{N_b} \right), \forall \quad s. \tag{16}$$

We define equilibrium in terms of vectors $\mathbb{P}_s^*$ and $\mathbb{P}_b^*$ for all s, b, such that $\mathbb{P}_b^*$ solves (15), given $\mathbb{P}_s^*$, and $\mathbb{P}_s^*$ solves (16), given $\mathbb{P}_b^*$. Given the adoption and acceptance probabilities, there is a unique vector of the equilibrium usage probabilities, which is given by

$$P_{bjm}^* = \sum_{\mathcal{M}_b \in \mathcal{M}} P_{b,\mathcal{M}_b}^* \times P_{bjm}(\mathcal{M}_b), \tag{17}$$

where $P_{b,\mathcal{M}_b}^* \in \mathbb{P}_b^*$ is the first-stage optimal adoption combination; $P_{bjm}(\mathcal{M}_b)$ is defined by equation (4) and depends on the transaction information status as well as the consumer adoption and merchant acceptance choices.

4 Specifications and Estimation

There are three layers of agents' decision making in our model: consumers choose which methods of payment to adopt and then use, while merchants choose which payment methods to accept. Given a vector of parameter values, our model generates probabilistic predictions for each of these choices. We use joint likelihood as a criterion function to match the model predictions to the observed consumer and merchant choices. This section defines the likelihood, describes the various distributional assumptions required, and outlines the algorithm used to obtain the estimates for the structural parameters. It is worth noting that, in the estimation, we do not impose any assumptions on the behaviour of debit and credit card issuers and acquirers and we take the fee structure in this market as given.[11] For simplicity, we assume that consumers always have enough cash to complete any desired transactions. Similarly, whenever consumers prefer to make debit transactions, we assume they always have a sufficient balance.[12]

4.1 Parametric restrictions

While our structural model can accommodate consumers and merchants choosing all four potential combinations of payment methods, we exclude combination $\{ca, cc\}$ from the choice set for both sides of the market. The main reason is that while this is theoretically possible, in practice, consumers who have a credit card also have a debit account. Credit card balances must be paid, and the routine use of cash for this purpose is cumbersome. This is particularly true given that a consumer who is already approved for a credit card almost certainly would qualify for a debit account. It is conceivable that consumers who report having cash and credit in fact also have debit accounts, albeit from different, possibly non-Canadian banks. On the merchant side, given that the cost of processing credit card transactions is strictly higher than the cost for debit cards, it seems unreasonable to combine cash with a more-expensive payment instrument, such as a credit card, while not accepting a debit card. Therefore, in the estimation we reclassify consumers and merchants and report the $\{ca, cc\}$ combination as those adopting/accepting all means of payment; i.e., $\{ca, de, cc\}$.

[11]Insights into the acquiring market in Canada are provided by Welte and Molnar (2020). In the counterfactual section, we make additional assumptions about the pass-through rate of the interchange fee from the card issuers to the consumers in the form of a cost reduction. Ho et al. (2020) study the monopoly pricing of the Chinese payment card network.

[12]Briglevics and Schuh (2020) build a model of optimal cash withdrawal and consumer choice behaviour but only focus on consumer costs and do not account for merchant acceptance.

Consumer adoption costs. We assume that the vector of consumer adoption costs $\left(F_{b,\{ca\}}, F_{b,\{ca,dc\}}, F_{b,\{ca,dc,cc\}}\right)$ can be written as

$$\begin{cases} F_{b,\{ca\}} & =\varepsilon_{b,\{ca\}}, \\ F_{b,\{ca,dc\}} & =Z_b\ f^b_{\{ca,dc\}} + \varepsilon_{b,\{ca,dc\}}, \\ F_{b,\{ca,dc,cc\}} & =Z_b\ f^b_{\{ca,dc,cc\}} + \varepsilon_{b,\{ca,dc,cc\}}, \end{cases}$$

where the mean adoption cost for the cash-only combination is normalized to zero, $f^b_{\{ca,dc\}}$ and $f^b_{\{ca,dc,cc\}}$ are vectors of the parameters, and $\varepsilon_b = \left(\varepsilon_{b,\{ca\}}, \varepsilon_{b,\{ca,dc\}}, \varepsilon_{b,\{ca,dc,cc\}}\right)$ is a vector of the random innovations that are realized at the time of adoption. Vector Z_b includes the observed demographic variables such as age, income, education, and gender. We also include additional variables such as consumer credit scores and characteristics of the consumer-transaction endowment, $\mathcal{J}_b$, such as the number and total value of transactions. These variables affect consumer adoption decisions but not consumer usage decisions and, therefore, satisfy the exclusion restrictions for separate identifications of the parameters in the first- and second-stage consumer decisions. It is worth noting that explicit exclusion restrictions are not necessary in our model because these decisions are modelled structurally. However, we believe these additional variables are important for consumer adoption choice and, therefore, use them to facilitate identification in the model. We return to this discussion in subsection 4.3.

Merchant acceptance costs. On the merchant side, we assume that the vector of acceptance costs $\left(F_{s,\{ca\}}, F_{s,\{ca,dc\}}, F_{s,\{ca,dc,cc\}}\right)$ can be written as

$$\begin{cases} F_{s,\{ca\}} & =\omega_{s,\{ca\}}, \\ F_{s,\{ca,dc\}} & =f^s_{0,\{ca,dc\}} + f^s_{1,\{ca,dc\}} S_s + \omega_{s,\{ca,dc\}}, \\ F_{s,\{ca,dc,cc\}} & =f^s_{0,\{ca,dc,cc\}} + f^s_{1,\{ca,dc,cc\}} S_s + \omega_{s,\{ca,dc,cc\}}, \end{cases}$$

where the mean acceptance cost for the cash-only combination is normalized to zero, $f^s_{0,\{ca,dc\}}$ and $f^s_{0,\{ca,dc,cc\}}$ are constant-acceptance-cost parameters, $f^s_{1,\{ca,dc\}}$ and $f^s_{1,\{ca,dc,cc\}}$ linearly relate the acceptance costs and market size, and $\omega_s = \left(\omega_{s,\{ca\}}, \omega_{s,\{ca,dc\}}, \omega_{s,\{ca,dc,cc\}}\right)$ is a vector of the choice-specific innovations at the POS.

To estimate the model parameters, we use the simulated maximum likelihood and make the following distributional assumptions:

Assumption 3: *A vector of random innovations to consumer adoption costs in the first stage,*

$$\epsilon_b = \left(\epsilon_{b,\{ca\}}, \epsilon_{b,\{ca,dc\}}, \epsilon_{b,\{ca,dc,cc\}}\right), \tag{A3.1}$$

a vector of consumer usage cost innovations at the POS,

$$\epsilon_{bj} = \left(\epsilon_{b,j,ca}, \epsilon_{b,j,dc}, \epsilon_{b,j,cc}\right), \tag{A3.2}$$

and a vector of merchant acceptance cost innovations,

$$\omega_s = \left(\omega_{s,\{ca\}}, \omega_{s,\{ca,dc\}}, \omega_{s,\{ca,dc,cc\}}\right) \tag{A3.3}$$

are given by independent and identically distributed random draws from a standard Gumbel distribution.

Given assumption 3, we obtain functional forms for the usage probabilities, expected utilities, and adoption and acceptance probabilities. In particular, by using properties of the Gumbel distribution, we can rewrite the probability of using m, given a generic choice set $\tilde{\mathcal{M}}$ in equation (3), as

$$\mathcal{P}^*_{bjm}(\tilde{\mathcal{M}}) = \frac{\exp(X_{bm}\beta + \alpha_c C_{bm}(p_{bj}) + \xi_m(D_b, T_j))}{\sum_{m' \in \tilde{\mathcal{M}}} \exp(X_{bm}\beta + \alpha_c C_{bm}(p_{bj}) + \xi_m(D_b, T_j))}.$$

Similarly, the expected per-transaction utilities summed up in equation (5) can be written as

$$\mathbb{E}_\epsilon \left[\max_{m \in \tilde{\mathcal{M}}} \{U_{bjm}\}\right] = \ln\left(\sum_{m \in \tilde{\mathcal{M}}} \exp\left(X_{bm}\beta + \alpha_c C_{bm}(p_{bj}) + \xi_m(D_b, T_j)\right)\right) + c,$$

where $c \approx 0.5772$ is the Euler constant. The probability a consumer adopts bundle $\mathcal{M}_b$ in equation (6) is

$$P_{b,\mathcal{M}_b} = \frac{\exp(EU_b(\mathcal{M}_b) - F_{b,\mathcal{M}_b})}{\sum_{\mathcal{M}'_b \in \mathcal{M}} \exp(EU_b(\mathcal{M}'_b) - F_{b,\mathcal{M}'_b})}.$$

Finally, the probability a merchant accepts bundle $\mathcal{M}_s$ in equation (13) becomes

$$P_{s,\mathcal{M}_s} = \frac{\exp(\mathrm{E}\Pi_s(\mathcal{M}_s) - F_{s,\mathcal{M}_s})}{\sum_{\mathcal{M}'_s \in \mathcal{M}} \exp(\mathrm{E}\Pi_s(\mathcal{M}'_s) - F_{s,\mathcal{M}'_s})}.$$

To conduct robustness checks, we also use alternative assumptions on the distribution of the merchant acceptance cost innovations in (A3.3).[13]

We categorize the structural parameters of the model into (1) first-stage consumer adoption cost parameters, θ^b_1; (2) second-stage consumer usage utility parameters, θ^b_2; and

[13] In particular, we experiment with the normal distribution where, in addition to the mean parameter values $\left(f^s_{0,\{ca,dc\}}, f^s_{0,\{ca,dc,cc\}}, f^s_{1,\{ca,dc\}}, f^s_{1,\{ca,dc,cc\}}\right)$, we also estimate the variances of the innovations. A detailed description of this exercise is provided in Appendix A, which discusses the model extensions and robustness checks.

(3) first-stage merchant acceptance cost parameters, θ_1^s, where

$$\theta_1^b = \left(f^b_{\{ca,dc\}},\ f^b_{\{ca,dc,cc\}}\right),\ \theta_2^b = (\beta,\ \alpha_c,\ \boldsymbol{\xi}),$$
$$\theta_1^s = \left(\gamma,\ f^s_{0,\{ca,dc\}},\ f^s_{0,\{ca,dc,cc\}},\ f^s_{1,\{ca,dc\}},\ f^s_{1,\{ca,dc,cc\}}\right).$$

In the data, we observe realizations of the adoption, acceptance, and usage decisions. Let $A_{b,\mathcal{M}_b} \in \{0,1\}$ for all b, and $\mathcal{M}_b$ denote the observed realizations of consumer adoption decisions; let $A_{s,\mathcal{M}_s} \in \{0,1\}$ for all s, and $\mathcal{M}_s$ denote the realizations of merchant acceptance choices; and let $a_{bjm} \in \{0,1\}$ denote the observed realizations of usage decisions that take place at the POS. Note that $\sum_{\mathcal{M}'_b \in \mathcal{M}} A_{b,\mathcal{M}'_b} = \sum_{\mathcal{M}'_s \in \mathcal{M}} A_{s,\mathcal{M}'_s} = \sum_{m \in \{ca,dc,cc\}} a_{bjm} = 1$ for all b, s, j.

To estimate the structural parameters in the model, we use the following likelihood function:

$$\mathcal{L}(\theta_1^b, \theta_2^b, \theta_1^s) = \prod_{b=1}^{N_b} \prod_{\mathcal{M}_b \in \mathcal{M}} P^{*\ A_{b,\mathcal{M}_b}}_{b,\mathcal{M}_b} \times \prod_{b=1}^{N_b} \prod_{j \in \mathcal{J}_b} \prod_{m \in \{ca,dc,cc\}} P^{*\ a_{bjm}}_{bjm} \times \prod_{s=1}^{N_s} \prod_{\mathcal{M}_s \in \mathcal{M}} P^{*\ A_{s,\mathcal{M}_s}}_{s,\mathcal{M}_s}, \tag{18}$$

where $P^*_{b,\mathcal{M}_b} \in \mathbb{P}^*_b$, $P^*_{s,\mathcal{M}_s} \in \mathbb{P}^*_s$, and P^*_{bjm} $\forall b, j, m$ are the equilibrium adoption, acceptance, and usage probabilities.

4.2 Estimation algorithm

In this subsection we describe our estimation algorithm. Before we begin, it is worth describing the technique we employ to "concentrate out" a large number of fixed effects in the usage stage.

Concentrating out usage fixed effects. Recall from equation (1) that the consumer usage utility is given by

$$U_{bjm} = X_{bm}\beta + \alpha_c C_{bm}(p_{bj}) + \xi_m(D_b, T_{bj}) + \epsilon_{bjm},$$

where $\xi_m(D_b, T_{bj})$ is a fixed effect that depends on the consumer's demographics, D_b, and the type of transaction, T_{bj}. For example, consumers participating in various reward programs often get cash-back rewards that depend on the transaction type. The fixed effect also captures any additional systematic convenience (or inconvenience) of using each payment method, m, for the various demographic groups in our model.

While, theoretically, there are no difficulties in estimating a large number of parameters in a non-linear structural model, the need to search over more than 200 parameters in our richest specification imposes a substantial computational burden.[14] To reduce this

[14]The complexity comes from the nature of the nested fixed point algorithms where, for each vector of

burden, we employ a technique that was originally proposed in Carranza and Navarro (2010). This method allows us to concentrate out unobservables $\xi_m(D_b, T_{bj})$, conditional on the rest of the structural parameters. The way we "solve" for $\xi_m(D_b, T_{bj})$ is similar to the inversion in discrete choice models that is frequently used in the literature that follows Berry et al. (1995).

We begin by classifying all consumer-transaction pairs into distinct groups according to income, age, education, gender, and transaction type variables. Each variable is divided into levels, as follows. Income: (1) ≤\$35,000 dollars, (2) between \$35,000 and \$75,000, and (3) \$75,000 or more. Age: (1) 18 to 39, (2) 40 to 55, and (3) 56 or older. Education: (1) those with some university experience and (2) those with no university experience. Gender: (1) female and (2) male. Transaction type: (1) grocery and retail, (2) entertainment and meals, and (3) other.

We define group g as an element of all possible combinations of the levels for the four demographic variables as well as the transaction type. Let $\xi_m(D_b, T_{bj}) = \xi_{gm}$ for all $(D_b, T_{bj}) \in g, g \in (Inc \times Age \times Edu \times Gen \times Ttype)$. For example, all male consumers with income of less than \$35,000, who are from 40 to 55 years of age, have some university education and make a gas purchase would constitute one group and, thus, would share the same match value for a given payment instrument. The intuition is that people in the same group are likely to be offered debit and credit cards with similar features, such as fees and reward structures. We normalize $\xi_{g,ca} = 0$ for all g and estimate the fixed effects for debit and credit cards.

Recall that the equilibrium usage probabilities are defined in equation (17) and can be written explicitly as a function of $\bar{\xi}_g = (\xi_{g,ca}, \xi_{g,dc}, \xi_{g,cc})$,

$$P^*_{bjm} = \sum_{\mathcal{M}_b \in \mathcal{M}} P^*_{b,\mathcal{M}_b} \times P_{bjm}(\mathcal{M}_b, \bar{\xi}_g),$$

where $\bar{\xi}_g$ enters $P_{bjm}(\mathcal{M}_b, \bar{\xi}_g)$ via operator $\mathcal{P}^*_{bjm}(\tilde{\mathcal{M}})$ in equation (3). Let $G_{gm}(\bar{\xi}_g)$ denote the expected frequency of usage of payment instrument m by group g, which is computed by integrating over all individuals and transactions in group g,

$$G_{gm}(\bar{\xi}_g) = \int_{(b,j)\in g} P^*_{bjm}(\bar{\xi}_g) dF_{(b,j)}.$$

Let P_{gm} denote the true group-specific usage probabilities and suppose we know them. Then, we can write the following system of equations with the true usage probabilities on

parameter values, we have to iteratively solve for an equilibrium in the market.

the LHS and the model prediction as a function of ξ_{gm} on the RHS:

$$\begin{cases} P_{1m} & = & G_{1m}(\bar{\xi}_1), \\ P_{2m} & = & G_{2m}(\bar{\xi}_2), \\ \vdots & & \vdots \\ P_{N_g m} & = & G_{N_g m}(\bar{\xi}_{N_g}), \end{cases} \tag{19}$$

where $m = (dc, cc)$ and N_g is the number of consumer-transaction groups. Note that the number of independent equations in (19) is $2N_g$ due to the adding-up condition on the usage probabilities within each group. Since we normalize the match values between all of the consumer-transaction types and the cash to zero; i.e., $\xi_{g,ca} \equiv 0$ for all g, the system of equations in (19) has the same number of equations and unknowns. We can rewrite the system more compactly by using vector notation:

$$\boldsymbol{P} = \boldsymbol{G}(\boldsymbol{\xi}),$$

where $\boldsymbol{P} = (P_{1,dc}, \ldots, P_{N_g,dc}, P_{1,cc}, \cdots, P_{N_g,cc})$ and $\boldsymbol{\xi} = (\xi_{1,dc}, \ldots, \xi_{N_g,dc}, \xi_{1,cc}, \ldots, \xi_{N_g,cc})$. Let

$$\boldsymbol{\xi} = \boldsymbol{G}^{-1}(\boldsymbol{P})$$

denote the solution to the system of equations (19). We discuss the conditions for the solution to exist in the context of the identification below.

While we do not directly observe group-specific usage probabilities, we can estimate them from the data,

$$\hat{P}_{gm} = \frac{1}{N_g} \sum_{(b,j) \in g} \mathbb{1}\{m^*_{bj} = m\}, \ \forall m, g,$$

and use the estimates $\hat{\boldsymbol{P}} = (\hat{P}_{1,dc}, \ldots, \hat{P}_{N_g,dc}, \hat{P}_{1,cc}, \cdots, \hat{P}_{N_g,cc})$ to solve for the unobservables; i.e.,

$$\hat{\boldsymbol{\xi}} = \boldsymbol{G}^{-1}(\hat{\boldsymbol{P}}). \tag{20}$$

We use this solution to concentrate out a large number of consumer-transaction-method-specific fixed effects that are conditional on the rest of the structural parameters. It is worth noting that the unobservables that satisfy (20) are not the maximum likelihood estimates (MLE) of ξ_{gm} (as discussed in Carranza and Navarro 2010, see equation 11 on p. 9). The MLE and the estimates that satisfy (20) are only equivalent when $\hat{\boldsymbol{P}}$ are estimated without errors. A requirement for the exact measure of the purchase probabilities or market shares is very common in the modern discrete choice literature and is related to the non-linearity of the $\boldsymbol{G}(\cdot)$ function.

In an attempt to find the right balance between the number of groups and, hence, the flexibility of our specification and the precision of the estimates for the group-specific usage probabilities, we end up with 108 groups. As a result, we must estimate 216 fixed effects (108 for debit and 108 for credit transactions). Summary statistics for the number of observations per group are reported in Table 7.

Table 7: Statistics for the number of observations per group

Mean	Min	p10	p25	p50	p75	p90	Max
111	16	46	72	100	143	186	278

Notes: Groups are defined as a combination of consumer demographics and transaction type.

Over 90 percent of groups are estimated by using 40 or more observations. We also conduct robustness checks by defining larger or smaller numbers of groups and we find that the estimates of the main structural parameters remain quite stable.[15] A related paper, Huynh et al. (2020), which uses similar data but focuses on the consumer side, estimates similarly defined fixed effects by using both a standard MLE and the method discussed above and finds that the approximation works well. To summarize, we use the concentrating-out technique with the purpose of obtaining computational savings and thus our estimator can be defined as an MLE with constraints, as defined in equation (20).

Algorithm. To estimate the parameters of the model, we use a nested fixed point algorithm within a simulated maximum likelihood framework with constraints. The algorithm initializes the vectors of the consumer adoption and merchant acceptance probabilities and begins with a trial vector of parameter values $(\theta_1^b, \theta_1^s, \theta_2^b \setminus \boldsymbol{\xi})$. We calculate the usage probabilities (3), which are then aggregated to the group level in the system of equations (19). The system is solved for a vector of $\boldsymbol{\xi}$ as in (20) by using the following update rule:

$$\xi'_{gm} = \xi_{gm} + \ln(\hat{P}_{gm}) - \ln\left(G_{gm}(\bar{\xi}_g)\right), \ \forall g, \ m = (dc, cc),$$

where ξ and ξ' are the current and next iteration values of the unobserved match value and the solution is found when the absolute difference between two consecutive values of the unobservables is very small; i.e., when $|\xi'_{gm} - \xi_{gm}| < 1.0e - 12$. After we solve for $\boldsymbol{\xi}$, given the other parameter values, we update the consumer adoption and merchant acceptance probabilities by using equations (6) and (13), respectively.

A new iteration starts with the updated (instead of initialized) vectors of the adoption and acceptance probabilities for consumers and merchants and repeats all of the steps until the joint best response mapping that consists of equations (15) and (16) is satisfied; that is, until the input vector of the merchant acceptance probabilities, $\{\mathbb{P}_s\}_{s=1}^{N_s}$, results in a collection of consumer best response adoption probabilities, $\{\mathbb{P}_b\}_{b=1}^{N_b}$, and vice versa. We allow for at most a $1.0e - 11$ difference between the probability vectors in the two

[15] Estimation results with alternative definitions of groups are available upon request.

consecutive iterations. When convergence is reached, in equation (18) we construct a joint likelihood function that consists of the following predictions: (1) the optimal consumer first-stage adoption probabilities, (2) the equilibrium usage probabilities in the second stage, and (3) the optimal merchant first-stage acceptance probabilities.

4.3 Identification

Identification in our model relies on distributional assumption 3. Note that separate identifications of the first- and second-stage parameters for consumers are established in two ways. First, consumers have heterogeneous transaction endowments, $\mathcal{J}_b$'s; i.e., they differ in the number and types of transactions as well as in the distribution of the transaction prices. Therefore, the heterogeneous consumer endowments of the transactions represent "shifters" of the first-stage decisions only. This is because individual second-stage usage decisions do not depend on the total number or the types of the other transactions in the consumer endowment. Hence, even without the variables explicitly included in the first-stage specifications, our model structure provides implicit exclusion restrictions via a summation over the elements of the set $\mathcal{J}_b$ as in the definition of the expected consumer utility in equation (5).

Second, we use the variables that satisfy the exclusion restrictions; i.e., the variables that are excluded from the second stage but are relevant for the adoption stage, such as the credit scores and the self-reported perceptions of merchants' acceptance decisions. In our most flexible specification, we also use the parameters of $\mathcal{J}_b$, such as the total number and value of transactions.

The distribution of merchant acceptance costs can be nonparametrically identified if we know the merchants' profit margins, γ_s. In this case, we would be able to assign a cardinal measure to the profits of the cash-only merchants and the variations in the market size and the merchant costs would identify the distribution of the acceptance costs (see Matzkin 1992, Theorem 1 on p. 244). However, we do not observe the profit margins but rather estimate them. Therefore, identification of the merchant acceptance costs and the profit margin rely on the constant-margin assumption 2 and parametric restrictions (8) and (9). It is worth noting that in the limiting case with zero consumer awareness, the profit margin parameter is not identified. Without incentives to increase sales by attracting consumers via larger acceptance combinations, the merchant profit maximization problem becomes a simple cost minimization problem. For the same reasons, under zero consumer awareness, the first-stage acceptance costs cannot be separately identified from the reduced-form profits that rationalize wider acceptance combinations.

Identification of the match values (fixed effects) between consumers and payment instruments at the POS requires the existence and uniqueness of a solution to the system of equations (19). If all transactions are informed, then $G_{gm}(\cdot)$ approaches arbitrarily close to zero as ξ_{gm} goes to $-\infty$, while $G_{gm}(\cdot)$ approaches arbitrarily close to one as ξ_{gm} goes to ∞. Furthermore, due to the discrete choice nature of the consumer usage choice, all payment instruments are substitutes. Therefore, the existence of a unique solution can be established as in Berry (1994) (see appendix, pp.260-261, on the inverse of the market-share equation). If some of the transactions are conducted in the uninformed state, then $G_{gm}(\cdot)$ would be bounded away from one, even when $\xi_{gm} \to \infty$. This is because $P_s(\mathcal{M}_s) < 1$; i.e., consumers should not expect to use a given payment instrument more often than a randomly picked merchant would accept it. Interestingly, the relationship between the proportion of the informed vs uninformed transactions and the existence of a solution to (19) can be used to identify the proportion of informed transactions. In our application, we fix the probabilities of the informed and uninformed states for each transaction by using external data as discussed above. The average probability of observing an informed transaction in the data is about 0.95 and we do not experience any problems with the existence of solution (20) for all trial parameter values.

5 Estimation Results

In this section, we discuss the estimates obtained under alternative assumptions about consumer awareness. Then we relate the consumer demographics and adoption costs. For all specifications, we use the same model of merchants. A robustness analysis for our alternative distributional assumptions about merchant acceptance costs is provided in Appendix A.

To illustrate how alternative assumptions about consumer awareness affect the estimates of structural parameters, we begin by estimating a simple version of our model under three different consumer awareness scenarios. First, similar to Huynh et al. (2019), we assume that consumers know only the overall average of merchants' acceptance probabilities and not individual merchants' choices. The estimation results for this specification are listed in Table 8, under column (1) "No Info." Second, we assume another extreme where consumers know every merchants' individual choices; that is, when consumers have full information. The parameter estimates under this assumption are listed in column (2) "Full Info." Third, we use our probability estimates to be informed for each transaction. To predict these probabilities, we employ data from the survey diary of the 2017 MOP, where consumers report each transaction and whether they had visited the same store before, and we relate this information to the 2013 data, as described in Section 2. These estimation results are reported in column (3). The first three specifications are estimated to illustrate the effects of alternative consumer awareness assumptions on the parameter estimates.

Finally, we extend our baseline model (3) by allowing consumer heterogeneity in the adoption costs. We experiment with a wide range of demographic variables and report our two favourite specifications in columns (4) and (5). Note that both extensions are estimated by using the imputed consumer awareness probabilities for each transaction as in (3). The parameter estimates reported in column (5) of Table 8 represent the most flexible specification and we use it later to conduct our counterfactual simulations. In addition to the results in Table 8, we conduct a number of robustness checks by including additional variables in the first stage of the model. We also experiment with alternative definitions of the consumer-transaction-method match values in the usage stage by conditioning these on other demographic variables and aggregating the transaction types differently. We find that the parameter estimates are robust to such perturbations. Some of the alternative specifications can be found in Appendix A. Appendix B discusses the fit of the model.

Before we discuss the parameter estimates for consumers and merchants, it makes sense to compare the estimates from a baseline model under various levels of consumer awareness about merchants' acceptance decisions. Note that the parameter estimates in specifications (2) and (3) in Table 8 are relatively similar and both are significantly different from the zero awareness case (1). This is not surprising, given that in the partial information case the average probability of being informed is about 0.95, which is very close to the full information case. One of the largest differences for the consumer side is found for the transaction cost parameter, which under the no information assumption is about two to three times smaller than the estimates under full or partial awareness. On the merchant side, the difference is even more striking. Under the no information assumption, we estimate the cost of accepting all payment methods to be negative, while the estimates for all the other specifications are positive. This suggests that the profits earned from the informed consumers, which are explicitly modelled in specifications (2) to (5), are captured in the reduced form of specification (1). We further discuss these findings in subsection 5.2 below.

5.1 Consumer preferences

Adoption stage. We begin with a discussion of the adoption cost parameters. Representative consumer versions of the model reported in specifications (1), (2), and (3) estimate slightly negative adoption costs. To convert the adoption cost coefficients to dollar values, we divide them by the coefficient of the transaction costs and multiply by 10 to pro-rate the value to a monthly level. If we assume zero consumer awareness about merchants' acceptance decisions, consumers on average earn about 30 cents per month when they adopt cash and debit payment, and 60 cents/mo when they adopt all means of payment.[16] The largest consumer benefits (\$1.38 and \$2.39 per month) are predicted when consumers are assumed to be aware of all merchants' acceptance decisions. These

[16] A detailed discussion of the case where consumers are fully unaware about the merchants' choices can be found in an earlier version of this paper, Huynh et al. (2019).

Table 8: Estimation results

		No info	Full info	Observed info		
		(1)	(2)	(3)	(4)	(5)
Consumers, stage 1						
$f^b_{0,\{ca,dc\}}$	constant	-0.465	-0.727	-0.709	-1.824	-2.318
(s.e.)		(0.192)	(0.183)	(0.184)	(0.597)	(0.607)
$f^b_{0,\{ca,dc,cc\}}$		-0.972	-1.264	-1.254	-1.892	-2.972
(s.e.)		(0.184)	(0.175)	(0.176)	(0.566)	(0.575)
$f^b_{age,\{ca,dc\}}$	age				0.029	0.028
(s.e.)					(0.010)	(0.010)
$f^b_{age,\{ca,dc,cc\}}$					-0.003	0.001
(s.e.)					(0.009)	(0.009)
$f^b_{\#t,\{ca,dc\}}$	number of trans.				-0.188	-0.224
(s.e.)					(0.101)	(0.101)
$f^b_{\#t,\{ca,dc,cc\}}$					0.000	-0.057
(s.e.)					(0.097)	(0.096)
$f^b_{Vt,\{ca,dc\}}$	total spending				1.141	0.969
(s.e.)					(0.288)	(0.269)
$f^b_{Vt,\{ca,dc,cc\}}$					1.311	1.078
(s.e.)					(0.283)	(0.262)
$f^b_{ac,\{ca,dc\}}$	accept. debit					-3.881
(s.e.)						(1.536)
$f^b_{ac,\{ca,dc,cc\}}$	accept. credit					-3.258
(s.e.)						(0.909)
$f^b_{ea,\{ca,dc\}}$	ease of use, debit					-5.416
(s.e.)						(1.586)
$f^b_{ea,\{ca,dc,cc\}}$	ease of use, credit					-5.779
(s.e.)						(1.213)
$f^b_{se,\{ca,dc\}}$	security, debit					-1.757
(s.e.)						(0.953)
$f^b_{se,\{ca,dc,cc\}}$	security, credit					-1.153
(s.e.)						(0.806)
$f^b_{sc,\{ca,dc\}}$	ease of setup, debit					-4.417
(s.e.)						(1.306)
$f^b_{sc,\{ca,dc,cc\}}$	ease of setup, credit					-5.202
(s.e.)						(0.778)
Consumers, stage 2						
Transaction cost		-15.965	-5.296	-7.173	-7.329	-7.302
(s.e.)		(0.289)	(0.117)	(0.176)	(0.184)	(0.184)
Ease of use		8.907	6.766	7.097	6.816	6.406
(s.e.)		(0.423)	(0.320)	(0.334)	(0.337)	(0.348)
Security		1.630	1.155	1.203	1.135	1.053
(s.e.)		(0.214)	(0.162)	(0.168)	(0.167)	(0.171)
Affordability		2.939	2.223	2.326	2.222	2.203
(s.e.)		(0.158)	(0.127)	(0.131)	(0.132)	(0.133)
Merchants, stage 1						
$f^s_{0,\{ca,dc\}}$	constant	2.162	1.850	2.190	2.200	2.196
(s.e.)		(0.228)	(0.255)	(0.251)	(0.251)	(0.247)
$f^s_{0,\{ca,dc,cc\}}$		-0.253	0.228	0.542	0.540	0.541
(s.e.)		(0.069)	(0.107)	(0.102)	(0.102)	(0.102)
$f^s_{1,\{ca,dc\}}$	slope	0.390	4.255	4.361	4.282	5.190
(s.e.)		(0.090)	(0.325)	(0.242)	(0.255)	(0.118)
$f^s_{1,\{ca,dc,cc\}}$		-5.383	6.026	6.079	5.742	8.030
(s.e.)		(0.078)	(0.878)	(0.642)	(0.661)	(0.201)
$\gamma = \frac{p-mc}{p}$	profit margin	0.045	0.044	0.045	0.044	0.052
(s.e.)		n.a.	(0.003)	(0.002)	(0.002)	(0.001)
F-value		-11,721.25	-12,332.92	-12,215.38	-12,149.02	-12,076.62

Notes: All specifications include consumer×transaction type×payment instrument fixed effects; the profit margin in specification (1) is not identified and is assumed to equal 0.045, which is an estimate from specification (3) with observed information status for each transaction. Subscripts ca, dc and cc stand for cash, debit card and credit card, respectively.

estimates are listed in specification (2). The estimates from the model with the known information status for each transaction (3) suggest benefits worth \$0.99 and \$1.75 per month for cash and debit and all means of payment combinations, respectively.

Specifications (4) and (5) in Table 8 are more flexible. They allow first-stage consumer adoption costs to vary with the consumer demographics and the number and value of transactions to be completed. Specification (5) also includes a set of variables that is based on consumer perceptions of merchants' acceptance decisions and the ease and security of use for the most advanced payment method in the consumer adoption bundle, as well as the perceived ease of setup for such a payment method.[17] We find that older consumers have higher costs of adopting debit cards and when the bundle also includes credit cards, the effect of age fades out. Appendix A.2 provides robustness analyses under alternative specifications of consumer adoption costs. We find these estimation results and corresponding counterfactual simulations to be quantitatively and qualitatively similar to the ones reported below.

It is worth noting that consumer perceptions of the ease of use and security for each payment instrument are already structurally included in the consumer decision problem via the expectation of the usage stage.[18] Therefore, a set of variables that satisfies the exclusion restrictions contains the number and value of all transactions in the consumer endowment, the perceptions of the merchants' acceptance choices, and the consumers' beliefs about how easy it is to set up the most advanced payment option in their adoption combination.

Consumers with larger total expenditures tend to have significantly higher fixed costs for both adoption bundles. When controlling for the total value of all transactions, their number tends to have weak negative effects on adoption costs. Our intuition is that consumers who use their cards more frequently learn to do this efficiently and with lower overhead costs. At the same time, holding the number of transactions fixed, larger expenses can imply higher fees and balances that revolve and accumulate fees over longer periods.

By comparing specifications (4) and (5), we find that consumer perceptions have important implications for their adoption decisions. Wider merchant acceptance of electronic means of payment reduces consumer adoption costs. That is, consumers with more-optimistic expectations of merchants' acceptance of a given payment instrument, on average, find it easier and cheaper to adopt a bundle that includes this payment instrument. Similarly, consumer adoption costs are lower when consumers find payment instruments easier and safer to use. At the same time, consumers reporting high perceived setup

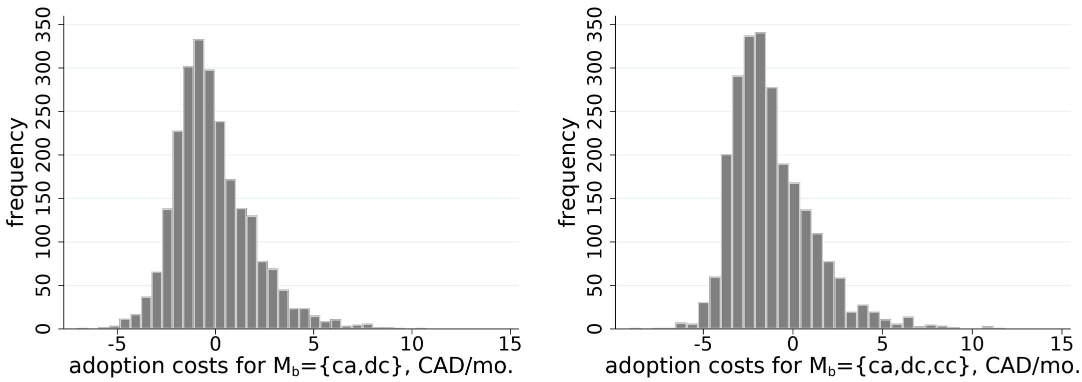
[17]We also experiment with including consumer income in levels and logs, and gender, education level, marital and urban status, as well as consumer credit scores and we did not find statistically significant effects for these covariates. The estimation results are available upon request.

[18]Recall that the consumer utility function 1 includes ease of use, security, and affordability as explanatory variables.

costs for either debit or credit cards behave accordingly; i.e., when their adoption cost is higher, the adoption probability is lower. Given the economic and statistical significance of consumer perceptions, all of the results discussed below are based on specification (5) in Table 8.

Figure 3 reports the estimated distribution of consumers' fixed adoption costs for each combination of payment instruments. On average, the choice of debit card generates benefits of about 15 cents per month. Consumers choosing to have all payment instruments in their wallets earn \$1.18 per month, on average. Overall, the distribution of adoption costs for cash and debit combinations is more centred around zero than the distribution of adoption costs for all payment instruments, which suggests the effect of reward programs offered by credit card issuers. Nearly all estimates of adoption costs for both combinations are within the range of $[-5, 5]$ dollars per month.

Figure 3: Expected adoption costs/benefits for $\mathcal{M}_b = \{ca, dc\}$ and $\mathcal{M}_b = \{ca, dc, cc\}$



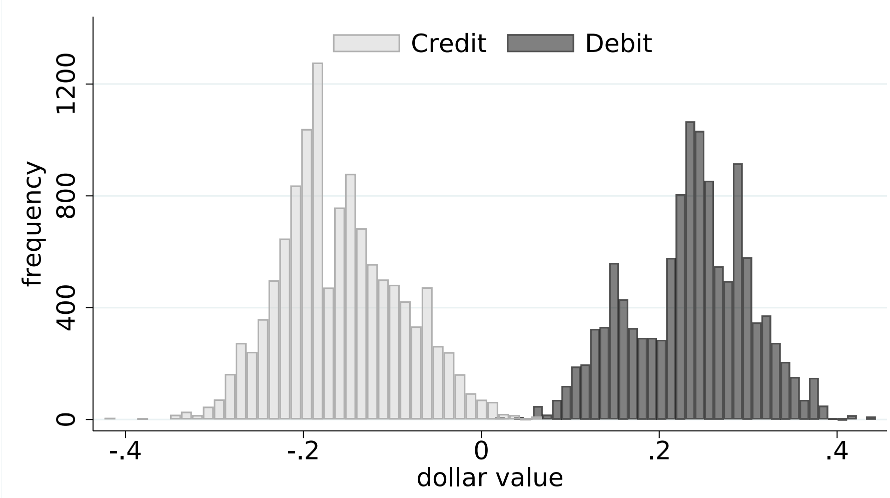
Adoption costs/benefits	Mean	Median	Min	Max	SD
Cash and debit	-0.15	-0.43	-7.01	10.70	2.01
All payment methods	-1.18	-1.61	-9.09	11.82	2.29

Notes: The left-hand panel is a histogram of adoption costs for the cash and debit combination, while the right-hand panel is a histogram of adoption costs for the combination including all means of payments. All numbers are in Canadian dollars per month.

Usage stage. Next, we discuss the consumer preference parameters in the usage stage. They include the observable characteristics of the payment methods as well as the unobserved match values between consumers' demographics, transaction type, and payment instrument, the latter of which are estimated as fixed effects. In the usage stage, consumers enjoy payment instruments that are easy to use, secure, and perceived as inexpensive. Our estimate of the coefficient on the actual transaction costs has a strong and statistically significant negative impact on the probability of use. The usage stage parameter estimates are robust to alternative specifications of the first stage for both sides of the market.

As we discuss in Section 4, we define 108 consumer-transaction-method fixed effects for debit and credit cards, while all cash match values are normalized to zero. Hence, the estimated match values for debit and credit cards are computed relative to cash.[19] Figure 4 illustrates histograms for the estimates, and the table beneath the figure reports the summary statistics, all numbers are in Canadian dollar values.[20] We find that debit cards

Figure 4: Match values between consumers, transactions, and payment methods



Fixed effect	Mean	Median	Min	Max	SD
Debit	0.24	0.24	0.02	0.44	0.07
Credit	-0.16	-0.16	-0.42	0.07	0.07

Notes: Match values are estimates as fixed effects. All numbers are in Canadian dollars.

tend to have positive match values, while the fixed effects for credit cards are typically negative. It is conceivable that debit cards can be easier to use (given they have been adopted), relative to cash, due to potential cash withdrawal costs. Credit use may require overhead costs related to various fees and interest on credit card balances.

To illustrate the main determinants of usage for alternative payment methods, we regress our estimates of debit and credit fixed effects on a set of demographic variables. Table 9 reports the results. For the consumer, the utility from electronic payment instruments declines with age, and there is a stronger decline for debit use. An increase in income increases the utility from using credit cards and decreases that from debit cards, which is consistent with higher-income people having credit cards with larger cash-back rewards and other non-pecuniary benefits. Higher education is associated with lower utility from debit and higher utility from credit cards. The latter explains the higher use of credit among more-educated consumers.[21] Male consumers reveal a strong preference for credit card transactions over cash and debit, with the latter being the least appealing to them. We did not find a significant effect of the consumer location variable–consumers living in rural and urban areas appear to have similar preferences for payment instruments.

[19]Specifications (3) through (5) estimate very similar fixed effects.

[20]Means of the fixed effects represent method-specific constant terms.

[21]In our data, the probability of using a credit card at the POS increases from about 16 percent for the lowest education category to more than 45 percent for the highest education category.

Table 9: Explaining consumer-transaction-method match values

Variable	Debit fixed effect		Credit fixed effect	
	coef.	(s.e.)	coef.	(s.e.)
Constant	3.861	(0.078)	-4.218	(0.078)
Age	-0.011	(0.000)	-0.001	(0.000)
Ln(income)	-0.038	(0.005)	0.138	(0.005)
Education	-0.125	(0.003)	0.151	(0.003)
Male	-0.138	(0.007)	0.155	(0.007)
Urban	0.000	(0.010)	-0.004	(0.010)
Married	0.014	(0.008)	0.026	(0.008)
Number of transactions	0.000	(0.001)	-0.010	(0.001)
Value of transactions	-0.006	(0.003)	0.017	(0.003)
Credit score	0.003	(0.008)	-0.007	(0.008)
Credit fixed effects, ξ_{cc}	0.601	(0.007)		
Debit fixed effects, ξ_{dc}			0.625	(0.007)
Observations	12,029		12,029	
R-squared	0.561		0.573	

Note: The estimation method is ordinary least squares.

Married consumers prefer using electronic means of payment over cash, with a stronger influence on credit card usage. A larger number of transactions (controlling for their total value) is associated with lower utility, but the coefficient is statistically significant only for credit use. Interestingly, consumers with larger expenditures (holding income and the number of transactions fixed) derive the highest utility from using credit cards and prefer cash to debit transactions. Our explanation is related to credit card reward programs. While both the number and value of credit transactions may lead to additional costs (in interest payments or late fees), larger transactions can generate larger rewards, particularly when the rewards are proportional to the transaction price, as is typical for cash-back programs. We do not find the credit score to be a significant determinant of the payment choice at the POS.[22] Finally, the unobserved match values for debit and credit cards demonstrate a strong positive correlation. Consumers who enjoy using one of these electronic payment instruments are also likely to enjoy the other one.

5.2 Merchant parameters

On the merchant side, we estimate acceptance costs as linear functions of market size. We also recover the constant-profit-margin parameter under the assumption that this is common for all merchants. All parameter estimates are statistically significant. First, consider the difference between the merchant-side parameter estimates for specification (1) and any other specification from (2) through (5). In the former case, consumers know only the average acceptance probability for each payment method, while in the latter case

[22]This finding is less surprising than the irrelevance of credit scores for adoption costs in the first stage.

they possess sufficiently accurate information about every merchant's choice. When all consumers are uninformed, a decision to accept a credit card does not result in a larger sale, but it does increase operating costs. Therefore, even with zero acceptance costs, merchants would find it optimal to accept only their favourite payment instrument, which is unlikely to be credit cards. Since in the data we observe that the vast majority of merchants accept credit cards, merchant acceptance costs for this combination must be attractive enough (e.g., negative), which is reflected in the negative parameter estimates for the acceptance costs of all payment instruments. Put differently, the negative estimates of acceptance costs can be viewed as reduced-form estimates of the additional profits that are derived from the informed consumers in the observed equilibrium. With this interpretation, the estimates can be rationalized; however, it becomes impossible to use them for reasonable counterfactual simulations because we do not know how the reduced-form parameter would change in response to a change in equilibrium.

Fortunately, we observe data on the probability that a given transaction is informed; that is, the probability that the consumer of this transaction knows where to find a merchant who accepts any given payment instrument. The introduction of consumer awareness allows for a structural interpretation of the merchant acceptance cost estimates. This is because with a significant level of consumer awareness, merchants have very clear incentives to accept credit cards because this would attract informed consumers who prefer using this payment method. A model without informed consumers cannot identify the merchant profit margin because, without consumer awareness, merchants solve a cost minimization problem. To rationalize the adoption of additional payment instruments that have higher usage costs for merchants, the acceptance costs must be negative. In this case, the negative acceptance cost parameters are effectively the summary of all markups collected from the informed consumers in the data. In the rest of this paper, we use the estimation results from our specification (5). This specification utilizes transaction-level data on consumer awareness and is the richest in terms of the variables included.

We estimate an average merchant profit margin of 5.2 percent. Out of this (gross) profit margin, merchants still have to pay operating expenses (e.g., banking fees) as well as acceptance costs for the chosen combination of payment methods. Table 10 summarizes the various measures of merchant profits and costs. The first column tabulates the merchant size in terms of total revenues. The second column reports the gross merchant profit, which is simply the revenue times the estimated profit margin defined in assumption 2. Out of gross profits, merchants pay various banking fees (e.g., interchange fee) as well as incur own operating expenditures related to processing each payment instrument used at the POS. Note that these costs can be more than half of the gross profits earned. Column (3) reports the average merchant profits after all operating costs are paid off, while column (4) computes the corresponding profit margin. Finally, merchants pay fixed acceptance fees for the combination of payment methods they choose to accept in the first stage.

Column (5) summarizes the average profits net of the acceptance costs, while the last column (6) calculates the net profit margin in the industry. Our estimates suggest that the net profit margin is substantially lower than the gross one, which is estimated at 5.2 percent. Interestingly, the average net profit margin for non-chain retail stores in Canada

Table 10: Merchant profit measures (thousands of Canadian dollars)

Revenue, R_s	Gross as given by $\gamma \times R_s$	Net of banking fees		Net of acceptance cost	
		profit	margin, %	profit	margin, %
50	2.58	1.67	3.34	1.00	2.01
175	9.02	5.89	3.37	3.10	1.77
375	19.32	12.84	3.42	5.23	1.40
625	32.20	21.00	3.36	8.96	1.43
875	45.08	29.75	3.40	11.92	1.36
3000	154.55	100.54	3.35	41.77	1.39
7500	386.37	248.80	3.32	105.09	1.40
Average	68.22	44.35	3.37	18.64	1.58

for businesses with net revenues of \$7.5 billion, in 2013, is 2.7 percent (Statistics Canada, Tables 20-10-0066-01 and 20-10-0068-01, Annual Retail Trade Survey), which is close to our estimates of the profit margins.[23]

In the data, we observe merchants' self-reported costs of operating debit and credit card terminals. Table 11 compares our estimates of acceptance costs with the terminal costs reported by merchants. By comparing the average cost of using terminals with our

Table 11: Merchant cost measures (Canadian dollars)

Revenue	Total acceptance cost		Cost of terminals	
	cash and debit	all methods	cash and debit	all methods
50,000	3,876	3,140	311.76	336.18
175,000	6,463	7,143	90.16	409.15
375,000	8,832	10,808	459.36	549.61
625,000	12,580	16,608	300.00	518.89
875,000	14,988	20,333	618.21	751.59
3,000,000	47,485	70,614	500.00	948.88
7,500,000	115,073	175,190	-	1,318.67
Average	22,837	32,477	407.66	695.34

Notes: We do not observe merchants with revenues of \$7.5 billion choosing cash and debit combinations in the data.

estimates of the overall acceptance costs, we conclude that the rental cost of terminals represents only a small proportion of the total costs. Various fees paid by the merchants to acquirers and own operational costs constitute the bulk of merchant expenditures related to the acceptance of electronic means of payment. Interestingly, merchant acceptance

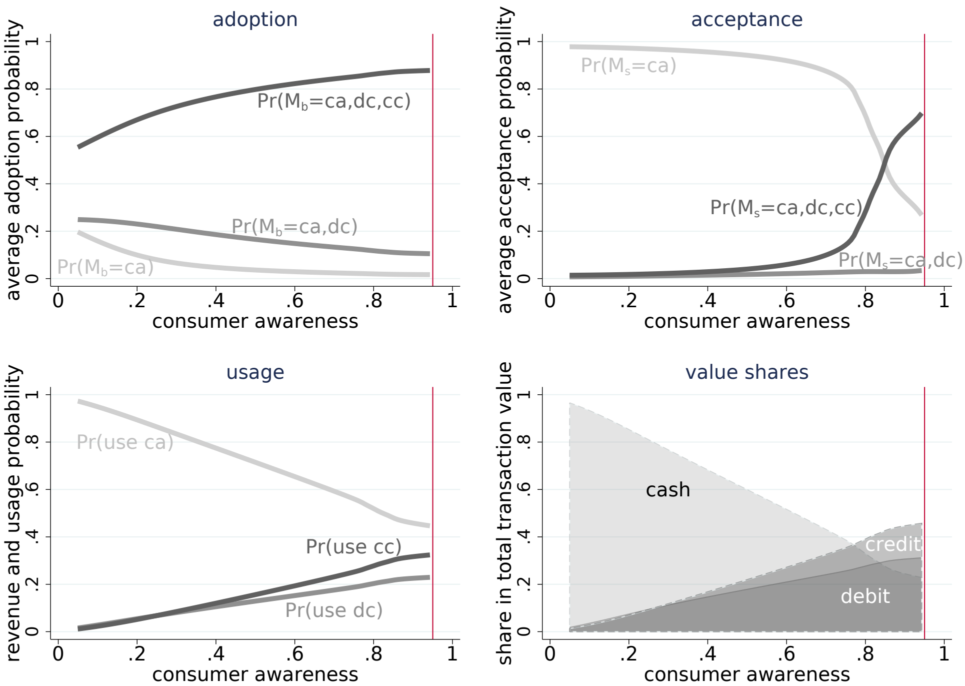
[23]Recall that the stores in our sample are typically smaller and may be less profitable. Also, the difference occurs due to the fixed costs, and it is not entirely clear whether these costs should be included in the profit margin as they do not vary with sales.

costs for all three payment instruments are initially lower than the cost of accepting only cash and debit. However, for businesses with revenues of $175,000 or greater, it becomes costlier to accept all methods of payment.

5.3 Consumer awareness and market equilibrium

In this section, we illustrate the role of consumer awareness for the equilibrium outcomes such as adoption, acceptance, and usage probabilities. Our model is estimated using data from a relatively stable time period, 2013-2014, where it is reasonable to assume that consumers knew a lot about the acceptance decisions of the merchants they patronized, something we confirm in the data. What happens when consumers' awareness about merchants' acceptance decisions exogenously decreases? This may happen if some local stores or restaurants close and their customers have to find other places to shop. Consumers may have less information about the acceptance decisions of these other merchants.[24] In what follows, we assume the information shock affects market equilibrium but only via increased consumer uncertainty. We gradually change the probability of consumer awareness for each transaction and obtain a sequence of equilibrium outcomes, which we summarize in Figure 5.

Figure 5: Equilibrium responses to changes in consumer awareness



Notes: The red vertical line is at the observed consumer awareness level. Subscripts ca, dc, and cc stand for cash, debit card, and credit card, respectively.

[24]In addition, merchants' acceptance decisions may change in response to an external shock, such as COVID-19. In this case, even repeat customers may no longer be sure about what is accepted at a given POS.

The simulation results suggest that with decreased awareness, consumers and particularly merchants would rely less on electronic and more on fiat versions of payment instruments. The intuition is simple: As long as cash maintains its legal tender status, uncertainty about merchant choices would reduce merchant incentives to accept more-expensive electronic payment instruments. This is because, with higher uncertainty, a smaller share of informed transactions will take place at the POS. On the consumer side, more uncertainty reduces the value of having debit and credit cards because their usage would depend significantly more on merchants' acceptance choices. Due to the network effects, lower merchant acceptance of debit and credit cards further reduces consumer incentives to adopt these cards.

6 Counterfactual Analysis

In this section, we describe our main counterfactual simulation, which relates the interchange fee to the market equilibrium and social welfare. By doing this we provide empirical evidence on credit card providers' degree of excessive intermediation. An additional counterfactual simulation that assesses the likelihood of a cashless society is provided in Appendix C.

6.1 Interchange fee and social welfare

The counterfactual simulation in this section is motivated by ongoing discussions on merchant credit card fees. For example, the level of merchant credit card fees in Canada has been subject to voluntary agreed-upon price reductions by the major credit card networks.[25] The theory of Rochet and Tirole (2011) shows how merchants may accept the added cost of cards in order to avoid losing customers, thereby allowing issuers to charge socially inefficient fees. The merchant indifference test (MIT) was designed based on this theoretical framework and has been subsequently used in Europe (European Commission 2015) to provide guidance on the fee level that makes merchants indifferent between the use of cards and other methods of payment. Unfortunately, Fung et al. (2018) highlight that the MIT does not account for the feedback effects between merchant and consumer decisions that would occur as a result of changes in the payment costs on one or more sides of the market.[26]

[25] On November 4, 2014, the Department of Finance announced individual voluntary proposals to reduce credit card fees to an average effective rate of 1.50 percent for the next five years (see http://www.canada.ca/2014). On August 9, 2018, the Department of Finance announced that VISA and Mastercard were expected to reduce their average merchant card fee rates for businesses by up to 15 per cent from their highest levels in 2014 (see http://www.canada.ca/2018)

[26] The same criticism can be applied to a reduced-form analysis conducted by Rysman (2007) or a simultaneous equations estimation with instrumental variables performed by Carbó-Valverde et al. (2016). These studies do not explicitly model consumer and merchant decisions and can only be informative about local responses by each side of the market in regard to small perturbations in the costs. To compute the

To empirically address the question of the potentially excessive intermediation by credit card providers, as predicted by the theoretical literature, we have to relate the level of the interchange fee to consumer and merchant decisions and define the relevant measures of welfare. The interchange fee is the amount transferred from the acquirer to the issuer for processing the card payment in a four-party system.[27] It is worth noting that, in addition to the fee, the merchant's card service fees also include the acquirer's margin and the network access fees paid by the acquirer and the issuer. We assume that all of these fees are included in the parameters of the merchant usage cost function, which is defined in equation (7). In particular, the fees and costs that do not depend on the transaction value are included in $c_{0s,cc}$, while the fees and costs that are proportional to the transaction value are included in $c_{1s,cc}$. The interchange fee depends on the transaction value and is, therefore, included in the latter. Since our focus is on the role of the interchange fee, we assume that all other fees remain fixed throughout the simulation.

On the consumer side, the fees and monetary benefits contribute to the transaction cost, which is defined in equation (2). Similar to merchants, we assume that any fixed fees a consumer faces contribute to $c_{0b,cc}$, while the fees that are proportional to the transaction price contribute to $c_{1b,cc}$. We also assume that consumers receive rewards via participation in cash-back programs, where the amount of the reward is proportional to the transaction value. Then, any change in the reward offered by the issuer would be reflected by the change in parameter $c_{1b,cc}$.

Our measures of consumer and merchant welfare are the expected maximum over the choices made in the first stage of the game; i.e.,

$$WF_b = \mathbb{E}\left[\max_{\mathcal{M}'_b \in \mathcal{M}} EU_b(\mathcal{M}'_b) - F_{b,\mathcal{M}'_b}\right], \quad WF_s = \mathbb{E}\left[\max_{\mathcal{M}'_s \in \mathcal{M}} \left\{\mathrm{E}\Pi_s(\mathcal{M}'_s) - F_{s,\mathcal{M}'_s}\right\}\right],$$

where the expectations are taken with respect to the random adoption, acceptance and usage cost innovations as well as to the decisions made on the other side of the market.

In the rest of this section, we discuss our counterfactual simulations under two alternative scenarios. In the first scenario, we ignore both the issuing and the acquiring upstream markets and assume that any change in the interchange fee set by the network would be fully passed on to consumers. That is, if the interchange fee increases by a given amount, then merchant parameter $c_{1m,cc}$ would increase and consumer parameter $c_{1b,cc}$ would decrease by exactly this amount. This experiment focuses on maximizing the sum of consumer and merchant welfare only. In the second scenario, we introduce a strategic monopolistic issuer that maximizes profits from the interchange fee by choosing the share

out-of-sample predictions that are induced by large changes in the cost structure, or long-run equilibrium effects, one would need to use a structural model that is analogous to the one presented in the earlier sections of this paper.

[27] Note that in a three-party system, such as American Express, there is no explicit interchange; rather, one can think of it as an internal transfer from the acquirer's department to the issuer's department.

of the interchange fee that is passed on to consumers as rewards. In both scenarios, we assume that merchants remain price-takers.

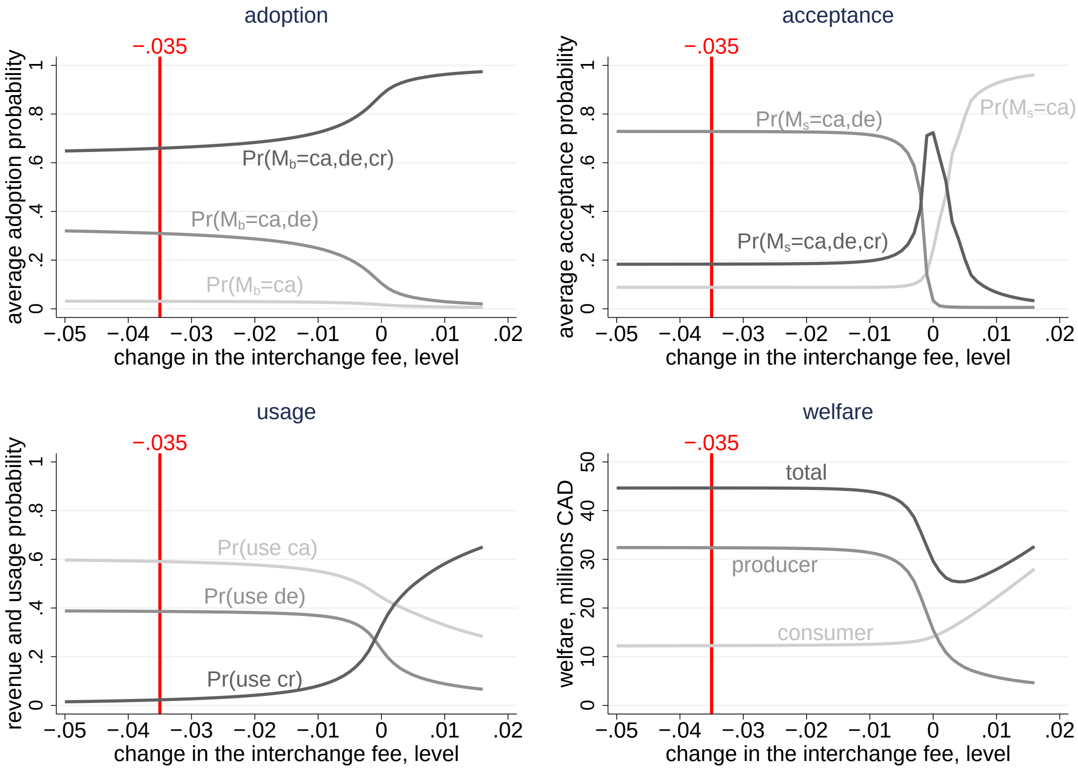
Full pass-through of merchant credit card fees. In this first scenario, we assume a full pass-through of the interchange fee from merchants to consumers. Let Δ_{IF} denote a change in the interchange fee. If $\Delta_{\mathrm{IF}} > 0$, then the merchant usage costs for transactions with value p_{bj} increase by $\Delta_{\mathrm{IF}} \times p_{bj}$, while the consumer usage costs for this transaction decrease by the same amount.[28] Similarly, for any $\Delta_{\mathrm{IF}} < 0$, this implies that merchants pay less and consumers pay more per unit of the price of the good purchased.

We choose Δ_{IF} to vary in the interval $(-0.05, 0.02)$. The upper bound of the interval is given by the merchant acceptance, which drops below 2 percent if the interchange fee further increases. We do this truncation on purpose to exclude the second maximum of the total welfare, which would occur at very high values of Δ_{IF}. The main reason is that at very low acceptance rates, the underlying assumptions in the model become unrealistic. Recall that for an informed transaction, consumers can always find a merchant who will accept their chosen payment method. This will happen even if only one merchant is willing to accept this payment instrument. In the model, the consumer's travel cost to find the merchant is zero; hence, we can end up in a situation where nearly all consumers shop at the only merchant who accepts credit. To preclude this mechanical increase in consumer welfare, we assume the merchants' card fee will never become so high that less than 2 percent of merchants will accept credit cards.

Figure 6 illustrates the sequence of equilibrium adoption and acceptance probabilities, usage probabilities and expected welfare, which can occur for alternative values of the interchange fee. Recall that our analysis suggests that credit cards were too expensive for society to use in 2013-2014. During this period, the total usage cost for credit cards for both sides of the market exceeded the total usage cost for cash or debit (see the right-hand panel of Figure 1). Hence, if we were to have chosen the cheapest payment option for society, then the credit card would not have been selected. At the same time, we assume that consumers derive additional utility from using electronic means of payment. Hence, even for the fixed number of transactions, a consumer's overall utility varies with the payment instruments used. Unfortunately, this additional utility would not have been enough for credit cards to gain much popularity because we estimate the maximum social welfare for a period when $0.035 \times p_{bj}$ was subtracted from the current level of the merchant's card fee. Given the merchant credit cards fee was below 2 percent, on average, in 2013, we would expect the payment direction to reverse and begin to flow from consumers to merchants (rather than vice versa, as in the current situation).

[28] Note that, in this case, the total cost given by the sum of the consumer and merchant's usage costs remains unchanged. What does change are the incentives for consumers and merchants to adopt, accept, and use payment instruments.

Figure 6: Equilibrium responses to changes in merchants' per-value cost of credit



Notes: The red vertical line is at the maximum total welfare calculated for our sample. A negative change decreases transfers from merchants to consumers, while a positive change increases transfers from merchants to consumers relative to the factual. Welfare is measured for our sample of consumers and merchants.

It is worth noting that in this counterfactual simulation we do not consider the dynamic benefits that electronic payment instruments may bring in the long run, nor do we consider the welfare of the upstream markets, such as the issuers and acquirers' market and the competition between credit card networks such as VISA, MasterCard, or American Express.

Optimal pass-through of the merchant credit card fees. In the previous simulation, we assumed that the interchange fee collected by the acquirers is passed on in full to consumers. This assumption may not appear realistic as these fees may represent an important source of revenue for the issuers. To account for the optimal pass-through rate, we define the profit function of a monopoly issuer who is maximizing profits from all credit card transactions in all markets, subject to an exogenously given level for the interchange fee. While we believe that the acquirers' choices are also important for market equilibrium, we do not have enough data to structurally model the decisions of these players. Therefore, on the acquiring side, we assume that the interchange fee collected from merchants are passed through in full to the issuing side.

In what follows, let $MC^I_{bj} = MC^I$ denote the constant marginal cost of providing credit service to consumers, which is the same for all transactions. We assume that this cost is proportional to the transaction value. As before, let $\text{IF}_{bj} = \text{IF}$ denote the interchange fee, i.e., the percentage of the transaction price that is transferred from the acquirers to the issuers, and let $B_{bj} = B$ denote the percentage of the transaction price that is passed on to the consumers in the form of cash-back rewards or lower costs of using credit cards. Then, a transaction j by consumer b completed with a credit card would generate $p_{bj} \times \left(\text{IF} - B - MC^I\right)$ dollars of profit for the issuer. A transaction is completed using a credit card with equilibrium probability $P^*_{bj,cc}(\text{IF}, B)$. We write it explicitly as a function of a pair of arguments (IF, B) to emphasize that the equilibrium usage probability depends on (1) the level of the interchange fee, IF, via the usage cost function $C_{m,cc}(p_{bj})$ in the merchant's cost function in equation (7) and (2) the share B of the interchange fee that is passed on to the consumers via the usage cost function $C_{b,cc}(p_{bj})$ in equation (1). Therefore, we can write the profit function for the monopoly issuer as follows:

$$\Pi_I(\text{IF}, B, MC^I) = \sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} P^*_{bj,cc}(\text{IF}, B) \times \left[p_{bj}\left(\text{IF} - B - MC^I\right)\right],$$

and the optimal level of consumer rewards is defined by the issuer's maximization problem,

$$B^*(\text{IF}) = \underset{B' \in \mathbb{R}}{\arg\max} \left\{\Pi_I\left(\text{IF}, B', MC^I\right)\right\},$$

where B' denotes a monetary transfer from issuers to consumers, which can be either negative (via cash backs) or positive (via banking fees).[29]

The first-order condition for the issuer's maximization problem of choosing the optimal level of rewards is then

$$\sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} \left[\frac{\partial P^*_{bj,cc}(\text{IF}, B^*)}{\partial B} p_{bj}\left(\text{IF} - B^* - MC^I\right) - P^*_{bj,cc}(\text{IF}, B^*) p_{bj}\right] \equiv 0$$

$$\implies \text{IF} - B^* - MC^I = \frac{\sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} P^*_{bj,cc}(\text{IF}, B^*) p_{bj}}{\sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} \frac{\partial P^*_{bj,cc}(IF, B^*)}{\partial B} p_{bj}}, \tag{21}$$

where $\text{IF} - B^* - MC^I$ represents the net profit margin retained by a monopolistic issuer.

Equation (21), which is evaluated at the estimated parameter values, suggests

$$\text{IF} - \widehat{B^* - MC^I} = 0.00352;$$

i.e., after deducting the marginal costs and consumer benefits from the interchange fee, a monopoly issuer earns \$3.52 per every thousand dollars in transaction value. Assuming

[29] The subscript s is omitted because the total profit is maximized independently in every market and the markets differ in their size only such that the optimal B^* is the same for all s.

$\mathrm{IF} = 0.018$ (the average value of the interchange fee in 2014), the price-cost margin analog for a profit-maximizing issuer is given by $\left(\mathrm{IF} - B^* - MC^I\right)/\mathrm{IF} = 0.2$.

Let Δ_B denote the optimal change in the consumer rewards paid by the issuer in response to an exogenous change in the interchange fee Δ_{IF}. Then, the issuer's profit maximization problem can be represented as follows:

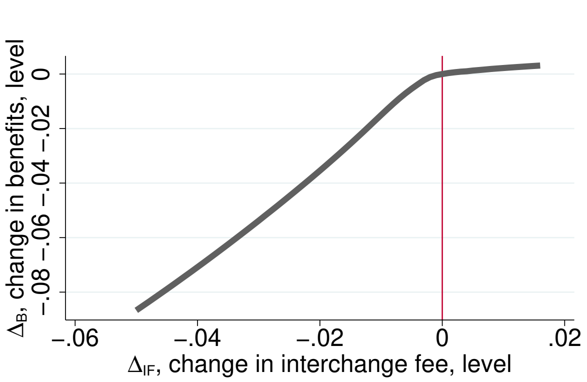
$$\max_{\Delta_B \in \mathbb{R}} \sum_{b=1}^{N_b} \sum_{j \in \mathcal{J}_b} P^*_{bj,cc}(\mathrm{IF} + \Delta_{\mathrm{IF}}, B^* + \Delta_B) \times \left[p_{bj} \left(\mathrm{IF} - \widehat{B^* - MC^I} + \Delta_{\mathrm{IF}} - \Delta_B \right) \right], \quad (22)$$

where the estimate of the issuer's markup in the observed equilibrium is $\mathrm{IF} - \widehat{B^* - MC^I} = 0.00352$ and $\Delta_B\left(\Delta_{\mathrm{IF}} = 0\right) = 0$ by construction. Given the estimate of the issuer's original markup and exogenously given Δ_{IF}, equation (22) can be solved for $\Delta^*_B\left(\Delta_{\mathrm{IF}}\right)$ maximizing the issuer's profit. We are interested in a sequence of market equilibria that results from exogenous variations in the interchange fee, subject to endogenous responses by profit-maximizing issuers.

To conduct this counterfactual simulation, similar to the full pass-through case, we vary the level of the interchange fee around its factual value by using $\Delta_{\mathrm{IF}} \in (-0.05, 0.02)$. Given the average interchange fee of 0.018 in 2013, this range covers the intervals where we observe a reversion of the payment flows (consumers start paying merchants for accepting credit cards), as well as the intervals where merchants face merchant card fees that are more than twice as high as they currently pay. Similar to the full pass-through scenario, we limit the increase in the interchange fee by 100 percent at most because, at this fee level, merchant acceptance of credit cards declines below 2 percent. As a result, it should become prohibitively costly for consumers to travel to their preferred merchant because only a few merchants would still accept credit cards. As there are no travel costs in our model, we believe the welfare predictions for very large changes in the fee structure may be less reliable.

Figure 7 illustrates a monopoly issuer's optimal response to exogenous changes in the interchange fee, $\Delta_B\left(\Delta_{\mathrm{IF}}\right)$. There is an interesting asymmetry in the issuer's response, where a decline in the interchange fee reduces consumer benefits very quickly, while a similar increase in the interchange fee results in only a modest increase in consumer benefits.

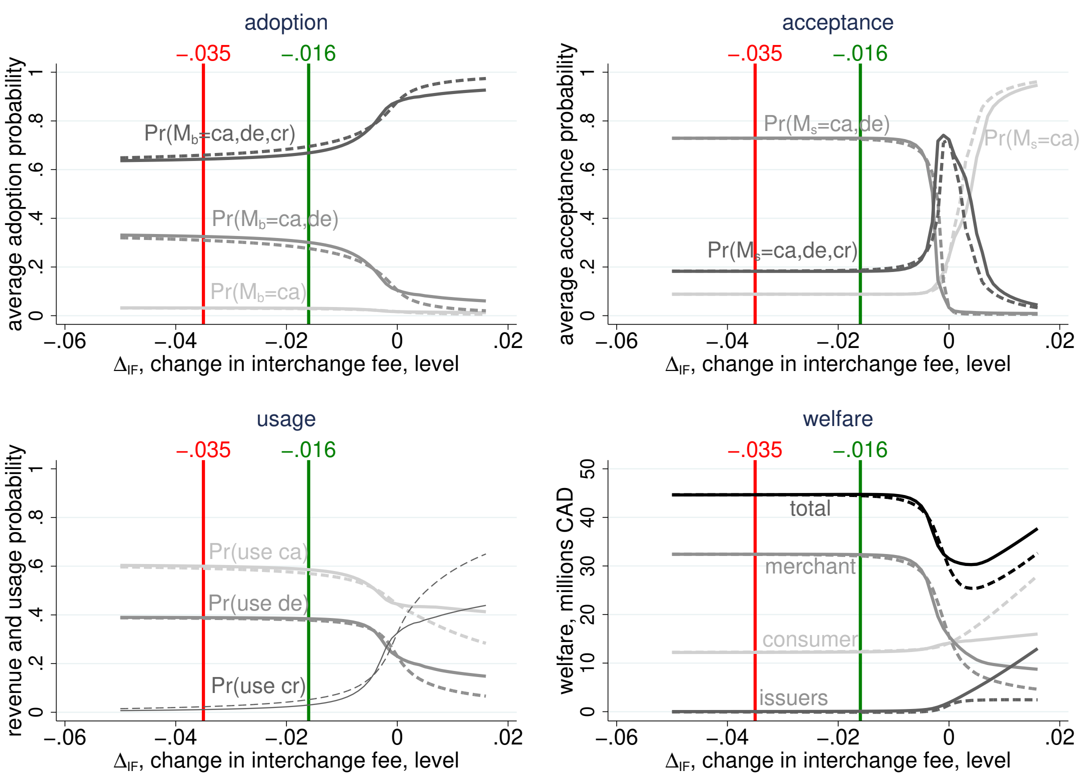
Figure 7: Response of consumer benefits to changes in the interchange fee



Notes: The issuer's best response is given by a change in consumer benefits that maximizes the monopoly profit when the interchange fee changes by Δ_{IF}.

Figure 8 overlays the simulation results under the optimal issuer pass-through against our earlier experiment with 100 percent pass-through, which is illustrated in Figure 6 above. The dashed lines correspond to the full pass-through situation and the solid lines depict the market outcomes for the optimal issuer's pass-through rate. When a measure

Figure 8: Equilibrium response to changes in merchants' per-value cost of credit



Notes: The red vertical line is at the original maximum total welfare with full pass-through. The green vertical line is at the total welfare maximum under the optimal issuer's pass-through. The dashed lines replicate Figure 6 for the full pass-through case. A negative change decreases transfers from merchants to consumers, while a positive change increases transfers from merchants to consumers relative to the factual. Welfare is measured for our sample of consumers and merchants.

of social welfare, in addition to the consumer and merchant surpluses, also accounts for the issuer's profits, total welfare is maximized when the merchant card fee is 0.016 lower than it was in 2013. This result is quite different from the one we obtain under the full pass-through assumption, where the interchange fee has to decrease by as much as 0.035, effectively making consumers pay merchants.

Figure 8 shows that when issuers optimize their reward programs, this can have an important impact on the equilibrium in the downstream market. It is clear that a decline in the pass-through rate decreases consumers' willingness to use credit cards due to the higher usage costs (lower rewards). It is interesting that the market power in the issuing market can be welfare improving. This effect is not new and has been pointed out in many markets with negative externalities and market power of the supplier. By charging price above the marginal cost, issuers with market power drive down the equilibrium usage of a more-expensive payment instrument and this improves total welfare.

It is worth noting several important caveats behind the results discussed above. First and foremost, our data is relevant for 2013-2014. Over time, the cost structure in the payment industry and consumers' perceptions about all aspects of their transactions (ease and cost of use, security, and merchant acceptance) may have changed. As a result, our conclusions should be viewed as relevant for 2013-14 and extrapolations to other years should be done with caution. Second, our model provides only partial equilibrium analyses. Independent profit maximization by the merchants, the exogeneity of the consumer-transaction endowment, the absence of consumer travel costs, the parametric restrictions on the payoff functions and the static maximization by all of the players in the model are just a few of the compromises made in this paper. The dynamic benefits of introducing a new technology are also not considered. At the same time, we believe that the estimation results and counterfactual analyses do provide important and useful insights into the economics of payment methods.

7 Conclusions

We develop and estimate a structural equilibrium model of interactions between consumers and merchants in a two-sided market for payment methods. The model distinguishes between "informed" transactions–those in which the consumer has foreknowledge regarding merchants' acceptance decisions–and "uninformed" transactions–those in which the consumer knows only the probability that a merchant accepts payment cards. We find that the share of the informed transactions has important implications for the equilibrium and estimation results.

We estimate the model by using data from payment surveys of consumers and merchants. We find that while many consumers face adoption costs, some enjoy benefits from adopting debit and credit cards. The vast majority of the monthly fixed costs from using electronic payment methods falls in the range of between negative 5 (cash-back benefit) to positive 5 dollars per month. The number and total value of transactions in a consumer endowment appear to be important determinants of their adoption decisions. We find that older consumers may face large adoption costs for the cash and debit combination, while there is no age effect on the adoption costs of all means of payment. Consumers with more-optimistic expectations of merchants' acceptance probabilities tend to adopt corresponding electronic payment instruments significantly more often. Similarly, consumers' perceptions of ease of setup and use as well as the security of a payment instrument make adoption significantly more likely.

At the POS, the transaction cost for each payment instrument has a strong negative effect on the probability of its use. Consumers value the ease of use, affordability, and security characteristics of payment methods. We estimate a large number of fixed effects that represent unobserved match values between consumers in various demographic groups, transaction types, and payment instruments. Estimates of these match values suggest that older consumers find it harder to use electronic methods of payment, such as debit and credit cards. With an increase in income, education, or observed expenditures, consumers begin to favour cash over debit transactions as well as credit transactions over both debit and cash. We do not find any correlation between the consumers' usage patterns and credit scores, perhaps because we already account for all of the demographics that are relevant for credit scores.

On the merchant's side, we estimate a profit margin of about 5.2 percent, which after deducting banking fees and operating costs drops down to 3.4 percent on average. Further, if fixed acceptance costs are included in the calculations, merchants can end up with a profit margin as low as 1.6 percent. Accepting all means of payment is typically more expensive than only cash and debit, with the difference increasing with merchant size. Our estimates suggest that terminal rental costs constitute only a small fraction of the total acceptance costs.

Our counterfactual simulation relates the interchange fee with the implied equilibrium in a two-sided market for payments and social welfare. Under an assumption of a monopolistic issuer choosing the profit-maximizing pass-through rate, we find that the total welfare is maximized if the interchange fee is reduced by 0.016 from its 2013 value. In contrast, under the full pass-through assumption, total welfare is maximized when the interchange fee is reduced by 0.035 from the observed level. Such an interesting effect of market power in the issuing market is explained by the margin issuers extract before passing the interchange fee on to consumers via rewards. Due to this extra margin, the equilibrium use of credit cards, which was a relatively expensive payment instrument in 2013, declines and becomes closer to the social optimum. Our empirical finding of excessive intermediation by credit card providers in the payment industry complements similar results in the theoretical literature on platform intermediation in multi-sided markets.

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A Robustness checks and model extensions (online)

A.1 Distribution of merchant acceptance costs

Assumption 3 restricts merchant acceptance cost innovations to following a standard Gumbel distribution. Below we provide robustness checks for this restriction by replacing it with an alternative version of (A3.3); namely,

Assumption 4: *First-stage merchant acceptance cost innovations*

$$\omega_s = \left(\omega_{s,\{ca\}}, \omega_{s,\{ca,dc\}}, \omega_{s,\{ca,dc,cc\}}\right)$$

which are independent identically distributed draws from a normal distribution,

$$\omega_{s,\mathcal{M}_s} \overset{iid}{\sim} N\left(\bar{\omega}_{\mathcal{M}_s}, \sigma^2_{\mathcal{M}_s}\right),$$

for all s, $\mathcal{M}_s$.

Then we estimate five versions of the model. First, we assume $\bar{\omega}_{\mathcal{M}_s} = 0$ and $\sigma^2_{\mathcal{M}_s} = 1$ for all merchants and acceptance combinations; i.e., we estimate the parameters under a standard normal assumption on the distribution of ω. Second, we assume that the variation in merchant acceptance costs comes from the variation in the rental cost of debit and credit card terminals. In the data, merchants report costs paid for renting terminals. Using these data, we (pre-)estimate the means and standard deviations of the rental costs. Since the distribution parameter values are directly supplied to our estimation algorithm as if they were known, we call these specifications a "calibration." Here we begin by assuming that the means and standard deviations are common for debit and credit use and that they vary only by the market size. Then, we allow the means and variances to vary by both the market size and the acceptance combination. The estimation results for the standard normal assumption and for the calibrated means and standard deviations are reported in Table 12 in the columns labeled (1), (2), and (3), respectively. Note that columns (2) and (3) estimate the same number of parameters as column (1).

Instead of pre-estimating the parameters of the merchant acceptance cost distribution, we can augment the likelihood function with the terminal costs data and estimate the means and variances of the cost innovations jointly with the rest of the model parameters. It is clear that without additional information $\bar{\omega}_{\mathcal{M}_s}$ is not separately identified from $f^s_{0,\mathcal{M}_s}$. We therefore identify $\theta_\omega = \left(\bar{\omega}_{\{ca,dc\}}, \bar{\omega}_{\{ca,dc,cc\}}, \sigma^2_{\{ca,dc\}}, \sigma^2_{\{ca,dc,cc\}}\right)$ by using additional data on the terminal rental costs. To do so, we augment the likelihood function (4.1) with the product

$$\mathcal{L}_2(\theta_\omega) = \prod_{s=1}^{N_s} \prod_{\mathcal{M}_s \in \mathcal{M}} \phi_{\mathcal{M}_s}\left(\omega_{s,\mathcal{M}_s}, \bar{\omega}_{\mathcal{M}_s}, \sigma^2_{\mathcal{M}_s}\right),$$

where $\phi_{\mathcal{M}_s}(\cdot)$ is the normal probability density function with mean $\bar{\omega}_{\mathcal{M}_s}$ and variance $\sigma^2_{\mathcal{M}_s}$. Column (4) in Table 12 reports the estimation results when $\sigma_{\{ca,dc\}} = \sigma_{\{ca,dc,cc\}}$, while column (5) allows for combination-specific variances of the innovations.

Table 12: Model extensions, normal distribution of merchant adoption costs

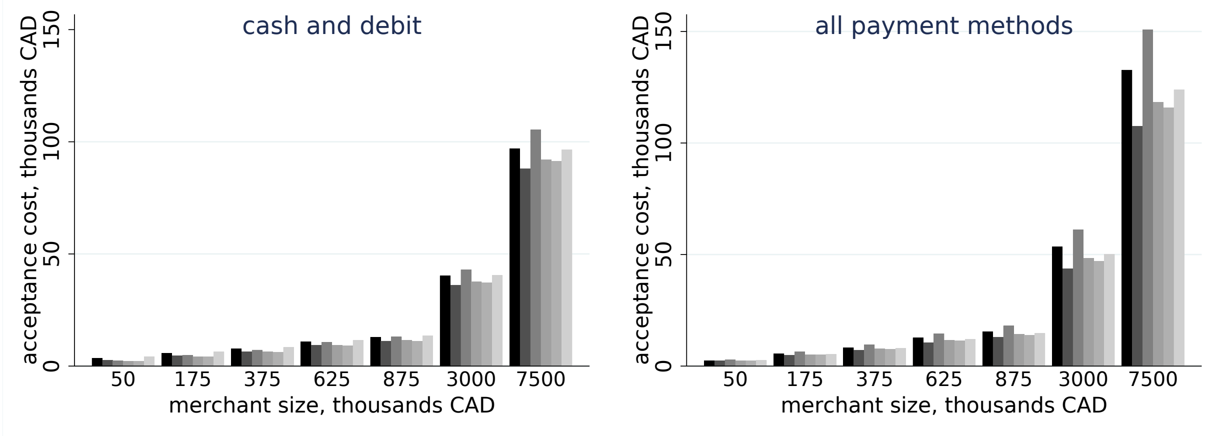
		Standard	Calibrated parameters		Estimated parameters	
		(1)	(2)	(3)	(4)	(5)
Consumers, stage 1						
$f^b_{0,\{ca,dc\}}$		-0.722	-0.740	-0.735	-0.752	-0.739
(s.e.)	constant	(0.184)	(0.184)	(0.183)	(0.184)	(0.184)
$f^b_{0,\{ca,dc,cc\}}$		-1.232	-1.201	-1.192	-1.180	-1.210
(s.e.)		(0.176)	(0.175)	(0.175)	(0.175)	(0.175)
Consumers, stage 2						
Transaction cost		-7.228	-7.188	-7.182	-7.090	-7.185
(s.e.)		(0.177)	(0.168)	(0.066)	(0.172)	(0.174)
Ease of use		7.131	7.149	7.143	7.144	7.139
(s.e.)		(0.335)	(0.335)	(0.335)	(0.335)	(0.335)
Affordability		1.209	1.212	1.211	1.211	1.210
(s.e.)		(0.168)	(0.169)	(0.168)	(0.168)	(0.168)
Security		2.335	2.341	2.340	2.340	2.338
(s.e.)		(0.131)	(0.132)	(0.131)	(0.131)	(0.131)
Merchants, stage 1						
$f^0_{\{ca,dc\}}$		1.384	0.591	0.597	0.442	2.492
(s.e.)	constant	(0.186)	(0.131)	(0.124)	(0.203)	(26.910)
$f^0_{\{ca,dc,cc\}}$		0.765	0.372	0.347	0.092	0.066
(s.e.)		(0.088)	(0.066)	(0.067)	(0.068)	(0.064)
$f^1_{\{ca,dc\}}$		3.984	4.754	4.179	4.161	4.303
(s.e.)	slope	(0.194)	(0.083)	(0.067)	(0.073)	(0.164)
$f^1_{\{ca,dc,cc\}}$		4.910	6.857	5.379	5.292	5.661
(s.e.)		(0.429)	(0.107)	(0.048)	(0.100)	(0.085)
$\gamma = \frac{p-mc}{p}$	profit margin	0.041	0.048	0.042	0.042	0.043
(s.e.)		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Cost of terminals, mean						
Debit		0.000		by size	0.408	0.411
(s.e.)		(n.a.)	by size		(0.152)	(26.901)
Credit		0.000		by size	0.695	0.695
(s.e.)		(n.a.)			(0.017)	(0.013)
Cost of terminals, standard deviations						
Debit		1.000		by size		4.258
(s.e.)		(n.a.)	by size		0.320	(0.649)
Credit		1.000		by size	(0.017)	0.276
(s.e.)		(n.a.)				(0.021)
F-value		12,413.38	12,543.21	12,555.20	12,672.84	12,600.36

Notes: (1) assumes standard normal distribution; (2) uses data on the means and standard deviations of the reported costs of terminals by merchant size, assuming no difference in terminal costs for debit and credit cards; (3) uses data on the means and standard deviations of the terminal costs by merchant size, separately for debit and credit card terminals; (4) estimates the means of the terminal costs, separately for credit and debit cards, but estimates common standard deviations; (5) estimates the means and standard deviations, separately for debit and credit cards.

The consumer parameters that are estimated in columns (1) through (5) are very similar. As expected, the estimates of the acceptance cost parameters are slightly different under alternative distributional assumptions. Figure 9 illustrates how differences in the parameters map into differences in the levels of the acceptance costs.

In Table 12, in the leftmost black bar, the cost estimates from a representative consumer model (3) with Gumbel errors are reported. The remaining bars represent the levels of the acceptance costs from specifications (1) through (5) in Table 12, with normally distributed errors.

Figure 9: Level of acceptance costs by specification



Notes: The leftmost black bar summarizes the cost estimates from the baseline model with standard Gumbel distribution. The remaining five bars correspond to estimates (1) through (5) in Table 12.

The main takeaway from these additional estimation results is that the key parameter estimates are robust to alternative assumptions about the distribution of merchant acceptance cost innovations. We choose to use the Gumbel assumption for the main specification and its extensions, as reported in the text, primarily because it results in partially analytic rather than simulated probabilities and expected maximums.[30]

A.2 Alternative specifications for consumer adoption costs

Specification (5) in Table 8 in the main text reports our favourite specification. Below, we provide robustness exercises with respect to alternative specifications for the consumer's first-stage adoption cost. In particular, we also estimate specification (1) in Table 13, where the first-stage adoption costs include only the variables that satisfy the exclusion restrictions; i.e., the variables that are only relevant for the adoption decisions, and not the usage decisions, at the POS. Specification (2) includes age as an explanatory variable, and specification (3) includes all of the perception variables available in our data.

As discussed in the main text, consumer perceptions of ease, security and affordability of use for each payment method are structurally included in the first stage via the consumer expectations of the usage stage, as is apparent from equation (5). The statistical significance of these variables in the first stage may indicate either precautionary consumer motives for adoption or a potential mismatch between consumer beliefs about the various attributes of the payment instruments and the actual realizations of consumer decisions in the usage stage.[31]

Overall, we find that the model predictions remain very robust to the choice of empirical specification for consumer adoption costs. The estimation results are very similar both qualitatively and quantitatively. The results from the counterfactual simulations are nearly identical. The post-estimation analysis and the counterfactual simulations for the alternative specifications of the model are available upon request.

[30] Another reason is that it provides a somewhat better model fit in terms of the likelihood function value.

[31] For instance, consumers may adopt more-secure payment methods "just in case," regardless of whether they expect the method to have an impact on their usage behaviour at the POS.

Table 13: Model extension, including usage perceptions in stage-one adoption

		(1)		(2)		(3)	
		coef	(s.e.)	coef	(s.e.)	coef	(s.e.)
Consumers, stage 1							
$f^b_{0,\{ca,dc\}}$	constant	-1.031	(0.322)	-2.067	(0.599)	-2.283	(0.609)
$f^b_{0,\{ca,dc,cc\}}$		-2.813	(0.302)	-2.761	(0.569)	-2.888	(0.577)
$f^b_{age,\{ca,dc\}}$	age			0.024	(0.010)	0.027	(0.010)
$f^b_{age,\{ca,dc,cc\}}$				0.000	(0.009)	0.001	(0.009)
$f^b_{\#t,\{ca,dc\}}$	number of trans.	-0.201	(0.101)	-0.190	(0.102)	-0.219	(0.101)
$f^b_{\#t,\{ca,dc,cc\}}$		-0.022	(0.096)	-0.015	(0.097)	-0.048	(0.096)
$f^b_{vt,\{ca,dc\}}$	total spending	1.053	(0.262)	1.033	(0.265)	0.960	(0.269)
$f^b_{vt,\{ca,dc,cc\}}$		1.147	(0.255)	1.149	(0.258)	1.073	(0.262)
$f^b_{ac,\{ca,dc\}}$	accept. debit	-5.221	(1.462)	-5.176	(1.461)	-3.963	(1.537)
$f^b_{ac,\{ca,dc,cc\}}$	accept. credit	-4.303	(0.878)	-4.206	(0.895)	-3.241	(0.917)
$f^b_{ea,\{ca,dc\}}$	ease use, debit					-5.448	(1.589)
$f^b_{ea,\{ca,dc,cc\}}$	ease use, credit					-5.798	(1.217)
$f^b_{se,\{ca,dc\}}$	security, debit					-1.872	(0.955)
$f^b_{se,\{ca,dc,cc\}}$	security, credit					-1.320	(0.826)
$f^b_{af,\{ca,dc\}}$	afford. debit					0.345	(0.812)
$f^b_{af,\{ca,dc,cc\}}$	afford. credit					0.697	(0.623)
$f^b_{sc,\{ca,dc\}}$	ease setup, debit	-6.300	(1.215)	-5.650	(1.204)	-4.493	(1.306)
$f^b_{sc,\{ca,dc,cc\}}$	ease setup, credit	-6.629	(0.724)	-6.049	(0.729)	-5.379	(0.800)
Consumers, stage 2							
Trans. costs		-7.322	(0.184)	-7.322	(0.184)	-7.305	(0.184)
Ease of use		6.698	(0.336)	6.707	(0.337)	6.387	(0.348)
Security		1.065	(0.166)	1.068	(0.166)	1.043	(0.171)
Affordability		2.165	(0.132)	2.170	(0.132)	2.237	(0.136)
Merchants, stage 1							
$f^s_{0,\{ca,dc\}}$	constant	2.199	(0.248)	2.199	(0.248)	2.197	(0.247)
$f^s_{0,\{ca,dc,cc\}}$		0.542	(0.102)	0.542	(0.102)	0.541	(0.102)
$f^s_{1,\{ca,dc\}}$	slope	5.193	(0.118)	5.315	(0.120)	5.221	(0.119)
$f^s_{1,\{ca,dc,cc\}}$		8.007	(0.205)	8.302	(0.206)	8.100	(0.202)
$(p - mc)/p$	profit margin	0.051	(0.001)	0.052	(0.001)	0.052	(0.001)
F-value		-12,104.28		-12,092.64		-12,075.97	

Notes: All specifications include consumer×transaction type×payment instrument fixed effects. Estimation results represent alternative specifications for consumer adoption costs.

B Model fit (online)

To assess the fit of our main specification (5) reported in Table 8 in Section 5, we overlay our model predictions against the raw data. Figure 10 reports the average adoption probability for each combination of payment instruments by the level of consumer expenditure as measured by the sum of all of the prices recorded by consumers in a three-day diary survey. We find that the model shows a decent fit for the consumer side of the market.

Figure 10: Model fit for three adoption combinations, consumers

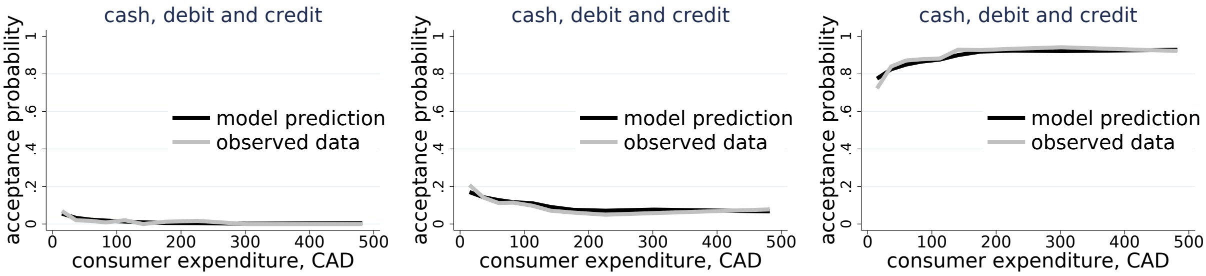
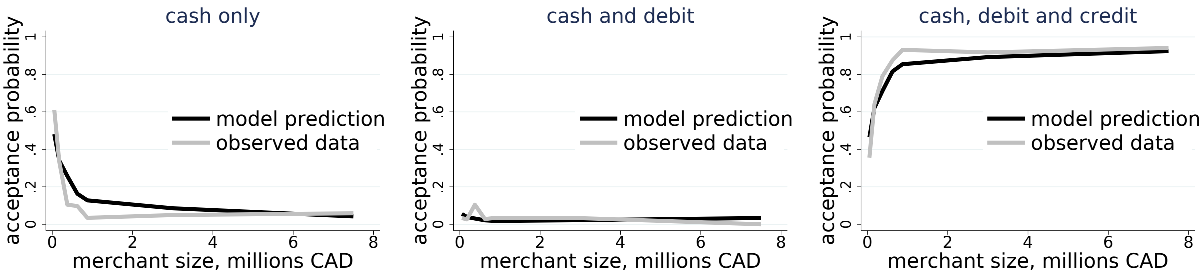


Figure 11 compares the model predictions against the data on the merchant acceptance probabilities. Our model predictions fit well for the behaviour of the relatively small and large merchants in our sample. Somewhat larger discrepancies occur towards the median merchant size in our sample. That being said, given the merchant sample size is only 733 as well as modest variation in the observed acceptance decisions, we can conclude that the overall model fit is good.

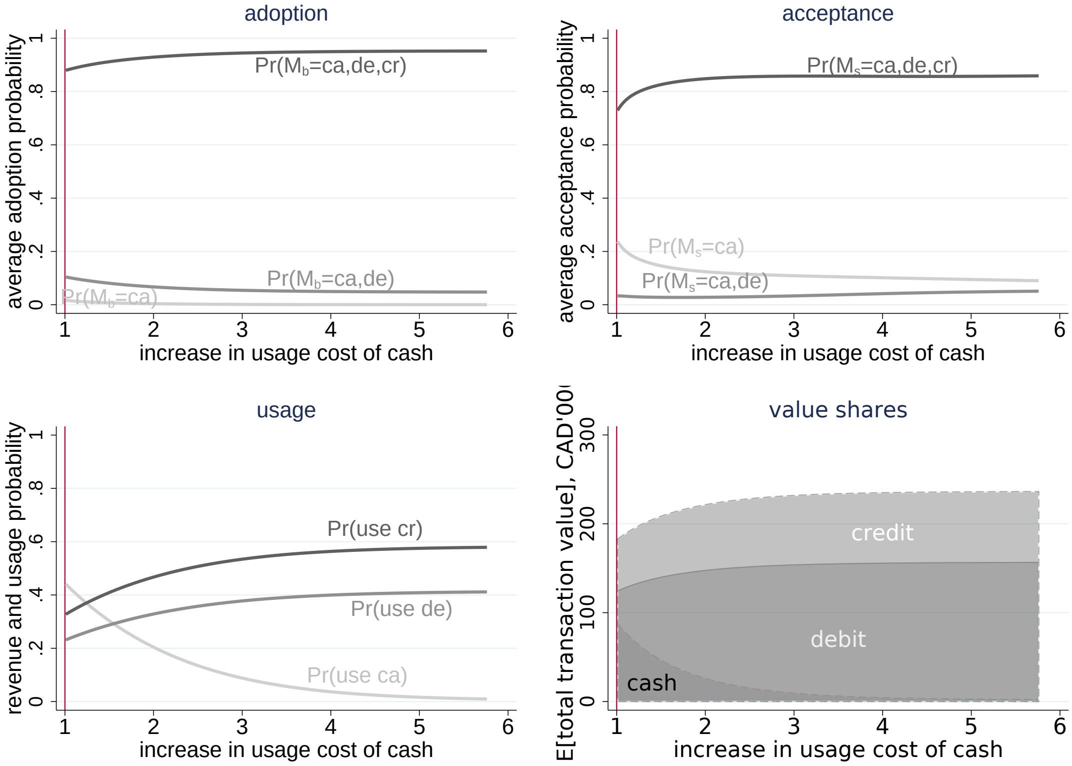
Figure 11: Model fit for three acceptance combinations, merchants



C What does it take to drive cash out? (online)

In this section, we simulate an increase in the usage cost of cash as a consequence of a sharp increase in withdrawal costs (e.g., due to closed bank branches and ATMs) or an increase in the risk of catching an infection via banknotes. In what follows, we gradually increase the transaction cost of cash by the same percentage amount for both sides of the market. An increase in the cost of using cash makes it less attractive at the POS for consumers. Since the relative (to cash) cost of both electronic payment methods declines, it is natural to expect an increase in their equilibrium usage probabilities. Similarly, the probability of choosing adoption and acceptance combinations that include either or both of the two electronic instruments is expected to increase as well. The fraction of cash-only consumers and merchants should gradually disappear.

Figure 12: Equilibrium response to an increase in the usage cost of cash



Notes: The red vertical line denotes the observed equilibrium.

Figure 12 describes the changes in the market outcomes that result from the increased cost of using cash. Under the current parameter values, it would take an increase of about 5.8 times in the cost of using cash to drive its equilibrium usage probabilities down below one percent. If we assume that the cash withdrawal cost can be measured in terms of the time to get to the nearest ATM or bank branch, then a five-minute trip should now take about 29 minutes. Of course, this is conditional on a comparable increase in the cost of using cash for the merchant.

We find that lower consumer awareness results in both sides of the market relying more on cash. In other words, with higher uncertainty, cash becomes the more-important payment instrument. Therefore, with higher uncertainty, it should be harder to drive cash out. To verify this hypothesis, we conduct a similar experiment where the usage cost of cash increases in an environment where consumer awareness is reduced by 30 percent. We find that cash would be used less often than one percent of the time, in equilibrium, if its usage costs increased by 8.5 times for both sides of the market.[32]

[32] For comparison, in a related work, Huynh et al. (2020), where we assume zero consumer awareness, the increase in the usage cost of cash must be 17 times in order to reduce its usage probabilities to below one percent.