Essays on the Economics of Payment Card Industry

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Abstract

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My dissertation consists of three chapters that address important questions in the payment card industry. Chapter 1 provides an overview of the institutional background, and introduces the problem of regressive distributional effects generated from credit card pricing. The regressive distributional effects arise when merchants pass on their costs associated with credit cards to all consumers by raising the retail prices. Since merchants typically do not differentiate prices across payment methods, these additional costs are cross-subsidized by cash and debit users. This induces a regressive transfer from low-income to high-income consumers because credit card usages tend to increase with income. Chapter 1 contributes to the literature by developing a measurement to quantify the regressive transfers made by the consumers to the merchants in a micro level. Using a unique shopping diary data conducted by Bank of Canada in 2013, I show that non-credit card users on average made a regressive transfer that is more than twice of that made by credit card users per transaction. The ratio of regressive transfers to transaction amount also decreases monotonically with income. These results suggest that how consumers choose between payment methods to make transactions have important implications on the distribution of regressive transfers, which motivates a structural estimation on consumer's payment method choices.

Chapter 2 constructs a structural model of consumer adoption and usage choices, and uses the parameter estimates to simulate the counterfactual outcomes on the distributions of regressive transfers under various institutional changes. The model is built upon Huynh et al. (2021), which features a two-stage process where consumers first choose which payment

bundle to adopt, then choose which payment method to use upon transaction. Heterogeneous preferences across consumer groups are estimated using a discrete-type of consumer demand model. Unlike most of the literature which ignores consumers' choices between the issuer banks, the model considers consumers' issuer bank choices among credit cards. Simulation results suggest that the model fits the observed data well, and generate reasonable demand elasticities of consumer usage and adoption probabilities. I conduct three policy experiments using the model estimates: a hypothetical removal of cash, a monopoly setting, and a perfect competition setting in the issuer banks. The results show that the regressive distributional effects are reduced under all three scenarios. Particularly, the monopoly setting has the strongest effects in the redistribution of regressive transfers, where it reduces the per-transaction and per-transaction value regressive transfers made by non-credit card users and low-income consumers, while increases those made by credit card users and high-income consumers. On the other hand, welfare comparisons show that perfect competition renders the highest increase in consumer surplus, while the monopoly setting and removal of cash on average hurt the consumers in terms of consumer surplus. This is the first paper to my knowledge that studies the regressive distributional effects with a structural demand model, and contributes to the literature by investigating the potential outcomes from changes in the market structure of the payment card industry.

Chapter 3 builds upon the previous chapters and introduces dynamics into consumer's payment method choices. In particular, I ask how consumer awareness on merchant acceptance affects consumer's adoption and usage choices, and how information diffusion drives the adoption and usage curve over time. I extend the model developed in Chapter 2 by considering consumer awareness that varies between payment methods. Using the parameter estimates, I conduct policy experiments where I introduce a hypothetical new payment instrument in the market, assuming different consumer inform probabilities for existing instruments and the new instrument. Simulation results on post-introduction adoption and usage probabilities show that there is a large impact of consumer awareness on consumers' adoption decisions, with a bigger impact when assuming different inform probabilities for the new instrument. To understand how consumers' adoption and usage decisions change over time when consumer awareness evolves, I borrow the literature of diffusion and simulate a diffusion process of consumer awareness using the Bass Diffusion model (Bass (1969)). The simulation results show that the adoption and usage of new payment instrument exhibits an S-shaped curve after its introduction in the market, where it takes over six years to reach the convergence. Welfare analyses show that consumer surplus initially drops after the introduction, due to the lack of information, and gradually increases when consumers become more informed. This suggests that there is an impactful welfare loss associated with information failure, and it is important for the policy makers to develop measurement that ensures a quick diffusion of information when introducing a new payment method.

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DEDICATION

To my dear husband, Po-Tsung, and my family.

Chapter 1

THE REGRESSIVE DISTRIBUTIONAL EFFECTS IN THE PAYMENT CARD INDUSTRY: EVIDENCE FROM THE CANADIAN PAYMENT CARD MARKET

1.1 Introduction

As the volume of market transactions increased, the payment service industry also grew rapidly to facilitate the transactions between consumers and merchants. Among all, credit cards have gained popularity over the past decades. Credit cards provide great efficiency and reduce transaction risks for both sides of the market. The consumers also benefit from the ability to "buy now and pay later", and numerous reward programs such as cash back, free miles and flights. However, the prevalence of credit card usage also raises controversies which have attracted governments' regulatory and legal scrutiny. Apart from several antitrust litigation over card networks including Visa and MasterCard[1], economists have argued that the pricing structure of credit cards has led to regressive distributional effects, where the non-credit card users cross-subsidize the benefits of credit card users and bear a disproportionate share of the burden of the costs of credit cards. (Carlton and Frankel (1995), Katz (2001), Marius and R. (2006), Schuh et al. (2010), Felt et al. (2020)).

The distributional effects come from the fact that merchants typically do not differentiate retail prices across payment methods, even though they face higher merchant costs in credit card transactions. The phenomenon of price coherence is mainly due to the *no-surcharge rule* (NSR) imposed on the merchants by the credit card companies. Under the agreement

[1]Examples include *United States v. Visa U.S.A., Inc.*, 344 F.3d 229, 238- 39 (2d Cir. 2003): The United States Department of Justice (DOJ) accused Visa and MasterCard of enacting exclusionary rules prohibiting their member banks from issuing cards using any payment system other than Visa or Mastercards such as American Express. The suit alleged the exclusionary rules harmed competition and violated the Sherman Act; *In re Visa Check/MasterMoney Antitrust Litigation, Case No. CV-96-5238, (E.D.N.Y. 2003)*: A class of approximately five million merchants alleged that Visa and MasterCard were illegally fixing the interchange fees and tying their debit products to their credit cards. This class-action lawsuit resulted in one of the largest federal court antitrust settlement in history, which amounted to an approximately $5.54 billion settlement fee from Visa and MasterCard.

of NSR, the merchants are prohibited to charge an additional fee for consumers who use a card. Although merchants are allowed to give cash or debit card discounts under the NSR, merchants are generally reluctant to do so.[2] To recoup the additional costs associated with the credit card transactions, the merchants pass through the merchants' costs to all consumers by raising the retail prices. Therefore, those who use low-cost payment methods such as cash and debit cards bear part of the financial burdens of the merchants' credit card accepting fees. Furthermore, since high-income consumers tend to use and spend more on credit cards, the cross-subsidies might become transfers of income from the low-income consumers to high-income consumers, a result that is firstly discussed in Frankel (1998).

In this paper, I examine whether there are regressive distributional effects generated by credit card merchant cost pass-through using an unique consumer-transaction-level data provided by the Bank of Canada. The data consist of a survey questionnaire and a diary survey instrument which records the respondents' every point-of-sale (POS) transactions made over a three-day period. To quantify the regressive distributional effects, I develop a measurement that estimates the regressive transfers incurred by each transaction and each consumer observed in the data due to merchant cost pass through. Specifically, I define the *regressive transfers* made by each transaction as the difference between the merchant cost pass-through born by the consumers in the form of retail price markup, and the actual cost associated with the payment method that the consumer imposed on the merchant. Therefore, this represents the money transfers the consumer made to the merchants which are not associated with the payment method of the consumer's choices. Then I compute the average regressive transfers per-transaction and per-dollar born by different cohorts, including income cohorts and consumers who adopt different payment methods. The goal is to lay down an analyzing framework that can be used to measure and compare outcomes of distributional effects under different scenarios.[3]

The data used in this paper are the 2013 Method-of-Payment (MOP) consumer survey

[2] Briglevics and Shy (2014) suggests that offering a cash and, especially, a debit card discount may not make financial sense for the merchants themselves.

[3] The second chapter of Yen (2021) builds a structural model of consumer payment method choices and examine how different institutional changes affect consumers' adoption and usage choices and their subsequent outcomes on the regressive distributional effects.

conducted by Bank of Canada. Data exploration shows that there are large differences in payment card ownership and usage patterns across consumer types. The ownership and usage of payment cards, particularly credit cards, increase monotonically with income and credit score. In terms of consumer perception, consumer value the payment method's security the most, followed by ease-of-use, affordability and perceived acceptance. Consumers also tend to use cash payments for small-value transactions, while increase the usage of debit or credit card when the transaction price increases. These observations are further supported in the results from a multinomial logit (MNL) regression framework, where I estimate consumers' likelihood of ownership, likelihood of usage conditional on ownership, and likelihood of usage, controlling for various consumer demographics.

Using the measurement of regressive transfers defined in this paper, I find that on average, credit card users bear an average per-transaction regressive transfers that is half of those born by non-credit card users. The credit-card users also have a smaller ratio of total regressive transfers to total transaction values (i.e. regressive transfers per-dollar). I also compute these measurement across six income cohorts, and find that both the mean regressive transfers per-transaction and per-dollar decrease monotonically with income level, suggesting that there are regressive distributional effects generated from merchant cost pass-through. This result is robust under alternative assumptions and scenarios. Specifically, in a hypothetical scenario where merchants were able to charge differently based on their respective merchant cost toward each payment method, the regressive transfers are eliminated across all income cohorts. This highlight the important role price coherence in the payment card markets plays in generating the regressive distributional effects.

This paper is related to several papers that estimate who loses and who gains from credit card payments in the aggregate economy. Schuh et al. (2010) computes the dollar-amount of transfers from cash payers to card users and from low-income to high-income households using aggregate data from the U.S. payment markets. Berkovich (2009) estimates the amount of gasoline and groceries rewards transferred from non-rewards consumers to rewards consumers in the U.S. market. Felt et al. (2020) computes the average net pecuniary cost incurred by consumers when they use different payment methods across income groups, and finds that the ratio of net pecuniary cost to point-of-sale (POS) purchase amount decreases with income.

My work differs with the existing literature in several ways. First, I focus on computing regressive transfers in the consumer-transaction level instead of the aggregate transfers made across consumer cohorts. I also focus solely on the regressive transfers caused by the pass-through from merchant fees, and abstract away from other sources of transfers such as pass-through from credit card issuing banks or the resource costs involved with each payment method. Secondly, I do not calculate transfers across consumers as in Schuh et al. (2010) and Berkovich (2009), but consider the regressive transfers made to the merchants by the consumers for each transaction. It is particularly difficult to determine who transfers to whom across consumers in a micro-level. To obtain such measurement, one need to have information about the proportion of customers who use versus customers who do not use credit card to make the payments at the merchant level, which is absent in most of the data.

The remaining paper is organized as follows. Section 1.2 provides the institutional background of the payment card industry, and introduce how the regressive distributional effect is measured in this paper. Section 1.3 describes the data source and presents detailed summary statistics of the data. Section 1.4 presents the estimates of regressive distributional effect as well as the results from robustness checks. Section 1.5 concludes.

1.2 Institutional Background

1.2.1 The Payment Card Industry

The payment card industry is commonly characterized as a *two-sided* market in the economics literature (Armstrong (2006), Evans and Schmalensee (2008), Rysman (2009)), where the payment cards serve as a medium that facilitates the transactions between the consumers and the merchants. Less known to the card users is the complex structure of the payment card system which entails multiple players. In an *open-loop* system where Visa and MasterCard operate in, a card transaction involves five players in the market: cardholders, merchants, card networks, issuer banks, and acquirer banks. Apart from the cardholders and the merchants, the *card networks* (i.e. Visa and MasterCard) provide payment card infrastructures and services for credit. They do not issue cards, extend credits, or set interest rates and fees for the card services. Rather, a consortium of member banks issue and process transactions on behalf of the card networks. In particular, the *issuer banks* issue the debit card or credit cards to the consumers. They are also the ones who set the annual fees, extend the credit lines, and offer rewards to the cardholders. The *acquirer banks*, on the other hand, are the merchants' banks who processes credit or debit card payments on behalf of a merchant. The merchants set up a merchant account with the acquirer bank of their choice, then enter into a contract with the acquirer where they are authorized to accept payment cards issued by the card networks. By contrast, American Express and Discover operate in a *closed-loop* payment card system where they run as individual businesses. The issuing and acquiring functions are integrated in the closed-loop system without the consortium of other financial institutions.

In practice, when a consumer makes a card payment upon merchant's acceptance, the merchant pays a *merchant fee* that is proportional to the transaction amount to its acquire bank. A small portion of the fee is retained by the acquirer as the *acquirer service fee*, while the majority of the merchant fee is paid to the cardholders' issuer bank, which is commonly known as the *interchange fee*. The interchange fees are set by credit card companies and typically range from 1 to 2.8 percent of the transaction amount depending on the size of the merchant and the type of card (e.g. non-reward, basic or premium cards). For each transaction, the card network also retains a small fixed amount of *network service fee* from the merchant fee.

The interchange fee implies that the two sides of the market pay different prices on the usages of credit cards. As the privilege of accepting credit cards, the merchants bear a merchant fee that comprises of interchange fee, acquirer fee and network fee. However, although consumers incur fees such as banking fee and annual fee in adopting debit or credit cards, the fees are usually more than offset by the rewards given to the card holders from the issuer banks. Existing literature has attributed the price differentiation to the *network externality* in the two-sided market(Rochet and Tirole (2002), Sujit (2010), Rysman (2009), Weyl et al. (2007)). In a two-sided market, the usage of one side increases with the number of users on the other side of the market. Therefore, when setting the prices, the platform (i.e. card networks) not only considers the demand and cost from one side, but the joint demand elasticities and marginal cost on each side. Since the merchants, especially small merchants, are typically less flexible in rejecting card payments due to the risk of losing customers, the platform has the incentives to charge a higher price due to their inelastic demand. On the other hand, lowering price for the consumers by offering rewards would attract elastic consumers to participate in the market and further increase the participation from the merchant side, due to positive network externalises. The increased participation in the merchant side further enhance the value of consumers' participation, leading to greater differences in prices paid between the two sides in the two-sided market.

1.2.2 Measuring the Regressive Transfers

Figure 1.1 presents a conceptual framework which illustrates how the fees and payments flow between the players in the payment card system when a cardholder purchase a good of $\$p$ dollars using a payment card at the POS. Following Schuh et al. (2010), I assume that the merchant fees, the interchange fees and the rewards are set proportional to the transaction price paid by the consumer. Although the merchants do not pay the interchange fee directly to the issuer banks (the acquiring bank exchanges the funds with issuer banks on behalf of the merchant), the interchange fee is generally considered to be fully funded by the merchant fees, therefore $\kappa < \mu$. I also assume that issuer banks set $\rho < \kappa$ to make a profit from each transaction. In reality, the interchange fees and rewards usually go hand in hand and the reward rates typically increase with the merchant fees associated with the credit cards.

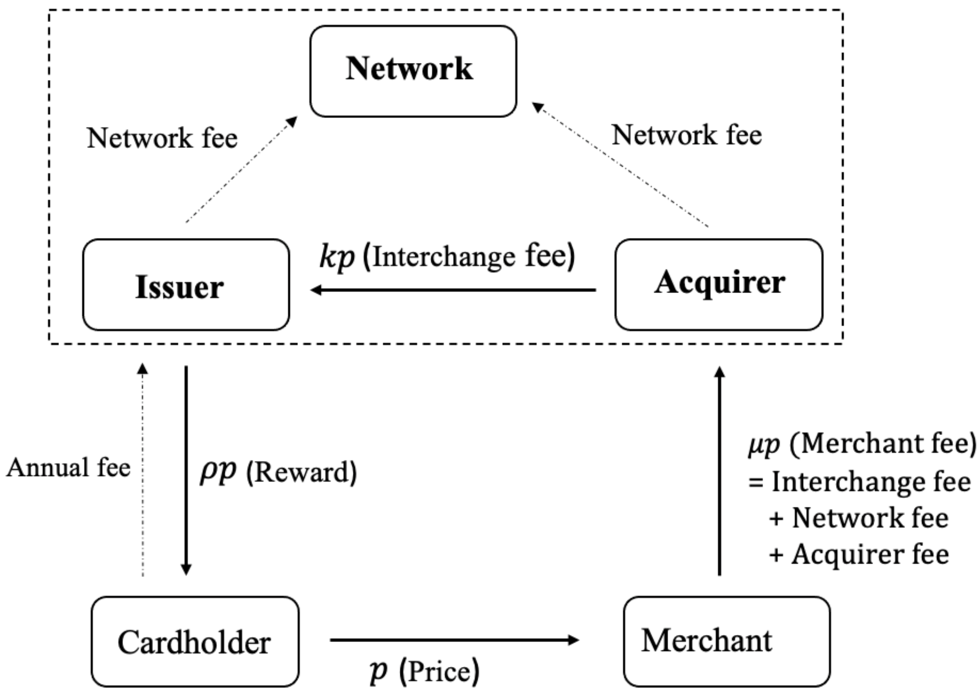
Most of the merchants face a fixed amount of acquirer fees and network fees per-transaction or per-period. For example, a transaction using Visa card involves an acquirer fee of \$0.0195 for each credit-card transaction and \$0.0155 for each debit-card transaction on average in 2018.[4] Unlike the interchange fees and network fees that are non-negotiable, merchants can negotiate with acquirers over the acquirer fees set by the acquirers. Therefore, even for the same card services, there can be substantial variation in acquirer fees due to heterogeneity in merchants' bargaining power.[5] For the network fees, the merchants are

[4] Dwyer (2020b)

[5] Ho et al. (2020) estimates a bargaining model between merchants and acquirers using data from China and finds significant variation in merchants' bargaining power across industry and sizes of the merchants

charged monthly and the monthly fees range from \$2 to \$15, depending on the merchant category, transaction volumes and acceptance method.[6]

Figure 1.1: Conceptual framework of a credit card network



The regressive distributional effects of credit cards occur when the merchants embed the merchant fees in the retail prices, thus distribute the costs of credit cards equally to all the consumers. This generates a regressive transfer from non-credit card users to merchants since the non-credit card users do not impose credit card cost from their transaction while bearing the cost from the merchant cost pass-through. To quantify the effects, I define each transaction's *regressive transfer* to the merchants as the difference between the merchant fee pass-through born by the consumer in the form of retail price markup and the actual cost the consumer's payment method imposes on the merchants. Denote TV_j the transaction value (i.e. the posted price) of transaction j, and denote $TV_{j|credit}$ the transaction value made by credit card payments. Assume that merchants pass through $\chi\% < 1$ of merchant fees onto

[6] Dwyer (2020a)

the retail price when they accept credit cards, then the amount of regressive transfers born by the consumer from transaction j is

$$R_j = \big(TV_j - \frac{TV_j}{(1+\mu\chi)TV_j}\big) \cdot \mathbb{1}(accept) - \mu \cdot TV_{j|credit} \tag{1.1}$$

$$= \frac{\mu\chi}{1+\mu\chi} \cdot TV_j \cdot \mathbb{1}(accept) - \mu \cdot TV_{j|credit} \tag{1.2}$$

The first term represents the differences between the posted price and the price that it would have been if the merchants *did not* pass through the merchant cost through the price. This term is only present if the merchant accepts the credit cards, denoted by $\mathbb{1}(accept)$, thus incur the credit card merchant fees. The second term represents the actual costs that the consumer imposes on the merchant by paying with a credit card.

For consumers who use credit cards to pay for the transactions, the regressive transfers will be negative, since $\frac{\mu\chi}{1+\mu\chi} < \mu$ for all values of $0 < \chi < 1$. This means that regardless of the pass-through rate, the credit card users will bear the merchant fees less than what they impose on the merchants. On the other hand, the consumers who use either cash or debit card in a credit card-accepting store will bear a positive regressive transfer as long as the merchants pass-through the merchant fees onto the price, i.e. $\chi > 0$, while imposing no cost associated with credit cards to the merchants (i.e. $\mu \cdot TV_{j|credit} = 0$). Therefore, how much total regressive transfers made by a consumer will depend on the amount of transactions they made in each payment methods, and the amount of transactions they made in credit card-accepting stores.

The regressive transfers defined in Equation 1.1 focuses on the transfers incurred from credit card payments. Similar calculations can be made to account for regressive transfers incurred from cash and debit card payment when merchants past through the costs involved with those transactions on to the retail prices. Previous studies have provided estimates for the merchant costs incurred in other payment methods that can be applied to the measuring method. Schuh et al. (2010) assumes a cash handling fee of 0.5% for cash transactions when calculating the transfers between cash and card users. Felt et al. (2020) assumes a merchant cost per transaction and per transaction value for each payment method including cash, debit cards and credit cards using estimates from Kosse et al. (2017). To measure the merchant cost pass-through, they assume that the merchants incur a per-transaction cost of \$0.21, \$0.29 and \$0.5, as well as a per-transaction value of 0.49%, 0.04% and a range from 1.47% to 2.05% for cash, debit card, and credit card payments respectively. The measurement described in Equation 1.1 can be easily adjusted to account for these data estimates.

Using this measurement, the total regressive transfers incurred by each consumer, R_i can be calculated by summing up the regressive transfers from each transaction made by the consumer. That is,

$$R_i = \sum_{j \in J_i} R_j \tag{1.3}$$

where J_i denotes all the transactions made by consumer i. I also compute the ratio of regressive transfers to transaction amount for each consumer as

$$r_i = \frac{R_i}{\sum_{j \in J_i} p_{ij}} \tag{1.4}$$

which represents the regressive transfers per-dollar born by each consumer.

1.3 Data

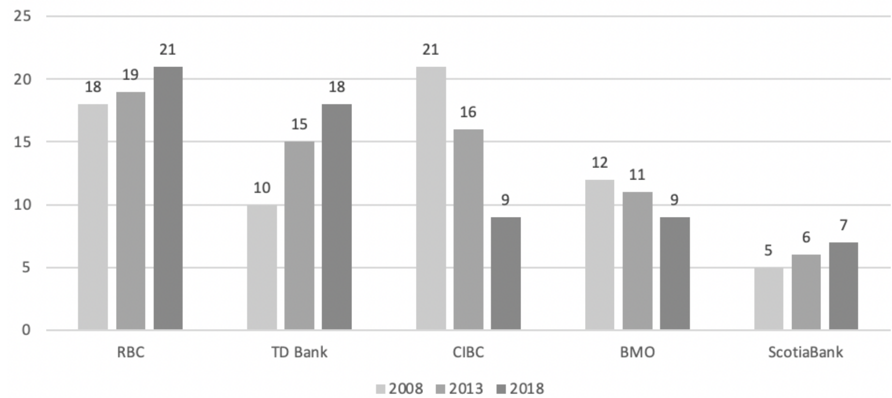
The data in this paper come from the Bank of Canada, which focuses on the Canadian market. In this section, I first describe the Canadian payment card industry and highlight the similarities and differences in the payment card industry between the U.S. and Canada. Then I present the data and provide detailed summary statistics of the data. To better understand the patterns of consumer adoption and usage of payment method, I also complement the section with a regression analysis, where I estimate the adoption and use of payment method as a function of consumer demographics and various characteristics of the payment methods.

1.3.1 Canadian Payment Card Industry

The banking industry in Canada is dominated by five largest banks (also known as Big Five): Royal Bank of Canada (RBC), Toronto-Dominion Bank (TD), Bank of Montreal (BMO), Canadian Imperial Bank of Commerce (CIBC) and Bank of Nova Scotia (Scotiabank). They are also the top issuer banks which offer card network branded payment cards to consumers in the Canadian market. Figure 1.2 presents the market shares in the Canadian issuer market in 2008, 2013, and 2018 from The Nilson Report. The figure shows that the Canadian issuer market is fairly concentrated, with RBC Royal Bank and TD being the largest issuer banks and have a combined market share of 40% in the recent years. CIBC and BMO followed with just under 10 percent of the market share each. On the other hand, the U.S. issuer market is relatively more competitive, with Chase, Bank of America, Citibank, and American Express almost equally sharing around 50% of market share in 2018. Similar to the U.S. market, the payment card network is dominated by Visa (41%) and MasterCard (26%) in Canada, while American Express plays a much smaller role in Canada (4%) compared to the U.S. (9.24%).

One notable distinction between the U.S. and Canada payment industry is the separation of debit and credit card networks in Canada. In the U.S., the card networks process both the debit and credit card transactions, and the debit- and credit-card system have similar structures as described in Figure 1.1. On the contrary, the debit card transactions in Canada are solely processed by Interact Corporation, a national debit card service which recently became a for-profit organization in 2018. Visa and MasterCard, on the other hand, only process the credit card payments in the Canadian market. Therefore, unlike the U.S. consumers who have to make decisions on which financial institutions to adopt the debit cards from, it does not concern the Canadian consumers since the debit card market is entirely integrated. Moreover, the U.S. merchants generally face a higher cost in debit card transactions than in cash transactions due to the merchant fees levied from the four-party payment card system. For the Canadian merchants, the debit card transactions are found to be less expensive compared to cash transactions if the transaction amount is sufficiently large (Garcia-Swartz et al. (2006), Fung et al. (2017), Felt et al. (2020)).

Figure 1.2: Canada credit shares by issuer banks: 2008, 2013, 2018



1.3.2 Data and Summary Statistics

In this paper, I employ the 2013 Methods-of-Payment (MOP) consumer survey conducted by Bank of Canada.[7] The survey includes a survey questionnaire (SQ) and a diary survey instrument (DSI), where the survey respondents record all transactions they made over a 3-day period. The survey questionnaire contains information on the respondents' demographics such as age, income, education, marital status, and employment status. They also provide important banking information such as their main bank account and main credit cards, as well as various rates and fees associated with them. The survey also asks the respondents' perceptions on attributes such as convenience and risk toward particular payment methods. The data also comes with the credit scores of each respondent estimated and provided from the Bank of Canada.[8]

The DSI collects transaction-level data from the respondents for three consecutive days. The data includes the transaction value, type of transaction, payment method used and other transaction characteristics (e.g. location, number of cash registry, number of staff, etc.) for each transaction. The respondents also report whether the transaction is made in

[7]The MOP survey is conducted every four years since 2009. The latest one is conducted in 2017. For descriptions on the survey design and data collection methodology, see Bank of Canada discussion paper by Henry et al. (2015)

[8]The credit scores are estimated using the nearest-neighbor estimators from the TransUnion credit registry, with banking information and consumer demographics as key predictors.

a cash-only store. The estimation sample is selected using the following criteria. First, I remove the transactions that exceed 300 Canadian dollars (CAD), which consists 1.36% of the sample, since the motives for the respondents' payment choice may be different from the other transactions. Secondly, I remove the respondents who made less than 3 transactions during the 3-day diary. Thirdly, I remove the respondents who reported inconsistent information on their ownership status of payment methods. For example, I remove respondents who reported that they do not own a credit card in the SQ, while recording a transaction made with a credit card in the DSI. Finally, I remove the respondents who have missing information about their issuer banks of their main credit card. The final sample contains 2,112 individuals and 10,482 transactions.

Table 1.1 summarizes payment method ownership by consumer demographics. I divide the consumers into who have no debit cards nor credit cards (i.e. cash-only users), who owns debit cards but not credit cards (i.e. cash and debit users), and who owns both debit cards and credit cards other than cash (i.e. cash, debit and credit users). Overall, 97.72% of consumers own a payment card of either debit or credit cards. The data shows that there is large heterogeneity in the payment method ownership across consumer types. Particularly, the ownership rates of obtaining both debit and credit cards increase monotonically with consumer income. For example, only one third of consumers with income less than 25,000 CAD obtain a credit card, while more than 90% of consumers with income more than 45,000 CAD obtain a credit card. It also increases with age and credit score.[9]

Table 1.2 summarizes consumer's perceptions toward payment method attributes including ease-of-use, security, affordability and perceived merchant acceptance. The consumers first rate the relative importance of the attributes on a seven-point scale, with larger values implying more important in their adoption decision (i.e. Column (1)). It shows that consumers care the most about the payment method's security, followed by ease-of-use, affordability and perceived acceptance, with decreasing importance. They also rate their perceptions on those attributes for cash, debit cards, and credit cards on a scale of 1-5 (i.e. Column (2)-(4)). A higher rating suggests the payment method is easier to use, less costly,

[9] I use the median of estimated credit score (=773) to categorize the credit score level.

Table 1.1: Summary statistics for payment method ownership by consumer demographics

		Cash only	Cash and Debit	Cash, Debit and Credit
Overall	N = 2,112	2.28%	11.29%	86.43%
Gender				
Female	53.35%	2.78%	12.59%	84.60%
Male	46.65%	1.84%	10.14%	88.02%
Age				
18-34	25.96%	1.85%	16.38%	81.76%
35-54	39.69%	1.80%	11.70%	86.49%
55+	34.33%	3.15%	6.95%	89.89%
Income				
$<$ 25K	17.23%	4.65%	27.44%	67.89%
25K to 45K	22.58%	2.22%	12.85%	84.92%
45K to 65K	20.74%	2.47%	6.61%	90.91%
65K to 85K	15.92%	1.10%	6.65%	92.24%
85K to 135K	16.61%	1.16%	5.56%	93.26%
$>$ 135K	6.88%	1.36%	4.27%	94.35%
Credit Score				
$<$ 773	50.75%	2.04%	16.69%	81.25%
$\geq$ 773	49.24%	2.52%	5.71%	91.76%

more secure, and more widely acceptable. Interestingly, despite the high adoption rates of credit cards in the observed sample, cash is scored the highest in every dimension of the attributes, while credit card is scored the lowest.

Table 1.3 summarizes the transaction data from the DSI across six income cohorts: less than \$25,000, \$25,000 to \$44,999, \$45,000 to \$64,999, \$65,000 to \$84,999, \$85,000 to \$134,999, and \$135,000 or more in CAD\$. For each income cohort, I compute the average number and value of transactions during the 3-day diary. I also compute the the share of payments consumers made in cash, debit cards and credit cards, respectively. On average, consumers in the sample made 5.9 purchases in three days, and the average transaction price is \$33 CAD. Although the average number and value of transactions are similar across income cohorts, consumers allocate their transactions across payment

Table 1.2: Consumers' average perceptions on payment method attributes

	(1)	(2)	(3)	(4)
	importance	Cash	Debit	Credit
Scale	1 to 7	1 to 5	1 to 5	1 to 5
Ease of use	6.25	4.69	4.49	4.48
Security	6.59	4.25	3.76	3.64
Affordability	6.24	4.59	3.74	2.98
Acceptance	6.01	3.95	3.75	3.65

Table 1.3: Summary statistic for transactions and usage of payment methods

		Annual Household Income (in CA$)					
	Overall	Less than 25K	25K to 45 K	45K to 65K	65K to 86K	85K to 135K	> 135K
Average of transaction	4.94	4.26	4.95	5.26	4.84	5.32	5.02
Average $ of transaction	33.90	30.26	33.98	32.16	37.71	34.77	37.02
% of cash payments	43.76%	56.28%	44.94%	43.72%	40.24%	36.25%	34.97%
% of debit payments	23.28%	24.07%	25.08%	24.16%	22.99%	22.17%	16.13%
% of credit payments	32.94%	19.64%	29.99%	32.11%	36.76%	41.56%	48.88%

methods quite differently. There is a clear trend where the share of cash payments decreases monotonically with income, while the share of credit card usage increases with income. In terms of debit card usage, the share of debit cards payments are similar across income cohort, with the least usages from the highest income cohort.

To see the relationship between payment method choice and transaction values, I plot the share of each payment method by the transaction value. As shown in Figure 1.3, as the transaction value increases, consumers tend to use credit cards more, and decrease the usage of cash and debit card payments. This may be because consumers find it less convenient and more risky to carry around a large amount of cash, or they face a higher ATM withdrawal fee. To further understand consumers' preferences toward payment method choices, I calculate the share of transaction values that each consumer devotes to each payment method. The results show that 44.05% of consumers devote the majority of transactions on credit card payment, followed by debit card (25.34%) and cash (23.45%). Moreover, 75% of consumers put more than 96% of their total transaction values on one single payment method. This result suggests that consumers tend to be single-homing on the choice of payment method.

Figure 1.3: Payment method share by transaction values

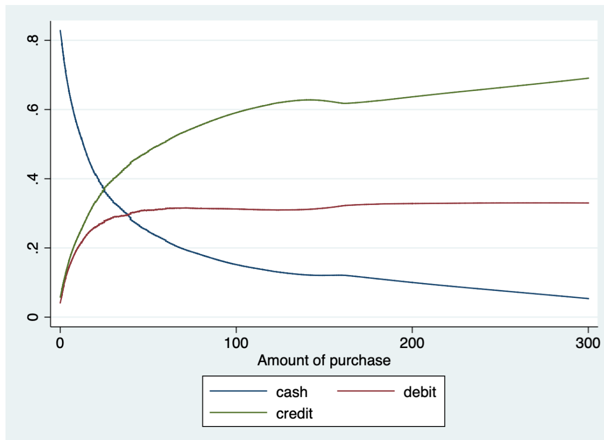


Table 1.4 summarizes the respondents' banking information regarding to their main bank account and main credit cards by income cohort.[10] It shows that RBC and TD have the largest share in terms of bank accounts in all income cohorts. In terms of the banks associated with the consumers' main credit cards, the result is more ambiguous and there are no clear patterns about which banks the consumers prefer to be associated with. However, it shows that higher income cohorts tend to use credit cards that have higher annual fees, higher interest rates and higher spending limit. Most of the credit cards give rewards, although the proportion of customers who have credit cards that give any rewards slightly increase with income. The largest difference lies in the reward programs for traveling. Only 3.63% of the credit cards held by the lowest income cohort give travel-related rewards (i.e. Airmiles), while 21.01% of the credit cards held by the highest income cohort provide the travel rewards. One limitation of the data is that although the respondents provide information on which credit card they use the most, there is no information about whether

[10]The main bank account and credit cards refer to the bank and the credit cards that the consumers use most often for day-to-day purchases

the respondent used the same credit card when making a credit card transaction in the 3-day DSI. Consumers may obtain multiple credit cards and choose to use different ones for different transaction purposes. However, Rysman (2007) has shown that consumers tend to be single-homoing, where they only use one credit card even though they own multiple credit cards.

1.3.3 Regression Analysis

In this section, I study consumer's adoption and usage choices using a multinomial logit (MNL) regression framework. The goal is to examine whether the correlations observed in the summary statistics have statistically significant effects on consumer decisions after controlling for other consumer demographics. I model consumers' choices of adoption and usage as a successive decision: Consumers first decide which payment methods to adopt, then decide whether to use each of the method at the point-of-sale (POS), given that they have adopted the payment method in the first place. The consumers' adoption is categorized into three choices: cash-only, cash and debit only, and cash, debit and credit cards. For convenience, I refer these three consumer adoption choices as *cash-only users*, *debit users* and *credit users*.

I run a set of three MNL models, which characterizes the consumers' sequential decision: The first model (i.e. adoption model) considers consumers' decision on whether to be a cash-only, debit, or cred users., where being a cash-user is the base outcome. The second model (i.e. conditional usage model) considers whether consumers choose to use the debit/credit card at the POS, given that they hold a debit card (in which case consumers are either debit users or credit users), or a credit card (in which case consumers are credit users). The third model is an unconditional logit regression (i.e. usage model), which considers whether consumer uses the debit or credit card at the POS, without conditioning on their ownership. Therefore, the last model represents the overall net effects of consumer demographics on consumer usage choices.

For all logistic models, I include the same set of consumer demographics variables, including age cohort, income level, gender, education level, employment status, urban, marital

Table 1.4: Summary statistics on banking information

	Annual Household Income (in CA$)					
	<25K	25K to 45 K	45K to 65K	65K to 85K	85K to 135K	>135K
Main bank account						
Banks						
RBC	7.53%	8.51%	7.02%	10.68%	6.42%	6.84%
TD	10.08%	10.10%	8.86%	11.06%	9.11%	10.13%
BMO	3.90%	6.71%	5.29%	4.19%	5.87%	6.69%
CIBC	2.40%	6.21%	5.43%	4.45%	4.61%	4.11%
Other banks	76.10%	68.46%	73.40%	69.62%	73.99%	72.23%
Main credit cards						
Banks						
RBC	10.29%	9.78%	12.88%	15.12%	12.84%	8.89%
TD	7.73%	7.55%	7.41%	9.65%	8.61%	7.90%
BMO	5.59%	10.43%	11.89%	10.67%	13.26%	14.49%
CIBC	6.03%	11.17%	5.79%	13.19%	12.78%	14.38%
Other banks	38.27%	46.00%	52.94%	43.62%	45.77%	48.69%
Characteristics						
Annual fee (CA$)	8.53	16.30	18.14	22.97	22.80	40.00
Annual interest rate	9.42%	12.00%	13.33%	13.12%	14.16%	13.87%
Spending limit (CA$)	3747.88	6238.97	7500.44	8675.99	9837.51	10723.64
Whether has rewards						
Any rewards	86.89%	87.04%	87.89%	88.66%	92.19%	96.43%
Cashback	8.07%	11.56%	16.66%	13.75%	11.38%	15.18%
Groceries	5.26%	6.08%	4.49%	4.90%	4.89%	4.46%
Travel	3.63%	13.21%	13.32%	15.86%	16.27%	21.01%

status, credit score level, and total number and values of transactions during the three-day DSI. Since all of the demographic variables are specified as dummy variables (except for the total number and value of transactions), the estimated effects are relative to the following reference group: age 18 to 34, earning income less than \$25,000, male, no high school diploma, not-married, living in rural area and with credit score less than 773.

Table 1.5 and Table 1.6 present the estimates for the ownership and usage of debit and credit cards respectively. The result from the ownership model (column (1)) shows that holding all else constant, the likelihood of adopting a debit card without a credit card declines with employment status and credit score. On the other hand, the likelihood of adopting a debit card *and* a credit card increases with income and education level at a 1% significance level. The result from the conditional usage model (column (2)) shows that the likelihood of using debit card conditional on being a debit user (i.e. consumers who do not hold a credit card) decreases with income and education level, suggesting that older and higher educated people who decided to adopt debit card only prefer to use cash at the POS. On the other hand, the likelihood of using credit card conditional on being a credit user (i.e. consumers who hold both debit and credit cards) increases significantly with income, education level, and credit store. This is consistent with the summary statistics presented in Table 1.3, where high income consumers tend to allocate more spending on credit payments.

Finally, the results from the usage model (i.e. column (3)) show that overall, income and credit score have statistically significant *negative* net effects on the usage of debit card, while they have statistically significant *positive* net effects on the usage of credit cards. Furthermore, consistent with the finding in Figure 1.3, the usage of payment cards increases with statistically significance with the total transaction values, where larger marginal effects of total transaction values on the credit card usage are found.[11] Interestingly, the number of transactions appear to have a significantly negative effect on the usage of both debit card and credit cards. This might be due to the smaller transaction values associated with each transaction, which leads to more cash payments.

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[11]This results are also found when the variable of total transaction values are replaced with transaction value of each transaction in the conditional and unconditional usage models.

Table 1.5: Regression results on debit card ownership and usage

Debit Card	$\mathbb{P}(Own)$	$\mathbb{P}(Usage\|Own)$	$\mathbb{P}(Usage)$
Age			
35 -54	-0.24	-0.23***	-0.30***
> 55	-1.27*	-0.49***	-0.67***
Income			
25K to 45K	0.22	-0.10	0.07
45K to 65K	-0.47	-0.14	0.03
65K to 85K	0.46	-0.30***	-0.12
85K to 135K	-0.09	-0.33***	-0.02
> 135K	-0.42	-0.55***	-0.09
Female	0.00	-0.13***	-0.15***
Education			
Completed High School	-0.14	-0.34***	-0.13
Completed University	-0.36	-0.91***	-0.56***
Employed	-0.77*	0.24***	0.20***
Urban	0.45	-0.04	-0.01
Married	-0.21	0.32***	0.40***
Credit score > 773	-0.82*	-0.15**	-0.04***
Number of transaction	0.13	-0.03***	-0.08***
Total (log) transaction value	-0.13	0.20***	0.49***

Table 1.6: Regression results on credit card ownership and usage

Credit Card	$\mathbb{P}(Own)$	$\mathbb{P}(Usage \mid Own)$	$\mathbb{P}(Usage)$
Age			
35 -54	-0.13	-0.12**	-0.19***
>55	-0.60	-0.35***	-0.46***
Income			
25K to 45K	0.86*	0.34***	0.53***
45K to 65K	0.80*	0.30***	0.50***
65K to 85K	1.69*	0.31***	0.50***
85K to 135K	1.25*	0.59***	0.83***
>135K	1.01	0.80***	1.00***
Female	-0.37	0.09**	0.00
Education			
Completed High School	0.88*	0.62***	0.79***
Completed University	1.82**	0.97***	1.11***
Employed	-0.21	-0.22***	-0.09
Urban	0.33	0.06	0.06
Married	-0.08	0.05	0.21***
Credit score >773	0.08	0.14***	0.24***
Number of transaction	0.06	-0.10***	-0.13***
Total (log) transaction value	0.23	0.51***	0.71***

1.4 Results

In this section, I calculate the regressive transfers incurred in each transaction by each consumer in the diary data, using Equation 1.1 described in Section 1.2. In the 2013 DSI, The respondents report whether the transaction was made in a cash-only store, while there is no information about whether the merchants accepted credit cards or not. In the estimation, I replace the indicator for merchant credit card acceptance, $\mathbb{1}(accept)$, with the average probability of merchant credit card acceptance estimated in Huynh et al. (2020).[12] Therefore, the regressive transfer consumer i incurred from making a transaction j with transaction price p_j becomes

$$R_{i,j} = \begin{cases} \frac{\mu\chi}{1+\mu\chi} \cdot p_j \cdot \mathbb{P}(accept), & \text{if paid in cash or debit card} \\ \frac{\mu\chi}{1+\mu\chi} \cdot p_j - \mu \cdot p_j, & \text{if paid in credit card} \\ 0, & \text{if paid in a cash-only store} \end{cases} \tag{1.5}$$

I calculate the total **r**egressive **t**ransfers (abbreviated to RT), the mean regressive transfers per transaction, and the ratio of regressive transfers to their transaction amount for each income cohort as well as the cohort by past adoption choice (i.e. cash-only users, debit users, and credit users). As a baseline measurement, I follow Felt et al. (2020) and Schuh et al. (2010) and assume an average merchant cost of 2% of transaction price and a merchant cost pass-through rate at 90% for all the credit card payments. Table 1.9 presents the results. The result shows that although the consumers having cash, debit and credit cards bear the highest total regressive transfers, the average regressive transfer per-transaction is half of those born by cash-only users and cash and debit users. The average ratio of the regressive transfer to the POS transaction value (i.e. regressive transfer per-dollar) is also the least for consumers who hold cash, debit and credit cards. In terms of the income cohorts, the mean regressive transfers and mean regressive transfer per-dollar decrease monotonically with income, while the amount of total regressive transfer does not have a clear pattern across income cohort. Since the number of total regressive transfer is mainly driven by

[12] The average probability of credit card acceptance is estimated from 2009 MOP DSI, where the merchant acceptance choice is exactly observed.

Table 1.7: Regressive transfers with different values of μ and χ

	$\mu = 2\%$ and $\chi = 100\%$		$\mu = 2\%$ and $\chi = 75\%$		$\mu = 2\%$ and $\chi = 100\%$		$\mu = 1\%$ and $\chi = 75\%$	
	Avg RT	Avg RT/$	Avg RT	Avg RT/$	Avg RT	Avg RT/$	Avg RT	Avg RT/$
By Adoption Choice								
$Mb = \{ca\}$	$0.40	1.17%	$0.26	0.82%	$0.20	0.59%	$0.13	0.41%
$Mb = \{ca, dc\}$	$0.39	1.39%	$0.29	1.05%	$0.20	0.70%	$0.15	0.53%
$Mb = \{ca, dc, cc\}$	$0.23	0.87%	$0.08	0.47%	$0.12	0.44%	$0.04	0.24%
By Annual Income								
Less than 25K	$0.31	1.14%	$0.19	0.77%	$0.15	0.58%	$0.09	0.39%
25K∼45K	$0.27	0.98%	$0.13	0.59%	$0.14	0.50%	$0.07	0.30%
45K∼65K	$0.23	0.94%	$0.10	0.55%	$0.12	0.48%	$0.05	0.28%
65K∼85K	$0.25	0.88%	$0.09	0.48%	$0.13	0.45%	$0.05	0.24%
85K∼135K	$0.21	0.80%	$0.06	0.40%	$0.11	0.41%	$0.03	0.20%
More than 135K	$0.17	0.69%	$0.01	0.28%	$0.09	0.35%	$0.00	0.14%

the number of consumers and amount of transactions they made in each cohort, it is not a suitable indicator for comparing distributional effects. However, the large differences in the per-transaction and per-dollar regressive transfers across the income cohorts and between non-credit card user and credit card users suggest that there are regressive distributional effects generated by credit card merchant cost pass-through.

The baseline estimation assumes that the merchant cost is $\mu = 2\%$ for merchants who accept credit card, and they pass through $\chi = 90\%$ of the cost onto the price as long as they accept credit cards. It also assumes that no merchant cost pass-through will incur if the merchants only accept cash. As robustness checks, I relax some of the assumptions and see if the patterns observed across consumer cohorts still hold. First, I consider different values of μ and χ, where μ is either 1% or 2%, and χ is either 75% or 100%. Table 1.7 presents the results. Consistent with the results observed in the baseline scenario, the per-transaction and per-dollar regressive transfers decrease monotonically with income, and the credit card users bear half of the regressive transfers compared to non-credit card users. The result also shows that the amount of regressive transfers decrease proportionally with the merchant cost and merchant cost pass-through.

Secondly, instead of assuming the merchants passing through the credit card costs to the retail prices, I consider a hypothetical scenario where merchants were able to charge differently based on their respective merchant cost toward each payment method. Assuming that consumers are charged accordingly to their payment method choice, we should observe the regressive transfers to be more equally distributed between consumers. To do so, I use the estimates of per-dollar merchant costs for cash and debit card payments from Felt et al. (2020), and recalculate the regressive transfers born by each transaction and each consumers. Specifically, I assume that merchants face a merchant cost of 0.49% and 0.04% of transaction amount for cash and debit card payments respectively and pass-through these costs with a pass-through rate of 90%. Therefore, regressive transfer consumer i incurs from making a transaction j becomes

$$R_{i,j} = \begin{cases} \frac{\mu_{ca}\chi}{1+\mu_{ca}\chi} \cdot p_j - \mu_{ca} \cdot p_j, & \text{if paid in cash} \\ \frac{\mu_{dc}\chi}{1+\mu_{dc}\chi} \cdot p_j - \mu_{dc} \cdot p_j, & \text{if paid in debit card} \\ \frac{\mu_{cc}\chi}{1+\mu_{cc}\chi} \cdot p_j - \mu_{cc} \cdot p_j, & \text{if paid in credit card} \end{cases} \tag{1.6}$$

where $\mu_{ca} = 0.49\%$, $\mu_{dc} = 0.04\%$ and $\mu_{ca} = 2\%$. The result is presented in Table 1.8. It shows that under price differentiation, the consumers are now subsidized from the merchants, as suggested by the negative values of the regressive transfers. This result is expected under the construction of regressive transfer described in Equation 1.1, which implies that consumers will always under-compensate how much they impose on the merchant costs (i.e. $\frac{\mu\chi}{(1+\mu\chi)} < \mu$ for all values of χ). Since higher income consumers and consumers holding credit cards tend to use more credit cards, the subsidies they receive are also higher. Although it is unlikely that merchants would price differentiate based on their payment method in practice,[13] this result highlights the important role price coherence and merchant cost pass-through play in generating the regressive distributional effects on low-income and non-credit card users.

[13] In 2003, the no-surcharge rule (NSR) was banned by Reserve Bank of Australia (RBA) in Australia. This resulted in an excessive surcharging behavior in Australian merchants, which was later found harmful to social welfare and was prohibited in the Competition and Consumer Amendment Act of 2016 (Tan and Deng (2020)).

Table 1.8: Regressive transfers assuming price differentiation

	Avg RT	Avg RT/dollar
By Adoption Choice		
$Mb = \{ca\}$	-\$0.24	-0.51%
$Mb = \{ca, dc\}$	-\$0.08	-0.29%
$Mb = \{ca, dc, cc\}$	-\$0.40	-0.88%
By Annual Income		
Less than 25K	-\$0.23	-0.60%
25K∼45K	-\$0.33	-0.76%
45K∼65K	-\$0.34	-0.80%
65K∼85K	-\$0.43	-0.86%
85K∼135K	-\$0.42	-0.94%
More than 135K	-\$0.51	-1.07%

Table 1.9: Regressive transfers born by consumers (in CAD$)

	Total RT	Avg RT	Avg RT/dollar
	Baseline: $\mu = 2\%$ *and* $\chi = 90\%$		
By Adoption Choice			
$Mb = \{ca\}$	\$62.73	\$0.34	1.03%
$Mb = \{ca, dc\}$	\$375.74	\$0.35	1.25%
$Mb = \{ca, dc, cc\}$	\$1,441.15	\$0.17	0.71%
By Annual Income			
Less than 25K	\$382.31	\$0.26	0.99%
25K∼45K	\$461.89	\$0.22	0.82%
45K∼65K	\$407.47	\$0.17	0.79%
65K∼85K	\$292.92	\$0.18	0.72%
85K∼135K	\$263.61	\$0.15	0.64%
More than 135K	\$71.42	\$0.10	0.53%

1.5 Conclusion

Merchants generally do not differentiate prices over different payment methods, while they pass through the costs uniformly to all consumers by raising the retail prices. In this paper, I examine whether there are regressive distributional effects attributed from the merchant cost pass-through by developing a measurement that estimates the regressive transfers consumers face in each transaction when they pay in different payment methods. Using an unique consumer survey and shopping diary data provided by the Bank of Canada, I measure the regressive transfers incurred from each transaction and for each consumer, and compute the per-transaction and per-dollar regressive transfers born by consumers in different income cohort and adoption cohort. The results show that low-income and non-credit card users on average bear a dis-proportionally higher regressive transfers compared to high-income and credit card users. This finding is robust under various assumptions and scenarios. Results from a hypothetical scenario where merchants do price differentiate according to payment methods suggest that regressive distributional effects could be eliminated under institutional changes.

The paper serves as the foundation for my studies in the payment card industry, where I lay down the analyzing framework that can be used to measure and compare outcomes of regressive distributional effects under different scenarios. Chapter 2 in Yen (2021) builds a structural model of consumer payment method choices, and explicitly examines how different institutional changes affect consumers' adoption and usage choices, and their subsequent outcomes on the regressive distributional effects.

Chapter 2

THE IMPACT OF MARKET STRUCTURE CHANGES ON THE REGRESSIVE DISTRIBUTIONAL EFFECTS: A STRUCTURAL ESTIMATION OF CONSUMER PAYMENT CHOICES.

2.1 Introduction

Pricing in the two-sided markets has received considerable attention in the literature of economics. The main result is an asymmetrical pricing strategy of the platform to treat one side as a profit center and the other as a loss leader, depending on each side's demand elasticities and their relative responses to the growth of the other side (Rysman (2009), Rochet and Tirole (2002)). For example, newspapers charge the advertisers with an advertising rate while readers do not pay for the advertisement in their newspapers. In the payment card industry, merchants are charged with a merchant fee in accepting credit cards, while many consumers are subsidized by the card associations to use the credit cards, with the reward programs such as cash backs and air mileages.

One feature in the payment card industry that is distinct from other two-sided market is the practice of price coherence of the merchants. Although merchants face a higher cost in accepting credit cards, they generally do not set differential prices for card users to recoup the costs. Instead, they pass through their own cost of accepting card payments by raising the retail prices. As a result, those who use cash take part of the financial burden of card processing, yet receive none of the rewards. Since credit card usages are closely related to consumers' abilities to build the credit line and pay the annual fees, the usages of credit card tend to increase with income. This potentially creates a disproportionate welfare loss to the low-income consumers. Quantifying the heterogeneity in consumer preferences and affordability is thus important in understanding how consumers make choices on the payment methods. Knowledge about the joint distribution of the structural parameters can help inform policy makers about the welfare effects under different regulations.

In this paper, I estimate a structural demand model of consumers' adoption and usage choices of payment methods at the point-of-sale (POS), and investigate the impact of institutional changes on consumer's payment method choices and the subsequent changes in the consumer welfare. Following Chapter 1 in Yen (2021), I also quantify the dollar values of regressive transfers consumer make for each transaction, defined as the differences between the merchant cost pass-through and the actual cost imposed on the merchant, and examine how changes in market structure affect the distributions of regressive transfers between the card users and non-card users, and between low-income and high-income consumers.

For the structural demand model, I set up a "discrete-type" random coefficient discrete choice model as in Berry and Jia (2010), which takes into account the heterogeneity in tastes among different types of consumers. Similar to Huynh et al. (2021), the model features a two-stage process, where consumers first choose the portfolio of payment methods to adopt (i.e. *adoption* stage), and then decide which payment method to use when randomly matched with a merchant for each transaction (i.e. *usage* stage). Unlike the existing literature which ignores consumers' choices on the issuer banks, the model considers consumers' brand choices among credit cards during the adoption stage.

To incorporate brand differentiation and issuer bank competition, I follow the approach taken in Huynh et al. (2021) and estimate each card issuing bank's net margin using the strategy of moment inequality. Specifically, I assume that the issuer banks choose a reward rate that maximizes their expected profits. Since a reduction in the reward rate increases the issuers' net margins, while decreases consumer usage probabilities thus decreases expected profit, the net margins are estimated such that no deviations from them would generate higher expected profits as observed from the data. This also highlights the important trade-off the issuer banks face between profitability and market penetration in the two-sided market.

My empirical analysis is based on the 2013 Methods of Payment (MOP) Survey provided by the Bank of Canada. The data contain a survey questionnaire which asks the respondents' demographics, ownership of payment instruments, banking information and their perceptions on various attributes toward payment methods, such as security, affordability and easiness-to-use. The data also contain a diary survey instrument (DSI) in which the respondents record all transactions made in a three day period. It includes information such as the value and type of the transactions (e.g. grocery, gas or meal), as well as the payment method used at the POS.

Preliminary data analyses[1] show that the choices of payment methods vary significantly across consumer demographics, where higher-income consumers tend to use more credit cards and decrease the usage of cash and debit cards. Results from the calculation of regressive transfers show that non-credit card users on average made a regressive transfer that is more than twice than that made by credit card users per transaction, and the ratio of regressive transfers to transaction amount tends to decrease monotonically with income. These results suggest that how consumers choose between payment methods have important implications on the distribution of regressive transfers, which further motivates a structural estimation on consumer's payment method choices.

The model is estimated using maximum likelihood estimation based on the transaction-level data. Parameter estimates for the usage stage show that consumers favor payment methods with easiness-to-use, affordability and security, with decreasing importance. Consumers also prefer to use cash for small-value transactions (e.g. below 10 CAD$). Consumers gain heterogeneous benefits when using a credit card for payment, with high-income consumers enjoying larger benefits. The cost of adopting both debit and credit cards is estimated to be lower for high-income consumers in the adoption stage. Simulation results suggest that the model fits the data well, and generate reasonable demand elasticities. Supply-side estimation shows that issuer banks on average earn a net profit margin of 2.1% to 2.5% for each transaction, which is consistent with the industry standard.

Using my structural estimates, I conduct a set of counterfactual experiments to see how institutional changes in the payment card industry affect consumer surplus and the distribution of regressive transfers. First, I consider a hypothetical elimination of cash in the society, which has been a growing interests among policy makers. Welfare comparisons show that eliminating cash hurt all the consumers, suggesting that consumers truly value the characteristics of cash. However, the result suggests that cash removal has beneficial impact on the regressive distributional effects. Particularly, the gap between the average

[1]Section 1.3 in Yen (2021) provides detailed summary statistics and regression analyses on consumer adoption and usage of payment methods.

per-transaction regressive transfers made between low-income and high-income consumers significantly shrinks. The regressive transfer per dollar also decreases by 40% for the lowest income cohort.

Secondly, I consider two extreme cases in the issuer bank competition: monopoly and perfect competition. I simulate the results with different consumers' usage cost by assuming different pricing strategies of the issuer banks. The results show that perfect competition renders an increase in consumer surplus for all of the consumers, while the monopoly setting on average hurts the consumers, with a more negative impact on the low-income consumers. In terms of the regressive distributional effect, I find that the effects are reduced under both extreme scenarios. Particularly, the monopoly setting *reduces* the per-transaction and per-transaction value regressive transfers made by non-credit card users and low-income consumers, while *increases* those made by credit card users and high-income consumers. On the other hand, perfect competition among issuer banks decreases the regressive transfers born by all consumers.

This paper is related to several strands of economics literature. The first strand studies the pricing in the two-sided market. The seminal work by Rochet and Tirole (2002) forms the theoretical framework for understanding the pricing structure in the payment card industry. Guthrie and Wright (2007) discussed how competitions between card associations affect the setting of interchange fees. Klein et al. (2006) emphasizes the role network effects play in determining the prices in the two-sided markets, and discusses its implications on the antitrust analyses. My paper contributes to this stream of literature by studying and quantifying the regressive distributional effects generated from the pricing structure in the payment card industry.

This work is also related to the growing literature that empirically investigates consumers' usage patterns between payment instruments. Koulayev et al. (2016) is the first paper to develop and estimate a structural model of consumer payment method choices. Huynh et al. (2020) estimates a two-stage consumer adoption and usage model and investigates the welfare implications of the introduction of new payment instruments. Huynh et al. (2021) constructs a two-sided structural model which explicitly models the decisions made by both consumers and merchants. My model is built upon Huynh et al. (2021).

However, I extend the model by considering the consumer substitution patterns between different brands of credit cards. I also consider a discrete-type version of the model where I estimate the heterogeneous preferences across consumer groups. Other papers that study the consumer's payment method choices include Rysman (2007), which finds a positive regional correlations between consumer usage and merchant acceptance within the card networks. O'Brien (2014) and Wakamori and Welte (2012) ask why consumers continue to use cash and find that cash usage in small-value transactions is mainly driven by consumer preferences.

This paper also contributes to the literature by first quantifying the different impacts of institutional changes on the consumer welfare and regressive distributional effects. Similar interests have shown in recent papers: Fujiki (2020) investigates the demand for cash and non-cash payment methods as the Japanese government aims at a cashless economy. Felt et al. (2020) uses aggregate data to compare the regressive distributional effects across income groups in the U.S.A and Canada. Tan and Deng (2020) investigates the welfare implications of banning the no-surcharge rule (NSR) in credit card markets.

The remaining paper is organized as follows. Section 2.3 presents the econometrics model and the estimation strategy. Section 2.4 discusses the results. Section 2.5 presents the counterfactual experiments. Section 2.6 concludes.

2.2 The Structural Model

In this section, I present a two-stage model of consumer choice of adoption and usage of payment methods. In stage 1, the consumers choose which payment methods to adopt. In stage 2, the consumers face transaction needs and select which payment method to use among available choices. I start from the consumer usage stage, then proceed to the consumer adoption stage with the idea of backward induction. In the end of the section, I present a model for the issuer banks.

2.2.1 Consumer Usage Stage

Let $b = 1, ..., B$ denote a customer (i.e. buyer), $j = 1, ..., J$ denote a transaction, and $m = 1, 2, ..., M$ denote a payment method. Each payment method m belongs to a payment method group $g(m) \in \{ca, dc, cc\}$, denoting cash, debit card and credit card. I use a "discrete-type" version of random coefficient discrete-choice model in the spirit of Berry and Jia (2010). Suppose there are R types of consumers. The utility that consumer b, who is of type r, receives from using payment method m for transaction j is given by

$$\begin{aligned} u_{bjm}(p_j) &= \beta_r X_{bg(m)} - \alpha_r c_{jm}(p_j, \rho_r) + \eta_{rg(m)} \mathbb{1}(p_j < \$10) + \xi_{bjm}(r, Tj, m) + \epsilon^u_{bjm} \\ &= \delta_{bjm}(p_j) + \epsilon^u_{bjm} \end{aligned} \tag{2.1}$$

where $X_{bg(m)}$ denotes a vector of consumer's perception variables on a set of payment method characteristics (e.g. easiness to use, security and affordability). The perception variables vary across consumers and payment method group $g(m)$, but are constant across transactions for the same consumer and the same payment method group. c_{jm} denotes the transaction cost associated with each payment method m, and is assumed to increase with p_j, and decrease with ρ_r, which represents the per-dollar reward from using a credit card, and is assumed to vary between consumer types. $\mathbb{1}(p_j < \$10)$ indicates whether the transaction value is less than 10 dollars. ξ_{bjm} represents a vector of *consumer type* $\times$ *transaction type* $\times$ *payment method* fixed effects. These represent the match values that consumers receive when using specific payment method for specific transaction types. Finally, ϵ^u_{bjm} represents an idiosyncratic random shock on b's utility when making a transaction j with payment method m.

The coefficients for the perception variables are β_r, which vary by the types of consumers. The transaction value coefficient α_r is also consumer-type specific, which captures the heterogeneity in consumer price sensitivity. Consumers receive different utilities for making small-value transactions with debit card or credit card, captured by $\alpha_{rg(m)}$. This small-value transaction coefficient is assumed to be zero for cash payment.

Each consumer is endowed with J_b transactions that they must complete. The number and transaction values of the transactions are assumed to be exogenous. At the time of each transaction, the consumer is matched with a merchant s (i.e. seller) who accepts payment method bundle M_s. The consumer then picks the payment method that maximizes her or her utility from the available payment method choices, which is the intersection of the consumer's adoption bundle M_b and the merchant's acceptance bundle M_s. Following Huynh et al. (2020), I assume that for each transaction, there is a probability ϕ that the transaction is an *informed* transaction, which means the consumer is aware of the merchant's acceptance bundle before making the transaction. In this case, the consumer simply picks the payment method that maximizes the consumer's utility. On the other hand, there is a $1-\phi$ probability that the transaction is a *uninformed* transaction. In this case, consumer picks the utility-maximizing payment method from the intersection of M_b and M_s.

Denote the probability that merchant accepts the bundle Ms as $\mathbb{P}_{Ms}$, the expected per-transaction utility for consumer who adopts M_b is given by

$$\begin{aligned} EU_{bj}(M_b) = \mathbb{E}_{\epsilon}\Bigg[&\phi \max_{m \in M_b} u_{bjm}(p_j) \\ &+ (1-\phi) \sum_{Ms} \mathbb{P}_{Ms} \max_{m \in M_b \cap M_s} u_{bjm}(p_j)\Bigg] \end{aligned} \tag{2.2}$$

where the first and second line of the equation represents the informed and non-informed transactions respectively. I assume that the informed probability ϕ and the probability distribution of merchant acceptance are the same at the observed level across consumers. The expectation is taking over the idiosyncratic utility shock of ϵ^u_{bjm}, which randomly shifts consumer's utility up and down.

Given Equation 3.2, the consumer b's expected utility from completing all the endowed transactions J_b, holding adoption bundle M_b, is given by:

$$EU_b(M_b) = \sum_{j \in J_b} EU_{bj}(M_b) \tag{2.3}$$

2.2.2 Consumer Adoption Stage

In the first stage, consumers make decision on which bundle of payment methods to adopt. The consumers are assumed to choose the bundle $M_b \in \mathbb{M}$ that maximizes the utility in the adoption stage, where $\mathbb{M}$ denotes all possible bundles. Denote the adoption cost for consumer b in adopting M_b as F_{bM_b}. The consumer's decision in the adoption stage is given by

$$\max_{M_b \in \mathbb{M}} \{EU_b(M_b) - F_{bM_b}(Z_b) + \epsilon^a_{bM_b}\} \tag{2.4}$$

where $\epsilon^a_{bM_b}$ is an idiosyncratic utility shock upon consumer's adoption. The adoption cost is assumed to be a function of consumer's characteristics Z_b, such as income, age, education, credit score, etc. The adoption cost for cash is normalized to be zero for all the consumers.

2.2.3 Issuer banks

The profit that each issuer bank s receives when a consumer b makes a payment of p_j using the payment card issued by the issuer, $s(m)$, is given by

$$\Pi_{bs(m)j} = (\kappa_{s(m)} - \rho_{rs(m)})p_j - mc_{s(m)} \tag{2.5}$$

where $\kappa_{s(m)}$ is the interchange fee received from the acquirer bank, and $\rho_{rs(m)}$ represents the reward that the issuer bank offers for every dollar consumer spent, which is assumed to vary between consumer types. $mc_{s(m)}$ is the marginal cost the issuer bank faces per transaction. It captures the cost that issuer bank involves to authorize the transaction from the consumer's account information. The expected total profit for the issuer s, denoted by $\mathbb{E}\Pi_s$, depends on the probability that consumer uses the payment card from the issuer bank:

$$\mathbb{E}\Pi_s = \sum_{b=1}^{N_b}\left[\sum_{J_b}\mathbb{P}(s(m) =_{m\in M_b\cap M_s} U_{bjm})\cdot \Pi_{bs(m)j}\right] \tag{2.6}$$

The issuer is assumed to set $\rho_{rs(m)}$ to maximize their expected profits.

2.3 Estimation

2.3.1 Empirical Specifications

Consumer Choice Set. I assume that the consumer's choice set of payment methods includes cash, debit card, and a set of credit cards issued by different issuer banks. In particular, I assume that consumers choose the credit card from Royal Bank of Canada (RBC), Toronto-Dominion Bank (TD), Bank of Montreal (BOM), Canadian Imperial Bank of Commerce (CIBC), and other banks (Else). In the adoption stage, the consumers decides whether to adopt cash, cash and debit card, or cash, debit card and a credit card from one of the issuer banks. This assumes that consumers always adopt cash, and if the consumer decides to adopt a credit card, they must also adopt the debit card. It also assumes that consumers do not make explicit decisions on the financial institutions associated with their debit cards. Since the Canadian debit card network in fully integrated with one single issuer, this is a valid assumption. Note that in adoption stage, the consumer's choice set is limited to at most *three* payment methods to adopt in their wallet. In reality, consumers may choose to adopt multiple credit cards. However, this model focuses on the main credit card that consumers report they choose to adopt and use.

Given the adoption decisions, the consumer then chooses which payment method to use in the usage stage. The merchants are assumed to be ignorant on which issuer bank of the credit card that the consumer uses to make the transaction. Instead, they either accepts cash only, cash and debit only, or all types of payment instruments, although in reality, the merchants must choose which card networks (e.g. Visa, MasterCard) to accept if they decide to accept credit cards.[2] Using estimates from Huynh et al. (2021), I assume the merchant acceptance rates are 22.02% for cash only, 4.22% for cash and debit and 73.66% for all payment methods in the sample.

Transaction Costs. Consumer's usage utility is assumed to vary with the transaction cost associated with each payment method. I use estimates from Kosse et al. (2017) to calculate transaction cost for each payment method, which is assumed to be a linear function of transaction prices. I also assume that the reward rates received by the consumers also directly affect the transaction cost. Specifically, I assume that the transaction cost that a consumer of type r faces by making a transaction j with payment method m which provides a reward rate of ρ_r is given by

$$c_{jm}(p_j, \rho_r) = c_{0m} + c_{1m} \cdot p_j \cdot (1 - \rho_r) \tag{2.7}$$

where $(c_{0m},\ c_{1m})$ are parameters estimated in Kosse et al. (2017).[3] Following Schuh

[2]Card networks usually impose a Honor-All-Card rules on the merchants, which requires the merchants to accept all types of credit cards (including non-reward card, basic cards and premium cards) as long as they accept any type of the credit cards from the same network.

[3]$c_{0,ca} = 0.122$, $c_{1,ca} = 0.005$, $c_{0,dc} = 0.536$, $c_{1,dc} = 0.00007$, $c_{0,cc} = 0.059$, and $c_{1,cc} = 0.000003$

et al. (2010), the reward rates for the high- and low-income consumers are assumed to be $(\rho_h, \rho_l) = (0.79\%, 0.57\%)$.

Adoption Costs. I assume that the adoption costs for each bundle M_b, $F_{bMb}(Z_b)$, is a linear function of consumer characteristics. Specifically, I assume that

$$F_{bM_b}(Z_b) = \begin{cases} 0 & \text{if } M_b = \{cash\} \\ \gamma_{0,M_b} + \gamma_{1,M_b} Inc + \gamma_{2,M_b} Age + \gamma_{3,M_b} N_b + \gamma_{4,M_b} TV_b & \text{if otherwise} \end{cases} \tag{2.8}$$

where Inc denotes consumer's income level, Age denotes the consumer's age. N_b and TV_b denotes the total number and total transaction value of transactions made over the 3-day diary for each consumer b.

Consumer Types. To capture the heterogeneity in consumer price sensitivity and consumer preferences, I allow for multiple type-specific parameters. The parameters on the consumer perceptions on ease-of-use, perceived affordability, security, the estimated transaction costs of each payment methods and transaction-specific match values are assumed to vary between consumer types. Specifically, I divide the consumers into high-income type (i.e. annual income above 55K) and low-income type (i.e. annual income below 55K), after experimenting with different ways of categorizing consumers.

Idiosyncratic Random Shocks. I assume that both the random shock in the usage stage, ϵ^u_{bjm} in Equation 3.1, and the random shock in the adoption stage, ϵ^a_{bMb} in Equation 3.4 follow the i.i.d. Type-1 Extreme Value distributions. Therefore, the expected per-transaction utility for consumer b who adopts bundle M_b in Equation 3.2 can be written as

$$\begin{aligned} EU_{bj}(M_b) = \phi \cdot \ln\big(\sum_{m \in M_b} e^{u_{bjm}(p_{bj})}\big) \\ + (1-\phi) \cdot \sum_{Ms} \mathbb{P}_{Ms} \cdot \big(\ln \sum_{m \in M_b \cap M_s} e^{u_{bjm}(p_{bj})}\big) \end{aligned} \tag{2.9}$$

where ϕ is the probability that the transaction is an informed transaction.[4] For example, the expected per-transaction utility for consumers holding $M_b = \{ca, dc\}$ is

$$
\begin{aligned}
EU_{bj}(M_b = \{ca, dc\}) = {} & \phi \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})}\right) \\
& + (1-\phi) \cdot \Big(\mathbb{P}_{Ms=\{ca\}} \cdot u_{b,j,ca}(p_{bj}) \\
& + \mathbb{P}_{Ms=\{ca,dc\}} \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})}\right) \\
& + \mathbb{P}_{Ms=\{ca,dc,cc\}} \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})}\right)\Big)
\end{aligned}
\tag{2.10}
$$

and the expected per-transaction utility for consumers holding $M_b = \{ca, dc, cc_{BOM}\}$ is

$$
\begin{aligned}
EU_{bj}(M_b = \{ca, dc, cc_{BOM}\}) = {} & \phi \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})} + e^{u_{b,j,cc_{BOM}}(p_{bj})}\right) \\
& + (1-\phi) \cdot \Big(\mathbb{P}_{Ms=\{ca\}} \cdot u_{b,j,ca}(p_{bj}) \\
& + \mathbb{P}_{Ms=\{ca,dc\}} \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})}\right) \\
& + \mathbb{P}_{Ms=\{ca,dc,cc\}} \cdot \ln\left(e^{u_{b,j,ca}(p_{bj})} + e^{u_{b,j,dc}(p_{bj})} + e^{u_{b,j,cc_{BOM}}(p_{bj})}\right)\Big)
\end{aligned}
\tag{2.11}
$$

Given the merchant acceptance probabilities, $\mathbb{P}_{M_s}$, the per-transaction usage probabilities of each payment method m for consumers holding payment method bundle M_b is:

$$
\begin{aligned}
\mathbb{P}_j(m|M_b) = {} & \phi \cdot \frac{\exp(\delta_{bjm})}{\sum_{k \in M_b} \exp(\delta_{bjk})} \\
& + (1-\phi) \cdot \sum_{M_s \supset \{m\}} \mathbb{P}_{M_s} \cdot \frac{\exp(\delta_{bjm})}{\sum_{k \in M_b \cap M_s} \exp(\delta_{bjk})}
\end{aligned}
\tag{2.12}
$$

where the first and second part of the equation respectively indicate the usage probabilities for informed and uninformed transactions. For example, the probability that a consumer who holds cash, debit card and a credit card from Bank of Montreal (BOM), i.e. $M_b = \{ca, dc, cc_{BOM}\}$ uses her/his debit card to pay for transaction j, i.e., $m = \{dc\}$ is:

[4] I take the estimated ϕ for each transaction provided by Bank of Canada, and use the average value of 88% as the informed probability for all the consumers.

$$\mathbb{P}_j(m = \{dc\}|M_b) = \phi \cdot \frac{\exp(\delta_{b,j,dc})}{\exp(\delta_{b,j,ca}) + \exp(\delta_{b,j,dc}) + \exp(\delta_{bj,cc_{BOM}})}$$
$$(1-\phi) \cdot \Bigg(\mathbb{P}_{M_s=\{ca,dc\}} \cdot \frac{\exp(\delta_{b,j,dc})}{\exp(\delta_{b,j,ca}) + \exp(\delta_{b,j,dc})}$$
$$+ \mathbb{P}_{M_s=\{ca,dc,cc\}} \cdot \frac{\exp(\delta_{b,j,dc})}{\exp(\delta_{b,j,ca}) + \exp(\delta_{b,j,dc}) + \exp(\delta_{bj,cc_{BOM}})} \Bigg) \tag{2.13}$$

On the other hand, the probability for the same consumer to use her/his Bank of Montreal credit card to pay for transaction j, i.e., $m = \{cc_{BOM}\}$ is:

$$\mathbb{P}_j(m = \{cc\}|M_b) = \phi \cdot \frac{\exp(\delta_{b,j,dc})}{\exp(\delta_{b,j,cc_{ca}}) + \exp(\delta_{b,j,dc}) + \exp(\delta_{bj,cc_{BOM}})}$$
$$(1-\phi) \cdot \Bigg(\mathbb{P}_{M_s=\{ca,dc,cc\}} \cdot \frac{\exp(\delta_{b,j,cc_{BOM}})}{\exp(\delta_{b,j,ca}) + \exp(\delta_{b,j,dc}) + \exp(\delta_{bj,cc_{BOM}})} \Bigg) \tag{2.14}$$

Given the assumption that the idiosyncratic adoption shock also follows a Type-1 Extreme Value i.i.d. distribution, the probability that consumer b adopts payment method bundle M_b can be written as

$$\mathbb{P}_b(M_b) = \frac{\exp(EU_b(M_b) - F_{bM_b})}{\Sigma_{M'_b \in M} \exp(EU_b(M'_b) - F_{bM'_b})} \tag{2.15}$$

Likelihood Function. Using these probabilities, I estimate the structural parameters in the two stages by constructing the joint likelihood function from the adoption and stage stages. Let $D_{bM} \in \{0,1\}$ denote the observed realization of consumer b's adoption decision, and denote $D_{bjm} \in \{0,1\}$ the observed realization of consumer b's usage decision. The likelihood function is given by:

$$\mathbb{L}(\theta) = \prod_{b=1}^{N_b} \prod_{j \in J_b} \prod_{m \in M_1} \mathbb{P}_j(m|M_b, \theta)^{D_{bjm}}$$
$$\cdot \prod_{b=1}^{N_b} \prod_{M \in M_2} \mathbb{P}_b(M_b, \theta)^{D_{bM}} \tag{2.16}$$

where M_1 denotes all the possible payment methods and M_2 denotes all the possible bundles of payment methods. The first line represents the consumer adoption probabilities and the second line represents the consumer usage decisions.

2.3.2 Estimation and Identification

The parameters in the structural model are $\theta = (\beta_r, \alpha_r, \eta_{rg(m)}, \xi_{bjm}, \nu_{bMb})$ for all consumer group r, payment method group $g(m)$ and adoption bundle M_b. There are a total of 78 parameters. I estimate them using the Powell minimization algorithm and compute the standard errors of the parameters using Fisher Information Matrix.[5] The identification of β_r comes from the variations in consumers' perceptions on the payment method characteristics toward different types of payment methods. It is worth noting that consumers having the same perceptions over the credit cards from different issuer banks does not impede the identification of β_r. This is because in the usage stage, the consumer faces at most one choice of credit card, due to the assumption that consumers only adopt one main credit card from the adoption stage. Therefore, the distributions over the $X_{bg(m)}$ must be different across payment methods, which ensures the identification of β_r.

The identification of α_r relies on the variations in the transaction costs, which varies across different types of payment methods and consumer-type specific reward rates. The $\eta_{rg(m)}$ is identified assuming that $\eta_{r,cash}$ are zero for both types of consumers r. To identify the unobserved match values of ξ_{bjm}, the match values of cash transactions are normalized to zero. The differences between the usage shares of payment methods across consumer types and transaction types identify the fixed effect match values. Similarly, the differences between the shares of adoption bundles across consumer demographics identify the ν_{bMb}, where the adoption cost of cash are normalized to zero.

In the standard discrete choice model in differentiated product markets, one can recover supply-side parameters using estimates from the demand parameters. For example, the firms' marginal costs can be estimated as the difference between prices and predicted markup derived from demand elasticities using first-order condition. However, the transaction prices are determined by the consumers in the payment card market. The issuer bank chooses

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[5] The empirical fisher information matrix given sample drawn from $p(x|\theta)$ is defined as

$$I_\theta = \frac{1}{N}\sum_{i=1}^{N} \nabla_\theta \log p(x_i|\theta) \nabla_\theta \log p(x_i|\theta)^T \tag{2.17}$$

where $\nabla_\theta \log p(x_i|\theta)$ is the FOC of log-likelihood with respect to parameters. The standard errors are obtained by taking the square root of the diagonal of the inverse of empirical fisher information matrix.

$\rho_{rs(m)}$ given the interchange fee, which are both unobserved in the data. To compute issuer banks' profit, I follow the method taken in Huynh et al. (2020), where I calibrate the issuers' marginal cost, and estimate the per-price profit margin (i.e. $\kappa_{s(m)} - \rho_{rs(m)}$) using the method of moment inequality. The idea is that by changing the profit margin by increasing (or decreasing) the reward rates, the consumer's usage cost decreases (or increases) which also affect consumer adoption and usage probabilities. Assuming that the observed data is under the optimality condition, then any deviation from the profit margin (through changes in reward rates) will generate lower expected profits.

Specifically, let $\omega = \kappa_{s(m)} - \rho_{rs(m)}$ be the profit margin per-dollar. Then the expected profit satisfies the following inequality,

$$\forall s : \mathbb{E}\Pi_s(\omega^*, mc) \geq \mathbb{E}\Pi_s(\omega^* + \Delta, mc) \ \forall \Delta \in \mathbb{R} \tag{2.18}$$

Note that a positive Δ (i.e. from lower $\rho_{rs(m)}$) has two opposing effects that change issuer banks' expected profits. First, it increases the issuer's profits from each transaction that is made with issuer bank's cards. Secondly, it increases consumer's usage cost for using their card, thus decreases the consumer usage probabilities. Therefore, the latter serves as a competitive force that bound the issuer bank's ability to extract profits from each transaction.

2.4 Results

In this section, I first present the parameter estimates from the consumer adoption and usage model. Then I assess the fit of the structural model, and compute consumer usage and adoption elasticities. I also present the marginal effects of each payment method attributes and the consumer substitution patterns between the attributes within the same payment method. In the end of the section, I present the estimation results from the issuer side.

2.4.1 Parameter Estimates

As discussed in Section 2.2.1, the consumer usage stage payment method choice is driven by consumers' perceptions on the payment method characteristics, the transaction price, and a set of match values determined by consumer types, transaction types and payment methods. The higher a consumer rates a characteristics for a payment method, the higher utility the consumer gains from using the payment method for transactions. The match values capture the reward or other non-pecuniary benefits that are unobserved in the data when consumers used the credit card for different types of transactions. In the adoption stage, the consumer's adoption choice is driven by the expected total utility gain in the usage stage, as well as the adoption cost. The adoption cost is assumed to vary with the number and total value of transactions. Consumer with greater transaction needs may select credit card with better reward programs thus incur more costs. However, consumers who make more transactions might be consumers with higher income, and they may involve less overhead costs in adopting credit cards since the credit card companies often target new customers based on consumers' income and credit scores. The parameters would inform us how these factors affect consumers' adoption choices.

Table 2.2 reports the parameter estimates in the usage and adoption stage, and their corresponding standard errors. Most parameters in the usage stage are precisely estimated and provide the expected sign. The perception parameters show that consumers prefer payment method that are easy to use, secure and perceived as inexpensive, with decreasing importance. The transaction price coefficients have the expected negative sign, with high-income consumers being slightly less price sensitive. Both types of the consumers experience a utility loss when they make a small-value transactions using a debit or credit card. This may be because merchant imposes an additional fee on small-value card transactions, or simply because consumers prefer using cash for small-value transactions. Wakamori and Welte (2017) shows that cash usages for small-transaction values are mainly driven by consumer preferences instead of merchant acceptance. The match values captures the utility gain (or loss) that consumers receive from using particular card payment for particular type of transactions relative to using cash. The results suggest that consumers generally lose from using a debit card, while incur utility gain from using a credit card. The utility gains from credit card payments are also larger for high-income consumers. This is consistent with the expectation that these fixed effects capture the (unobserved) rewards that consumers receive when they pay by credit cards, and high-income consumers tend to receive better rewards with more premium cards. On the other hand, since debit cards can be viewed as a close substitute with cash, the consumers may find it less convenient and even more time-consuming to use debit card instead of cash, due to additional processes such as typing PIN numbers or giving a signature[6] Interestingly, the fixed effects of using debit card for grocery/drug shopping are statistically positive. This may be because some issuer banks also reward debit card users with cash back for grocery/drug shopping[7]. Another possibility is that there is a positive correlation between debit and credit card usage. Therefore, consumers who have strong preferences for electronic card payment may enjoy using both debit and credit cards to make payments.

The parameters in the adoption stage have the expected sign but are mostly insignificant, which is consistent to the results found in Chapter 1 using a multinomial regression framework. These parameters capture the relative cost that consumers incur when adopting payment method besides cash (i.e. the adoption cost of adopting cash-only is normalized to zero). The results show that consumers gain a significant benefit from adopting a debit card, other than cash. This may be because adopting a debit card provides greater convenience for making transactions. On the other hand, consumers incur an adoption cost in adopting both debit and credit cards, perhaps due to the search cost of selecting a credit card that best suits their need, as well as an pecuniary annual fees.

I report parameter estimates of alternative specifications on the reward rates ρ_r in Table A.1 and Table A.2 in Appendix. The estimates are robust to different specifications on the pre-determined reward rates. I also show the model fit by comparing the usage and adoption probabilities predicted by the model with the ones observed in the data. Table 2.1 shows the comparisons of overall consumer choice probabilities and the choice probabilities broken down by the consumer types. The results show a good match between the model and the observed data in all dimensions.

---

[6] In the U.S., the consumers are usually exempted from typing PIN numbers or giving a signature for small-value transactions. However, in Canada, consumers must complete the confirmation procedure in order to use electronic card payments, even for small-value transactions.

[7] For example, RBC Royal Bank used to have a partnership with Shoppers Drug Mart between 2012 and 2016, where consumers with RBC Shoppers Optimum Bank Account would earn reward points from using RBC debit card on selected retailers.

Table 2.1: Model fit

	Overal		**Low income**		**High income**	
Usage	**model**	**data**	**model**	**data**	**model**	**data**
ca	42.85%	44.42%	46.41%	48.22%	37.63%	38.85%
dc	22.37%	23.01%	23.49%	24.44%	20.72%	20.92%
cc_{RBC}	5.35%	5.15%	5.06%	4.92%	5.79%	5.49%
cc_{TD}	2.81%	2.59%	2.51%	2.44%	3.24%	2.82%
cc_{BMO}	4.12%	3.86%	3.52%	3.20%	5.01%	4.84%
cc_{CIBC}	4.53%	4.27%	3.21%	2.64%	6.47%	6.67%
cc_{else}	17.97%	16.68%	15.80%	14.14%	21.14%	20.41%
Adoption	**model**	**data**	**model**	**data**	**model**	**data**
ca	1.00%	0.92%	1.21%	1.44%	0.68%	0.12%
cc, dc	10.01%	11.22%	13.34%	15.00%	4.89%	5.40%
ca, dc, cc_{RBC}	12.02%	11.94%	11.45%	11.17%	12.90%	13.13%
ca, dc, cc_{TD}	8.16%	8.12%	7.75%	7.58%	8.80%	8.96%
ca, dc, cc_{BMO}	10.94%	10.88%	10.10%	9.90%	12.23%	12.39%
ca, dc, cc_{CIBC}	10.47%	10.15%	8.56%	7.98%	13.41%	13.50%
ca, dc, cc_{else}	47.40%	46.76%	47.60%	46.93%	47.10%	46.50%

Table 2.2: Parameter estimates results

Usage stage	**Type 1**		**Type 2**		**Adoption stage**		
	coef.	**S.E.**	**coef.**	**S.E.**		**coef.**	**S.E.**
Perception					*Debit*		
easiness to use	8.108***	0.401	8.433***	0.561	Constant	1.450*	0.852
security	2.375***	0.206	0.714***	0.281	Type 2	-0.604	0.919
affordability	1.839***	0.163	2.349***	0.219	Num. of purchases	0.236**	0.113
Transaction Value					Total $ purchase	0.001	0.004
transaction cost	-0.932***	0.004	-0.819***	0.111	Age	-0.022	0.014
below $10 (debit)	-0.463***	0.089	-0.754***	0.127	*Debit + RBC*		
below $10 (credit)	-0.929***	0.104	-0.712***	0.110	Constant	-0.997	0.847
Match values					Type 2	0.285	0.914
Debit x grocery	0.103*	0.057	0.440***	0.083	Num. of purchases	0.064	0.114
Debit x meal	-0.441***	0.065	-0.465***	0.080	Total $ purchase	0.001	0.004
Debit x other type	-0.175***	0.063	0.026	0.084	Age	0.005	0.013
RBC x grocery	0.545***	0.101	0.814***	0.154	*Debit + TD*		
RBC x meal	0.192	0.136	-0.031	0.159	Constant	-0.947	0.869
RBC x other type	0.351***	0.118	0.614***	0.161	Type 2	0.297	0.919
TD x grocery	0.261	0.180	0.697***	0.222	Num. of purchases	-0.034	0.117
TD x meal	-0.131	0.213	-0.360	0.232	Total $ purchase	0.000	0.004
TD x other type	0.257	0.186	0.749***	0.222	Age	0.008	0.014
CIBC x grocery	0.487***	0.148	0.804***	0.178	*Debit + CIBC*		
CIBC x meal	-0.235	0.184	0.087	0.183	Constant	-0.849	0.864
CIBC x other type	0.354**	0.171	0.695***	0.183	Type 2	0.375	0.917
BMO x grocery	0.439**	0.178	0.879***	0.164	Num. of purchases	0.028	0.115
BMO x meal	0.279	0.188	0.437***	0.161	Total $ purchase	-0.001	0.004
BMO x other type	0.148	0.203	1.002***	0.159	Age	0.008	0.014
Other banks x grocery	0.332***	0.079	1.009***	0.107	*Debit + BMO*		
Other banks x meal	-0.109	0.088	0.295***	0.098	Constant	-1.481*	0.871
Other banks x other type	0.139*	0.085	0.712***	0.105	Type 2	0.614	0.916
					Num. of purchases	-0.001	0.116
					Total $ purchase	0.000	0.004
					Age	0.017	0.014
					Debit + others		
					Constant	0.905	0.829
					Type 2	0.095	0.907
					Num. of purchases	0.011	0.112
					Total $ purchase	0.000	0.004
					Age	0.004	0.013

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

[2] $Likelihood = 12653.847$

2.4.2 Elasticities

Table 2.3 and Table 2.4 reports the own and cross-elasticities of usage and adoption probabilities with respect to usage cost and adoption cost, respectively. The gray-shaded cells represent the own-price elasticities and the rest of the cells represent cross-price elasticities. Specifically, the usage cost elasticities are computed by increasing the transaction cost through the transaction prices in the consumer usage stage, i.e. p_j in Equation 3.1, while the adoption cost elasticities are computed by increasing the adoption cost in the consumer adoption stage, i.e. F_{bM_b} in Equation 3.4. For each case, I use the parameters estimated in Section 2.4.1 and compute the new equilibrium usage and adoption probabilities when the usage cost (or adoption cost) of one of the payment method changes, keeping all else constant.

Table 2.3 reports the elasticities of usage and adoption probabilities with respect to change in the usage costs. The diagonal elements show the demand elasticities are the largest for cash payment, followed by debit card and credit card payments. Among the credit cards, the four dominant issuer banks (RBC, TD, CIBC and BMO) are shown to be fairly price inelastic, while the other banks have a larger price elasticities. The cross-price usage elasticities are smaller among the four dominant issuer banks than between cash, debit card and credit card issued by other bank. On the other hand, the adoption elasticities with respect to usage cost turns out to be mostly inelastic, where the diagonal elements are mostly between 0 and -1. The magnitude of the adoption elasticities are also in generally smaller than the usage elasticities when the usage cost changes. This suggests that when consumers perceive a higher usage cost in the usage stage, they tend to switch the payment method conditional on their adopted bundle, but would not necessarily change their adoption decisions.

Table 2.4 reports the elasticities of usage and adoption probabilities with respect to change in the adoption costs. Recall that the adoption costs are not directly observed in the data, but was estimated as a function of consumer demographics and transaction characteristics. I assume that consumers never incur an adoption cost if they only adopt cash, and refrain from calculating the elasticities with respect to changes in the adoption cost of cash. The result shows that consumers generally don't respond to change in adoption cost in the usage stage. On the other hand, all the own-price adoption elasticities have the expected negative sign. Similar to the finding in usage cost elasticities, cash and credit card from non-dominant banks have the highest elasticities among all methods. However, the magnitude of the elasticities are fairly small. This may be because the adoption parameters do not capture enough factors to have meaningful variations toward adoption decisions. Another possible explanation is that consumers tend to focus more on the costs of payment method at the transaction level, and the transaction cost of a payment method plays a more important role when consumers make decision on which bundle of payment methods to adopt. The intuition is that adoption costs are fixed while usage cost is a variable cost. When the number of transaction increases, the total cost consumer incurs would increase proportionally as the usage cost increases. However, when consumer faces a one-time increase in adoption cost, this cost is spread over to all transactions and would be negligible if the number of transactions is very large. Therefore, if consumers expect to have enough transactions for them to enjoy the benefits from using the payment method, the increase in adoption cost would not have a big impact on their adoption decisions.

2.4.3 Substitutions between Payment Method Attributes

To provide the intuitions on how consumers choose payment methods with respect to payment method characteristics, I calculate the marginal effects of each characteristics and measure the consumer substitution patterns between payment characteristics within one payment method. This answers questions such as: if we sacrifice the aspect of easiness-to-use for cash by some amount, how much more security or affordability we need to compensate for the consumers to continue using cash for payment?

Specifically, let ${\mathbb{P}^*}_{bjm}$ be the ex-ante average usage probabilities of payment method m, and let $\{X_{bm,ease}, X_{bm,risk}, X_{bm,cost}\}$ represent consumers' perceptions on the easiness-to-use, security and affordability for payment method m. For each payment method, I perturb

Table 2.3: Usage cost elasticities of usage and adoption probabilities

Usage elasticities with respect to usage cost							
	ca	dc	cc_{RBC}	cc_{TD}	cc_{CIBC}	cc_{BMO}	cc_{else}
ca	-5.55	2.09	0.55	0.30	0.40	0.44	1.77
dc	1.94	-4.12	0.37	0.19	0.25	0.27	1.10
cc_{RBC}	1.05	0.62	-1.14	-0.05	-0.07	-0.07	-0.34
cc_{TD}	0.23	0.17	0.02	-0.53	0.02	0.02	0.07
cc_{CIBC}	0.32	0.22	0.03	0.02	-0.72	0.03	0.10
cc_{BMO}	0.37	0.26	0.05	0.02	0.03	-0.85	0.14
cc_{else}	1.48	1.02	0.18	0.08	0.11	0.14	-3.01
Adoption elasticities with respect to usage cost							
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
$M_1 = ca$	-0.17	-1.69	0.33	0.17	0.24	0.24	0.88
$M_2 = ca, dc$	0.08	-0.98	0.21	0.08	0.12	0.10	0.38
$M_3 = ca, dc, cc_{RBC}$	0.11	3.14	-1.15	-0.19	-0.25	-0.25	-1.40
$M_4 = ca, dc, cc_{TD}$	0.00	0.02	0.05	-0.33	0.04	0.04	0.17
$M_5 = ca, dc, cc_{CIBC}$	0.00	0.03	0.08	0.04	-0.45	0.06	0.25
$M_6 = ca, dc, cc_{BMO}$	0.00	0.03	0.11	0.05	0.07	-0.57	0.33
$M_7 = ca, dc, cc_{else}$	0.01	0.13	0.41	0.20	0.28	0.31	-1.34

Table 2.4: Adoption cost elasticities of usage and adoption probabilities

Usage elasticities with respect to adoption cost							
	ca	dc	cc_{RBC}	cc_{TD}	cc_{CIBC}	cc_{BMO}	cc_{else}
dc	-0.02	-0.01	0.01	0.00	0.00	0.00	0.02
cc_{RBC}	0.00	0.00	0.02	0.00	0.00	0.00	-0.01
cc_{TD}	0.00	0.00	0.00	0.02	0.00	0.00	-0.01
cc_{CIBC}	0.00	0.00	0.00	0.00	0.02	0.00	-0.01
cc_{BMO}	0.00	0.00	0.00	0.00	0.00	0.02	-0.01
cc_{else}	0.01	0.00	0.02	0.01	0.02	0.02	-0.08
Adoption elasticities with respect to adoption cost							
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
$M_2 = ca, dc$	0.00	-0.09	0.01	0.01	0.01	0.01	0.05
$M_3 = ca, dc, cc_{RBC}$	0.00	0.01	-0.04	0.00	0.01	0.00	0.02
$M_4 = ca, dc, cc_{TD}$	0.00	0.01	0.01	-0.06	0.01	0.01	0.03
$M_5 = ca, dc, cc_{CIBC}$	0.00	0.01	0.01	0.00	-0.06	0.01	0.03
$M_6 = ca, dc, cc_{BMO}$	0.00	0.01	0.02	0.00	0.01	-0.08	0.05
$M_7 = ca, dc, cc_{else}$	0.00	0.03	0.06	0.03	0.04	0.05	-0.21

the value of $X_{bm,k}$ by 1%, and solve the Δ's in the following equation:

$$\mathbb{P}^*{}_{bjm}(1.01 \cdot X_{bmk}) - \mathbb{P}^*{}_{bjm}(X_{bml}) = \mathbb{P}^*{}_{bjm}(X_{bmk}) - \mathbb{P}^*{}_{bjm}(1.01 \cdot X_{bmk}, X_{bml} \cdot (1 - \Delta_{lm}\%) \ \forall l \neq k \tag{2.19}$$

The left-hand side is the change in ex-ante usage probabilities for payment method m when its attribute k is increased by 1%. The right-hand side represents the change in ex-ante usage probabilities for the same payment method when the attribute k is increased by 1% and the attribute l is decreased by Δ_{lm}%. That is,

$$\mathbb{P}^*{}_{bjm}(1.01 \cdot X_{bmk}) = -\mathbb{P}^*{}_{bjm}(1.01 \cdot X_{bmk}, X_{bml} \cdot (1 - \Delta_{lm})) \ \forall l \neq k \tag{2.20}$$

The substitution effects are then computed as Δ_{lm} multiplied by 100.[8]

Table 2.5 summarizes the results. Column (2)-(4) represents how much higher the perception variable needs to increase (independently) in order to compensate one unit decrease

[8]The change in $\mathbb{P}^*{}_{bjm}$ is shown to be approximately linear with X_{bmk} around the base value of X_{bmk} for all attribute k.

in consumer's perception over the attribute of the payment method specified in the first column. The results show that the substitution effects between payment method characteristics are quite robust across cash, debit card and credit card. Particularly, a decrease in consumers' perceived easiness-to-use requires the largest amount of compensation on the other dimensions of the payment method. The estimated substitution effect of 6.11-6.4 between easiness-to-use and risk means that worsening the easiness-to-use on a payment method by one unit would require six units of increase on consumers' perceived security with the payment methods.

One possible explanation to this finding is that easiness-to-use is a characteristic that can be more easily conceived and differentiated by consumers, while consumers generally don't have a clear understanding about the differences between security and privacy infrastructure behind each payment method. For example, imagine a situation where consumers are asked to provide their ID every time consumers use a payment method to make transactions in a store. To attract consumers to use this method, consumers need to be convinced that this action would improve the security by a considerable magnitude. Now imagine a tap-and-go feature is introduced to a payment method. Although this feature involves more risk of credit card fraud, consumers may still use it as long as it speeds up transactions and provides more convenience. This result is consistent to the parameter estimates in subsection 2.4.1, which shows that easiness-to-use is the most important attribute that drives consumers' usage decisions.

2.4.4 Net Margins for Issuer Banks

This section presents the estimated profit margin per-dollar for the issuer banks using the method of moment inequality described in Section 2.3.2. Recall that for each transaction consumer makes using the credit card from an issuer, the issuer receives a percentage of transaction price from the acquirer as the interchange fee. The issuer then offers a reward to the consumer, also as a percentage of the transaction price. The *profit margin* is thus defined as the difference between the interchange fee and the reward rate that issuer offers to the consumers. Since the interchange fees and reward rates are not observed in the data,

Table 2.5: Substitution effects between perception variables

(1)	(2) Ease	(3) Risk	(4) Affordability
Cash (ease ↓)	1	6.4	3.51
Cash (risk ↓)		1	0.55
Cash (cost ↓)			1
Debit (ease ↓)	1	6.11	3.53
Debit (risk ↓)		1	0.55
Debit (cost ↓)			1
Credit (ease ↓)	1	6.27	3.52
Credit (risk ↓)		1	0.55
Credit (cost ↓)			1

the profit margin is recovered such that it generates the highest expected profit margin in the observed data.

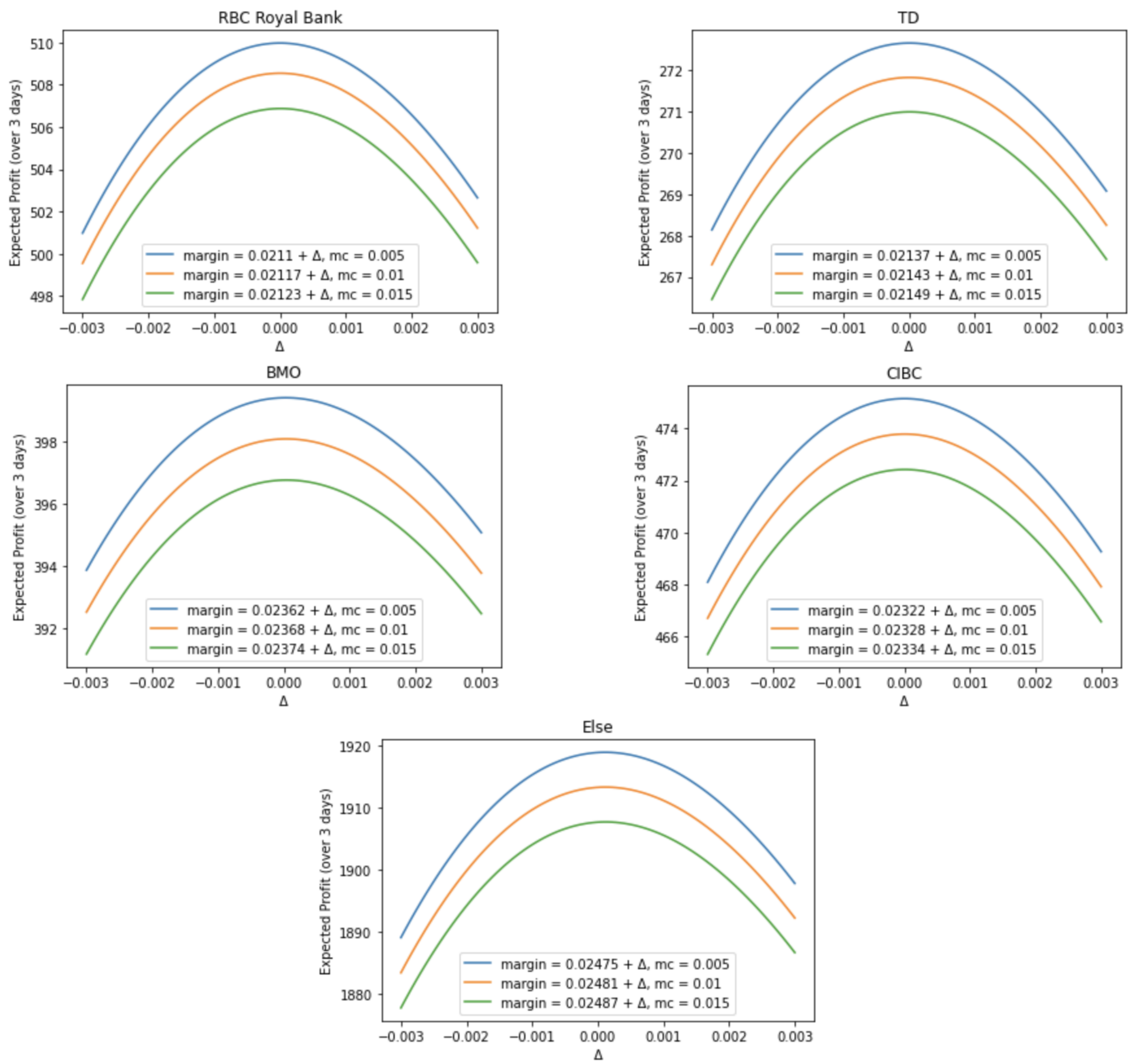
Figure 2.1 presents the estimated net margin for each issuer bank. I consider three calibrations on the per-transaction marginal cost: \$0.005, \$0.01, and \$0.015. For simplicity, I assume that issuer banks receive the same profit margins from all the consumers.[9] The result shows that the estimated net margin is between 2.1% to 2.5% on average. Interestingly, the dominant banks, including RBC and TD banks, on average earn a smaller profit margins per-dollar of around 2.1% to 2.2%, compared to other banks, which earn an average of 2.4% to 2.5% per dollar. However, RBC and TD gain the highest total expected profits compared to other banks, mainly due to its higher transaction amount as well as transaction volume. This may be because RBC offers a better reward rate which negatively affects their profit margin, while increases the consumer's loyalty toward their cards thus increases its transaction volume.

The estimates of the profit margins suggest that the interchange fees faced by the merchants in the sample are higher than 2.1% to 2.5%. In reality, merchants face significantly different interchange fees, even from the same issuing banks. The factors include the size of

[9] Although high-income consumers tend to use cards with higher reward rates, the interchange fee tends to increase with the reward rates.

the merchants, merchant types, the tier of credit card the consumer uses, and the form of payment (e.g. in-store or mobile pay).[10] The common estimate of the average interchange rate is 1.8% for credit card payments, which is below our estimates. However, since the data shows that 70% of the transactions in the sample are made at stores with less than 4 cash registers, the small size of the merchants in the sample might explain the high interchange fees implied from the estimates.

Figure 2.1: Estimated profit functions by issuer banks



[10] For example, see how interchange fees vary in the U.S. market at Wamala (2021) and Resendiz (2021).

2.5 Counterfactual Analyses

In this section, I consider a set of policy experiments and investigate their impact on the changes in consumer welfare as well as the regressive distributional effects. For each of the policy experiments, I use the parameter estimates to simulate the new consumer usage and adoption probabilities under different scenarios. To calculate the consumer welfare, I follow Huynh et al. (2021) and define the consumer surplus as the expected maximum over the adoption choices. That is,

$$\begin{aligned} CS_b &= \mathbb{E}_\epsilon[\max_{M'_b \in \mathbb{M}} \{EU_b(M'_b) - F_{bM'_b} + \epsilon_{M'_b}\}] \\ &= \ln[\sum_{M'_b} \exp(EU_b(M'_b) - F_{bM'_b})] \end{aligned} \tag{2.21}$$

To convert the consumer surplus to monetary equivalent, I divide the expression by the parameter estimates on the usage cost variable, which varies by consumer type. Therefore, the consumer surplus of a consumer of type r is given by

$$CS_r = \frac{1}{\beta_r} \ln[\sum_{M'_b} \exp(EU_b(M'_b) - F_{bM'_b})] \tag{2.22}$$

In terms of the regressive distributional effects, I use the measurement defined in Chapter 1 in Yen (2021), which computes the regressive transfers consumer b made in transaction j with transaction price p_j as

$$R_{b,j} = \begin{cases} \frac{\mu\chi}{1+\mu\chi} \cdot p_j \cdot \mathbb{P}(accept), & \text{if paid in cash or debit card} \\ \frac{\mu\chi}{1+\mu\chi} \cdot p_j - \mu \cdot p_j, & \text{if paid in credit card} \\ 0, & \text{if paid in a cash-only store} \end{cases} \tag{2.23}$$

where μ is the rate of merchant fee, χ is the merchant cost pass-through rate, and $\mathbb{P}(accept)$ is the probability that the merchant accepts credit cards. In the counterfactual simulations, the regressive transfers are calculated as the weighted sum of regressive transfers where the weights are given by the predicted usage probabilities over the payment methods.

2.5.1 Impact of removing cash payment

Given the decreasing number of consumers paying with cash[11] as well as the potential regressive distributional effects imposed on the remaining cash users, a reasonable question to ask is what if there were no cash? In fact, there has been a growing interest from policy makers across the world where cashless society is promoted and operated. For example, a Sweden national survey shows that the percentage of cash users in Sweden has decreased from 40 percents to less than 13 percents in the past decade.[12] The central bank of Sweden has been testing a digital currency called e-krona from 2017, which would give the general public access to a digital complement for cash payments.[13] Other countries such as France,[14] Spain,[15] and Japan[16] has established policies that restrict the usage of cash.

There are a variety of reasons behind the government's decision to move toward a cashless society, such as prevention of money laundering, reduction on cash handling and storing fees, easier transfers of funds. This counterfactual experiment focuses on the impact of elimination of cash on the changes in regressive distributional effects and consumer welfare. Specifically, I simulate a hypothetical situation where none of the consumers use or adopt cash, and none of the merchants accept cash payment. Therefore, the consumers' choice set of payment instruments decreases from seven alternatives to six alternatives at the point-of-sale, where the new choice set of payment methods becomes $\tilde{M} = \{dc, cc_{RBC}, cc_{TD}, cc_{CIBC}, cc_{BMO}, cc_{else}\}$ for the consumers. In other words, debit cards become the default payment methods in the cashless society and consumers either choose to adopt debit card only, or adopt a debit card along with a credit card from one of the issuer banks. Similarly, merchants either only accept debit cards, or accept both debit cards and credit cards (regardless of the identities of the issuer banks). In effect, this prohibits the possibility that consumers only adopt cash, or merchants only accept cash

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[11] Federal Reserve (2019)

[12] Sveriges Riksbank (2018)

[13] Sveriges Riksbank (2021)

[14] A ban on cash payment over Euro 1,000 has been enacted in France in September 2015.

[15] The government of Spain cuts the limit of cash payment and plans to gradually eliminate cash.

[16] Fujiki (2020) discusses the recent Japanese government endeavor to move toward a cashless society.

payment. Since I do not model merchant acceptance decisions directly, I assume that out of the two possible acceptance choices, merchants choose to accept only debit cards with probability r, and choose to accept both debit and credit cards with probability $1-r$. Then I compute how consumer usage and adoption probabilities changes with respect to different values of r, i.e. the probabilities of merchant accepting credit cards.

I use *compensating variations* to measure changes in consumer welfare from the elimination of cash payment, as described in Petrin (2002). Compensating variation is the dollar amount a consumer would need to be compensated for her/him to be indifferent between the scenario with cash and the scenario without cash. One complication of this simulation is that the equilibrium "price" of the payment method, which is the interchange fees or rewards transferred to the consumers, is not observed in the data.[17] Since I do not model the issuer banks' pricing strategies explicitly, mainly due to lack of data, and the net margins were recovered using the method of moment inequality, the new "equilibrium prices" of the issuer banks can not be estimated in the counterfactual scenarios. Therefore, I assume that the pricing decisions of the issuer banks would remain the same, keeping the net margins of the issuer banks at the observed (estimated) level. This might well be the case in reality because credit cards are not close substitutes to cash payments for the consumers in the sample. As shown in the results in Table 2.3, the elasticities between cash and debit cards are much higher compared to the elasticities between cash and credit cards. The elimination of cash is unlikely to change how issuer banks compete with each other and set the interchange fees and rewards.

One risk of comparing consumer welfare directly between the factual seven payment method alternatives and the counterfactual six payment method alternatives is that the consumer welfare may mechanically decrease simply due to the smaller size of the choice set. As shown in Equation 2.22, the random tastes of each alternative are assumed to be additively separable. If the expected utility from each adoption bundle is positive, then the consumer welfare will decrease with the number of adoption choices. To avoid this

[17] In Petrin (2002), to estimate the changes in consumer welfare under the counterfactual of no introduction of minivan, he first solves the new equilibrium prices for the other vehicles with the absence of minivan, and computes how market shares change with the new equilibrium prices.

bias, I keep the number of alternatives fixed in the counterfactual simulation, while adding the utility of cash payment by a sufficiently large negative number such that no consumer would rationally choose to use or adopt cash.[18] In other words, I compare the consumer welfare between the factual situation where consumers may optimally choose to use cash, to a counterfactual scenario where cash is so bad that it would never be used.

I start with the observed merchant acceptance probabilities, and assume that merchants who used to accept cash only would start to accept debit cards while continue to reject credit cards. The merchants who used to accept cash and debit cards would continue to do so without accepting the credit cards. Merchants who used to accept all payment instruments would do the same, except that there would be no cash payments in the cashless society. Table 2.6 and Table 2.7 compare the average usage and adoption probabilities respectively under different scenarios. The result from the adoption probabilities suggests that the consumers who did not hold a credit card would start to use credit cards when cash is arbitrarily removed from the society. Specifically, it shows that 98.5% of former cash-only adopters and 96.6% of consumers who used to adopt cash and debit card only would adopt a credit card under the cashless scenario. This finding is interesting because one might think that a consumer who chose not to adopt credit cards when they are available may stick to using the debit cards due to their preferences towards non-card payments. This suggests that consumers who use cash-only may prefer using a credit card over a debit card.

Table 2.8 presents the distribution of the compensating variations among consumers. The estimated mean and median compensation variation is CAD$ 30.44 and CAD$ 23.42 per month. Comparing across consumer's former adoption bundle, the consumers who adopted cash-only before would be willing to pay at least CAD$ 38.28 a month so that they can use cash payment, similar to the amount that former cash and debit card users would pay. On the other hand, consumers who used credit cards before would pay CAD$ 29.38, only two thirds of how much the non-credit card users would pay in order to have the option of cash in the wallet when making purchases.

This result shows that eliminating cash hurt the consumers across all consumer groups,

[18]Specifically, I decrease the utility of using cash at the usage stage by 1000 utils for each consumer

Table 2.6: Comparison of simulated adoption probabilities under different scenarios.

				Issuer bank				
Adoption bundle	Cash-only	+ Debit	+ Debit & Any Credit	RBC	BMO	CIBC	TD	Others
Overall								
Factual	1.05%	11.08%	87.86%	11.88%	8.07%	10.82%	10.14%	46.95%
Cashless	0.00%	4.06%	95.94%	13.01%	8.69%	11.80%	11.02%	51.43%
Monopoly	1.33%	14.80%	83.87%	16.77%	16.77%	16.77%	16.77%	16.77%
Perfect Competition	0.52%	2.60%	96.89%	11.47%	7.90%	11.88%	10.85%	54.80%
Low income								
Factual	1.33%	14.81%	83.87%	11.17%	7.56%	9.87%	8.01%	47.25%
Cashless	0.00%	5.61%	94.39%	12.80%	8.44%	11.14%	8.96%	53.05%
Monopoly	1.73%	20.60%	77.67%	15.53%	15.53%	15.53%	15.53%	15.53%
Perfect Competition	0.67%	3.75%	95.58%	11.60%	7.85%	11.26%	8.89%	55.99%
High income								
Factual	0.64%	5.33%	94.04%	12.99%	8.86%	12.28%	13.42%	46.49%
Cashless	0.00%	1.66%	98.34%	13.34%	9.07%	12.81%	14.19%	48.93%
Monopoly	0.72%	5.84%	93.44%	18.69%	18.69%	18.69%	18.69%	18.69%
Perfect Competition	0.28%	0.82%	98.90%	11.26%	7.98%	12.83%	13.87%	52.96%

Table 2.7: Comparison of simulated usage probabilities under different scenarios.

				Issuer bank				
Usage stage	Cash	Debit card	Any credit	RBC	BMO	CIBC	TD	Others
Overall								
Factual	44.17%	23.28%	32.54%	5.00%	2.63%	3.86%	4.13%	16.92%
Cashless	0.00%	44.23%	55.77%	8.55%	4.46%	6.68%	6.86%	29.22%
Monopoly	44.70%	23.67%	31.64%	6.33%	6.33%	6.33%	6.33%	6.33%
Perfect Competition	30.01%	8.32%	61.67%	7.57%	4.27%	7.24%	7.20%	35.40%
Low income								
Factual	47.93%	24.69%	27.38%	4.56%	2.24%	3.15%	2.76%	14.68%
Cashless	0.00%	49.42%	50.58%	8.31%	4.09%	5.86%	4.98%	27.33%
Monopoly	48.50%	25.08%	26.42%	5.28%	5.28%	5.28%	5.28%	5.28%
Perfect Competition	33.13%	10.18%	56.69%	7.50%	4.02%	6.41%	5.37%	33.39%
High income								
Factual	38.63%	21.20%	40.17%	5.65%	3.22%	4.92%	6.16%	20.22%
Cashless	0.00%	36.58%	63.42%	8.91%	5.00%	7.89%	9.62%	32.01%
Monopoly	39.09%	21.58%	39.33%	7.87%	7.87%	7.87%	7.87%	7.87%
Perfect Competition	25.41%	5.57%	69.02%	7.67%	4.63%	8.46%	9.90%	38.35%

Table 2.8: Compensating variation for cash (per month)

	Compensating Variation
Mean	\$30.44
Median	\$23.42
Std	\$27.84
By (former) M_b:	
cash only	\$38.28
cash and debit	\$38.07
cash, debit and credit	\$29.38
Welfare changes from difference in:	
(a) Deterministic component in the *adoption stage* : $EU_b(M_b) - F_{bM_b}$	\$29.64
(b) Logit error in the *adoption stage*: ϵ^a_{bMb}	\$0.79
Welfare changes from difference in:	
(c) Deterministic component in the *usage stage*: δ_{bjm}	\$25.61
(d) Logit error in the *usage stage*: ϵ^u_{bjm}	\$5.97

suggesting that consumers still benefit from the option of using cash and there is still a need of cash payments for consumers. This result is consistent with Wakamori and Welte (2017), where they show that the cash usage would decrease by only 8 percentage points even under universal card acceptance from the merchants.

To better understand how much the compensation variation come from, I decompose the compensating variations into two components: One component captures the welfare effects due to changes in the deterministic component entering the utility function. The second component is the welfare changes associated with the idiosyncratic logit term. Recall from Equation 2.21 that consumers choose payment method bundle which maximizes their expected utility, taking into account the idiosyncratic random shock at the adoption stage, and the consumer surplus for consumer b is defined as

$$CS_b = \mathbb{E}_\epsilon[\max_{M_b \in \mathbb{M}} \{EU_b(M_b) - F_{bM_b} + \epsilon_{M_b}\}] \tag{2.24}$$

Let $V_{bM_b} = EU_b(M_b) - F_{bM_b}$. The change in consumer welfare before and after the elimination of cash payment can be decomposed into

$$\tilde{CS}_b - CS_b = \mathbb{E}_\epsilon[\max_{M_b'\in\tilde{M}}\{V_{bM_b'} + \epsilon_{bM_b'}\}] - \mathbb{E}_\epsilon[\max_{M_b\in\mathbb{M}}\{V_{bM_b} + \epsilon_{bM_b}\}] \tag{2.25}$$

$$= \underbrace{\left[\left(\mathbb{E}_\epsilon[\max_{M_b'\in\tilde{M}}\{V_{bM_b'} + \epsilon_{M_b'}\}] - \max_{M_b'\in\tilde{M}}\{V_{bM_b'}\}\right) - \left(\mathbb{E}_\epsilon[\max_{M_b\in\mathbb{M}}\{V_{bM_b} + \epsilon_{bM_b}\}] - \max_{M_b\in M}\{V_{bM_b}\}\right)\right]}_{\text{random shock component}}$$

$$- \underbrace{\left(\max_{M_b'\in\tilde{M}}\{V_{bM_b'}\} - \max_{M_b\in M}\{V_{bM_b}\}\right)}_{\text{deterministic component}}$$

The first term is the changes in consumer welfare excluding the effect from the deterministic component, while the second term is the difference in welfare changes from deterministic component in the adoption stage.[19]

Similarly, I also decompose the welfare changes from the observed characteristics and idiosyncratic random shocks within the usage stage. Recall from Equation (3.2) that the expected utility of holding bundle M_b can be written as,

$$EU_{bj}(M_b) = \mathbb{E}_\epsilon\left[\phi \max_{m\in M_b} u_{bjm}(p_{bj}) + (1-\phi)\sum_{Ms}\mathbb{P}_{Ms}\max_{m\in M_b\cap M_s} u_{bjm}(p_{bj})\right] \tag{2.26}$$

Denote the term in the bracket as $\mathbb{U}_{\mathbb{bjm}}$, the welfare changes from the usage stage can be decomposed into

$$\tilde{EU_{bj}}(M_b) - EU_{bj}(M_b) = \underbrace{[(\tilde{EU_{bj}}(M_b) - \tilde{U}_{bjm}) - (EU_{bj}(M_b) - U_{bjm})]}_{\text{random shock component}} \tag{2.27}$$

$$- \quad \underbrace{(\tilde{U}_{bjm} - U_{bjm})}_{\text{deterministic component}}$$

The deterministic component captures the welfare effect from observables and estimated consumer preferences, while the random shock component captures the changes in consumer welfare from the idiosyncratic random shock at the point-of-sale. Table 2.8 shows that the compensation arising from the loss of the cash's observed characteristics is at CAD$ 29.64,

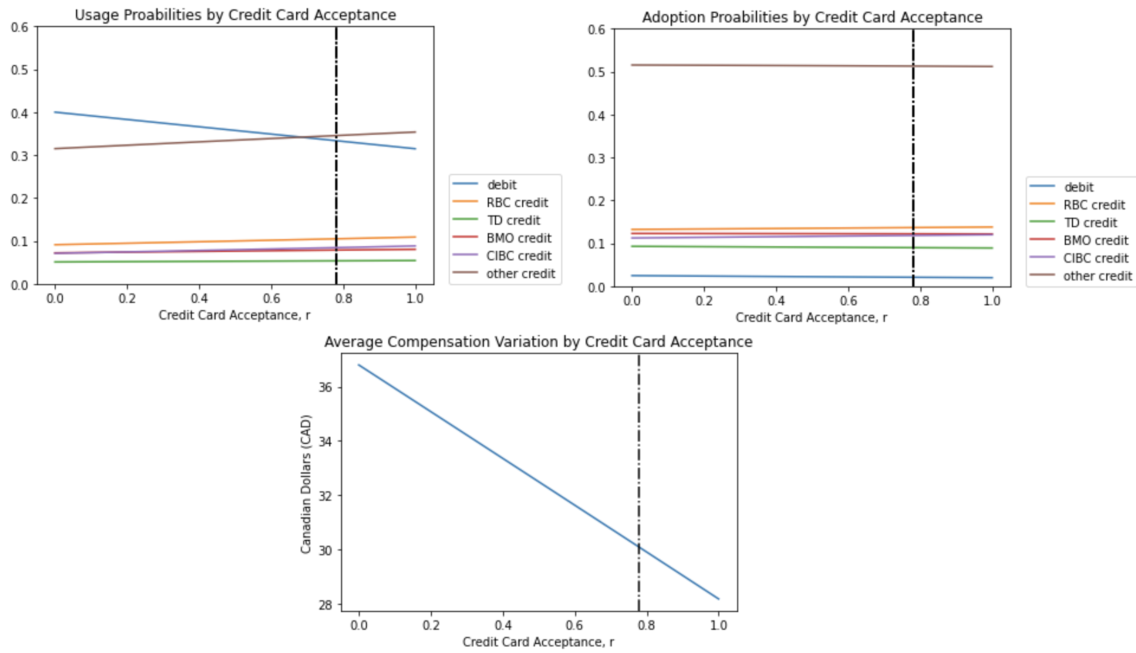
[19] Note that this term include both the effect from consumer characteristics *and* the random shock in the usage stage. This is because the EU_{bM_b} already takes the expectation over the random shocks realized in the usage stage.

and the welfare change implied by the random shock logit term is CAD$ 0.79. In the usage stage, cash's observed characteristics also explains 80% of consumer loss at the point-of-sale. These results of decomposition suggest that the loss of consumer surplus from elimination of cash payment were generated in a non-random way, and consumers truly value the observed characteristics of cash payment.

Figure 2.2 shows how the usage probabilities, adoption probabilities and resulting average compensation variations change with the probabilities of merchant credit card acceptance, i.e. r. The vertical black dashed line represents the observed merchant acceptance probabilities. The result shows that consumers' usage and adoption probabilities under cashless scenario are quite robust across the assumptions on merchant acceptance probabilities. Consistent with the expectations, the usage probabilities of credit cards increase with the probabilities that merchant accept credit cards, while the debit card usage probabilities decrease with the credit card acceptances. The usage of credit card from non-dominant issuer banks starts to surpass the usage of debit card when the merchant credit card acceptance reaches 70%. The compensation variations are also quite robust across merchant acceptance probabilities, ranging from 28 CAD to 36 CAD. This suggests that the conclusion that consumers generally lose from the counterfactual of cash elimination is robust with different assumptions on the merchant acceptance probabilities.

Finally, I compute how the removal of cash affects the amount of regressive transfers born by consumers in different cohorts. Table 2.9 summarizes the consumers' regressive transfers by consumers' previous adoption choices under different scenarios. Under the factual scenario, assuming the baseline rate of 2% of merchant cost and 90% of merchant cost pass-through, the non-credit card users on average pay a regressive transfer that is twice as the amount born by credit card users per transaction. They also incur a higher regressive transfer per dollar compared to credit card users, with 1.03% for cash-only users, 1.25% for cash and debit users, and 0.71% for the credit card users. Under the counterfactual elimination of cash, the amount of average regressive transfer born by non-credit card users decreased by 50%, and regressive transfer per transaction value drop from 1.03% to 0.52% for cash-only users, and from 1.25% to 0.71% for cash and debit users. The regressive transfer per transaction and per transaction dollar also drop for the credit-card users, while

Figure 2.2: Choice probabilities and compensation variations by the value of r



the decrease is much smaller in size compared to non-credit card users.

Table 2.10 summarizes the regressive transfers born by different income cohorts under different scenarios, assuming 2% of merchant cost and 90% of merchant cost pass-through. The result shows that under factual scenario, the lowest-income cohort on average bear an average regressive transfer per-transaction that is more than 2.5 times than those born by the highest-income cohort. The regressive transfers born by the lowest-income cohort consists of around 1% of their total transaction amount, while the highest-income cohort bear around 0.5 %. Under the no-cash scenario, the gap between the low-income and high-income consumers significantly shrinks, where the lowest-income now bear an additional 45% of regressive transfers per transaction compared to the highest-income cohort. The regressive transfer per dollar also decreases from 1% to 0.6% for the lowest income cohort. These results suggest that the hypothetical elimination of cash payment decreases the regressive distributional effect, and shrinks the gap of regressive transfers born by low-income and high-income consumers.

Table 2.9: Regressive distributional effects under different scenarios, by former adoption

	$\chi = 90\%$		$\chi = 75\%$		$\chi = 100\%$	
	Avg RF	Avg RF/$	Avg RF	Avg RF/$	Avg RF	Avg RF/$
Factual						
$M_b = \{ca\}$	$0.34	1.03%	$0.26	0.82%	$0.40	1.17%
$M_b = \{ca, dc\}$	$0.35	1.25%	$0.29	1.05%	$0.39	1.39%
$M_b = \{ca, dc, cc\}$	$0.17	0.71%	$0.08	0.47%	$0.23	0.87%
Counterfactual: No Cash						
$M_b = \{ca\}$	$0.18	0.52%	$0.09	0.28%	$0.24	0.68%
$M_b = \{ca, dc\}$	$0.17	0.71%	$0.11	0.47%	$0.22	0.87%
$M_b = \{ca, dc, cc\}$	$0.13	0.41%	$0.04	0.16%	$0.19	0.58%
Counterfactual: Monopoly						
$M_b = \{ca\}$	$0.26	0.88%	$0.18	0.66%	$0.32	1.03%
$M_b = \{ca, dc\}$	$0.24	1.02%	$0.17	0.80%	$0.28	1.17%
$M_b = \{ca, dc, cc\}$	$0.20	0.77%	$0.12	0.53%	$0.26	0.93%
Counterfactual: Perfect Competition						
$M_b = \{ca\}$	-$0.01	0.40%	-$0.11	0.16%	$0.06	0.56%
$M_b = \{ca, dc\}$	$0.02	0.58%	-$0.05	0.34%	$0.07	0.74%
$M_b = \{ca, dc, cc\}$	-$0.02	0.30%	-$0.12	0.04%	$0.04	0.47%

Table 2.10: Regressive distributional effects under different scenarios, by income cohort

	Factual		No Cash		Monopoly		Perfect Competition	
Income level	Avg RF	Avg RF/$	Avg RF	Avg RF/$	Avg RF	Avg RF/$	Avg RF	Avg RF/$
<25K	$0.26	0.99%	$0.16	0.61%	$0.24	0.95%	$0.01	0.48%
25K to 45K	$0.22	0.82%	$0.16	0.50%	$0.24	0.86%	-$0.01	0.37%
45K to 65K	$0.17	0.79%	$0.14	0.49%	$0.22	0.86%	$0.00	0.39%
65K to 85K	$0.18	0.72%	$0.12	0.33%	$0.18	0.66%	-$0.04	0.20%
85K to 135K	$0.15	0.64%	$0.11	0.33%	$0.17	0.68%	-$0.03	0.22%
>135K	$0.10	0.53%	$0.11	0.31%	$0.17	0.69%	-$0.04	0.24%

2.5.2 Impact of competition in the issuer banks

In this section, I consider the effects of issuer bank competition on consumer welfare and the regressive distributional effects. This is motivated by the gradual consolidation not only in the Canadian issuer market but the payment service industry as a whole in the recent years. Policymakers have considerable interests in understanding how competition in the payment services market would affect consumer welfare. The degree of competition in the issuer markets have been an important focus for government agencies. For example, Visa's attempt to acquire Plaid, a fintech startup which enables applications to connect with users' bank accounts, was recently opposed by the US Department of Justice (DOJ). The concern is that it would create significant barriers to entry in the online debit transaction market, with Visa currently holding 70% of the market share, compared to 25% by MasterCard.[20] On the other hand, MasterCard's acquisition of Finicit a fintech startup which also facilitates real-time transfers by linking financial service providers to consumers and merchants, was approved by the DOJ in the same year.[21]

To analyze the welfare impact of issuer bank competition, I focus on the credit card payments and consider two extreme hypothetical scenarios: (1) a monopoly setting where there exists only one single issuer of credit cards in the market, and (2) a perfect competition setting among issuer banks, where all the issuers receive zero profit margin. For each case, I simulate the new consumer usage and adoption probabilities and the consequent changes in consumer welfare. I also calculate the implied changes in the distribution of regressive transfers under the hypothetical scenarios.

Monopoly. In the counterfactual monopoly scenario, consumers only have one brand of credit card to choose from. In other words, consumers now only chooses between using cash, debit card or credit card. As discussed in the no-cash scenario, the size of the choice set has to be the same to make comparable comparison. In this simulation, I keep the number of payment methods the same as the original scenario (i.e. seven alternatives), while assuming

[20]Visa to Pay $5.3 Billion for Fintech Startup, *Wall Street Journal*, January, 2020.

[21]Mastercard gets U.S. DoJ green light for Finicity deal, *Reuters*, November 2020.

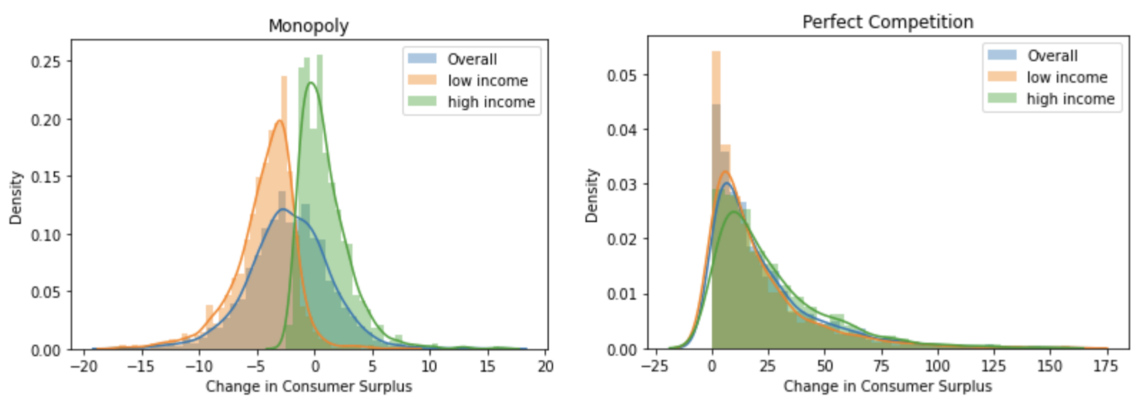
that consumers now receive the same utilities from using (or adopting) any of the credit cards. Specifically, for each consumer, I set the match values (i.e. ξ_{bjm} in Equation (3.1)) for any credit card in the counterfactual setting the same value, which is assumed to be the average of the factual match values received from each issuer banks for each consumer. Similarly, in the adoption stage, the adoption cost (i.e. F_{bMb} in Equation (3.4)) for any credit card is assumed to be the same for each consumer, which is the average adoption cost the consumer would have incurred in the factual scenario. With these assumptions, the credit card usage and adoption probabilities of each issuing bank will be the same for each consumer in the counterfactual simulation.

Comparisons of the simulated adoption and usage probabilities, presented in Table 2.6 and Table 2.7, show that removing competitions in the issuer banks decreases the probabilities of consumer holding a credit card, especially for low-income consumers which drops from 83.87% to 77.67%. The probabilities of consumers using the credit card at the POS also decrease for both the low-income and high-income consumers. Overall, the monopoly setting induces the low-income consumers to substitute away from credit card toward adopting only cash and debit card, while it doesn't have a big impact on the adoption and usage decisions for the high-income consumers. Figure 2.3 plots the distribution of the changes in consumer surplus under different scenarios. The result shows that under the monopoly setting, there are significantly different welfare effects on consumers of different types. Consumers with high-income are generally not affected, while most of the low-income consumers are hurt if there is only one brand of the credit card to choose from.

Note that these simulations are under several assumptions: First, I assume that the merchant acceptance probabilities are kept the same under monopoly. This may not be true in reality. For example, the cost in accepting credit card for merchant might decrease due to the integration of the acceptance processes. If so, the probability that merchant accepts credit cards might increase which affects the consumer's usage probabilities. However, due to the lack of data, it is infeasible for me to recover or simulate the responses from the merchants. Future research can be conducted to investigate how competition in the issuer bank affects merchants' acceptance decisions. Secondly, I do not explicitly model the pricing decisions of the issuer banks. In this experiment, I assume that the consumers' usage costs for credit card are kept the same under monopoly. For example, it is possible that the monopolistic firm would reduce the amount of rewards thus increase their profits to a level that consumers are just slightly better off when using the credit card. If so, the welfare loss would be even bigger than the estimates if the monopoly setting were realized.

Perfect Competition. To conduct a counterfactual simulation on perfect competition, I assume that issuer banks receive zero margins. Therefore, the profit margins estimated in Section 2.4.4 are fully transferred to the consumers as a decrease in the per-dollar usage cost. Table 2.6 and Table 2.7 present the simulated outcomes on consumer adoption and usage probabilities. The result shows that both the usage and adoption probabilities of credit card increase significantly under perfect competition. The probabilities that consumers adopt a credit card increases by 13.9% for the low-income consumers, and increases by 5.1% for the high-income consumers. The probabilities that consumers use a credit card at the POS increases by 51.7% for the low-income consumers, and by 71.8% for the high-income consumers. The right panel of Figure 2.3 presents the distribution of changes in consumer welfare under perfect competition. The result shows that both types of the consumers benefit from this scenario. However, the distributions of welfare gain are skewed to the right, suggesting a a sizable variations in welfare gains across consumers.

Figure 2.3: Distribution of changes in consumer welfare per month, by income level



Regressive Distributional Effects. Finally, I consider the regressive distributional effects implied by the simulated adoption and usage probabilities under the monopoly and perfect competition settings. As shown in Table 2.9, under the monopoly setting, the average regressive transfers per-transaction made by non-credit users decreases from \$0.34 to \$0.26 per-transaction for previous cash-only users, and from \$0.35 to \$0.24 per-transaction for consumers who used to adopt only cash and debit cards. The regressive transfers per-dollar also decrease for both consumer groups. On the other hand, the average regressive transfers per-transaction made by credit users increases from \$0.17 to \$0.20 per-transaction, and from 0.71% to 0.77% per-dollar for credit card users. These results are robust under different assumptions on the merchant cost pass-through rates - 75 percent and 100 percent. It suggests that the monopoly setting in effect redistributes the regressive transfers from low-income or non-credit card users to high-income or credit card users. Similar result is observed when the consumers are divided into six income cohorts. Table 2.10 shows that under the monopoly setting, both the average per-transaction and per-dollar regressive transfers decrease for the lowest-income cohort consumers, but increases for all the rest of the cohorts. Particularly, the highest-income cohort consumers face the largest increase both in terms of per-transaction and per-transaction values. Although the absolute values of regressive transfers are still higher for low-income and non-credit card users due to the presence of merchant cost pass-through, the gap between the cohorts are significantly decreased, suggesting a more equal financial burden born by low-income and high-income consumers.

The results from the scenario where issuer banks compete under perfect competition show that the regressive transfers are largely eliminated for all the consumer cohorts, where the mean regressive transfers consumers make per transaction are dropped to almost zero. The average regressive transfer per-dollar drops by more than 60% for cash-only users, 46% for the cash and debit users, and 42% for the credit-card users. Unlike the factual scenario where the average regressive per-dollar decreases monotonically with income, it decreases first then increases when income increases. This result suggests that a perfect competition setting, which effectively drives down consumers' usage cost of credit cards, also improves the distribution of regressive transfers among consumers.

2.6 Conclusion

This paper uses a unique consumer diary data to quantify the regressive distribution effects in the payment card industry, and studies how market structure changes affect consumer welfare and the distribution of regressive transfers. Specifically, I estimate a structural consumer demand model over payment methods, which incorporates the heterogeneity in tastes on payment method characteristics and issuer bank choices. The estimated parameters fit the data well and are able to capture the substitution patterns observed in the data. My results show that consumers prefer payment method that are easy to use, secure and perceived as inexpensive. High-income consumers in general enjoy a significantly higher utility from using a credit card, compared to low-income consumers, and also incur a smaller adoption cost in adopting cash, debit and credit cards.

Using the parameter estimates, I conduct a set of policy experiments: (1) hypothetical cash removal, (2) a monopoly setting, and (3) a perfect competition setting among issuer banks. The results show that the regressive distributional effects are reduced under all three scenarios. Particularly, the monopoly setting has the strongest effects in the redistribution of regressive transfers, where it reduces the per-transaction and per-transaction value regressive transfers made by non-credit card users and low-income consumers, while increases those made by credit card users and high-income consumers. On the other hand, welfare comparisons show that perfect competition renders the highest increase in consumer surplus, while the monopoly setting and removal of cash on average hurt the consumers in terms of consumer surplus.

Data availability limits the way I model the pricing of the issuers and the impact of its competition on merchant acceptance decisions. However, the results have shown robustness under different assumptions of merchant decisions. This paper contributes to the literature by estimating the consumer substitution patterns between different issuers, which is absent in the existing literature. With the gradual consolidation of issuer banks in recent years, understanding the effects of issuer competition on consumer welfare is important. It is the also the first paper to my knowledge that investigates the regressive distributional effects using a structural demand model.

Chapter 3

INFORMATION DIFFUSION AND THE DEMAND FOR NEW PAYMENT INSTRUMENTS.

3.1 Introduction

With the rapid technological advancement in the telecom industry, there have been many innovations in payment methods, including mobile wallets, contactless payments, instant payments and cryptocurrencies. These new products provide improved characteristics of existing payment methods such as security, convenience and privacy, and gradually shift the consumers away from traditional payment methods such as cash and checks. Facing a greater breadth of payment solutions, the consumers not only consider the type and quality of the new payment methods, but also whether the new payment methods are widely used and accepted in the market. In the two-sided market, consumer knowledge about the behaviors of other market participants plays an important role in driving the demand of new payment services.

Consumer awareness is particularly relevant when the market faces great uncertainties. For example, the Covid-19 crisis, which started to spread worldwide in 2020, significantly altered the buying and selling behavior in the retail sector. Since the pandemic, MasterCard saw a 40% jump in the use of contactless payments including tap-to-pay and mobile pay during the first quarter of 2020.[1] The global lockdowns and the fear of contagion also changed the way merchants deliver their products to their consumers. The number of retail stores that provide curbside pickup more than doubled during the pandemic.[2] The dramatic changes in the shopping and selling behavior coupled with lack of information may have crucial impacts on how consumers make their adoption and usage decisions on the new payment instruments.

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[1] Rooney (2020)

[2] Thomas (2020)

In this paper, I explore the effect of consumer awareness on consumer adoption and usage of new payment instruments, and ask how the diffusion of information drives the adoption and usage of new payment methods over time. To address these questions, I estimate a structural model of demand for payment instruments, taking into account both product characteristics and consumer awareness about merchants' acceptance decisions. The model is built upon Huynh et al. (2021) and Chapter 2 in Yen (2021), which represents the consumer decisions as a two-stage process. In the first stage, consumers decide which payment instruments to adopt. In the second stage, consumers face transaction needs and are matched with a merchant. The consumers are either *informed* or *uninformed* about the merchant acceptance decisions prior to the purchase. If the former, the consumers simply use the payment method that provides them the highest utility among their adopted payment methods. If the latter, the consumers face uncertainties and are constrained to use the payment methods that are accepted by the merchants. Different from Yen (2021) and Huynh et al. (2021), I assume that the uncertainties about merchant acceptance may vary with the payment methods. For example, the uncertainties about merchants' acceptance decisions on credit cards may be different from that of the debit cards. This allows us to disentangle the information effects across different products and generate more realistic substitution patterns.

Using the parameter estimates, I conduct a set of counterfactual experiments to investigates the effect of consumer awareness. I first introduce three alternatives of **n**ew **p**ayment **i**nstruments (abbreviated to NPI) which have characteristics similar to cash, debit cards and credit cards respectively. Then I simulate the post-introduction consumer adoption and usage decisions, keeping the consumer awareness at the fixed level. The simulation results suggest that an NPI that combines the observed and unobserved characteristics of the credit cards will be used the most at the point of sale (POS), compared to the other two alternatives. The usage probabilities of the credit-like NPI are higher than the existing credit card as long as the adoption cost of the credit-like NPI is less than 3 CAD dollars a month. The adoption probabilities generally decrease with adoption cost, while the effect of adoption cost has the strongest effect on the adoption of the debit-like NPI.

Secondly, to see what happens when consumer awareness about merchant acceptance decisions changes, I gradually change the level of consumer awareness and simulate the resulting outcomes on consumer adoption and usage probabilities. I consider two scenarios in this simulation, one without the introduction of new payment instruments, and one with them. The results under no introduction of NPI show that, overall, the consumer awareness is positively correlated with the usage of credit cards and debit cards, and has a negative effect on cash usage. These effects are more prominent when the consumer awareness is assumed to vary independently between debit and credit cards. Under the scenario of hypothetical introduction of new payment instruments, the consumer awareness has a larger impact on the usage probabilities of cash-like and credit-like NPI, compared to its impact on the usage probabilities of debit-like NPI. It also displays a strong cross-effect of information across payment methods. For example, if the consumers have no prior knowledge about merchants' acceptance of the new payment instrument but are fully aware of their acceptance decisions on existing payment methods, the adoption rates of the new payment instruments will be 20 percentage points lower than they would have been if consumers have no knowledge about merchant acceptance at all. This result highlights the importance of modeling consumer awareness separately across payment methods.

Finally, I provide a model that extends the empirical results and illustrates how the diffusion of consumer awareness would drive the cumulative adoption and usage of new payment instruments in the long run. I postulate that information would dissipate with a process similar to contagion, where individuals learn about new knowledge when they come in contact with others who have obtained the knowledge. This process is commonly described as the *Bass diffusion model* of new product diffusion (Bass (1969), Bass (1980)), and is the most widely used diffusion model in the literature outside of economics. The model boils down to two parameters that governs the diffusion of innovation: a coefficient of *imitation* which describes the rate of contagion when people come in contact with previous adopters, and a coefficient of *innovation* which describes the rate of contagion from external source. To determine the two parameters for the diffusion of consumer awareness, I fit the Bass diffusion model on the data that record the number of adopters at the early stage of product launch from Venmo, a major peer-to-peer (P2P) mobile payment technology. I then predict the changes in consumer awareness over time using the parameter estimates from the

Bass diffusion model. Finally, I simulate how the consumer adoption and usage probabilities of the new payment instruments are projected in the long run, assuming consumer awareness follows the trend predicted by the Bass diffusion model. I also compute the resulting changes in consumer welfare when the consumer awareness gradually increases.

The simulation results show that the adoption and usage probabilities generally exhibit an S-shaped curve after the introduction of the new products. Overall, the adoption and usage curve stay flat in the first two years, and start to accelerate after the second year. The peak of adoption/usage would occur between the 3rd and 4th year of introduction and gradually converge after the 6th year. The credit-like NPI exhibits the highest growth rates in the usage probabilities compared to the others, while the growth rates of adoption probabilities are similar across the three alternative NPIs. Welfare calculations show that consumer surplus initially drops after the introduction due to lack of consumer information, and gradually increases when consumers become more informed about the merchant acceptance decisions. For example, it takes 137 weeks (2.62 years) for the credit-like NPI to generate a positive welfare gain for a consumer on average, which amounts to an estimate of $50 CAD loss of consumer welfare. The results suggest that it is important to develop measurements that ensure a fast diffusion of consumer knowledge for a new payment method to be successful.

The rest of the paper is organized as follows. Section 3.2 discusses the related literature. Section 3.3 presents the structural demand model and the results of parameter estimates. Section 3.4 discusses the three counterfactual simulations, including the hypothetical introduction of new payment instruments, information shocks and the innovation diffusion using Bass diffusion model. Finally, Section 3.5 concludes.

3.2 Literature Review

This paper contributes to the literature that studies the diffusion of technologies in the financial innovations. Several papers investigate the factors that determine the successful diffusion of new products. For example, Allen et al. (2008) studies the role that market structure plays in affecting the diffusion of electronic banking. Crowe et al. (2010) examines why the mobile payments fail to take off in the US compared to Japan. Yang and Ching

(2010) develops a dynamic consumer life-cycle model which investigates consumers' adoption and usage decisions of ATM cards and recovers the heterogeneous adoption costs faced by consumers at different ages. Crouzet et al. (2020) also studies the diffusion of technologies in a dynamic setting and investigates how a temporary cash crunch in India in 2016 caused a persistent increase of the growth rate in the usage of electronic wallet technology. This paper focuses on the impact of consumer awareness on the diffusion of new products in the payment method markets.

Recent developments and innovations in the payment method market motivate the counterfactual simulations in the paper. My paper is closest to Huynh et al. (2020), which studies the welfare effects of the introduction of central bank digital currency. This paper extends their work by considering a diffusion process of the new payment methods. Other works that study the impacts of new products in the payment method market include Agarwal et al. (2020), which documents the higher growth rate in business creation and consumer spending after the introduction of mobile payment technology in Singapore. Fu and Mishra (2020) studies the global impact of COVID-19 pandemic on the adoption of digital finance and fintech technologies.

This paper is also related to the literature that studies the two-sided market in the platform economics and the identification and estimation of network effect, including Rysman (2019), Manski (1991), Manski (1992). Applications in a structural demand model setting similar to my paper includes Fan (2013) for newspapers and Jeziorski (2014) for radio stations. Specifically, the model in this paper takes into account the network effects by controlling for merchant acceptance probabilities and consumer's awareness on merchant acceptance decisions. Finally, this paper borrows the literature in diffusion theory (e.g. Young (2009), Bass (1969), Bass (1980), Horsky (1990) and Zarwi et al. (2017)) and considers a process of information diffusion in the payment card industry.

3.3 Model

The model in this chapter builds upon the structural model of consumer adoption and usage choices of payment method described in Huynh et al. (2020), Huynh et al. (2021), and Chapter 2 in Yen (2021), and extends it by accounting for consumer awareness more explicitly. The consumer decisions are featured as a two-stage process. In the first stage, consumers choose which payment methods to adopt (i.e. the adoption bundle). In the second stage, consumers face a series of transactions and decide which payment method to use at each point-of-sale (POS), conditional on their adoption bundle *and* merchant acceptance bundle. This highlights the nature of two-sided market in the payment card industry: the merchant acceptance plays an important role in shifting the choice of payment method at transaction, and consumers must take into account these uncertainties while deciding which payment methods to adopt in the first stage.

Recall from subsection 2.2.1 that in the second stage (i.e. usage stage), the utility that each consumer b receives from using payment method m to complete the transaction j with transaction price p_j is given by,

$$\begin{aligned} u_{bjm}(p_j) &= \beta_r X_{bg(m)} - \alpha_r c_{jm}(p_j, \rho_r) + \eta_{rg(m)} \mathbb{1}(\tilde{p_j}) + \xi_{bjm}(r, Tj, m) + \epsilon^u_{bjm} \\ &= \delta_{bjm}(p_j) + \epsilon^u_{bjm} \end{aligned} \tag{3.1}$$

where $X_{bg(m)}$ denotes a vector of consumer perceptions on method characteristics. $c_{jm}(p_j, \rho_r)$ denotes the consumers' usage cost associated with each payment method, which is assumed to increase with transaction price and decrease with reward rate (if any). $\mathbb{1}(p_j < \$10)$ indicates whether it is a small-value transaction, and ξ_{bjm} represents a vector of *consumer type* $\times$ *transaction type* $\times$ *payment method* fixed effects, which represents the unobserved utility gain consumer gets from using specific payment method for specific transaction occasions. Finally, ϵ^u_{bjm} represents an idiosyncratic random shock upon transaction and is assumed to follow an i.i.d. Type-1 Gumbel distribution.

If there is no uncertainty about merchant acceptance decisions, then the consumers would simply choose to use and adopt the payment methods that derive the highest utility. However, in the two-sided market, the merchants also make decisions on which payment methods to accept and consumers are not always aware of merchants' acceptance bundle. To account for this, I follow the approach in Huynh et al. (2021) and assume that each transaction observed in the data could be either an *informed* transaction or an *uninformed* transaction. The *informed* transactions refers to transactions that consumers have prior knowledge on the merchant acceptance bundle and thus choose to transact at the POS which they know would accept their preferred method of payment. On the other hand, the transactions that consumers have no prior knowledge on merchant acceptance are the *uninformed* transactions. In this case, consumers are randomly matched with a merchant and they choose their preferred method of payment from the intersection of the merchant acceptance bundle and their own adoption bundle.

Different from Huynh et al. (2021), I assume that the inform probabilities may vary with consumer's adoption bundle. To illustrate this, consider two cases. Suppose the consumer only uses cash and prefers to use cash. The consumer is almost certainly know that the merchants will accept cash, which is also her/his preferred payment method. Now suppose the consumer adopts debit and credit cards. The consumer is likely to be less aware of the merchant's acceptance decision and they take into account these higher uncertainties into their adoption and usage decisions. Unlike Huynh et al. (2021), which assumes the same informed probabilities across payment methods for each consumer,[3] I assume that the informed probabilities may be payment method-specific.

Specifically, the expected utility (prior to the purchase) that consumer b will receive for transaction j, given that the consumer chooses to hold adoption bundle M_b in the first stage, is assumed to be

$$EU_{bj}(M_b) = \mathbb{E}_\epsilon \left[\phi_{M_b} \max_{m \in M_b} u_{bjm}(p_j) + (1 - \phi_{M_b}) \sum_{Ms} \mathbb{P}r(Ms) \max_{m \in M_b \cap M_s} u_{bjm}(p_j) \right] \tag{3.2}$$

where $\mathbb{P}r(Ms)$ denotes the average probability a merchant accepts payment method bundle M_s, which is assumed to be a common knowledge. The consumer awareness is dependent upon consumers' adoption bundle and is denoted as ϕ_{M_b}

Let J_b be the set of all purchases made by consumer b. The expected utility that consumer b will receive by completing all the transactions with adoption bundle M_b is given by

$$EU_b(M_b) = \sum_{j \in J_b} EU_{bj}(M_b) \tag{3.3}$$

In the adoption stage, consumer chooses the bundle that maximizes her/his expected

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[3]Huynh et al. (2021) estimates the probability of being a repeated purchase for each transaction using a logit model of consumer awareness on MOP 2017, and uses the estimates to fit on the MOP 2013.

utility, taking into account the adoption cost for each bundle, F_{bM_b}. Therefore, the consumer's decision in the adoption stage can be written as

$$\max_{M_b \in \mathbb{M}} \{EU_b(M_b) - F_{bM_b}(Z_b) + \epsilon^a_{bM_b}\} \tag{3.4}$$

The adoption cost is assumed to be a function of consumer demographics Z_b, and $\epsilon^a_{bM_b}$ represents an idiosyncratic random shock upon adoption, and is assumed to follow a Type-1 Gumbel distribution.

Given consumer's decision in the adoption stage, the per-transaction usage probabilities of each payment method m, conditional on their adoption decision M_b is:

$$\mathbb{P}_j(m|M_b) = \phi_{M_b} \times \frac{\exp(\delta_{bjm})}{\sum_{k \in M_b} \exp(\delta_{bjk})} \tag{3.5}$$

$$+(1 - \phi_{M_b}) \times \sum_{M_s \supset \{m\}} \mathbb{P}_{M_s} \times \frac{\exp(\delta_{bjm})}{\sum_{k \in M_b \cap M_s} \exp(\delta_{bjk})} \tag{3.6}$$

In the data, we observe realizations of consumer adoption and usage decisions. The structural parameters of the model is then estimated by the following joint likelihood function:

$$\begin{aligned} \mathbb{L}(\theta) = &\prod_{b=1}^{N_b} \prod_{M_b \in M_1} \mathbb{P}_b(M_b;\theta)^{D_{bM_b}} \\ &\times \prod_{b=1}^{N_b} \prod_{j \in J_b} \prod_{m \in M_2} \mathbb{P}_j(m|M_b;\theta)^{D_{bjm}} \end{aligned} \tag{3.7}$$

where M_1 denotes all the possible payment methods and M_2 denotes all the possible bundles of payment methods. $D_{bM_b} \in \{0,1\}$ denotes whether consumer b adopts the bundle M_b, i.e. $\sum_k D_{bk} = 1$ for all b. $D_{bjm} \in \{0,1\}$ denotes whether consumer b uses method m to complete transaction j, i.e. $\sum_k D_{bjk} = 1$ for all j.

3.3.1 Estimation Results

The model is estimated using Maximum Likelihood Estimation (MLE) similar to the approach described in Section 2.3 in Chapter 2 in Yen (2021). Table 3.1 and Table 3.2 respectively compares the estimates of the main parameters under different assumptions of consumer awareness in the usage stage and adoption stage. Specifically, I compare the

Table 3.1: Comparison of parameter estimates in the usage stage.

	No info		Full info		observed info	
Usage stage	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
Easiness-to-use	7.867***	11.349***	6.273***	8.041***	8.108***	8.433***
(s.e.)	(0.476)	(0.946)	(0.380)	(0.616)	(0.401)	(0.561)
Risk	1.640***	0.958**	1.297***	0.723**	2.375***	0.714***
(s.e.)	(0.236)	(0.405)	(0.188)	(0.287)	(0.206)	(0.281)
affordability	2.312***	3.697***	2.076***	2.486***	1.839***	2.349***
(s.e.)	(0.195)	(0.300)	(0.160)	(0.228)	(0.163)	(0.219)
Transaction price	-5.527***	-6.869***	-2.548***	-3.567***	-0.932***	-0.819***
(s.e.)	(0.688)	(1.130)	(0.180)	(0.270)	0.004)	(0.111)
Below $10 (debit)	-0.895***	-1.780***	-0.838***	-1.260***	-0.463***	-0.754***
(s.e.)	(0.114)	(0.197)	(0.079)	(0.112)	(0.089)	(0.127)
Below $10 (credit)	-1.485***	-2.136***	-1.406***	-1.502***	-0.929***	-0.712***
(s.e.)	(0.123)	(0.199)	(0.086)	(0.099)	(0.104)	(0.110)

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

results from assuming consumers with no info at all (i.e. $\phi_{M_b} = 0$), with full info (i.e. $\phi_{M_b} = 1$), and with info at the (average) observed level. The results show that parameter estimates are significantly different between the models. Specifically, the parameters in the usage stages are mostly overestimated if assuming consumers having no information about merchant decisions at all. In terms of adoption stage variables, the result found in the no-info model that high-income consumers face significantly lower adoption cost becomes non-significant when assuming consumers having some knowledge about merchant's acceptance decisions. These results suggest that consumer awareness plays an important role in affecting consumer's adoption and usage decisions. Table B.1 and Table B.2 report the full results from the model estimation.

Table 3.2: Comparison of parameter estimates in the adoption stage.

	No info		Full info		observed info	
Adoption stage	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
$M_b = \{ca, dc\}$						
constant	1.819***	(0.567)	1.589***	(0.570)	1.450*	(0.852)
High income	0.375	(0.542)	-0.337	(0.430)	-0.604	(0.919)
$M_b = \{ca, dc, cc_{RBC}\}$						
constant	-0.491	(0.576)	-0.868	(0.576)	-0.997	(0.847)
High income	1.176**	(0.568)	0.471	(0.437)	0.285	(0.914)
$M_b = \{ca, dc, cc_{BOM}\}$						
constant	-0.546	(0.599)	-0.822	(0.596)	-0.947	(0.869)
High income	1.379**	(0.577)	0.502	(0.444)	0.297	(0.919)
$M_b = \{ca, dc, cc_{CIBC}\}$						
constant	-0.345	(0.589)	-0.759	(0.586)	-0.849	(0.864)
High income	1.141**	(0.572)	0.601	(0.438)	0.375	(0.917)
$M_b = \{ca, dc, cc_{TD}\}$						
constant	-1.226	(0.603)	-1.676	(0.598)	-1.481*	(0.871)
High income	1.053*	(0.570)	0.937**	(0.439)	0.614	(0.916)
$M_b = \{ca, dc, cc_{else}\}$						
constant	1.437***	(0.533)	1.095**	(0.537)	0.905	(0.829)
High income	0.617	(0.535)	0.298	(0.421)	0.095	(0.907)

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

3.4 Counterfactual Simulations

3.4.1 Introduction of New Payment Instrument (NPI)

In this section, I consider a hypothetical introduction of new payment instrument, and examine how consumer adoption and usage decisions change in the presence of the new payment method. In the era of digital financial innovation, it is important for policy makers to understand how consumers choose between traditional and new payment methods. Specifically, in the counterfactual analyses, the consumer adoption bundle is expanded to include one new payment instrument, abbreviated as NPI. Under the original model setup, the consumers can choose to adopt either (i) cash only, (ii) cash and debit cards, or (iii) cash, debit cards and one credit card from five options of issuer banks: Royal Bank of Canada (RBC), Bank of Montreal (BMO), CIBC, TD or any others. In the hypothetical scenario, the number of choice set over adoption bundles is doubled, where each original adoption bundle is now added with one NPI.

To construct the hypothetical new product, I consider three alternatives: (1) The NPI is identical to cash, where its attributes are identical to cash in every dimension (i.e. $X_{b,ca}$); (2) The NPI is similar to debit cards, where its attributes are identical to debit cards in every dimension (i.e. $X_{b,dc}$), and (3) The new payment instrument is similar to credit cards, where its attributes are identical to credit cards in every dimension (i.e. $X_{b,cc}$). I assume that for the credit-like NPI, consumer receives a transaction specific match values that is assumed to be the highest match value the consumer can attain from the five issuer banks under the factual scenario. That is, $\xi_{bj,NPI} = \max\{\xi_{bjm,m\in\{cc_{RBC},cc_{BMO},cc_{CIBC},cc_{TD},cc_{else}\}}\}$. This can be thought of as introducing a new credit card that guarantees the best rewards the consumers can get from paying with credit cards.

For each of the scenarios, I simulate the new consumer adoption and usage probabilities, and focus on the optimal range of adoption cost for each new payment alternatives, in the sense that it would make the adoption rates of the new product as high as their counterparts. In this simulation, I assume that consumer awareness is fixed at $\phi_{M_b} = 0.95$ for all M_b and b. In the next section, I will relax this assumption and focus on the impact of consumer awareness on consumers picking up the new product.

For the merchants, I assume that a fixed proportion of merchants decide to accept the new payment instrument, with respect to merchant groups who accept different bundles of payment method. Recall that in the original setting, the merchants could either accept (i) cash only, (ii) cash and debit cards, or (3) cash, debit cards and credit cards (regardless of the issuing banks), and the probability that merchant accepts bundle M_s is $\mathbb{P}_{M_s}$. In the counterfactual analyses, I assume that r% of the merchants from each merchant group decides to accept the new payment instrument. Denote the new merchant acceptance bundle as M_s'. This means the probability that a cash-only merchant decides to accept the new instrument under the counterfactual scenario is $\mathbb{P}_{M_s'=\{ca,NPI\}} = r\mathbb{P}_{M_s=\{ca\}}$, and the probability that the merchant remains cash-only is $\mathbb{P}_{M_s'=\{ca\}} = (1-r)\mathbb{P}_{M_s=\{ca\}}$. Similarly, $\mathbb{P}_{M_s'=\{ca,dc,NPI\}} = r\mathbb{P}_{M_s=\{ca,dc\}}$ and $\mathbb{P}_{M_s'=\{ca,dc,cc,NPI\}} = r\mathbb{P}_{M_s=\{ca,dc,cc\}}$.

Figure 3.1 plots the usage probabilities and consumer adoption probability of the new payment instrument as a function of the adoption costs of the new payment instrument, assuming the merchant acceptance rate $r = 50\%$.[4] The simulation results suggest that even without any adoption cost (i.e. depicted as the vertical black line), the cash-like NPI and debit-like NPI will not be used as often as their original counterparts. However, the credit-like NPI will be used more often than the credit card counterpart. The usage probabilities of the credit-like NPI remain higher than credit cards if the adoption cost is less than 3 CAD dollars a month. In terms of the adoption probabilities, the adoption cost has a more negative effect on the adoption of debit-like NPI than the cash-like and credit-like NPI. The adoption probability is also lower for the debit-like NPI compared to the others when the adoption cost is set at zero. The adoption probabilities drop below 50% for the debit-like NPI if its adoption cost surpasses 7 CAD dollars, while the adoption probabilities of cash-like and debit-like NPI do not drop below 50% unless their adoption cost is as high as 13 CAD dollars. This might be because the debit-like payment methods do not provide sufficient pecuniary incentives for the consumers to use, and are also less convenient to use compared to cash. This is reflected in the fact that debit card is used the least by the consumers in the observed sample.

[4]The adoption cost is converted to dollar values using the parameter estimates on consumer usage cost (i.e. α_r in Equation 3.1), and is prorated to monthly rates.

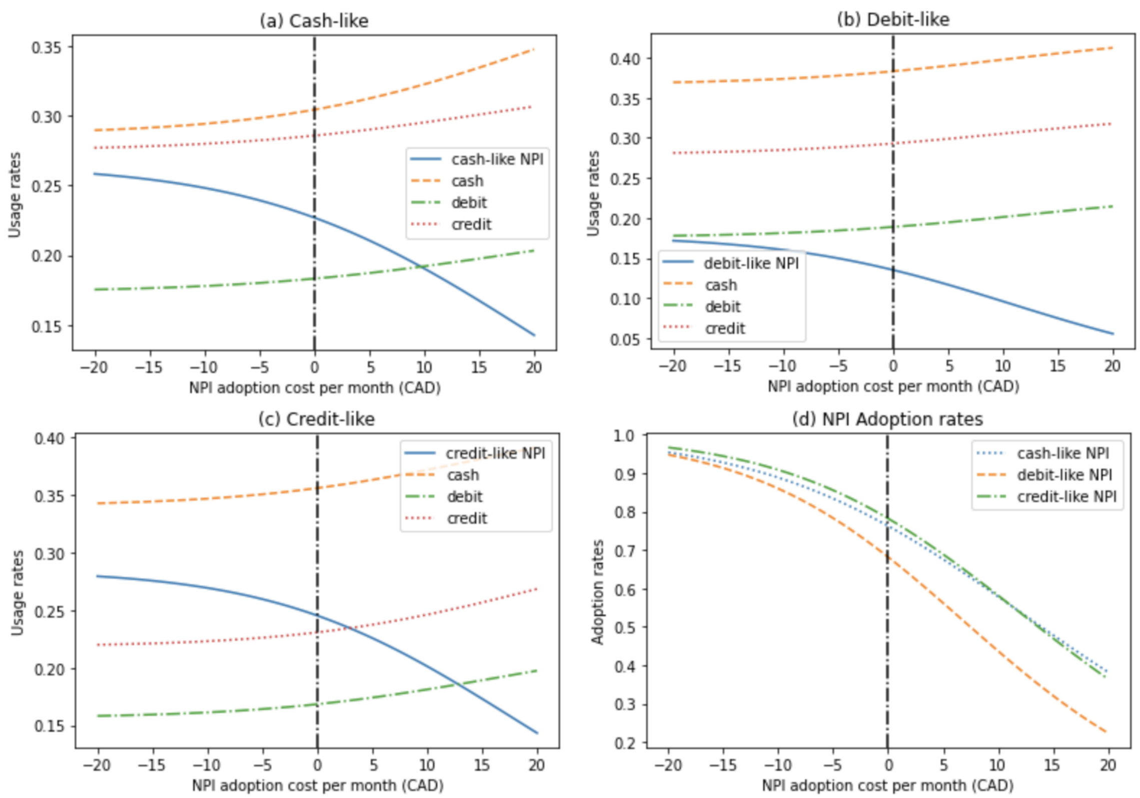
Figure B.1 plots the adoption and usage probabilities as a function of NPI adoption costs under different values of merchant acceptance rates: $r \in (100\%, 66\%, 33\%, 0\%)$. Similar patterns are observed with different values of merchant acceptance rates. One interesting observation is that the merchant acceptance of new payment instrument have a larger effect on cash usage compared to debit or credit card usage, even for the credit-like new payment instrument. This suggests that cash payment may be more replaceable to the consumers when there is new payment instrument introduced in the market. As more merchants accept the new payment method, more consumers substitute away from cash payments to the new payment method.

3.4.2 Information Shock

This section explores how consumer awareness on merchant acceptance affects consumers' adoption and usage choices on payment methods. Besides the actual merchant acceptance probability which may directly constrain consumers' usage choices, how consumer *perceives* the merchant acceptance also affect their adoption and usage choices. In this simulation, I consider a hypothetical situation where consumer awareness about merchant acceptance changes exogenously. The current COVID-19 is a perfect example where consumer awareness might be significantly reduced. Due to the pandemic, some merchants decided to stop accepting cash to prevent their exposure to physical infection. Some merchants, on the other hand, may decided to reject credit cards in order to save from the higher merchant fees when they faced the period of decreased sales and revenues. Therefore, consumers are more likely to experience surprises or uncertainties regarding to merchants' acceptance decision at the POS. Furthermore, since many stores and local shops were temporarily or permanently closed due to the pandemic, consumers may have to shop from other merchants they never encountered before, and thus are less likely to know about their acceptance decisions prior to the purchases.

To measure how consumer awareness affects consumers' adoption and usage choices, I conduct two sets of simulations. The first simulation consider a scenario where there is no introduction of new payment methods, thus focuses on the impact of changes in

Figure 3.1: Usage probabilities and NPI adoption (bottom right) given NPI adoption costs



Notes: Plots (a), (b), and (c) describe the changes in estimated usage probabilities at the POS over the monthly adoption cost of new payment instrument (NPI), when alternative forms of the NPI are introduced. Plot (d) describes the changes in estimated adoption probabilities over the monthly adoption cost of NPI, when alternative forms of the NPI are introduced. Note that the merchant acceptance is fixed at 50% in this figure.

consumer awareness on existing payment instruments. The second simulation consider a scenario where a new payment method appears in the market, and investigate how consumer awareness on this new product affect their adoption and usage choices on existing and new payment service. For each simulation, I compare the results from assuming the same inform probabilities across consumer adoption bundle (i.e. $\phi_{M_b} = \phi_{M_b'}\ \forall M_b \neq M_b'$ in Equation 3.2), versus assuming different inform probabilities across adoption bundle.

Without New Payment Instruments

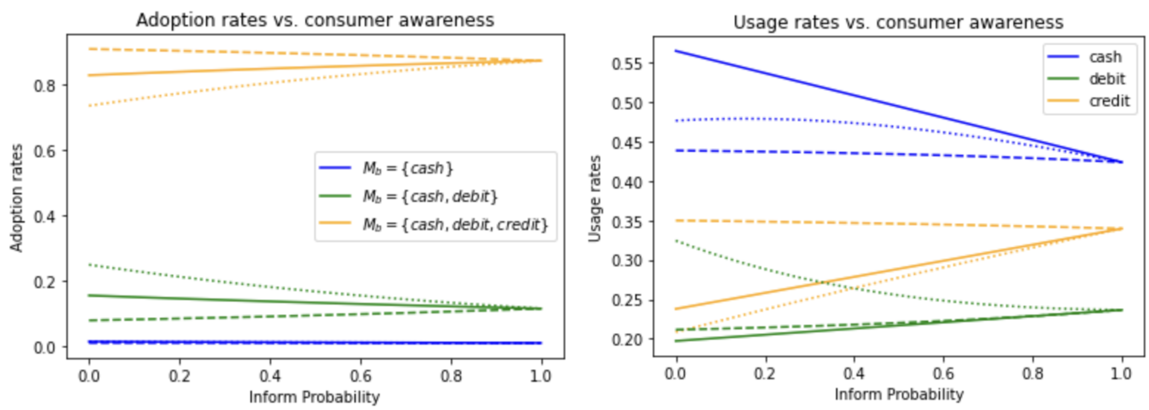
Figure 3.2 plots the predicted adoption and usage probabilities as a function of consumer awareness, keeping the merchant acceptance probabilities at the observed rates. The solid lines describe the changes in adoption/usage probabilities when the inform probabilities change uniformly for all consumers (i.e. overall consumer awareness). The dashed and dotted line, respectively, describe the changes in adoption/usage probabilities when the inform probabilities for consumers holding $M_b = \{ca, dc\}$ and consumers holding $M_b = \{ca, dc, cc\}$ change, assuming full awareness for the rest of the consumers. These can be interpreted as sudden changes on consumers' confidence toward debit- or credit- card acceptance.

The result shows that the adoption of credit cards increase with the overall consumer awareness, and the probabilities that consumers do not adopt credit cards decrease with the overall consumer awareness. The same patterns are observed when we assume that only the consumer awareness toward credit cards are changed. On the other hand, the overall consumer awareness increases with both the usage probabilities of debit and credit cards. However, consumer awareness toward credit card acceptance increases the usage of credit cards while decreases the usage of debit cards. Similarly, consumer awareness toward debit card acceptance increases the usage of debit cards while decreases the usage of credit cards. In general, the probabilities that consumers only adopt cash are fairly low, regardless of the level of consumer awareness. However, consumer awareness has a strongly negative effect on the usage of cash.

It is worth noting that these effects are purely from the changes in consumers' *perception* about merchant choices, and the actual merchant acceptance are kept as fixed in these simulations. Since I do not model merchants' acceptance decision explicitly, this does not take into account merchants' responses toward changes in consumer awareness. For example, if merchants anticipate that consumer would decrease the usage of credit cards when information is reduced, they may respond by reducing the acceptance of credit cards, which drives the consumer adoption and usage of credit cards further down via the network effects.

To illustrate the potential effects from changes in merchants' acceptance, I simulate the predicted adoption and usage probabilities when the inform probabilities change, assuming

Figure 3.2: Adoption and usage probabilities over consumer awareness

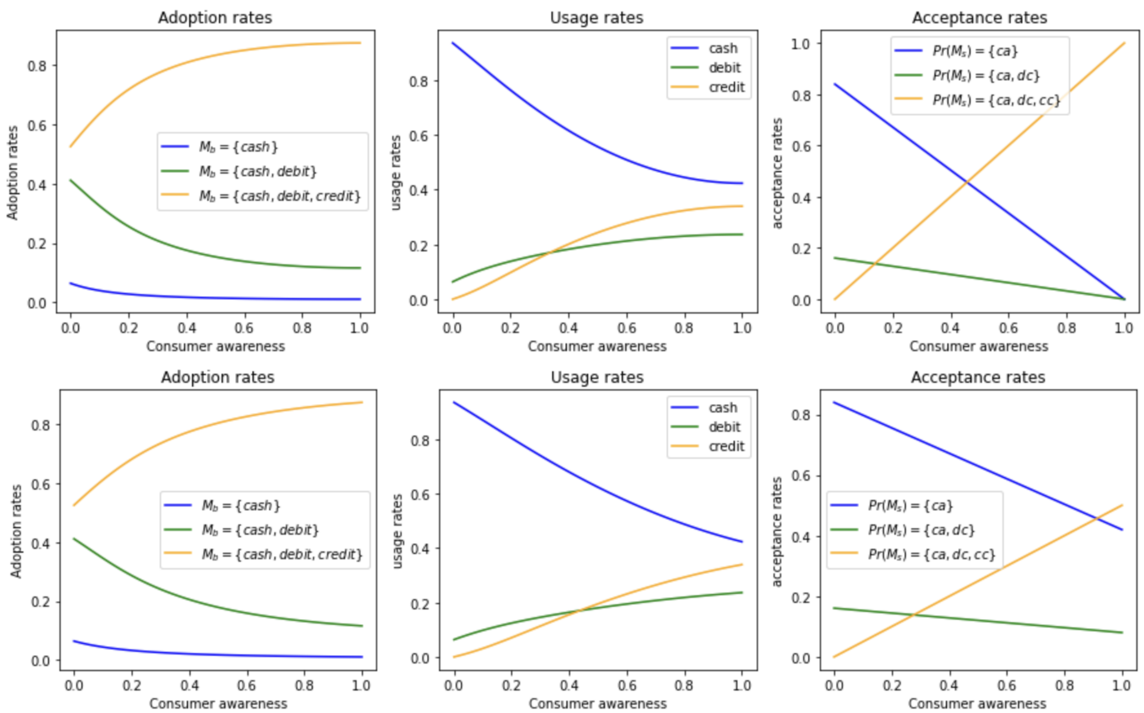


Notes: The figure plots the predicted adoption (left) and usage probabilities (right) as a function of consumer awareness, keeping the merchant acceptance probabilities at the observed rates. The solid lines describes the changes in adoption/usage probabilities when the inform probabilities are the same across consumers. The dashed (-) and dotted (.) lines, respectively, describes the changes in adoption/usage probabilities when the inform probabilities for consumers holding $M_b = \{ca, dc\}$ and consumers holding $M_b = \{ca, dc, cc\}$ change, assuming full awareness for the rest of the consumers.

two potential response functions of the merchants. Figure 3.3 shows that the consumer awareness has a much stronger effect on adoption and usage probabilities when the responses from the merchant sides are taken into account. The adoption rates of credit card could drop below 60% if merchant decreases their acceptance of credit cards when consumers are less informed. Although this is not an accurate estimation because the equilibrium effects can not be property estimated without merchant-side data, this illustrates that the outcomes shown Figure 3.2 can be considered as an lower bound of the effects from changes in consumer awareness.[5]

[5] For full-equilibrium effects, see Huynh et al. (2021) where they calculate the elasticities of merchant acceptance with respect to consumer awareness.

Figure 3.3: Adoption and usage probabilities as a function of consumer awareness, given different merchant response functions.



Notes: The first row plots the changes in predicted adoption (left) and usage (middle) probabilities as a function of consumer awareness, assuming that a change in consumer awareness results in the same changes in merchant acceptance probabilities of the credit cards (right). The second row plots the changes when merchants responds by half of the changes in consumer awareness.

With New Payment Instruments

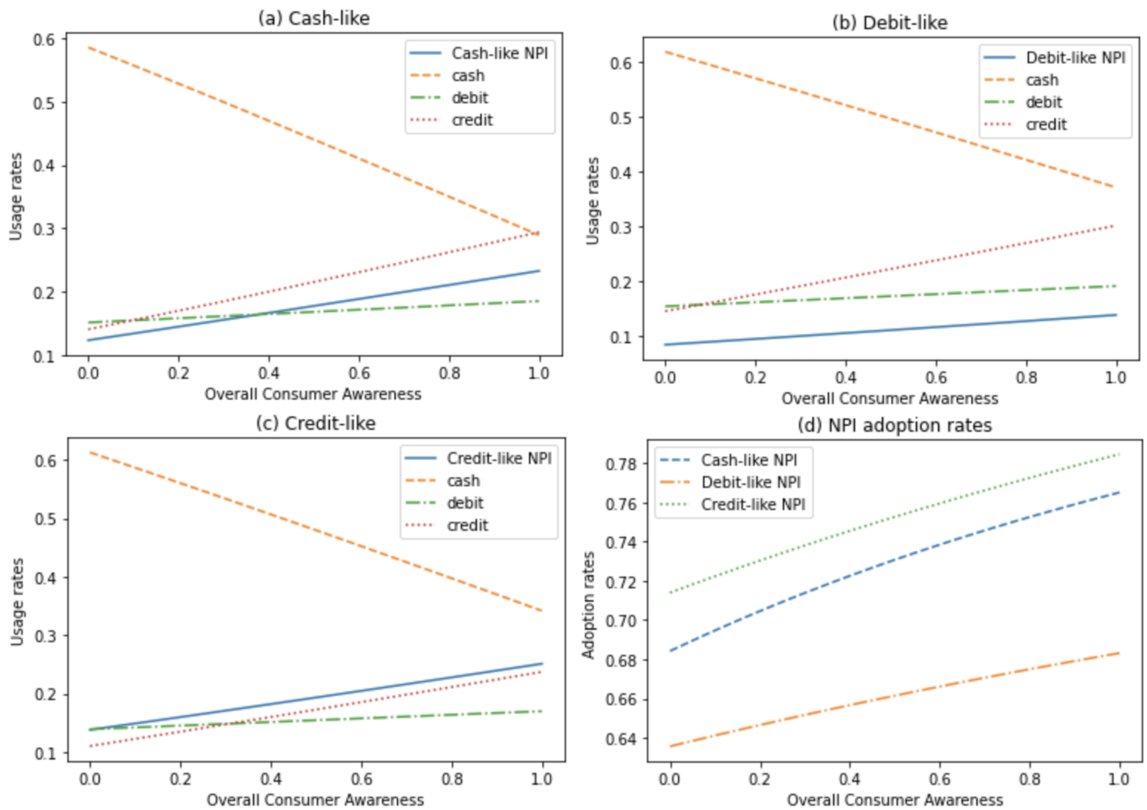
In this simulation, I examine how consumer awareness about merchants' acceptance of new payment instruments affect consumer's adoption and usage choices. As described in subsection 3.4.1, I consider three alternatives of the new payment instruments: (i) cash-like (ii) debit-like, and (iii) credit-like new payment method. The goal is to understand how information plays a role in affecting consumers' willingness to take up the new payment method. Similar to the previous section, for each of the alternatives, I compare the changes in adoption/usage probabilities from changes in the overall inform probabilities versus from changes in the inform probabilities toward the new payment method only.

Figure 3.4 plots the adoption and usage probabilities of the new payment instruments when the overall consumer awareness changes. To abstract from other factors, I set the adoption cost of the new payment instrument at zero and the merchant acceptance rates at $r = 50\%$. The results show that overall consumer awareness increases the adoption and usage of the new payment instrument for all alternatives. It also increases with the usage of debit and credit card payments and decreases with cash payments. Similar to the patterns observed in subsection 3.4.1, the usages of cash-like and debit-like are smaller than their counterparts even if consumers are fully aware of merchant acceptance of the new payment instruments. On the other hand, the usage probabilities of credit-like new payment instruments are higher compared to the credit cards for all level of consumer awareness.

Figure 3.5 illustrates the adoption and usage probabilities of the new payment instruments when consumer awareness *toward the new payment instrument* changes, keeping the consumer awareness regarding other payment methods at 100%. As the intuition suggests, the adoption and usage of new payment instrument will increase with consumer awareness about the merchants' acceptance decision on the new payment instruments. As consumer awareness toward the new payment instrument grows, fewer transactions will be made by cash. However, it does not have a significant negative impact on the usage probabilities of debit and credit cards.

Interestingly, the results show that the effect of consumer awareness are much larger if we assume separate inform probabilities for the existing and new payment instruments. For example, if the consumers have no prior knowledge about merchants' acceptance of the new payment instrument but are fully aware of their acceptance decisions on the existing payment methods, the adoption rates of the new payment instruments will be 20 percentage points lower than they would have been if consumers have no knowledge about merchant acceptance at all. This same patterns are observed in the usage probabilities of the new payment instruments. This suggests that there is a strong negative cross-effects of consumer information between payment methods.

Figure 3.4: Usage probabilities and NPI adoption given overall consumer awareness

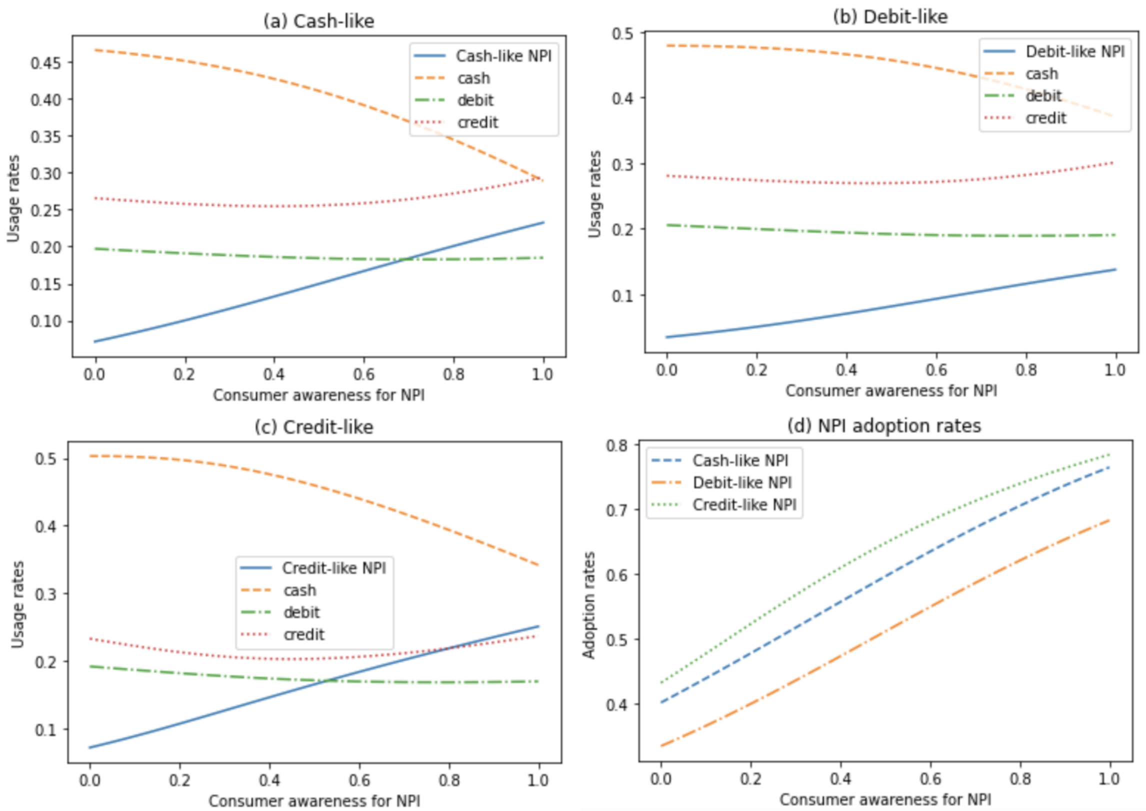


Notes: Plot (a), (b), and (c) describe the usage probabilities of all payment methods when the overall consumer awareness changes. Plot (d) describes the changes in adoption probabilities of the new payment instruments when the overall consumer awareness changes. The adoption cost of the new payment instrument is set at zero and the merchant acceptance rate of the new payment instrument is set at $r = 50\%$ in all the plots.

3.4.3 Information Diffusion

In this section, I borrow the literature from diffusion and social learning models and consider how consumer adoption and usage choices change over time when consumer awareness toward the new payment instrument gradually increases. Typically, when a new product is firstly introduced, the adoption of the new product will start off slowly with only the

Figure 3.5: Usage probabilities and NPI adoption given consumer awareness toward NPI



Notes: Plot (a), (b), and (c) describe the usage probabilities of all payment methods when the consumer awareness toward the new payment instrument changes. Plot (d) describes the changes in adoption probabilities of the new payment instruments when the consumer awareness toward the new payment instrument changes. The adoption cost of the new payment instrument is set at zero and the merchant acceptance rate of the new payment instrument is set at $r = 50\%$ in all the plots.

early adopters, then experience a rapid growth of adoption from social contagion or word-of-mouth, until it gradually levels off when most customers have adopted the product. This S-shaped adoption curve has been studied extensively in the marketing literature (e.g. Mansfield (1961), Sultan et al. (1990), Bass (1969), Bass (1980), Srinivasan and Mason (1986), Boswijk and Franses (2005), Fourt and Woodlock (1960), den Bulte and Joshi

(2007), Young (2009)).

Among all, the most commonly used diffusion model in the literature is the Bass model proposed in Bass (1969), which provides the foundation of most of the works in the literature. The Bass model describes the contagion process where people adopt a new product when they come in contact with others who have adopted it. The idea is to divide individuals into two types: the *innovators* and the *imitators*. The *innovators* are the individuals who likes innovations and tend to purchase at the launch of the new products. The *imitators* are individuals who purchase new products primarily because of the influence from the previous adopters.

The diffusion model of Bass (1969) can be summarized by the following ordinary differential equation:

$$\dot{p}(t) = (\gamma + \lambda p(t))(1 - p(t)) \tag{3.8}$$

where $\dot{p}(t)$ represents the rate of adoption. $1-p(t)$ represents the proportion of potential adopters who have *not* adopted the new product at time t. The equation is governed by the two parameters γ and λ: The parameter γ is the "coefficient of innovation", which represents the contagion rate where a non-adopter learns about the new product from external sources such as advertisement and news or blogs, and decides to own the new product. The parameter λ is the "coefficient of imitation", which represents the contagion rate where the non-adopters learn about the innovation from a previously adopter and were influenced to adopt the new product. Therefore, the adoption rate, $\dot{p}(t)$, can be summarized as the overall probability that a non-adopter decides to adopt the new product (i.e. $\lambda p(t) + \gamma$), times the percentage of potential adopters who have not adopted the new product (i.e. $1 - p(t)$).

Since the inform probability has a monotone relationship with the adoption and usage probabilities, as suggested by the results from subsection 3.4.2, I consider a diffusion process in the consumer awareness and explore how the propagation of consumer awareness drives the growth of consumer adoption and usage probabilities. Specifically, I assume that the inform probabilities over a new payment method follows the ordinary differential equation:

$$\dot{\phi}(t) = (\lambda\phi(t) + \gamma)(1 - \phi(t)) \tag{3.9}$$

where $\phi(t)$ can be interpreted as the proportion of consumers who *have knowledge* about merchants' acceptance decision on the new payment instrument by time t. At every period t, some fixed proportion (γ) of customers who have not known the information learns the merchant decisions from external sources and become known. Some proportion of other customers who have not known (λ) get in contact with the group of individuals who have known the merchant decisions prior to t, and become known. Therefore, the stock of individuals who have acquired the knowledge about merchant decisions increase over time until everyone is fully aware.

To determine the two parameters λ and γ in the Bass model, I estimate the parameters using an analogous products' past adoption curve, and inputted the parameter values into the model to generate potential forecasts for the growth of information. I follow the literature on the econometric estimation of Bass diffusion model as outlined in Peres et al. (2010), Ganjeizadeh et al. (2017) and Peers (2011), and estimate the parameters by running the following Ordinary Least Square regression

$$n(t) = a + bN_{t-1} - cN_{t-1}^2 \tag{3.10}$$

where $n(t)$ is the adoption growth at time t and N_{t-1} is the accumulative adoption by time $t-1$. The parameters γ and λ are then calculated as

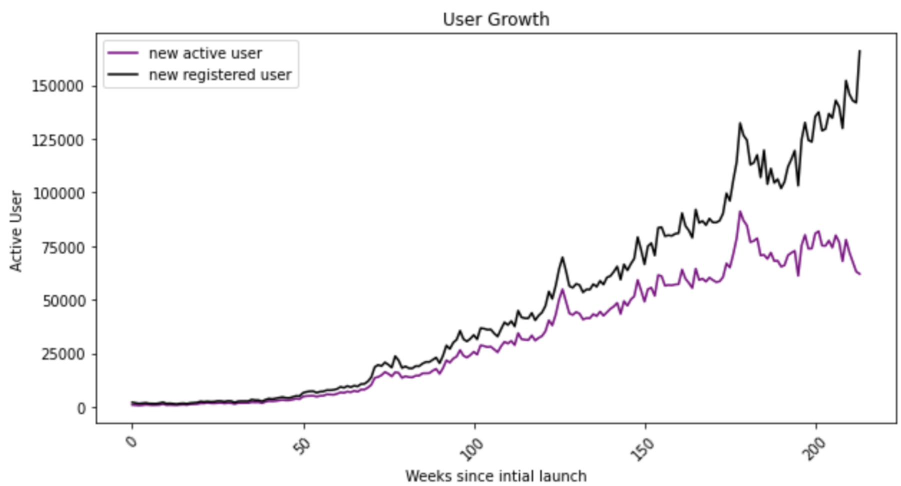
$$m = \frac{-\hat{b} - \sqrt{\hat{b}^2 - 4\hat{a}\hat{c}}}{2\hat{c}} \tag{3.11}$$

$$\gamma = \frac{\hat{a}}{m} \tag{3.12}$$

$$\lambda = \gamma + \hat{b} \tag{3.13}$$

where $\hat{a}, \hat{b}, \hat{c}$ are the estimates from Equation 3.10, and m represents the total potential adopters in the market.

Figure 3.6: Weekly growth trend of Venmo.



Notes: The graph plots the weekly user growth of Venmo from April 2012 to May 2016.

For the analogous product, I use the aggregate data on the weekly new active users on Venmo from March 2012 to May 2016. Venmo is one of the biggest mobile payment service in the U.S. which allows account holders to transfer funds to others via a mobile phone app. The service was firstly open to public users in March 2012, and gradually became one of the top four most popular person-to-person (P2P) payment apps in the U.S. (Others include Apply Pay, Facebook Messenger and Quickpay). The data are provided by the authors of Zhang et al. (2017), in which they collect records of all 91 million public transactions conducted on Venmo since its introduction in 2012.

Figure 3.6 plots the trend of weekly user growth on Venmo. The graph shows that the adoption rate of Venmo was nearly flat in the beginning, then experienced a linear growth for both the new active users[6] and new registered users. This is similar to what the Bass model would predict in the early stage of new product diffusion. Although more recent data for the number of new users are available from the quarterly financial statements of Venmo (now Paypal), these data consisting the early years of initial launch may represent

[6]Active user is defined as a person who used the service at least once during the week.

the diffusion process better due to Venmo's several new acquisitions of other P2P payment services, which bump up their user base from time to time over the recent years.[7]

I use the weekly data of new active users on Venmo to estimate the parameters of Bass Diffusion model. Table 3.3 and Figure B.4 present the estimates and the model fit respectively. The result shows that the prediction fits the data well, and the effect of coefficient of imitation is greater than that of innovation. This implies that people who adopted Venmo are more likely to be under the influence of interpersonal recommendations from their peers, while fewer people learn about the new technology through external sources. These results are consistent with other studies which analyze the diffusion of innovative products and financial technologies in the payment service industry. For example, Kapur et al. (2019) estimates the adoption patterns of mobile payments in India using Bass diffusion model and finds the coefficient of innovation to be 0.043 and that of imitation to be 0.058. Hinayon (2020) estimates and provides estimates on the rate of the diffusion of debit cards and credit cards in seven ASEAN countrie and finds a larger coefficient of imitation in most of the countries. Table B.3 summarizes the results from Kapur et al. (2019) and Hinayon (2020).

Figure 3.7 and Figure 3.8 illustrate the predicted post-introduction trends in the consumer adoption and usage probabilities of the new payment instruments, respectively. For all simulations, I assume that the merchant acceptance probabilities are fixed at 50%. The results show that the usage/adoption probabilities generally exhibit a S-shaped curve after the introduction of the new products. Overall, the adoption and usage stay flat in the first two years and the start to grow rapidly after the 2nd year after introduction. The peak of adoption/usage generally occur between the 3rd and 4th year after the introduction and gradually converge after the 6th year. The credit-like NPI exhibits the highest growth rate in the usage probabilities compared to cash-like and debit-like NPIs, despite the fact that they are under the same Bass parameters. On the other hand, the growth rate of adoption probabilities are similar across the three alternative NPIs, even though the credit-like NPI adoption probabilities are higher than the other two in every period.

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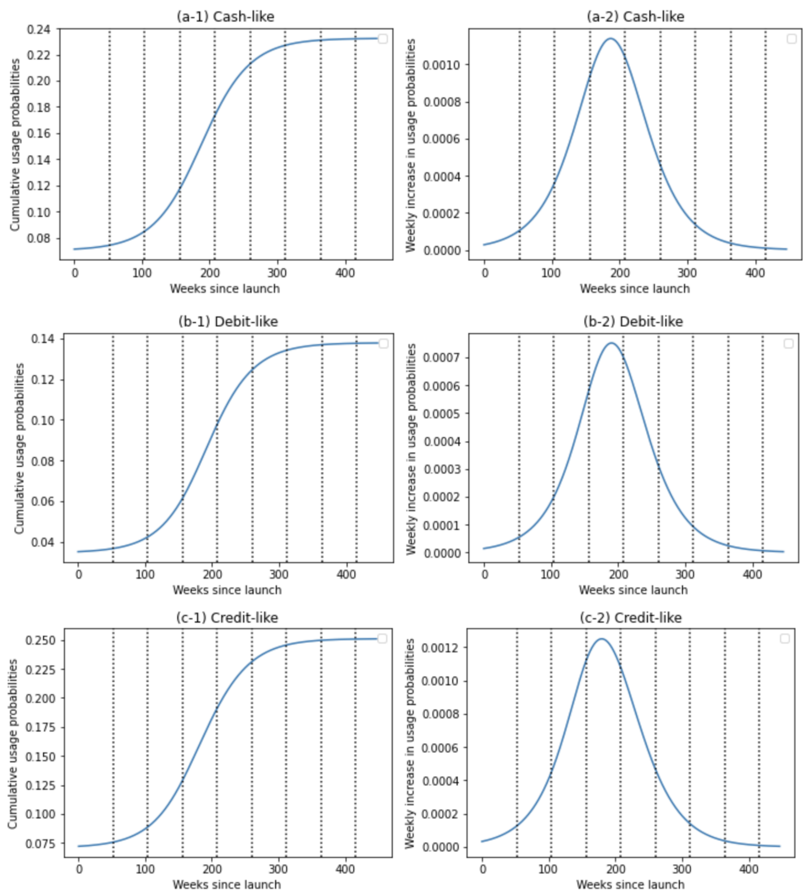
[7] In the fourth quarter of 2018, Venmo acquired Hyperwallet and iZettle, which increased the user account by 4.7 millions. In the first quarter of 2020, Venmo acquired Honey which increased the number of accounts by 10 millions.

I also compute the changes in consumer surplus during the diffusion of consumer awareness. The idea is to measure how much welfare improvements the consumer would gain if we allow for a faster diffusion of information. Similar to Huynh et al. (2020) and Huynh et al. (2021), I define each consumer's consumer surplus as the expected maximum utility that a consumer can obtain in the adoption stage. Then I calculate the welfare gains in each period after the introduction by computing the differences in the average consumer surplus before and after the introduction of the new payment instruments. Since consumer surplus tends to increase with the size of choice sets, to make comparable comparisons, I increase the choice set in the pre-introduction period by making exact copies for each of the original adoption bundles. Recall that the post-introduction choice set is simply the pre-introduction adoption bundles plus each of the pre-introduction adoption bundles expanded with the new payment instrument. This allows us to compare the pre- and post-introduction consumer surplus with the same size of the choice set, while ensuring that the new payment instrument will never be used in the pre-introduction period.

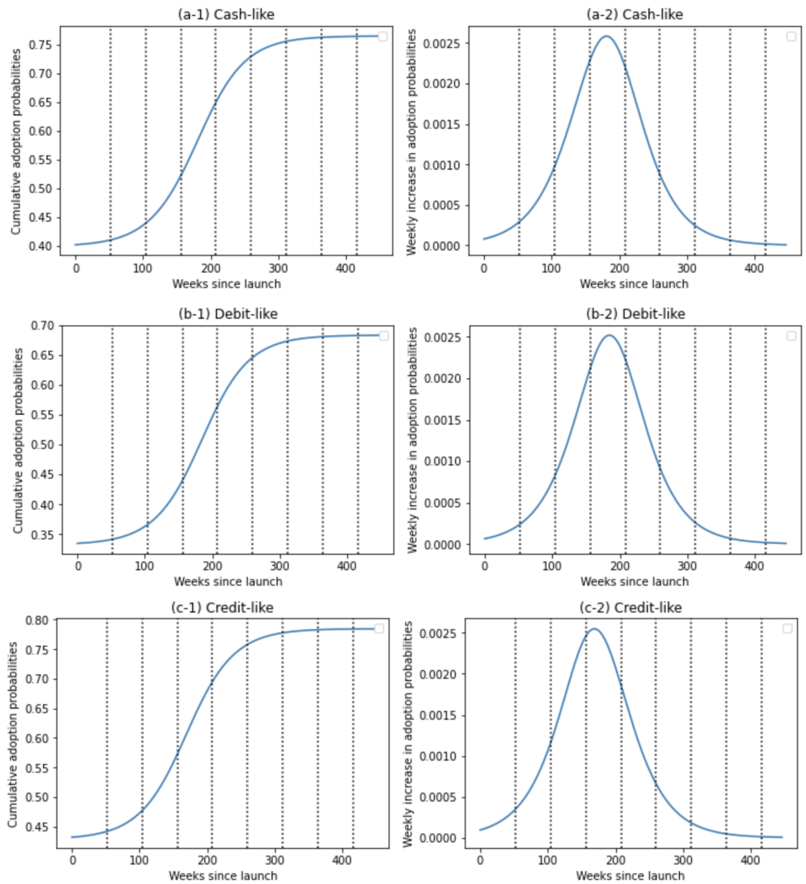
Figure 3.9 illustrates the predicted weekly trend of the consumer surplus (left) and the welfare gains (right) after the introduction of the new payment instruments, assuming a 50% merchant acceptance rate of the new payment instrument. The result shows that credit-like NPI generates higher utilities both in terms of the level and the welfare gain in every period compared to other new payment instruments. Interestingly, the results show that there would be a drop in consumer surplus in the beginning of the introduction of the new products. For example, the credit-like NPI takes 137 weeks (2.62 years) to generate positive gains in average consumer surplus after the introduction, while the cash-like NPI takes 144 weeks (2.76 years) and the debit-like NPI takes 192 weeks (3.68 years). The consumer surplus gradually increases as more and more people are informed about the merchant acceptance decision, and more people decide to adopt and use the new payment instruments. This suggests that consumer awareness plays an important role in affecting the success of the new payment instruments, and there is an impactful welfare loss associated with the failure of information diffusion.

Figure 3.7: Predicted trend of cumulative (left) and weekly added (right) usage probabilities of NPIs at 50% merchant acceptance.



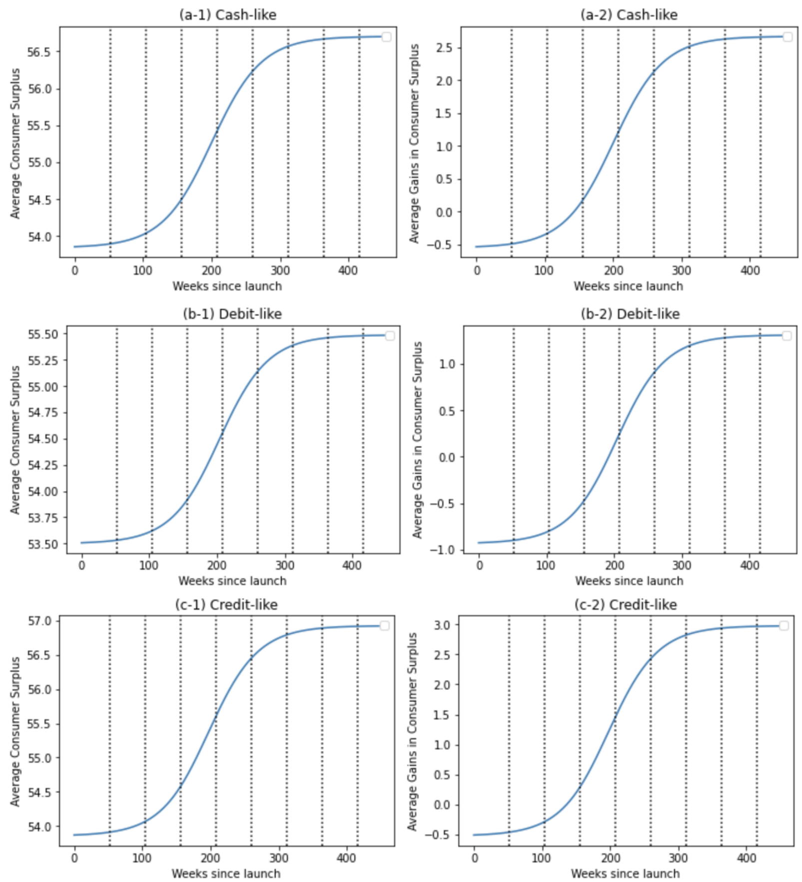
Notes: The left panel plots the predicted post-introduction cumulative usage probabilities of the new payment instruments (NPI), and the right panel plots the predicted increase in usage probabilities of the NPIs using the Bass Diffusion Model. For each iteration, I update the consumer awareness (i.e. inform probabilities) using the Bass diffusion model and calculate the resulting outcomes on consumer usage probabilities. The prediction is made in weeks and I denote the yearly intervals with the vertical black dotted lines.

Figure 3.8: Predicted trend of cumulative (left) and weekly added (right) adoption probabilities of NPIs at 50% merchant acceptance.



Notes: The left panel plots the predicted post-introduction cumulative adoption probabilities of the new payment instruments (NPI), and the right panel plots the predicted increase in adoption probabilities of the NPIs using the Bass Diffusion Model. For each iteration, I update the consumer awareness (i.e. inform probabilities) using the Bass diffusion model and calculate the resulting outcomes on consumer adoption probabilities. The prediction is made in weeks and I denote the yearly intervals with the vertical black dotted lines.

Figure 3.9: Predicted trend of the level (left) and gains (right) of the average consumer surplus after the introduction of the NPIs at 50% merchant acceptance (weekly, CAD).



Notes: The left panel plots the estimated post-introduction average consumer surplus after the introduction of the new payment instruments (NPI), and the right panel plots the estimated changes in average consumer surplus compared to the pre-introduction period. The consumer surplus is prorated to weekly values in Canadian Dollars. The vertical dotted lines represents yearly intervals.

Table 3.3: Estimation of γ and λ using Venmo data

Parameter	Value
γ (Coefficient of innovation)	0.0002
λ (Coefficient of imitation)	0.0259

3.5 Conclusion

This paper extends the previous chapters by introducing dynamics in the consumer payment method choices through the diffusion of information. In particular, the structural model developed in Chapter 2 is extended such that consumers' uncertainties about merchant acceptance vary with different payment methods. Using the model estimates, I conduct a policy experiment where I introduce a hypothetical new payment method in the market. The simulation of the post-introduction consumer adoption and usage decisions shows that a new payment instrument that combines the best features of a credit card will be used the most at the point of sale, than a new payment instrument similar to cash or debit card. Furthermore, by changing the level of consumer awareness exogneously, it shows that consumer awareness has significant effect in driving consumer adoption and usage choices. Assuming different consumer awareness toward different payment methods generate significantly stronger effects.

To consider the long-term effects of consumer awareness, I borrow the literature of diffusion and consider a diffusion process of consumer information using Bass diffusion model (Bass (1969)). The simulation results show that consumer adoption and usage exhibit a S-shaped curve after the introduction of the new products. Welfare analyses show that consumer surplus initially drops after the introduction, and gradually increases when consumers become more informed. It suggests that there is impactful welfare loss due to lack of consumer information, and it is important to develop measurements that ensure a fast diffusion of consumer knowledge for a new payment method to be successful.

This paper contributes to the literature by providing a framework to analyze the diffusion of new payment instrument in the payment card industry, which is absent in the literature. It is worth noting that in this paper, I do not model merchant acceptance decisions explicitly. Extending this analysis with merchant-side data that incorporate the equilibrium effects from the merchants would provide more refined estimates of the impacts of information. However, the results in this paper have shown to be robust under different assumptions on the level of merchant acceptance probabilities.

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Appendix A

THE IMPACT OF MARKET STRUCTURE CHANGES ON THE REGRESSIVE DISTRIBUTIONAL EFFECTS: A STRUCTURAL ESTIMATION OF CONSUMER PAYMENT CHOICES (CHAPTER 2)

Table A.1: Model estimates under alternative specifications: $\rho_l = \rho_h = 1\%$

Usage stage	**Type 1**		**Type 2**		**Adoption stage**		
	coef.	**S.E.**	**coef.**	**S.E.**		**coef.**	**S.E.**
Perception					*Debit*		
easiness to use	8.594***	0.400	8.453***	0.649	Constant	1.131	0.800
security	1.809***	0.207	0.672**	0.284	Type 2	-0.512	1.054
affordability	1.724***	0.162	2.240***	0.222	Num. of purchase	0.199***	0.048
Transaction					Total $ purchase	0.002	0.003
transaction cost	-0.933***	0.004	-0.818***	0.088	Age	-0.019	0.014
below $10 (debit)	-0.355***	0.089	-0.470***	0.127	*Debit + RBC*		
below $10 (credit)	-0.778***	0.104	0.004	0.111	Constant	-0.795	0.808
Match values					Type 2	0.341	1.058
Debit x grocery	0.062	0.057	0.440***	0.085	Num. of purchase	0.033	0.045
Debit x meal	-0.466***	0.065	-0.465***	0.080	Total $ purchase	0.000	0.003
Debit x other type	-0.217***	0.062	0.026	0.085	Age	-0.001	0.014
RBC x grocery	0.369***	0.101	0.763***	0.157	*Debit + TD*		
RBC x meal	0.097	0.135	-0.055	0.158	Constant	-0.750	0.823
RBC x other type	0.242**	0.117	0.571***	0.165	Type 2	0.348	1.060
TD x grocery	0.056	0.179	0.597***	0.223	Num. of purchase	-0.068	0.051
TD x meal	-0.332	0.219	-0.414*	0.234	Total $ purchase	0.000	0.003
TD x other type	0.049	0.186	0.654***	0.223	Age	0.002	0.014
CIBC x grocery	0.294**	0.148	0.720***	0.180	*Debit + CIBC*		
CIBC x meal	-0.396**	0.188	0.036	0.184	Constant	-0.671	0.817
CIBC x other type	0.154	0.172	0.609***	0.184	Type 2	0.423	1.059
BMO x grocery	0.273	0.177	0.789***	0.166	Num. of purchase	-0.008	0.047
BMO x meal	0.123	0.192	0.369**	0.162	Total $ purchase	-0.001	0.003
BMO x other type	-0.083	0.208	0.918***	0.160	Age	0.003	0.014
Other banks x grocery	0.125	0.079	0.910***	0.110	*Debit + BMO*		
Other banks x meal	-0.289***	0.089	0.218**	0.099	Constant	-1.393*	0.808
Other banks x other type	-0.085	0.085	0.606***	0.107	Type 2	0.697	1.057
					Num. of purchase	-0.029*	0.015
					Total $ purchase	0.000	0.003
					Age	0.012	0.014
					Debit + others		
					Constant	0.680	0.780
					Type 2	0.168	1.049
					Num. of purchase	0.011	0.039
					Total $ purchase	0.000	0.003
					Age	0.003	0.013

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

[2] $Likelihood = 12603.902$

Table A.2: Model estimates under alternative specifications: $\rho_l = \rho_h = 0$

Usage stage	**Type 1**		**Type 2**		**Adoption stage**		
	coef.	**S.E.**	**coef.**	**S.E.**		**coef.**	**S.E.**
Perception					***Debit***		
easiness to use	6.365***	(0.360)	8.114***	(0.640)	constant	1.164*	(0.678)
security	1.388***	(0.200)	0.650**	(0.276)	type 2 dummy	-0.625	(0.987)
affordability	1.875***	(0.159)	2.175***	(0.218)	no. of purchase	0.292**	(0.112)
Transaction					total $ purchase	-0.001	(0.003)
transaction cost	-0.918***	(0.010)	-0.815***	(0.014)	age	-0.019*	(0.011)
below $10 (debit)	-0.442***	(0.089)	-0.869***	(0.127)	***Debit + RBC***		
below $10 (credit)	-1.051***	(0.103)	-1.077***	(0.108)	constant	-0.715	(0.691)
Match values					type 2 dummy	0.289	(0.986)
Debit x grocery	0.026	(0.056)	0.400***	(0.084)	no. of purchase	0.025	(0.114)
Debit x meal	-0.485***	(0.065)	-0.472***	(0.080)	total $ purchase	0.001	(0.003)
Debit x other type	-0.248***	(0.063)	-0.007	(0.084)	age	-0.003	(0.011)
RBC x grocery	0.710***	(0.100)	1.087***	(0.154)	***Debit + TD***		
RBC x meal	0.370**	(0.130)	0.212	(0.152)	constant	-0.687	(0.705)
RBC x other type	0.572***	(0.115)	0.920***	(0.154)	type 2 dummy	0.302	(0.989)
TD x grocery	0.408**	(0.180)	0.978***	(0.222)	no. of purchase	-0.075	(0.117)
TD x meal	0.028	(0.204)	-0.204	(0.225)	total $ purchase	0.001	(0.003)
TD x other type	0.424**	(0.180)	1.029***	(0.215)	age	0.000	(0.011)
CIBC x grocery	0.600***	(0.147)	1.041***	(0.175)	***Debit + CIBC***		
CIBC x meal	-0.103	(0.178)	0.290	(0.177)	constant	-0.605***	(0.700)
CIBC x other type	0.458***	(0.169)	0.981***	(0.176)	type 2 dummy	0.372	(0.987)
BMO x grocery	0.541***	(0.178)	1.143***	(0.158)	no. of purchase	-0.018	(0.115)
BMO x meal	0.400**	(0.182)	0.672***	(0.155)	total $ purchase	-0.001	(0.003)
BMO x other type	0.351	(0.195)	1.270***	(0.155)	age	0.002	(0.011)
Other banks x grocery	0.449***	(0.077)	1.246***	(0.103)	***Debit + BMO***		
Other banks x meal	0.000	(0.086)	0.498***	(0.092)	constant	-1.225*	(0.649)
Other banks x other type	0.265**	(0.083)	0.962***	(0.099)	type 2 dummy	0.598	(0.980)
					no. of purchase	-0.048	(0.116)
					total $ purchase	0.001	(0.003)
					age	0.010	(0.010)
					Debit + others		
					constant	0.620	(0.656)
					type 2 dummy	0.150	(0.977)
					no. of purchase	-0.009	(0.111)
					total $ purchase	0.000	(0.003)
					age	0.005	(0.010)

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

[2] $Likelihood = 12813.061$

Appendix B

INFORMATION DIFFUSION AND THE DEMAND FOR NEW PAYMENT INSTRUMENTS (CHAPTER 3)

Table B.1: Parameter estimates assuming full information

Usage stage	**Type 1**		**Type 2**		**Adoption stage**		
	coef.	**S.E.**	**coef.**	**S.E.**		**coef.**	**S.E.**
Perception					*Debit*		
easiness to use	6.273***	(0.380)	8.041***	(0.616)	constant	1.589***	(0.570)
risk	1.297***	(0.188)	0.723**	(0.287)	type 2 dummy	-0.337	(0.430)
affordability	2.076***	(0.160)	2.486***	(0.228)	no. of purchase	0.052	(0.084)
Transaction					total $ purchase	0.002	(0.002)
transaction price	-2.548***	(0.180)	-3.567***	(0.270)	age	-0.026***	(0.010)
below $10 (debit)	-0.838***	(0.079)	-1.260***	(0.112)	***Debit + RBC***		
below $10 (credit)	-1.406***	(0.086)	-1.502***	(0.099)	constant	-0.868	(0.576)
Match values					type 2 dummy	0.471	(0.437)
Debit x grocery	0.837***	(0.070)	1.508***	(0.106)	no. of purchase	-0.062	(0.085)
Debit x meal	0.490***	(0.082)	0.949***	(0.108)	total $ purchase	-0.001	(0.002)
Debit x other type	0.513***	(0.076)	1.054***	(0.106)	age	0.002	(0.009)
RBC x grocery	0.158	(0.110)	0.531***	(0.162)	***Debit + TD***		
RBC x meal	0.040	(0.143)	-0.084	(0.168)	constant	-0.822	(0.596)
RBC x other type	0.011	(0.127)	0.194	(0.181)	type 2 dummy	0.502	(0.444)
TD x grocery	0.072	(0.186)	0.470**	(0.234)	no. of purchase	-0.176**	(0.088)
TD x meal	-0.241	(0.232)	-0.188	(0.268)	total $ purchase	-0.001	(0.002)
TD x other type	-0.057	(0.195)	0.394	(0.241)	age	0.005	(0.010)
CIBC x grocery	0.215	(0.152)	0.495***	(0.190)	***Debit + CIBC***		
CIBC x meal	-0.314	(0.200)	0.196	(0.197)	constant	-0.759	(0.586)
CIBC x other type	0.132	(0.180)	0.388*	(0.202)	type 2 dummy	0.601	(0.438)
BMO x grocery	0.209	(0.181)	0.517***	(0.175)	no. of purchase	-0.104	(0.086)
BMO x meal	0.207	(0.196)	0.345*	(0.177)	total $ purchase	-0.002	(0.002)
BMO x other type	-0.157	(0.212)	0.622***	(0.177)	age	0.006	(0.010)
Other banks x grocery	0.092	(0.094)	0.682***	(0.129)	***Debit + BMO***		
Other banks x meal	-0.148	(0.103)	0.255**	(0.125)	constant	-1.676	(0.598)
Other banks x other type	-0.164	(0.100)	0.358***	(0.129)	type 2 dummy	0.937**	(0.439)
					no. of purchase	-0.137	(0.087)
					total $ purchase	0.000	(0.002)
					age	0.018*	(0.010)
					Debit + others		
					constant	1.095**	(0.537)
					type 2 dummy	0.298	(0.421)
					no. of purchase	-0.110	(0.081)
					total $ purchase	-0.001	(0.002)
					age	-0.002	(0.009)

[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

[2] $Likelihood = 13360.96$

Table B.2: Parameter estimates assuming no information

Usage stage	**Type 1**		**Type 2**		**Adoption stage**		
	coef.	**S.E.**	**coef.**	**S.E.**		**coef.**	**S.E.**
Perception					*Debit*		
easiness to use	7.867***	(0.476)	11.349***	(0.946)	constant	1.819***	(0.567)
risk	1.640***	(0.236)	0.958**	(0.405)	type 2 dummy	0.375	(0.542)
affordability	2.312***	(0.195)	3.697***	(0.300)	no. of purchase	-0.247	(0.078)
Transaction					total $ purchase	-0.003	(0.003)
transaction price	-5.527***	(0.688)	-6.869***	(1.130)	age	-0.022	(0.010)
below $10 (debit)	-0.895***	(0.114)	-1.780***	(0.197)	***Debit + RBC***		
below $10 (credit)	-1.485***	(0.123)	-2.136***	(0.199)	constant	-0.491	(0.576)
Match values					type 2 dummy	1.176**	(0.568)
Debit x grocery	2.603***	(0.217)	3.934***	(0.352)	no. of purchase	-0.423	(0.079)
Debit x meal	2.142***	(0.222)	3.230***	(0.342)	total $ purchase	-0.004	(0.003)
Debit x other type	2.112***	(0.215)	3.402***	(0.343)	age	0.002	(0.009)
RBC x grocery	0.888***	(0.182)	1.759***	(0.311)	***Debit + TD***		
RBC x meal	0.452**	(0.201)	1.083***	(0.304)	constant	-0.546	(0.599)
RBC x other type	0.300	(0.203)	1.496***	(0.321)	type 2 dummy	1.379**	(0.577)
TD x grocery	0.372	(0.224)	1.246***	(0.353)	no. of purchase	-0.465	(0.082)
TD x meal	0.206	(0.245)	0.648	(0.357)	total $ purchase	-0.004	(0.003)
TD x other type	0.396	(0.213)	1.369***	(0.347)	age	0.007	(0.010)
CIBC x grocery	0.729***	(0.197)	1.615***	(0.320)	***Debit + CIBC***		
CIBC x meal	0.174	(0.221)	1.030***	(0.317)	constant	-0.345	(0.589)
CIBC x other type	0.188	(0.216)	1.445***	(0.330)	type 2 dummy	1.141**	(0.572)
BMO x grocery	0.524**	(0.211)	1.814***	(0.314)	no. of purchase	-0.414	(0.081)
BMO x meal	0.494**	(0.213)	1.295***	(0.306)	total $ purchase	-0.005	(0.003)
BMO x other type	0.194	(0.226)	1.632***	(0.316)	age	0.006	(0.009)
Other banks x grocery	0.556***	(0.167)	1.758***	(0.299)	***Debit + BMO***		
Other banks x meal	0.218	(0.173)	1.195***	(0.290)	constant	-1.226	(0.603)
Other banks x other type	0.181	(0.175)	1.398***	(0.307)	type 2 dummy	1.053	(0.570)
					no. of purchase	-0.428	(0.082)
					total $ purchase	-0.004	(0.003)
					age	0.017	(0.010)
					Debit + others		
					constant	1.437***	(0.533)
					type 2 dummy	0.617	(0.535)
					no. of purchase	-0.431	(0.073)
					total $ purchase	-0.005	(0.003)
					age	0.003	(0.009)

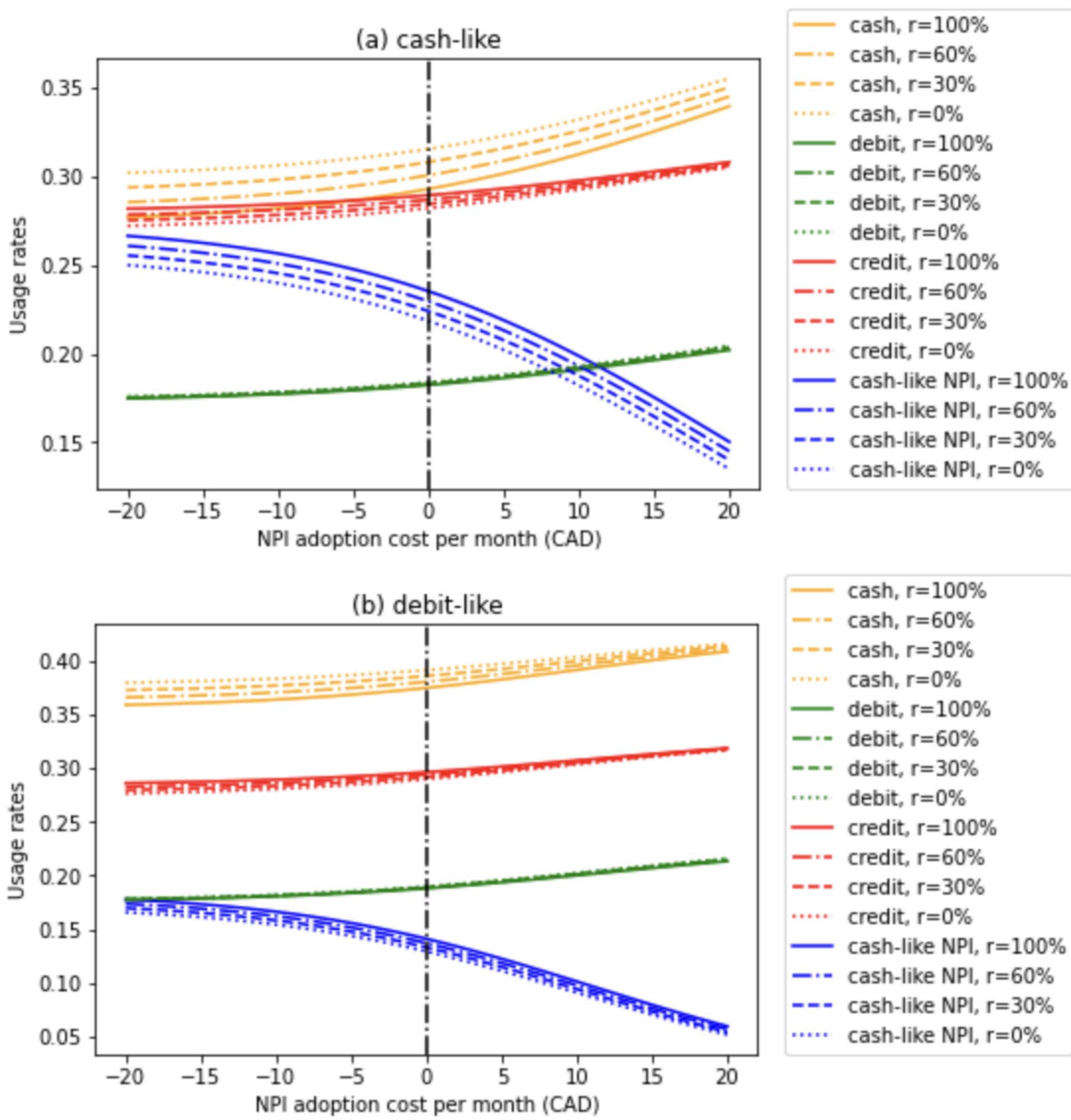
[1] Note: Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***.

[2] $Likelihood = 13413.01$

Table B.3: Comparisons on Bass diffusion model parameters in cashless payment services

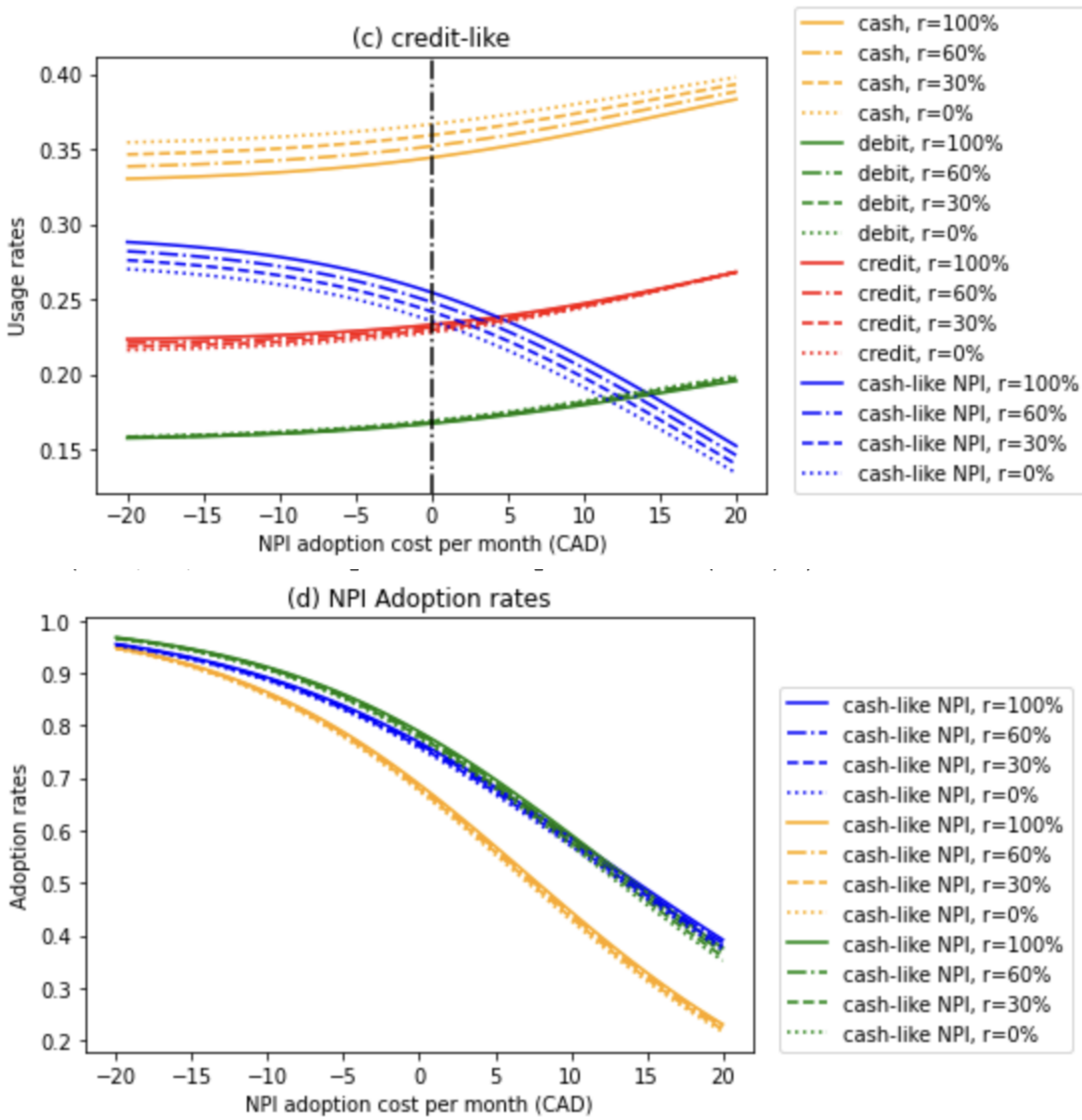
	γ (Coefficient of innovation)	λ (Coefficient of imitation)
Hinayon (2020)		
Indonesia	0.00067	8.49598
Vietnam	0.00910	2.87670
Thailand	0.04204	1.36866
Malaysia	0.03784	0.85384
Singapore	0.44649	0.19368
Philippines	0.00532	12.87907
Cambodia	0.00635	151.34019
Kapur (2019)		
India	0.043	0.058

Figure B.1: Usage probabilities and NPI adoption given the adoption costs and merchant acceptance rates (r) of the NPI.



Notes: This figure plots the estimated usage and adoption probabilities under different values of adoption costs and merchant acceptance rates of the new payment instrument.

Figure B.1: Usage probabilities and NPI adoption probabilities given the adoption costs and merchant acceptance rates (r) of the NPI.



Notes: This figure plots the estimated usage and adoption probabilities of alternative NPIs under different values of adoption costs and merchant acceptance rates of the new payment instrument.

Figure B.2: Adoption and usage probabilities given different levels of inform probabilities, assuming no acceptance of debit or credit card payments.

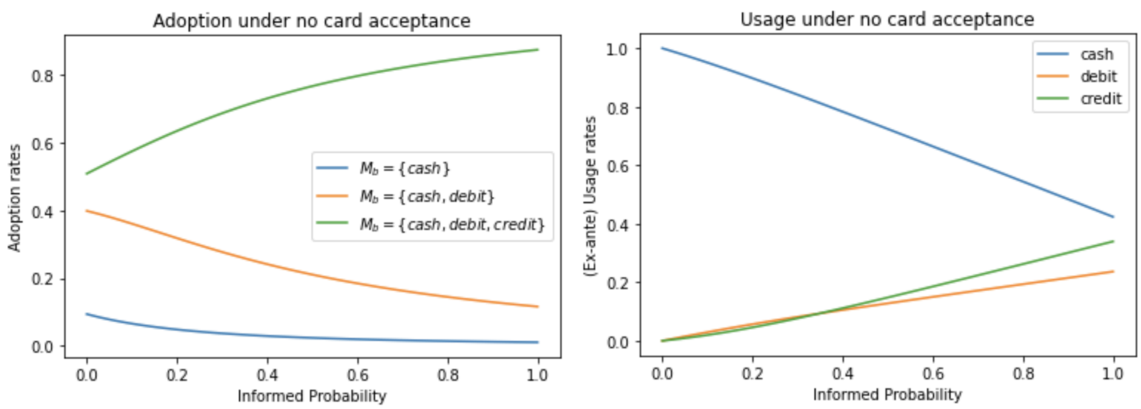


Figure B.3: Adoption and usage probabilities given different levels of inform probabilities, assuming universal acceptance of debit and credit card payments.

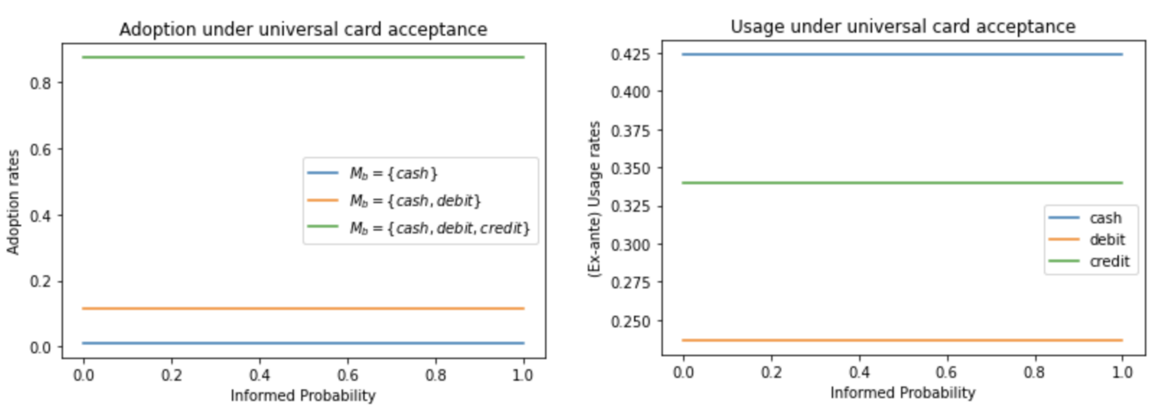


Figure B.4: Fitted and actual weekly growth trend of Venmo