Substitution Patterns among Cash, Credit Cards, and Debit Cards: Evidence from Canadian Shopping Diary Data

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Abstract

This paper address a question of how much cash transaction would decrease at the point-of-sale between consumers and merchants, if the merchants must accept any payment methods regardless of the transaction values. The question is motivated by policy makers' recent interest in understanding the demand for cash under such a counterfactual scenario, as many studies reveal that cash is a still dominant method of payment for small-value transactions. I estimate the generalized multinomial logit model (G-MNL) of consumers' payment choice, using newly collected individual-level three-day shopping diary data from Canada, which enables us to separately identify the effects of demand and the supply factors of payment choices.

Keywords: Cash demand, Choice of Payment method, Consumer financial behavior, Generalized multinomial logit model

JEL Classification: G2, D1, C2

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1 Introduction

In recent years, consumers' method of payment choice has attracted the attention of researchers and policy-makers, as the rise of new payment technologies, such as mobile payment and contactless credit cards. Despite such emergence of new technologies, cash still keeps its dominant position at the point-of-sale, in particular, for small-value transactions. This phenomena is quite ubiquitous all over the world. For example, recent studies on the consumer micro-payment by Klee (2008) and Arango, Huynh and Sabetti (2011) reveal that the dominant payment method in the U.S. and Canada, respectively, is cash, if the transaction value is less than 25 dollars. At the same time, they have also reported credit and debit cards' transactions increases as the transaction values increase. Similar findings are also documented by Bolt, Jonker and van Renselaar (2010) and Simon, Simith and West (2010) for Netherlands and Australia, respectively.

This dominance of cash usage for small value transactions at the point-of-sale might be partially due to the supply side problem: Many merchants tend to reject the use of credit card for small value transactions to exempt from paying the interchange fees.[1] At the same time, however, it might be due to the demand side problem: Many consumers prefer paying in cash for its ease of use and speed of settlements.[2] Such observations bring up a following question: how would consumers pay at the point-of-sale, if the merchants must accept any payment methods regardless of the transaction values? This question is challenging because it is difficult to separately identify supply side and demand side factors. The distinction is, however, essential to understand the mechanism of demand for cash, and to answer various policy-related questions.

This paper attempts to answer the question by estimating consumers' payment choice model at the point-of-sale, using unique Canadian three-days shopping diary data. It has two key features; "quasi-panel" structure, and "perceived" acceptance. First, thought the number of shopping opportunities is not constant across the samples, we can observe multiple transactions for each individual with slightly different shopping opportunities, in terms of shopping types and transaction values, which enables us to extract consumer heterogeneity. Observing only one transaction per person would not be enough to identify the individual specific effect of choosing a particular method of payment. Second, consumers reported the methods of payment that would have been accepted at each shopping opportunity, as well as

[1]For debit cards, merchants need to pay fixed amount of interchange fees per transaction to network providers.

[2]See Section 2 for more detailed data.

actual method of payment they used. Although this self-reported information might contain huge measurement errors, it is still useful to limit the consumers' choice sets. These two features of the data, as a result, enable us to separately identify the demand side factors from the supply side factors.

Payment choice is modelled as the generalized multinomial logit (G-MNL) model, proposed by Fiebig, Keane, Louviere and Wasi (2010), to capture two key heterogeneities observed in data. When closely looking at the data, we can potentially categorize consumers into four groups: (i) consumers who only use cash (cash-only users), (ii) consumers who use debit cards whenever accepted and cash otherwise (debit card committed users), (iii) consumers who use credit cards whenever accepted and cash otherwise (credit card committed users), and (iv) consumers who use all three methods of payment (mixing users). This observation suggests that some sets of consumers have strong preference for a particular method of payment, such as credit cards or debit cards, and use them as long as these methods are accepted. Thus, firstly, the model should be able to capture such a heterogeneous taste for each method of payment. Secondly, the model also should be able to capture the heterogeneity in "scale," meaning that the vector of utilities for each choice is heterogeneously scaled up or down proportionally for some consumers to let their choices look randomly.[3] This "scale" heterogeneity allows us to have consumers categorized in (iv).

The importance of such individual heterogeneities can be confirmed in the estimation results. The preliminary estimation results show that the parameters that govern individual heterogeneities are statistically and economically significant. [TBA]

Simulation results should be added [TBA]

Literature Reviews should be added [TBA]

This paper is organized as follow: Section 2 describes the data, and displays some summary statistics and motivating facts for modelling framework. In Section 3, I present the model and the estimation procedure. The estimation results and the counterfactual simulation results are presented in Section 4 and 5, respectively. Section 6 concludes.

[3]This is observationally equivalent that the standard deviation of the idiosyncratic error term might be greater or smaller than for others. See Fiebig, Keane, Louviere and Wasi (2010).

2 The Data and Motivating Facts

2.1 Overview of the Methods of Payment Survey

The data used in this study is the 2009 Methods of Payment Survey, conducted by the Bank of Canada in 2009. The survey consists of two parts: a Survey Questionnaire and a three-day Diary Survery.[4] Survey Questionnaire (hereinafter SQ) includes some questions about demographic information, such as age, annual income, gender, education level, marital status, employment status, and so on. Moreover, it includes his/her main bank account and main credit card, which enables me to associate with the number of free debit transactions per month, and credit cards' rewards and annual fees.[5] SQ also contains some attitudinal information, such as perceptions of convenience and safety for some particular methods of payment. The importance of such attitudinal data is emphasized in Harris and Keane (1999) and Ching and Hayashi (2010).

The other part, Diary Survey Instrument (hereinafter DSI), asks all shopping data, including the transaction value, types of transaction, the perceived accepted methods of payment, the method of payment chosen, and major reasons for their choice, for consecutive three days. There are two strengths of this data; "quasi-panel" structure of the data and "perceived" acceptance. As for "quasi-panel" structure, the data provide multiple shopping observations for each individual with slightly different shopping opportunities, which allows us to study the source of individual heterogeneity. Comparing to some studies using transaction-level (micro) such as Klee (2008) and Arango, Huynh and Sabetti (2011), I can extract the individual heterogeneity more with this survey data. Observing multiple shopping opportunities allows us to have individual-specific effects for method of payment choice. Moreover, "perceived" acceptance, another feature of this data, is also prominent aspect of this survey. When consumers answer the each transaction detail, they needed to answer what methods would have been accepted. Knowing this information, we can limit the choice sets for each transaction. Therefore, together with the characteristics of the multiple observations per individual, we can separately identify the demand side factors from the supply side factors.

The data is sampled from two sources; on-line access panel, which is administrated by a market research firm, and off-line panel. As it is not representative data of Canada, I need

[4]Originally, there are about 6,800 respondents for SQ part, and among them about 3190 respondents proceed to DSI survey. For this study, I need both information. Therefore, I limit the sample to the respondents who finished both SQ and DSI.

[5]In Canada, about half of the banking accounts offer the unlimited free debit transactions, whereas the rest of the bank accounts offer only several times or zero free debit card transactions and consumers need to pay fees after attaining the upper limit of free transactions, depending on their banking accounts.

to use a sample weight to correct the sampling bias.[6]

2.2 Summary Statistics

The analysis is restricted to the subset of the original samples. First, I show some statistics for all samples, and then for sub-samples who recorded at least four shopping opportunities.[7] In this subsection, I describe some important statistics:(1) the number of shopping opportunities and the average expenditure, (2) attitudinal data, and (3) other key demographic variables.

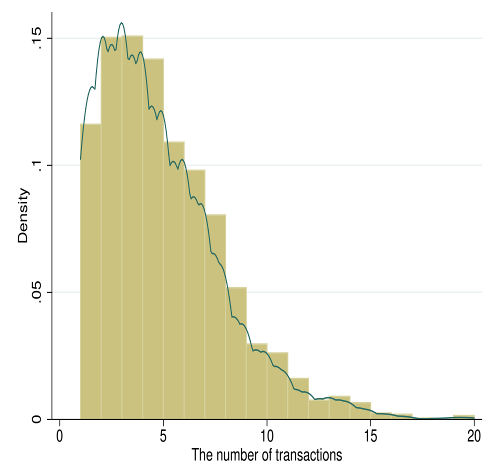
2.2.1 Heterogeneities in Payment Choice

Table 1 and Figure 1 show that how many times of shopping opportunities each individual had during three days. Not surprisingly, each individual has 4.76 times of shopping opportunities during three days on average, implying that more than one time of shopping occasions per day. The fact that we have multiple transactions per person immediately raises a question: Do we observe any individual-specific patterns in payment choices?

TABLE 1: Number of Shopping Times

	Unweighted		Weighted
	Freq.	Percent	Percent
1	239	12.08	10.87
2	304	15.36	14.45
3	303	15.31	13.82
4	277	14.00	15.34
5	225	11.37	10.78
6	191	9.65	9.34
7	154	7.78	8.70
8	98	4.95	6.57
9 or more	188	9.50	10.13
Total	1,979	100.00	100.00

FIGURE 1: # of Shoppings (Unweighted)



I show the consumers' tendencies of payment choice in Table 2. To make this table, first I categorize the samples into four types by their methods of payment choice patterns, regardless of their number of shopping opportunities. The seven types can be found the first column: (1) Cash users, who only use cash, displayed in the first row, (2) Debit-committed users who mainly use debit cards, and cash for some cases, displayed in the third and fourth rows,

[6]For more details, see Arango, Huynh and Sabetti (2011) and Arango and Welte (n.d.).

[7]"All samples" means the samples who have remained after dropping by some criteria. A detailed construction method of the estimation samples is described in the Appendix.

(3) Credit-committed users who mostly use credit cards, and cash for some cases, displayed in the sixth and seventh rows, and (4) Non-committed (Mixed) users who use both credit cards and debit cards, and cash, displayed in the ninth and tenth rows. Then, I count the number of individuals who fall into each category, and calculate their numbers of shopping opportunities and average transaction values, depending on their types.

There are two important observations in this table. The first and the most important observation is the fact that the fractions of debit-committed users and credit-committed are sizeable, accounting one-third and one-fourth of total number of individuals if we limit the samples with more than 6 shopping opportunities, even though they have more than 9 times of shopping opportunities on average. This observation suggests that the substitution between credit and debit cards are very small for those committed users. Small changes in transaction values do not necessary enough them to switch their payment methods from debit to credit, or credit to debit. And thus, the model should take into account the individual-specific effects for their preferred payment methods. Secondly, there exist some mixed users who use all three methods quite randomly. Although the average numbers of shopping opportunities are slightly larger than the corresponding numbers for other types, the average transaction values for them are almost identical to the corresponding numbers for credit-committed users. Thus, they intentionally or unintentionally use three methods, which inspires me to use a generalized-multinomial logit model.

2.2.2 Perceived Acceptance

In addition to the consumer's side, I also describe the supply side information, "perceived acceptance," which might have some measurement errors.

2.2.3 Attitudinal and Demographic Data

In the questionnaire, respondents were asked to rate the usage of cash, credit cards, and debit cards for (1) the ease of use, (2) record keeping capabilities, and (3)the cost of use, using five points scale.[8] For identify perspective, I normalize those three rating by cash. Namely, ease of use for credit cards and debit cards are obtained by

$$a_{ijl} =$$

for $j =$ credit and debit, and $l =$ the ease of use, record keeping, and the cost of use.

[8]For example, a respondent needs to choose a number (1 to 5) to rate the ease of use for the cash, credit cards, and debit cards.

TABLE 2: Patterns of Payment Choice

	All Samples (No Restrictions)				Samples with more than 3 Shopping Opportunities				Sample with more than 6 Shopping Opportunities			
Type of Consumers	#of obs.	%	avg # of shopping	avg TV	#of obs.	%	avg # of shopping	avg TV	#of obs.	%	avg # of shopping	avg TV
(1) Cash Users	**391**	19.76	4.5	19.7	**111**	9.80	6.4	18.1	**24**	5.45	9.5	17.4
(2) Debit Users												
Only Debit	**201**	10.16	4.4	44.8	**45**	3.97	6.8	42.3	**13**	2.95	9.4	43.5
Cash & Debit	**497**	25.11	6.6	32.1	**361**	31.86	7.2	31.0	**139**	31.59	9.1	30.2
(3) Credit Users												
Only Credit	**152**	7.68	4.5	71.7	**40**	3.53	6.5	62.3	**12**	2.73	8.7	52.5
Cash & Credit	**393**	19.86	6.5	44.7	**287**	25.33	7.1	40.4	**105**	23.86	9.1	39.5
(4) Mixed Users												
Debit & Credit	**90**	4.55	4.8	56.9	**47**	4.15	5.8	48.3	**9**	2.05	8.3	58.9
All three	**255**	12.89	8.6	43.3	**242**	21.36	8.8	42.6	**138**	31.36	10.2	39.3
Total # of individuals	**1,979**				**1,133**				**440**			
Total # of transactions	**9,057**		4.6	39.5	**7,301**		6.4	37.1	**3,922**		8.9	36.2

FIGURE 2: Perception 1: Ease of Use

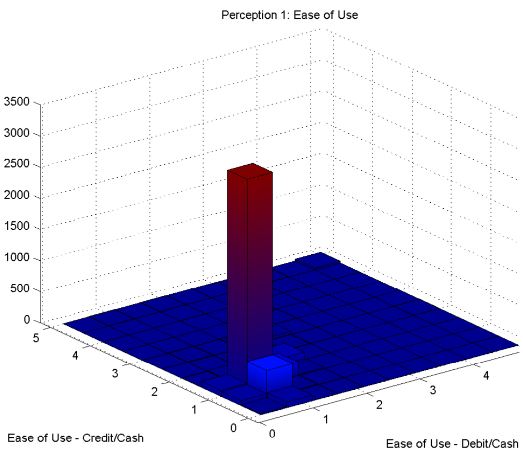


FIGURE 3: Perception 3: Acceptance

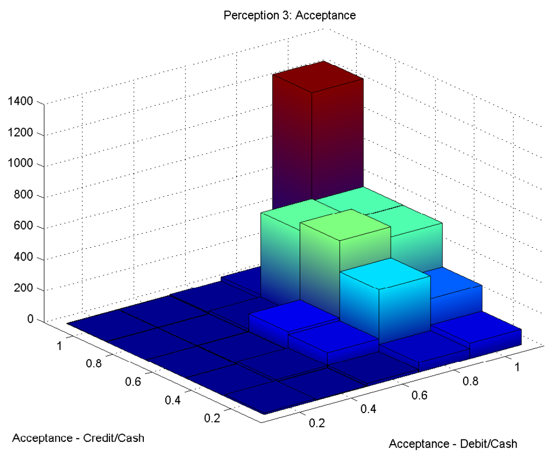
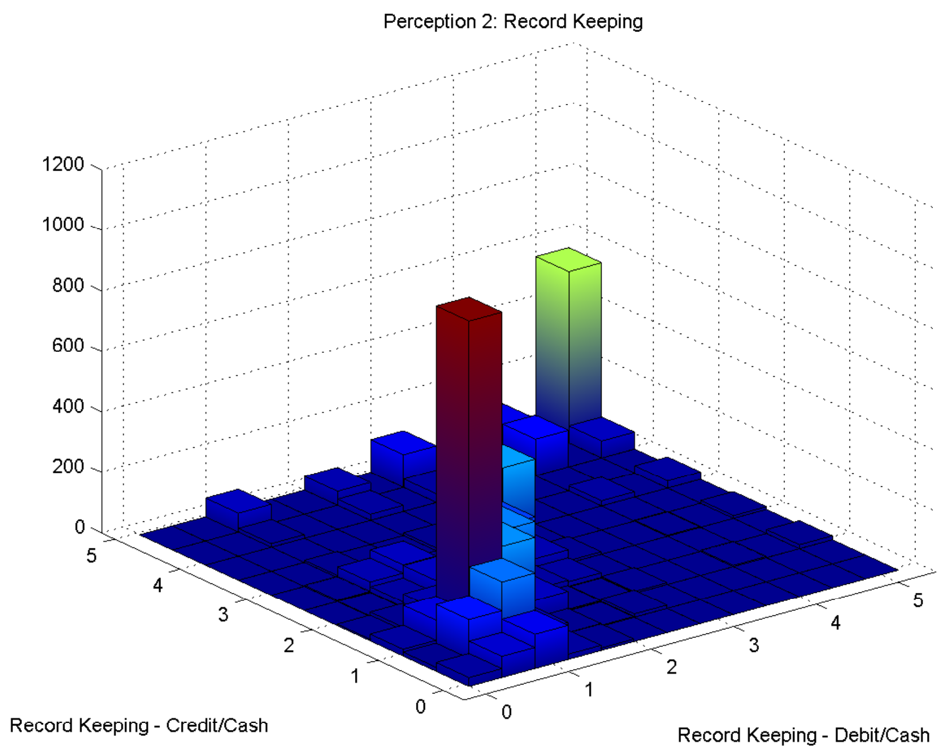


FIGURE 4: Perception 2: Record Keeping



3 Econometric Model

This section provides a payment choice model for consumers. Motivated by some patterns that I display in Section 2, the generalized multinomial logit (hereinafter G-MNL) model, proposed by Fiebig, Keane, Louviere and Wasi (2010), is exploited in this paper. One of the prominent features of this G-MNL model is capability of capturing consumer heterogeneity in two ways: the heterogeneous taste (individual-level fixed effect) in payment choice, and the scale heterogeneity (for some individuals, methods of payment choice is more random).

3.1 Payment choice model

Suppose the utility function of individual i, $i = 1, 2, \cdots, N$, at shopping opportunity t, $t = 1, 2, \cdots, T_i$, from choosing payment method $j \in \mathscr{J}_{it}$ is given by:

$$u_{ijt} = \boldsymbol{X}_{it}\boldsymbol{\beta}_i + \boldsymbol{A}_{ij}\boldsymbol{\gamma} + \boldsymbol{D}_j\boldsymbol{\delta} + \varepsilon_{ijt}, \tag{1}$$

with

$$\begin{aligned} \beta_{im} &= \sigma_i\beta + \gamma\eta_i + (1-\gamma)\sigma_i\eta_i, && (2)\\ \sigma_i &= \exp(\bar{\sigma} + \tau\epsilon_{i0}), \quad \text{with} \quad \epsilon_{i0} \sim N(0,1), && (3) \end{aligned}$$

where $\boldsymbol{X}_{it}$ is a M_X-dimensional vector of shopping characteristics, $\boldsymbol{A}_{ij}$ is a M_a-dimensional vector of individual i' attitudinal characteristics towards the payment method j, $\boldsymbol{D}_i$ is a M_d-dimensional vector of individual i's demographic information, $\boldsymbol{\beta}_i$, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ are coefficients vectors, and ε_{ijt} is an i.i.d. random utility shock which follows Type 1 extreme value distribution, η_i is individual-specific deviation from the mean which follows a standard normal or log-normal distribution, and ϵ_{i0} is an scale heterogeneity which follows, again, a standard normal distribution. Both shocks of (σ_i, ϵ_i) captures the individual heterogeneity.

The importance of η_i is capturing the individual-specific taste heterogeneity. This term enables individuals to have some tendency to choose specific choice, such as debit card committed users and credit card committed users. The reason why I use a random effect model to capture individual heterogeneity in this model is the fact that we can observe only one or two times of shopping for some individuals. As *** suggested, in order to deal with η_i as individual fixed effects, we need to have 8 or more period for each individuals.[9] In this model, η_i is assumed to follow the multivariate normal distribution, which rules out the correlation

[9] The further investigation is required for this modelling: I will try a fixed effect estimator by limiting the estimation samples to individuals who had more than 8 shopping opportunities.

in tastes across characteristics. It is, however, allows us to have correlation in taste across alternatives.

The other heterogeneity for changing the scale is captured by σ_i. The reason why we have an exponential operator in equation (3) is to avoid the negative scaling. Notice that the class of this model includes a lot of models as special cases, as Fiebig, Keane, Louviere and Wasi (2010) mention. For example, assuming $\sigma_i = 1$ for all m, this model will be the identical model to Train (1998). Assuming $\sigma_i = 1$ and $\gamma = 1$, β_{im} can be simplified as $\beta_{im} = \beta + \eta_i$, which is the standard random coefficient model, or heterogeneous mixed logit model.

The choice set for consumer i at shopping opportunity t is defined by $\mathscr{J}_{it}$. Fortunately, we can partially observe this information. Although it might have measurement errors, we can observe the consumers' "perceived" acceptance at the time of transaction and I use that information to limit the choice set for consumers.

3.2 Maximum Simulated Likelihood Estimates

Given the parameter values $\boldsymbol{\theta}$ and random draw of (σ_i, η_i), we can obtain the analytical choice probability of individual i choosing payment method j at the shopping opportunity t as

$$\mathrm{P}(y_{ijt} = 1 | \boldsymbol{X}, \boldsymbol{\theta}, \sigma_i, \eta_i) = \frac{\exp(\boldsymbol{X}'_{ijt}\boldsymbol{\beta}_i)}{\sum_{l \in \mathscr{J}_{it}} \exp(\boldsymbol{X}'_{ilt}\boldsymbol{\beta}_i)}. \tag{4}$$

Using this choice probability, the likelihood contribution for each person is given by:

$$\mathscr{L}_i(\boldsymbol{\theta}) = \prod_{t=1}^{T_i} \prod_j \left[P(y_{ijt} = 1 | \boldsymbol{X}, \sigma_i, \eta_i)\right]^{d_{ijt}}. \tag{5}$$

where d_{ijt} is the observed decision defined by

$$d_{ijt} = \begin{cases} 1, & \text{if } i \text{ choose option } j \text{ at shopping opportunity } t, \\ 0, & \text{otherwise.} \end{cases}$$

This is a product over the shopping opportunities for T_i times, which might be differ across the observations as displayed in Table 1. Unfortunately, we cannot calculate this likelihood function analytically, and thus I use the simulation technique to approximate it. Namely, suppose a random draw is indexed by s, i.e., we have $\{\sigma_i^s, \eta_i^s\}_{s=1}^S$ for each sample. Then, likelihood contribution for each individual should be approximated by

$$\mathscr{L}_i(\boldsymbol{\theta}) \approx \frac{1}{S} \sum_{s=1}^S \prod_t \prod_d \left[P(y_{ijt} = 1 | X_{it}, \sigma_i^s, \eta_i^s)\right]^{d_{ijt}}, \tag{6}$$

which enables us to define the simulated maximum likelihood (SML) estimator is given by:

$$\hat{\boldsymbol{\theta}}^{\text{SML}} = \arg\max_{\boldsymbol{\theta}} \sum_{i=1}^{N} w_i \log(\mathscr{L}_i(\boldsymbol{\theta})).$$

Notice that the log likelihood value is the weighted by w_i to correct the sampling bias, as discussed in Section 2.

4 Estimation Results

4.1 A List of estimated models

This section provides the estimation results, focusing on the differences among alternative modellings. To understand the importance of each heterogeneity, I estimate six variations of the model, summarized in Table 3. In order to address the importance of the "perceived

TABLE 3: Variation of Estimated Models

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
(1) Transaction/Individual	Trans.	Trans.	Ind.	Ind.	Ind.	Ind.
(2) Choice Sets	Unlimited	Limited	Limited	Limited	Limited	Limited
(3) Scale Heterogeneity (σ_i)	No	No	No	Yes	No	Yes
(4) Random Coefficients (μ_i)	No	No	No	No	Yes	Yes

Note: In the first row, Trans. and Ind. stand for transaction-level and Individual-level, respectively. Transaction-level means that I collapse the data into transaction-level data, i.e., log likelihood contribution can be calculated by each transaction.

acceptance," I estimate the model without and with the Furthermore, to understand the difference between transaction-level and individual-level data, I estimate Finally, to see the importance of variations of individual heterogeneities, I estimate four models with and without including σ and ν.

4.2 Estimation Results

Table **??** shows the estimation results and some statistics. In the first and second column, I show the results from a multinomial logit model with ignoring the individual-specific effect, i.e., I break down the data into each transaction, without and with using the 'perceived' acceptance data. Thus, the differences between two models are driven by limiting the choice sets for each transaction. [TBA]

5 Counterfactual Simulation

[TBA]

6 Conclusion

[TBA]

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