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Why Do Shoppers Use Cash? Evidence from Shopping Diary Data

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Why Do Shoppers Use Cash? Evidence from Shopping Diary Data

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October 24, 2013

Abstract

Recent studies find that cash remains a dominant payment choice for small-value transactions despite the prevalence of alternative methods of payment such as debit and credit cards. For policy makers an important question is whether consumers truly prefer using cash or merchants restrict card usage. Using unique shopping diary data, we estimate a payment choice model with individual unobserved heterogeneity (demand-side factors) while controlling for merchants' acceptance of cards (supply-side factors). Based on a policy simulation where we impose universal card acceptance among merchants, we find that overall cash usage would decrease by only 7.7 percentage points, implying that cash usage in small-value transactions is driven mainly by consumers' preferences.

Keywords: Money demand, Payment methods, Consumer financial behavior

JEL Classification: G2, D1, C2

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1 Introduction

In recent years, as new payment technologies such as mobile payments and contactless credit cards have been developed, consumers' method of payment choice has attracted the attention of a wide range of private firms – credit-card-issuing companies, credit and debit network providers, and mobile phone companies – as well as researchers and policy makers. Despite the emergence of these new technologies, cash retains its dominant position at the point-of-sale, in particular, for small-value transactions. This phenomenon is found all over the world. For example, recent studies on consumer micro-payments by Klee (2008) and Arango, Huynh, and Sabetti (2011) reveal that in the U.S. and Canada, respectively, cash is the dominant payment method for transactions of less than 25 dollars. At the same time, these authors also report that the use of credit and debit cards increases as transaction values increase. Similar findings are also documented by Bolt, Jonker, and van Renselaar (2010) and Simon, Smith, and West (2010) for the Netherlands and Australia, respectively.

This dominance of cash usage for small-value transactions at the point-of-sale might be partially supply driven: To avoid interchange fees, merchants tend not to accept credit or debit cards for small-value transactions.[1] At the same time, however, it might be demand driven: Many consumers prefer paying in cash for its ease of use and speed of settlements. Such observations bring up the following question: How would consumers pay at the point-of-sale if the government regulated merchant fees of credit and debit cards to a very low level so that all merchants would be willing to accept any cards? Answering this question is challenging because it is difficult to separately identify supply-side and demand-side factors in payment choices. The distinction, however, is essential for understanding the mechanism of demand for cash and for answering various policy-oriented questions.[2]

This paper attempts to answer these questions by estimating a model of consumers' payment choices at the point-of-sale, using unique Canadian data based on three days of shopping diaries. The data have two key features: multiple observations per subject, and

[1] In Canada, merchants pay a small fixed fees to network providers for each debit card transaction.

[2] For instance, policy makers are required to understand the substitution between cash and other payment methods to discuss potential regulation on surcharges and interchange fees to implement a socially optimal payment system. As a sole issuer of the bank notes, central banks also needs to understand the substitution patterns to predict the cash demand.

"perceived" acceptance. First, since the survey keeps track of the shopping diaries at the individual level, we can observe multiple transactions for each individual with slightly different shopping contexts, in terms of shopping types and transaction values. Observing only one transaction per subject would not be enough to identify the individual-specific effect of choosing a particular method of payment. In the data, however, we can observe multiple transactions for each individual, which enables us to model consumer heterogeneity in payment choice. Second, consumers report the methods of payment that would have been accepted at each shopping opportunity, as well as the actual method of payment used. Although this self-reported information might contain measurement error and might not be perfectly exogenous, it is still useful in limiting the consumers' choice sets. These two features of the data, as a result, enable us to separate the demand-side factors from the supply-side factors.

Payment choice is modeled as a generalized multinomial logit (G-MNL) model, proposed by Fiebig, Keane, Louviere, and Wasi (2010), to capture the heterogeneity observed in the data. A close look at the data shows that consumers can be potentially categorized into four groups: (i) consumers who only use cash (cash users), (ii) consumers who use debit cards whenever they are accepted and cash otherwise (debit users), (iii) consumers who use credit cards whenever they are accepted and cash otherwise (credit users), and (iv) consumers who use all three methods of payment (mixed users). This observation suggests that some sets of consumers have strong preferences for a particular method of payment, such as credit cards or debit cards, and use them whenever these methods are accepted by merchants. Another type of heterogeneity in payment choice is heterogeneous thresholds: Some people within the same category might choose different payment methods when they are faced with the same transaction values and types.[3] In the G-MNL model, we can capture such heterogeneity by introducing scale coefficients – scaling up/down the utility of one particular method of payment – and random coefficients – changing substitution patterns among alternatives.

The importance of such consumer heterogeneity in payment choices is confirmed in the estimation results. The estimation results show that the parameters that govern individual

[3] For example, some credit users might choose credit cards even for a $5 transaction, whereas others might use credit cards only for transactions above $20. Similarly, within the category of mixed users, their payment choice between credit and debit cards might be random across individuals.

heterogeneity are statistically and economically significant. Moreover, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), both of which measure the goodness of fit of a model, improve dramatically by including such heterogeneity.

Using the estimated model, we conduct a policy experiment where all merchants accept any payment method regardless of the transaction value. This policy experiment can be interpreted as follows: Suppose the government regulates merchant fees to a very low level, possibly zero, so that all merchants are willing to accept credit and debit cards for all transactions. In this scenario, every consumer could use his preferred method of payment at any merchant. Would consumers still use cash?

We demonstrate that overall cash usage would decrease by about 7.7 percentage points in terms of transaction frequency and by 7.5 percentage points in terms of transaction values, whereas the model without any individual heterogeneity predicts smaller changes in both transaction frequency and values. This difference can be explained as follows: Without taking individual heterogeneity into account, homogeneous consumers would not use cards as frequently for small-value transactions. Taking individual heterogeneity into account, however, some people who truly prefer using credit and debit cards would use these cards even for small-value transactions under the counterfactual scenario, leading to the slightly larger decrease in overall cash usage. Moreover, the relatively smaller decreases in cash usage in any model can be also interpreted to mean that cash usage in small-value transactions is driven mainly by the demand side, i.e., consumers would often choose to pay with cash even if all merchants accepted credit and debit cards.

Furthermore, the simulation results can be also translated into welfare changes, in particular, for firms.[4] [5] As for the credit card industry, the total value purchased through Visa and MasterCard in Canada in 2009 was about 264 billion dollars comprising 2.51 billion

[4] As for consumer surplus, we cannot quantify the change in monetary terms due to the absence of 'price' for choosing a certain method of payment. Unlike the standard discrete choice models in differentiated product markets, the choice of payment method does not incur any explicit costs, so we cannot calculate the willingness to pay for switching from one payment choice to another. However, judging from the relatively small shift from cash to other payment methods demonstrated above, we can conclude the welfare gain for consumer side would not be very big.

[5] In subsequent analysis, when we calculate the fees paid by merchants to merchant acquirers (or card network providers), we use the median merchant fees on credit and debit cards reported by Arango and Taylor (2008). These fees were 2.0% of the transaction value for credit cards and 0.12 dollars per transaction for debit cards, according to the Bank of Canada's 2006 survey of merchants on accepted means of payment.

transactions, yielding approximately 5.28 billion dollars in fees paid by merchants to credit card acquirers.[6] Under the counterfactual scenario, the total value purchased would be 303 billion dollars comprising 3.09 billion transactions, yielding approximately 6.06 billion dollars in fees. The scenario in the debit card industry is similar. The total value purchased through Interac, a not-for-profit organization which solely offers a debit card network in Canada, was 171 billion dollars comprising 3.88 billion transactions, yielding approximately 0.466 billion dollars in fees paid by merchants to debit card acquirers.[7] Under the counterfactual scenario, the total value purchased would be 182 billion dollars comprising 4.41 billion transactions, yielding approximately 0.529 billion dollars in fees. Thus, merchants would need to pay 843 million dollars more in fees to credit and debit card acquirers, which can be viewed as the cost of implementing universal card acceptance: All merchants would be willing to accept cards if the additional cost were compensated by the government.

Research on micro-payments has attracted attention from many sources: major retail stores, mobile phone companies, credit card companies, credit card network providers, commercial banks, policy makers, and central banks. Traditional payment methods – cash, and credit and debit cards – face increasing competition from newly emerging payment methods such as online payments and mobile phone payments. Because of the need to understand the substitution between these payment methods, many empirical studies, as well as some theoretical studies, attempt to reveal the substitution between cash, credit cards, and debit cards.[8] For example, Schuh and Stavins (2010) focus on the extinction of check usage in the U.S., while Ching and Hayashi (2010), Simon, Smith, and West (2010), Arango, Huynh, and Sabetti (2011), and Sieber (2011) examine the role that credit cards' reward programs play in the choice of payment method. Rysman (2007) asks why people use only one credit card, even though they carry several credit cards in their wallet. Borzekowski, Kiser, and Ahmed (2008) and Zinman (2009) study debit card usage.[9] The most recent work by Koulayev, Rysman, Schuh, and Stavins (2012) develops a structural model of adoption and use of pay-

[6]See http://www.cba.ca/en/component/content/publication/69-statistics.

[7]See http://www.interac.ca/media/stats.php.

[8]Theoretical studies include the monetary theoretic approach, as in Telyukova and Wright (2008) and Monnet and Roberds (2008), and the two-sided market approach, as in Rochet and Tirole (2002), Rochet and Wright (2010), and Shy and Wang (2011).

[9]For a more comprehensive survey, see Humphrey (2010).

ment instruments to examine the effect of the U.S. regulation of interchange fees on debit cards. This paper, however, contributes to this empirical literature by studying consumers' unobserved heterogeneity in payment choices and examining their counterfactual aggregate demand for cash, using unique data on perceived acceptance and multiple observations per subject.

This paper is organized as follows: Section 2 describes the data and gives some summary statistics and motivating facts for the modeling framework. In Section 3, we present the model and the estimation procedure. The estimation results and the counterfactual simulation results are presented in Section 4. Section 5 concludes.

2 Data and Background Information

2.1 The 2009 Method of Payment Survey

Data Description and Sample Construction The data used in this study are from the 2009 Bank of Canada Method of Payment Survey. The survey consists of two parts: a survey questionnaire and a three-day diary survey instrument.[10] The survey questionnaire (hereafter 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 information about respondents' main bank account and main credit card, which enables us to associate their payment choices with the number of free debit transactions per month, and credit card rewards and annual fees.[11] SQ also contains some attitudinal information, such as perceptions of convenience and safety for some particular methods of payment. This study includes such attitudinal data as explanatory variables, since the importance of such attitudinal data is emphasized in Harris and Keane (1999) and Ching and Hayashi (2010).

The diary survey instrument (hereafter DSI) asks about shopping data, including the transaction value, type of transaction, the perceived accepted methods of payment, the

[10] Originally, there were about 6,900 respondents to the survey questionnaire, and among them about 3300 respondents proceeded to the diary survey instrument. For this study, we need both sets of information and use the respondents who finished both.

[11] In Canada, about half of bank accounts offer unlimited free debit card transactions, whereas the remaining bank accounts offer only limited free or zero free debit card transactions. For the latter type of accounts, consumers need to pay some fees after exceeding the limit on free debit card transactions.

method of payment chosen, and the major reasons for their choice, for three consecutive days. There are two strengths of these data: (1) multiple observations per subject and (2) perceived acceptance. As for the first feature, the data provide multiple shopping observations for each individual with slightly different shopping opportunities, which allows us to study the source of individual heterogeneity. Compared with other studies using transaction-level (micro) data such as Klee (2008) and Arango, Huynh, and Sabetti (2011), we can extract the individual heterogeneity more readily 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 these data, is also a prominent aspect of this survey. When consumers give details for each transaction, they need to state what payment 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 separate the demand-side factors from the supply-side factors.

Since the sample is not representative, we need to use a sample weight to correct the sampling bias.[12] Moreover, the analysis is restricted to the subset of the original samples.[13] We construct the sample by excluding consumers who have missing information regarding the perceived acceptance, demographics, and transaction value, which are key variables in this study. Moreover, in order to estimate a random effects model, we need to have at least three shopping observations per subject to identify the individual-specific effect. Thus, we also exclude the samples with fewer than three shopping observations. This process leaves a total of 1,452 individuals with 7,908 transactions.

Canadian Payment Landscape Figure 1 shows the frequency of payment choice by transaction value. The black solid line, the blue dotted line, and the red dashed line show the frequency of cash, credit card and debit card usage, respectively. For example, if the transaction value is about \$10, then 60%, 25%, and 15% of transactions are completed by cash, debit and credit cards, respectively. Notice that if the transaction value is less than \$25, cash usage dominates other payment methods, namely credit and debit cards, and this

[12]For more details, see Arango, Huynh, and Sabetti (2011) and Arango and Welte (2012).
[13]For more detailed sample construction procedure, see Appendix.

dominance is reversed as the transaction value increases, as Arango, Huynh, and Sabetti (2011) point out.

In the following subsection, we show some summary statistics and descriptive statistics to motivate why this study uses a generalized multinomial logit model, focusing on the heterogeneity in payment choices observed in the data.

2.2 Heterogeneity in Payment Choice

Table 1 shows how many shopping trips each individual made over the three days. The second and fifth, and the third and sixth columns display the unweighted and weighted percentage of consumers depending on the number of shopping trips, before and after truncating the data by the number of shopping trips. These four columns suggest that the shape of the histogram would not change dramatically, even though we use the unweighted samples. Moreover, not surprisingly, each individual makes 4.03 shopping trips over the three days on average, implying that there is more than one shopping trip per day, and about half of them have at least four shopping trips.[14] The fact that we have multiple transactions per person immediately raises a question: Are there any individual-specific patterns in payment choices?

We show consumers' tendency toward payment choice in Table 2. To construct this table, first we categorize the samples into four types by their method of payment choice patterns, regardless of the number of shopping trips. Four types can be found in the first column: (1) Cash users, who use only cash, displayed in the first row, (2) Debit users, who mainly use debit cards, and cash in some cases, displayed in the second and third rows, (3) Credit users who mostly use credit cards, and cash in some cases, displayed in the fourth and fifth rows, and (4) Mixed users who use credit and debit cards, and cash, displayed in the sixth and seventh rows. Then, we count the number of individuals who fall into each category and calculate the number of shopping trips and average transaction values, depending on their types. There are three important observations in this table.

[14] This is after dropping observations that are missing perceived acceptance. If we calculate the average shopping trips in the original data, we find that this number should be about 4.7 times per person over the three days.

The first and most important observation is the fact that the fractions of debit users and credit users are sizeable, accounting for one-third and one-fourth, respectively. This observation suggests that the substitution between credit and debit cards is very small for those committed users. Small changes in transaction values or in the characteristics of transactions are not necessarily enough for them to switch their payment methods from debit to credit or credit to debit. Thus, the model should take into account the individual-specific effects for their preferred payment methods.

Second, there are some mixed users who use all three methods quite randomly. Although the average number of shopping trips is larger than the corresponding number for other types, the average transaction values for them are not so different from the corresponding numbers for credit users. Moreover, as Figure 2 suggests, the distribution of transaction values is quite similar to each other, though their payment choices are quite different. Moreover, we also show each consumer type's payment choice by transaction values in Figure 3. Thus, their preferences should be different from credit users preferences, which should be captured by the model.

As a final remark about Table 2, the distribution of consumer types will be preserved if we limit the samples to consumers with more than 1 shopping opportunity. In order to extract individual-specific effects, e.g., fixed effect estimators and/or random effect estimators, each sample should have multiple observations for identification purposes. Thus, to model the heterogeneity mentioned above, we need to discard the samples. To see not only the average but also the distribution of transaction values, we also show the distribution of transaction values depending on the type of consumer, demonstrated in Figure 2. The average transaction values and the distribution of the transaction values for each type of consumer are quite similar to each other, implying that consumers with more than three shopping trips are still representative for each type of consumer. Therefore, we estimate the model using the samples with more than two shopping opportunities.[15]

[15] In order to check the robustness of the results, we also estimate the model using samples with more than six shopping trips.

2.3 Perceived Acceptance

In addition to the consumer's side, we also describe supply-side information, "perceived acceptance," which is reported by consumers. Although it might have some measurement errors, it is still useful in separating consumers' preference in choosing the method of payment from supply-side factors. Table 3 shows the acceptance of debit and credit cards depending on consumer type. For example, cash users had 1,086 shopping trips in total, and they faced 283 situations where neither debit cards nor credit cards were accepted. Similarly, they could use only cash and debit cards 255 times, and they could use only cash and credit cards 53 times; for the rest of 459 shopping trips, they could use all three methods.

According to Table 3, we can see that the distributions of acceptance are different from each other depending on the type of consumer. For example, debit users are more likely to go to shops that accept debit cards than are credit users, and credit users are more likely to go to shops that accept credit cards than are debit users. However, the differences are quite small between credit users and mixed users. On the other hand, the distributions for cash users and debit users are slightly different from those for other types of people, i.e., they are more likely to go to shops that accept debit or credit cards than are other types of consumers. This difference suggests that there is a potential endogeneity problem, that is, people who prefer using cards might choose shops where these cards are more likely to be accepted. However, the relative number of cash users is small compared to other types, and the patterns of distribution of acceptance are similar to those for other types, i.e., the highest frequency occurs when both credit and debit cards are accepted, and the second highest frequency occurs at shops where neither is accepted, except for debit users. Therefore, this study treats all samples equally in the estimation and we further discuss the potential endogeneity problems in Section 4, together with other issues.

2.4 Attitudinal and Other Demographic Variables

In the questionnaire, respondents were asked to rate the usage of cash, credit cards, and debit cards for (1) the ease of use, and (2) record keeping capabilities, using a five-point scale, e.g., a respondent needs to choose a number from 1 (strongly disagree) to 5 (strongly

agree) to rate the ease of use for each method of payment. We normalize those two ratings by cash. That is, each index for credit card and debit card usage is obtained by

$$a_{i,j,l} = \log\left(\frac{r_{i,j,l}}{r_{i,cash,l}}\right)$$

where $r_{i,j,l}$ is the rating of individual i for payment method j, j = credit and debit, and l denotes the ease of use or record keeping. Taking logarithm normalizes the indexes so that $a_{i,j,l}$ can take a value between -1.6094 to 1.6094, and 0 if payment method j is identical to cash.

Figures 4 and 5 graphically show the respondents' attitudinal and perceptual data, using 3-dimensional histograms. For example, Figure 4 shows that many respondents are located at the center, at the point of $(0, 0)$, implying most of them think the ease of use for all three methods are the same. On the other hand, Figure 5 shows that many respondents are located north of $(0, 0)$, implying that credit and debit cards are more convenient as a record keeping device than cash.

3 Econometric Model

This section provides a payment choice model for consumers. As indicated in Section 2, consumers' payment choice is a discrete outcome variable. Thus, given the discrete nature of the data and motivated by some patterns observed in Section 2, this paper uses a generalized multinomial logit model, as proposed by Fiebig, Keane, Louviere, and Wasi (2010).[16] As a benchmark case, we also estimate a series of multinomial logit models to compare the estimation results and statistical fitness of the model.

[16]There exist other approaches: semiparametric and nonparametric approaches. For example, after the pioneering work of Manski (1975), Briesch, Chintagunta, and Matzkin (2002) use a semi-parametric method, known as maximum score estimator, to extract unobserved heterogeneity in discrete choice models. More recently, Fox (2007) shows that the semiparametric estimator is consistent when using data on a subset of choices. Similarly, Briesch, Chintaguanta, and Matzkin (2010) use nonparametric approach to extract unobserved heterogeneity in discrete choice models.

3.1 Payment Choice Model

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

$$u_{ijt} = \alpha_j + \boldsymbol{Z}_{it}\boldsymbol{\beta}_i^Z + \boldsymbol{A}_{ij}\boldsymbol{\beta}_i^A + \boldsymbol{D}_i\boldsymbol{\beta}_i^D + \varepsilon_{ijt}, \tag{1}$$

where α_j is a payment method specific constant term, $\boldsymbol{Z}_{it}$ is an M_Z-dimensional vector of shopping characteristics, $\boldsymbol{A}_{ij}$ is an M_A-dimensional vector of individual i's attitudinal characteristics toward the payment method j, $\boldsymbol{D}_i$ is an M_D-dimensional vector of individual i's demographic information, $\boldsymbol{\beta}_i = [\boldsymbol{\beta}_i^Z \ \boldsymbol{\beta}_i^A \ \boldsymbol{\beta}_i^D]$ is a coefficient vector, and ε_{ijt} is an i.i.d. random utility shock that follows a Type I extreme value distribution.[17] Each individual i chooses a payment method j which gives the highest utility at shopping trip t. As a matter of convention, the utility from using cash is normalized as zero, i.e., we assume that $u_{i,cash,t} = 0$. For notational simplicity, we use $\boldsymbol{X}_{ijt} = [\boldsymbol{Z}_{it} \ \boldsymbol{A}_{ij} \ \boldsymbol{D}_i]$, which gives us a standard notation of the utility:

$$u_{ijt} = \alpha_j + \boldsymbol{X}_{ijt}\boldsymbol{\beta}_i' + \varepsilon_{ijt}.$$

Though $\boldsymbol{\beta}_i$ may depend on a payment method j, we suppress the subscript for transparency. Here, we specify an m-th element of $\boldsymbol{\beta}_i$ as

$$\beta_{im} = \sigma_i\bar{\beta}_m + \gamma\eta_{im} + (1-\gamma)\sigma_i\eta_{im}, \quad \text{where } \eta_{im} \sim N(0, \beta_m^u) \tag{2}$$

$$\sigma_i = \exp(\bar{\sigma} + \tau\epsilon_{i0}), \quad \text{where } \epsilon_{i0} \sim N(0, 1), \tag{3}$$

where η_{im} is individual-specific deviation from the mean, which follows a standard normal or log-normal distribution, σ_i is a scale heterogeneity, which follows a log-normal distribution,

[17] As Fiebig, Keane, Louviere, and Wasi (2010) point out, a choice specific constant term, α_j, cannot be individual-specific, i.e., we cannot identify when α_j is replaced by α_{ij}. This problem is known as "incidental parameter problem," studied by Neyman and Scott (1948) and thus we explicitly write α_j separately from other characteristics. For more details, see Lancaster (2000) which is a comprehensive survey of this issue. Moreover, a recent study by Fox, il Kim, Ryan, and Bajari (2012) shows that the distribution of the random coefficients in the multinomial logit model is nonparametrically identified, and we can straightforwardly apply their identification argument to this model.

and γ is a mixing parameter that decides the degree of two heterogeneous effects.[18] As for a scaling heterogeneity σ_i, we use an exponential operator to avoid negative scaling and τ can be seen as a scaling parameter, because it essentially changes the absolute scale of σ_i. we explain the roles of these two heterogeneity parameters below.

In the standard (multinomial) logit model, $\beta_{im} = \bar{\beta}_m$, which implies that all individuals have exactly the same taste for all characteristics. As repeatedly emphasized in this paper, however, the data show heterogeneity in payment choice. Thus, as in equation (2), the model includes two heterogeneity parameters: σ_i and $\boldsymbol{\eta}_i$, where $\boldsymbol{\eta}_i = [\eta_{i1}, \cdots, \eta_{iM}]$. To see the importance of $\boldsymbol{\eta}_i$, assume that $\sigma_i = 1$ and $\gamma = 1$. Then, equation (2) can be simplified as

$$\begin{aligned} \text{Mixed (Heterogeneous) Logit:} \quad & \beta_{im} = \bar{\beta}_m + \eta_{im}, \quad \text{where } \eta_{im} \sim N(0, \beta_m^u), \\ \text{cf. A Standard Logit:} \quad & \beta_{im} = \bar{\beta}_m. \end{aligned}$$

Now, it is clear that the $\bar{\beta}_m$ is a mean valuation for $m-$th characteristics and the η_{im} is an individual specific taste deviation from the mean in payment choice. For example, suppose each shopping trip is characterised by its transaction value and consumers only care about the transaction value (TV) when they make a decision. Some consumers who use credit cards regardless of the transaction values and rarely use cash have higher values of $\eta_{i,TV}$, whereas consumers who only use cash have smaller (or negative) values of $\eta_{i,TV}$. Therefore, this term enables individuals to have heterogeneous tastes by changing the thresholds of each payment method. This model is called mixed logit, heterogeneous logit, or random coefficients model.[19]

The other heterogeneity parameter, σ_i, is a scale heterogeneity. To emphasize the importance of σ_i, again, assume $\gamma = 0$. Then, equation (2) can be rewritten as

$$\beta_{im} = \sigma_i(\bar{\beta}_m + \eta_{im}), \quad \text{where } \eta_{im} \sim N(0, \beta_m^u).$$

[18] As Fiebig, Keane, Louviere, and Wasi (2010) mention, there is no good economic interpretation for γ.

[19] This model can be seen as one of the random effects models. The reason we use a random effects model here is the fact that we can only have several observations for most of the samples. In order to deal with this heterogeneity as fixed effects, we need to have more observations per each individual.

As the name suggests, the scale heterogeneity is indeed scaled up or down the valuation for the particular choice, which is constant across m, and can capture the committed users' behavior well.

Notice that this class of model includes a lot of models as special cases, as indicated above. For example, assuming $\sigma_i = 1$ and $\beta_m^u = 0$ for all m, this model boils down to the simplest (multinomial) logit model. Also, as mentioned above, assuming $\sigma_i = 1$, this model will be identical to the models in Revelt and Train (1998), i.e., β_{im} can be simplified as $\beta_{im} = \bar{\beta}_m + \eta_{im}$, which is the standard mixed logit or heterogeneous logit model. In this study, we assume that $\gamma = 0$, which gives us $\beta_{im} = \sigma_i(\bar{\beta}_m + \eta_{im})$ and we call σ_i a scale heterogeneity and η_{im} random coefficients. Moreover, we also assume that the variance-covariance matrix of $\boldsymbol{\eta}_i$ is diagonal to ease computational complexity.

A scale coefficient might be explained by the individual demographic information. For example, credit card users are likely to have high income. Thus, the scale heterogeneity for credit cards might be explained by users' income. Generally speaking, if we want to explain σ with some demographic information, it can be written as

$$\sigma_i = \exp(\bar{\sigma} + \boldsymbol{Q}_i \boldsymbol{\beta}^q + \tau \epsilon_{i0}) \tag{4}$$

where $\boldsymbol{Q}_i$ denotes the individual demographics, such as income or age, which might explain the scale heterogeneity, and $\boldsymbol{\beta}^q$ is a coefficient vector. This seemingly slight change requires huge computational complexity, because we need to find $\bar{\sigma}$ that satisfies

$$\int_{\epsilon_{i0}} \exp(\bar{\sigma} + \boldsymbol{Q}_i \boldsymbol{\beta}^q + \tau \epsilon_{i0}) dF(\epsilon_{i0}) = 1,$$

as a normalization.[20] Thus, first we need to find $\bar{\sigma}$ as a function of the parameter values of $\boldsymbol{\theta}$, including τ, and then we plug $\bar{\sigma}$ into the equation to simulate the choice probabilities.

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

[20] In order to identify multiplicative heterogeneity, one of the heterogeneity parameters should be normalized. See Fiebig, Keane, Louviere, and Wasi (2010).

that information to limit the choice set for consumers. Moreover, we can observe whether consumer i owns any credit or debit cards. Thus, if individual i does not have credit and/or debit cards, we exclude credit or debit cards from individual i's choice set.

3.2 A Maximum Simulated Likelihood Estimator

Given the parameter values $\boldsymbol{\theta} = \{\{\alpha_j, \{\bar{\beta}_{mj}, \beta^u_{mj}\}_{m=1,\cdots,M_j}, \tau_j\}_{j=CC,DC}\}$, where CC and DC denote the credit card and debit card, and a pair of random draws of $(\boldsymbol{\epsilon}_i, \boldsymbol{\eta}_i)$ that are fixed over the estimation procedure, we can obtain the analytical choice probability of individual i choosing payment method j at shopping trip t as

$$\mathrm{P}(y_{ijt} = 1|\boldsymbol{X}_{ijt}, \boldsymbol{\theta}, \boldsymbol{\epsilon}_i, \boldsymbol{\eta}_i) = \frac{\exp(\alpha_j + \boldsymbol{X}'_{ijt}\boldsymbol{\beta}_i)}{\sum_{l\in\mathscr{J}_{it}} \exp(\alpha_l + \boldsymbol{X}'_{ilt}\boldsymbol{\beta}_i)}, \tag{5}$$

where

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

Notice that the denominator in equation (5) is a summation over available choices. For example, if a choice set only includes cash and debit card, the denominator is a summation of exponentiated utility from cash usage and debit card usage. Using this choice probability, the likelihood contribution for each individual is given by:

$$\mathscr{L}_i(\boldsymbol{\theta}) = \int_{(\epsilon_i,\eta_i)} \prod_{t=1}^{T_i} \prod_j [\mathrm{P}(y_{ijt} = 1|\boldsymbol{X}_{ijt}, \boldsymbol{\theta}, \boldsymbol{\epsilon}_i, \boldsymbol{\eta}_i)]^{d_{ijt}} dF(\boldsymbol{\epsilon}_i, \boldsymbol{\eta}_i), \tag{6}$$

where d_{ijt} is the observed decision defined by

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

As in equation (6), the individual likelihood contribution is a product over the shopping trips for T_i times. In other words, we stack multiple transactions at the individual level. In this

way, we can capture the individual heterogeneity. If we do not stack multiple transactions at the individual level, the model is unable to capture individual heterogeneity and is identical to assuming that each transaction is independent and identically distributed.

Unfortunately, we cannot directly calculate this likelihood function, and thus we use the simulation technique to approximate it. Namely, suppose a random draw is indexed by s, i.e., we have $\{\boldsymbol{\epsilon}_i^s, \boldsymbol{\eta}_i^s\}_{s=1,\cdots,S}$ for each individual. Then, the likelihood contribution for each individual should be approximated by

$$\mathscr{L}_i(\boldsymbol{\theta}) \approx \frac{1}{S}\sum_{s=1}^{S}\prod_{t=1}^{T_i}\prod_{j}[\mathrm{P}(y_{ijt}=1|\boldsymbol{X}_{ijt},\boldsymbol{\theta},\boldsymbol{\epsilon}_i^s,\boldsymbol{\eta}_i^s)]^{d_{ijt}}$$

which enables us to define the simulated maximum likelihood (SML) estimator 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 weighted by w_i to correct the sampling bias, as discussed in Section 2. The standard errors reported in this study are calculated by

$$\text{Avar}(\hat{\boldsymbol{\theta}}^{\text{SML}}) = \sum_{i=1}^{N} w_i \boldsymbol{s}_i(\hat{\boldsymbol{\theta}}^{\text{SML}})'\boldsymbol{s}_i(\hat{\boldsymbol{\theta}}^{\text{SML}}),$$

where $\boldsymbol{s}(\hat{\boldsymbol{\theta}}^{\text{SML}})$ is a score vector evaluated at $\hat{\boldsymbol{\theta}}^{\text{SML}}$. Notice, again, that we need to take into account the sample weight to adjust the sampling bias. Under regularity conditions, this estimator is consistent and asymptotically normal.

4 Results

4.1 Estimation Results

This section provides the estimation results, focusing on the differences among alternative modelings. To emphasize the importance of each heterogeneity, we estimate six variations of the model, summarized in Table 4. In order to address the importance of the "perceived acceptance," we estimate the model with and without limiting consumers' choice sets based

on their reported perceived acceptance. Furthermore, to understand the difference between transaction-level and individual-level data, we estimate the model at transactional level, assuming each transaction is i.i.d, and individual level storing the multiple transactions per subject. Finally, to see the importance of variations of individual heterogeneity, we estimate four models with and without including $\boldsymbol{\epsilon}$ and $\boldsymbol{\mu}$. As for simulation, we use 500 sets of random draws per subject, i.e., $\{\boldsymbol{\epsilon}_i^s, \boldsymbol{\eta}_i^s\}_{i=1,\cdots,N;s=1,\cdots,500}$.[21]

Parameter Values and Statistics Tables 5 and 6 show the estimation results and some summary statistics. As mentioned in Section 3, we normalize the utility of using cash to zero. Thus, we show the coefficients for credit and debit cards, listing the included variables in the first column of each table. Each coefficient is interpreted as follows: Transaction value (abbreviated as TV in the first column) and its squared term for credit cards is positive and negative, respectively, implying that the utility of using credit cards is increasing in transaction values with marginally decreasing. Those people who valuate the ease of use and record keeping facility of credit cards are likely to use credit cards, since the utility of using credit cards is higher. Estimation results also suggest that if people have multiple credit cards, a higher credit limit, or higher reward points for their primary credit cards, their latent utility of using credit cards is high. On the other hand, when people face very low transaction values or are young, they are less likely to use credit cards.

As for debit card usage, consumers are more likely to use debit cards, if the transaction value is very low, or if consumers are young and have less income. On the other hand, as transaction values increase, or if the transactions took place at a grocery store, and consumers have multiple debit cards or evaluate debit cards' ease of use and record keeping facility, then they are more likely to use debit cards. Although the magnitude of significance might change across the models, these coefficients basically show the same sign and statistical significance.

In terms of the summary statistics, the values of log likelihood, AIC and BIC improve by limiting the choice sets, shifting from Model (i) to Model (ii). Notice that the estimation results for Models (ii) and (iii) are the same, as the objective functions are identical when the models do not have any random coefficients. Although the estimates are the same, the

[21] Revelt and Train (1998) use the same number of simulations for their estimation procedure. Notice that the estimator is consistent and asymptotically normal under regularity conditions.

standard errors should be different as indicated in Table 5. Thus, without taking into account the unobserved individual-specific effects, the usage of transaction-level and individual-level data should yield the same estimates.[22]

When we introduce the heterogeneity terms in Models (iv) to (vi), the log likelihood, AIC and BIC further improve dramatically as indicated in Table 6.[23] In Model (iv), we introduce a scale coefficient and it is indeed statistically significant. Moreover, in Model (v), we use the random coefficients for transaction values, ease of use, and so on. In Table 6, 'RC' indicates a random coefficient and the bold numbers indicate statistical significance at the 5% level. Although some random coefficients are statistically insignificant, more than half of the random coefficients are statistically significant, implying that consumers' valuations for payment characteristics are quite heterogeneous. Furthermore, we introduce both random and scale coefficients in Model (vi). Again, most of the parameters are statistically significant.

As for the statistical fitness of the model, we present AIC and BIC at the bottom of Tables 5 and 6. Models (i) to (iii) force everybody to have homogeneous taste parameters, and these models show relatively larger AIC and BIC than Models (iv) to (vi). Thus, the statistical fitness of the model and the statistical significance of some random coefficient terms indicate the importance of individual heterogeneity. Model (vi) achieves the smallest log-likelihood, AIC, and BIC. These statistics for the fitness of the models are enough for us to proceed to the counterfactual simulations, we also show some predicted probabilities using the estimated models to show other aspects of the fitness of the models.

Predicted Probabilities Table 7 demonstrates the overall fitness of the estimated models. Each column shows the shares of cash, credit and debit cards in terms of the frequency (volume) share in the top three rows and value share in the bottom three rows. Since the objective function of the models is based on the individual log-likelihood contribution, we use the weight multiplied by the number of transactions per person. That is, we use $w^P = w_i T_i$, where T_i is the total number of shopping trips that individual i had, and the estimated

[22] You can also see these results analytically.

[23] When adding more parameters in a statistical model, the statistical goodness of fit, say likelihood value, may improve. Thus, the Akaike information criterion and the Bayesian information criterion solve this problem by having a penalty term for the number of parameters.

parameters to calculate the predicted shares.[24]

Model (iii) or (vi) can be seen as one of the most promising models in Table 7, as both models mimic the data quite well in both frequency and values share. At the same time, other models also mimic each share within almost ±1% range. Moreover, even for value shares that we do not match directly in the estimation procedure, these four models mimic the data well. However, Table 8 suggests that Model (iii) cannot give good fitness for micro-moments; in particular, the model cannot capture the substitution between cash and debit card. Table 8 shows the fitness of the model conditioned on merchants' acceptance. In the top panel, 'Merchants Accepting Cash and Credit,' we calculate the frequency and value share where merchants accept only cash and credit cards. Unfortunately, all models predict higher numbers for cash usage. On the other hand, in the bottom panel, 'Merchants Accepting Cash and Debit,' as we include more unobserved heterogeneity, these models capture the substitution between cash and debit cards quite well. For example, cash usage is about 64.22% in the data, and Model (vi) predicts 61.91% for 'Merchants Accepting Cash and Debit.' These observations allow us to proceed to the counterfactual simulations using these estimated models and parameters.

4.2 Simulation Results

Using the estimated model demonstrated above, we conduct a policy simulation where all merchants accept any payment method regardless of transaction values. This question is motivated by policy makers' recent interest in understanding the demand for cash under such a counterfactual scenario, as many recent studies reveal that cash is still a dominant payment method for small-value transactions.

Simulation Details We hypothetically allow consumers to use their credit and debit cards without incurring any additional costs for using them, even though, in reality, they

[24]Each predicted share can be obtained via:

$$s_j^F = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[\frac{1}{R} \sum_{r=1}^{R} w^P \mathrm{P}(y_{ijt} = 1 | \boldsymbol{X}_{ijt}, \boldsymbol{\theta}, \sigma_i^r, \eta_i^r) \right]$$

where $R = 1,000$ and each choice probability is given by Equation (5).

sometimes would not be able to use their cards. We also assume that all consumers can use debit and credit cards. For those consumers who do not have any credit cards, we hypothetically give them a credit card with zero rewards and the lowest credit limit, i.e., \$500. For those consumers who do not have any debit cards, we hypothetically give them a debit card so that they can use their debit cards for any transaction. To conduct this policy experiment, we use the fact that the estimator satisfies asymptotic normality. Thus, we prepare $r = 2,000$ sets of normal random draws of $\boldsymbol{\nu}^r$ and construct $\boldsymbol{\theta}^r = \hat{\boldsymbol{\theta}} + \hat{\boldsymbol{\sigma}}\boldsymbol{\nu}^r$, where $\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\sigma}}$ denote the estimates and standard errors for the estimates. We also prepare the $r = 2,000$ draws for each random coefficient and scale coefficient, $(\boldsymbol{\epsilon}^r, \boldsymbol{\eta}^r)$. Then, we simulate the choice probabilities for all methods of payment, whereas consumers' choice sets are restricted by merchants' acceptance in the estimation. Finally, we subtract the former predicted shares from the latter predicted shares.[25] Notice that we use the weight w_i here, whereas we use the 'weighted' weight for showing the fitness of the models, as in Tables 7 and 8, i.e., the predicted shares are calculated via

$$s_j^C = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left[\frac{1}{R} \sum_{r=1}^{R} w_i \mathrm{P}(y_{ijt} = 1 | \boldsymbol{X}_{ijt}, \boldsymbol{\theta}^r, \boldsymbol{\epsilon}_i^r, \boldsymbol{\eta}_i^r) \right].$$

4.2.1 Overall Effects

Table 9 presents an overview of the simulation results. First, in terms of the frequency, overall cash usage would decrease by 6.9 percentage points to 8.0 percentage points, depending on the model, whereas the transaction amount of cash usage would decrease by 6.9 percentage points to 7.9 percentage points. The most important observation here is that the dominance of cash usage in small-value transactions is driven by consumers – consumers would not decrease their use of cash even if merchants accepted credit and debit cards. Although one might think this change is relatively small, this small overall effect is driven by the fact that many people use cash for small-value transactions even if these merchants accept cards, as indicated in Figure 6. The right panel of Figure 6 shows the frequencies of three methods of payment by transaction values only transactions that accepted all three method of payment,

[25] As indicated in Table 7, the predictions from the models cannot predict the data shares exactly. Thus, we calculate the difference between predicted shares under the current choice sets and under the counterfactual choice sets.

whereas the left panel includes all transactions.

There is one more important remark about Table 9. The table indicates the importance of the unobserved individual heterogeneity. The decrease in cash usage is smaller in Model (iii), which does not have any unobserved heterogeneity, than in other models that have heterogeneity. This result implies that Model (iii) fails to capture the behavior of debit users and credit users. Those committed users should be likely to use their cards under the counterfactual situation where all merchants accept cards, and Models (iv) through (vi) capture such patterns. However, Model (iii) does not have any individual-level heterogeneity and cannot capture such patterns.

4.2.2 Detailed Effects

Acceptance Types In Table 10, we show the models' prediction depending on the merchants acceptance. For example, in the top panel, 'Merchants Accepting Cash,' we calculate the percentage point change only for the merchants that currently accept only cash. For those transactions, the decrease in cash usage is huge, since many consumers would use credit and debit cards if merchants accepted cards. Thus, cash share would decrease by about 34 percentage points.

On the other hand, in the next two panels 'Merchants Accepting Cash and Credit' and 'Merchants Accepting Cash and Debit,' we can see much smaller changes. This is partially because merchants have already accepted cash and one electronic payment method. However, here, we can see the clear difference between Model (iii) and Model (vi). For example, Model (iii) predicts decreases of about 11.49 percentage points and 5.21 percentage points for cash and credit card share, whereas Model (vi) predicts decreases of about 13.96 percentage points and 3.61 percentage points for cash and credit card. This is because, in this case, we should expect that the most substitutions would happen from cash share to debit card share, with a slight decrease in credit cards share. Some mixed users, who wanted to use debit cards but could not because they were not accepted and used credit cards instead, would use debit cards, which leads to a small decrease in credit usage. However, the number of such mixed users should be small and the effect should be limited. Therefore, we should expect most of the decrease in cash and the Model (vi) support our intuitions. The same thing happens for

merchants that accept cash and debit cards.

Last, in the bottom panel, which shows merchants accepting every payment method already, the changes are very limited for any payment method and any model. This is because the merchants have already accepted any payment method and consumers choose their method of payment optimally. Therefore, we should not see huge changes here and the results validate the models.

Transaction Values In Table 11, we show the models' prediction depending on the transaction values. For instance, in the top panel, 'Less than $10,' we calculate the percentage point change only for the transactions which are less than $10. Though the market share of cash in the data is quite huge for less than $10 transactions, the percentage change is small. On the other hand, transactions between $10 and $25, the decreases are about 10 percentage points, even though the original market share is much smaller than less than $10 transactions. Therefore, these observations support that the results – cash usage in small-value transactions is driven by consumers – is robust.

4.3 Some Discussions

As mentioned in Sections 2 and 3, there may exist some potential endogenity problems in the estimation and the counterfactual simulation. We summarize and discuss them briefly in this section.

Measurement Errors in Perceived Acceptance and Endogeneity First, we use the reported perceived acceptance data, which may have measurement errors, since consumers tend to go to merchants that are likely to accept their preferred method of payment and report inaccurately about acceptance of their non-preferred method of payment. Unfortunately, in these data, we cannot verify whether their reported acceptances are correct. However, as in Table 3, we do have a number of observations where some merchants accept only credit cards or debit cards, which validate the accuracy of data. Thus, this paper uses their reported perceived acceptance without any imputation.

This perceived acceptance might create a bias in the counterfactual experiment. In

particular, when we measure the welfare gain in the counterfactual experiment, we might underestimate it. As indicated in Table 3, currently many consumers choose shops that accept their preferred method of payment, e.g., credit users are more likely to go to merchants that accept credit cards. However, under the counterfactual scenario, they would not have to choose merchants by their acceptance. Since this paper does not measure the welfare gain/loss, this problem cannot be a major concern.

There might be another concern of a selection problem of credit cards. As Arango, Huynh, and Sabetti (2011) investigate, those consumers who tend to use their credit cards are likely to have good reward programs on their cards. Under the couterfactual scenario, some cash users and debit users might obtain new credit cards which have better reward programs and start using them. This model cannot capture such behavior, as their credit card selection behavior is not explicitly modeled. Therefore, the results indicated above should be interpret as a short term effect where consumers continue to use the same credit cards.

Supply Effects and Externalities Finally, this paper cannot capture any externalities in the counterfactual simulation. For example, as a result of forcing merchants to accept electronic cards, merchants might get used to processing cards and therefore the speed of settlement for these cards would be faster than before. Observing this faster settlement for cards, consumers might use cards more frequently. This is one of the externalities for forcing merchants to accept cards.

Moreover, the models do not take into account merchants' behavior nor the behavior of credit and debit card network providers. They might potentially change their behavior, in particular, they might charge higher interchange and surcharge fees to exploit their monopolistic or oligopolistic market power. To fully predict what would happen if merchants were forced to accept cards, we need to take into account their behavior.

5 Conclusion

This paper investigates consumers' method of payment choices. To exploit the individual heterogeneity in payment choice, we use a generalized multinomial logit model, taking advantage of the data where we can observe multiple transactions for each individual. Moreover, "perceived" acceptance, which partially gives supply-side information, enables us to separately identify demand-side factors from the supply-side factors. Estimation results confirm that such unobserved heterogeneity in method of payment choice is indeed significant both statistically and economically. Using the estimated model, we conduct the counterfactual simulation where all merchants accept cards regardless of transaction values. Simulation results show that cash usage would indeed decrease but the magnitude is quite limited: cash usage decreases at most about 8 percentage points in frequency share. The implication of this result is that current cash usage is driven by demand-side factors – consumers prefer using cash, in particular, for small-value transactions.

As this paper focuses on consumer's method of payment choice, we abstract from other potential issues listed in Section 4. Considering issues, e.g., competition among network providers or measurement error in choice sets, would be an interesting extension for future research.

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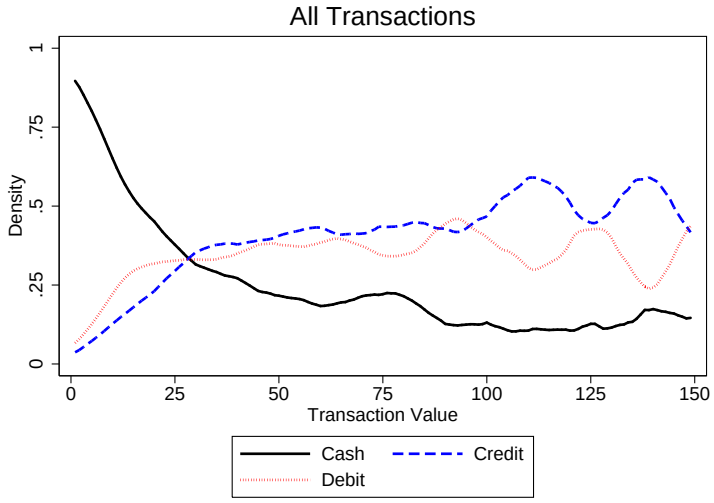
Figure 1: Method of Payment Choice by Transaction Value



Note: This figure is based on 7,908 transactions.

Table 1: Histogram of the Number of Shopping Opportunities

	Before Truncation			After Truncation		
	Raw Freq.	Raw Percent	Weighted Percent	Raw Freq.	Raw Percent	Weighed Percent
1	456	19.52	18.84	-	-	-
2	428	18.32	18.48	-	-	-
3	361	15.45	13.30	361	24.86	21.21
4	289	12.37	13.22	289	19.90	21.09
5	247	10.57	11.74	247	17.01	18.73
6	180	7.71	7.86	180	12.40	12.55
7	120	5.14	6.38	120	8.26	10.08
8	91	3.90	3.47	91	6.27	5.54
9+	164	7.02	6.71	164	11.29	10.80
Total	2,336	100.00	100.00	1,452	100.00	100.00

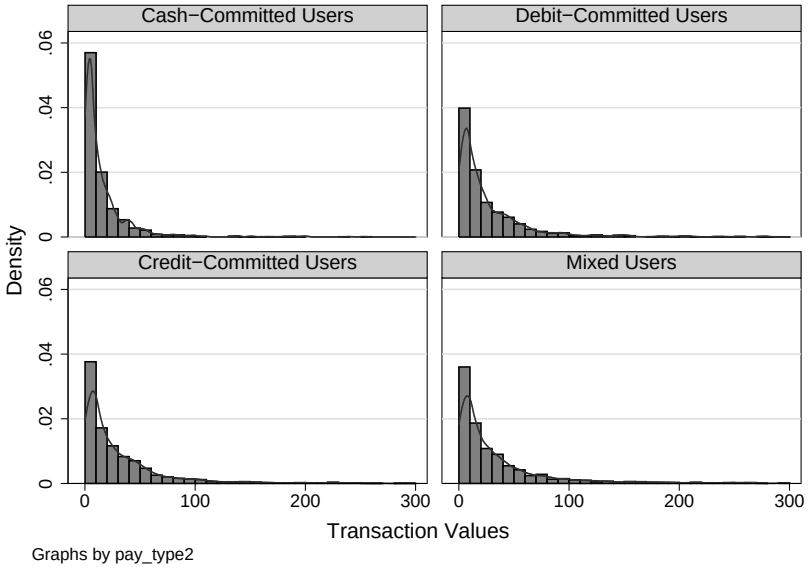
Note: 'Raw Percent' and 'Weighted Percent' indicate whether or not I use the sample weights to correct the sampling bias in the data, respectively. 'Before Truncation' and 'After Truncation' indicate whether or not these samples are truncated by a criterion of having more than 2 shopping trips.

Table 2: Patterns of Payment Choice

	Samples with more than 2 shopping opportunities			
Type of Consumers	#of obs.	Weighted %	avg # of shopping	avg TV
(1) **Cash Users**	**244**	21.81	4.45	16.58
(2) **Debit Users**				
Only Debit	**65**	4.47	4.43	39.65
Cash & Debit	**455**	31.26	5.45	26.53
(3) **Credit Users**				
Only Credit	**60**	3.24	4.40	43.84
Cash & Credit	**360**	22.82	5.52	29.26
(4) **Mixed Users**				
Debit & Credit	**49**	2.96	4.18	39.73
All three	**219**	13.44	7.30	33.54
Total # of individuals	**1,452**		5.45	
Total # of transactions	**7,908**			28.66

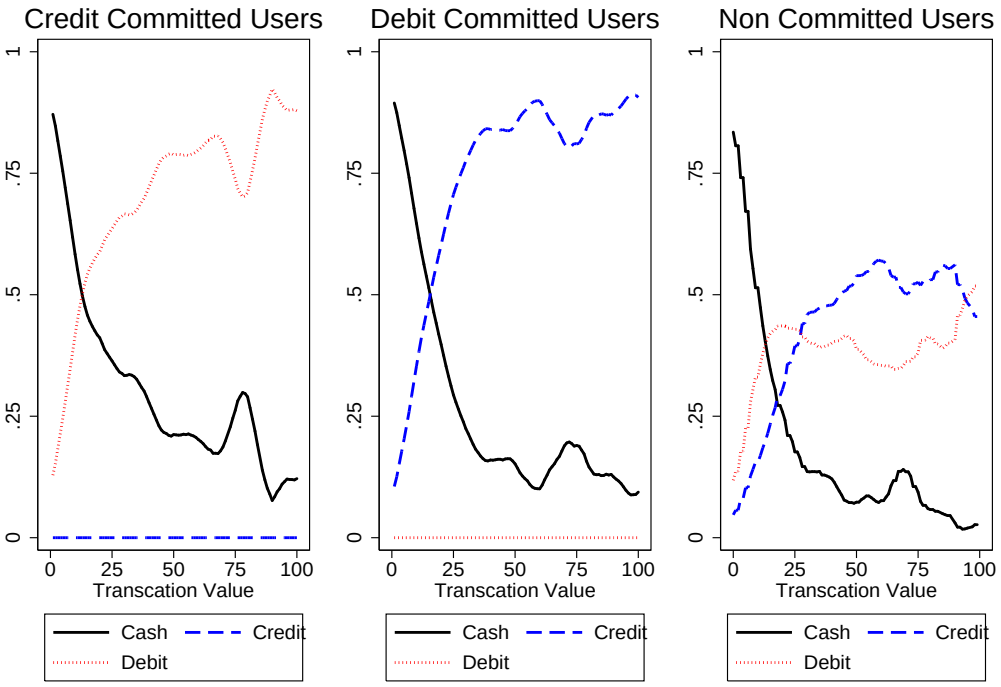
Note: Each row shows the types of consumers, and each column shows the number of observations, the average numbers of shopping opportunities, and average transaction values.

Figure 2: Transaction Value Distributions



Note: As indicated in each graph, top-left, top-right, bottom-left, and bottom-right panes show the transaction value distributions for each consumer type.

Figure 3: Methods of Payment by Consumer Type



Note: The left, center, and right panel show the frequency of payment choices by transaction value, for credit, debit, and mixed users, respectively.

Table 3: Acceptance by Consumer Type

	Cash Users		Debit Users		Credit Users		Mixed Users		Total	
(Debit, Credit)	#	%	#	%	#	%	#	%	#	%
(Unaccepted, Unaccepted)	283	26.06	359	12.97	308	13.69	212	11.75	1,162	14.69
(Accepted, Unaccepted)	255	23.48	531	19.18	116	5.16	108	5.99	1,010	12.77
(Unaccepted, Accepted)	53	4.88	73	2.64	153	6.80	48	2.66	327	4.14
(Accepted, Accepted)	495	45.58	1,805	65.21	1,673	74.36	1,436	79.60	5,409	68.40
Total	1,086		2,768		2,250		1,804		7,908	

Note: For each user, the first column # is the raw number and the second column % is the unweighted percentage.

Figure 4: Ease of Use

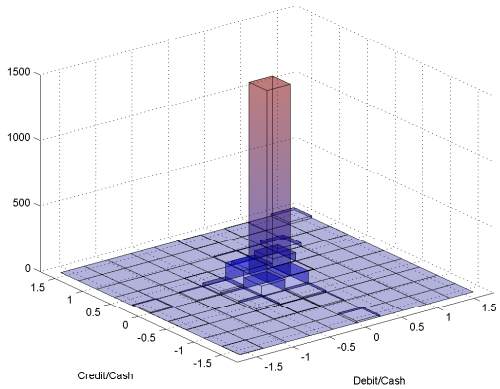
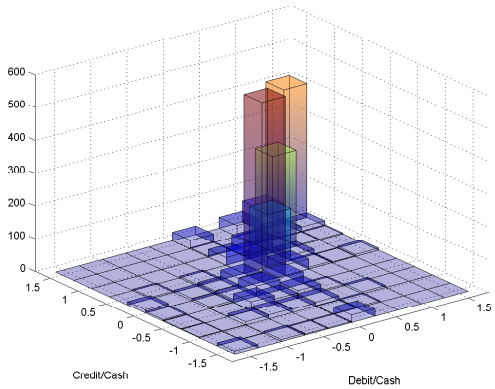


Figure 5: Record Keeping



Note: The left graph shows the 3-dimensional histogram of ease-of-use for credit and debit cards relative to cash. Similarly, the right graph shows the 3-dimensional histogram of consumers perception of record keeping facility for credit and debit cards relative to cash.

Table 4: Variations of Estimated Models

	Model					
	(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 Hetero. (σ)	No	No	No	Yes	No	Yes
(4) Random Coeff. (μ)	No	No	No	No	Yes	Yes

Note: In the first row, 'Trans.' means that I use transactional-level data, assuming each transaction is independent and identically distributed and 'Ind.' means that I stack multiple observations for each individual to extract individual heterogeneity. In the second row, 'limited' and 'Unlimited' stand for limiting and not limiting choice sets by perceived acceptance data reported by respondents.

Table 5: Estimation Results 1/2

	Model (i)		Model (ii)		Model (iii)	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
Credit Cards						
Constant	**-3.0099**	0.2491	**-2.4129**	0.2582	**-2.4129**	0.1638
TV	**1.1451**	0.0936	**1.1125**	0.1189	**1.1125**	0.0783
TV sq	**-0.2733**	0.0318	**-0.2337**	0.0517	**-0.2337**	0.0394
Less than $5	**-1.5953**	0.2067	**-1.4850**	0.2128	**-1.4850**	0.2200
Less than $10	**-0.9901**	0.1393	**-0.8560**	0.1500	**-0.8560**	0.1372
Grocery Store	-0.01646	0.1054	**-0.4068**	0.1112	**-0.4068**	0.0881
Entertainment	**-0.4971**	0.1123	**-0.6468**	0.1237	**-0.6468**	0.1131
Age	**-1.5787**	0.1561	**-1.2256**	0.1676	**-1.2256**	0.1145
Income	0.1654	0.1023	**0.2192**	0.1096	**0.21917**	0.0727
Ease of Use	**0.0882**	0.0155	**0.1039**	0.0172	**0.1039**	0.0103
Record Keeping	**0.4444**	0.0543	**0.4968**	0.0590	**0.4968**	0.0381
Num. of CC	**0.1780**	0.0571	**0.1493**	0.0616	**0.1493**	0.0405
Credit Reward	**0.1102**	0.0289	**0.1654**	0.0287	**0.1654**	0.0174
Credit Limit	**2.0117**	0.1473	**1.5700**	0.1505	**1.5700**	0.1010
RC for TV	–	–	–	–	–	–
RC for Ease	–	–	–	–	–	–
RC for Record	–	–	–	–	–	–
RC for Num. CC	–	–	–	–	–	–
RC for Rewards	–	–	–	–	–	–
RC for C Limit	–	–	–	–	–	–
Scale Coeff.	–	–	–	–	–	–
Debit Cards						
Constant	-0.1693	0.1943	0.2316	0.2056	0.2316	0.1393
TV	**0.8697**	0.0864	**0.8684**	0.1087	**0.8684**	0.0558
TV sq	**-0.2320**	0.0315	**-0.2070**	0.0489	**-0.2070**	0.0329
Less than $5	**-1.1890**	0.1380	**-1.0181**	0.1424	**-1.0181**	0.1389
Less than $10	**-0.8779**	0.1118	**-0.8427**	0.1190	**-0.8427**	0.1097
Grocery Store	**0.7652**	0.0870	**0.3927**	0.0910	**0.3927**	0.0790
Entertainment	-0.1574	0.0995	**-0.3056**	0.1060	**-0.3056**	0.0886
Age	**-1.3127**	0.1260	**-1.1877**	0.1319	**-1.1877**	0.0906
Income	**-0.3166**	0.0767	**-0.3562**	0.0818	**-0.3562**	0.0552
Ease of Use	**0.0999**	0.0158	**0.1094**	0.0172	**0.1094**	0.0116
Record Keeping	**0.1548**	0.0449	**0.2293**	0.0483	**0.2293**	0.0310
Num. of DC	**0.4817**	0.0646	**0.4212**	0.0682	**0.4211**	0.0445
RC for TV	–	–	–	–	–	–
RC for Ease	–	–	–	–	–	–
RC for Record	–	–	–	–	–	–
RC for Num DCs	–	–	–	–	–	–
Scale Coeff.	–	–	–	–	–	–
Summary Statistics						
No. of Param.	26		26		26	
Log Likelihood	-5420.2		-4694.7		-4694.7	
AIC	10892		9441.5		9441.5	
BIC	11074		9622.9		9578.8	

Note: The bold numbers in the estimates columns are statistically significant at the 5% level.

Table 6: Estimation Results 2/2 (Continued)

	Model (iv)		Model (v)		Model (vi)	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
Credit Cards						
Constant	**-4.6344**	0.4396	**-3.5565**	0.4551	**-3.5420**	0.4901
TV	**1.7639**	0.1542	**1.7726**	0.1558	**1.6815**	0.1656
TV sq	**-0.3526**	0.0995	**-0.3177**	0.0820	**-0.3119**	0.0749
Less than $5	**-1.1668**	0.8146	**-2.0460**	0.3124	**-2.0309**	0.3138
Less than $10	**-0.8620**	0.2731	**-1.4553**	0.2199	**-1.4935**	0.2204
Grocery Store	**-0.4510**	0.1528	**-0.7376**	0.1671	**-0.7305**	0.1680
Entertainment	**-0.9530**	0.1820	**-1.2977**	0.1743	**-1.3001**	0.1784
Age	**-0.6100**	0.2234	**-1.5259**	0.3996	**-1.4413**	0.4005
Income	**0.5825**	0.1433	**0.6159**	0.2393	**0.6415**	0.2403
Ease of Use	0.0023	0.0310	0.1508	0.0949	0.1743	0.0969
Record Keeping	**0.4492**	0.0766	**0.7474**	0.1659	**0.7970**	0.1414
Num. of CC	0.2622	0.0788	**0.3608**	0.2038	**0.2809**	0.1722
Credit Reward	**0.3717**	0.0413	**0.4113**	0.1645	**0.4135**	0.1553
Credit Limit	**2.0087**	0.2180	**1.2755**	0.4348	**1.3860**	0.4184
RC for TV	–	–	**-0.4567**	0.1875	0.2108	0.2982
RC for Ease	–	–	**-0.3803**	0.0912	**-0.4017**	0.0985
RC for Record	–	–	-0.1079	0.5921	–	–
RC for Num. CC	–	–	-0.1824	0.6545	–	–
RC for Rewards	–	–	**0.8540**	0.2385	**0.8210**	0.2201
RC for C Limit	–	–	**1.8205**	0.2132	**-1.5863**	0.2161
Scale for CC	**-0.5342**	0.0457			**-0.2338**	0.0956
Debit Cards						
Constant	**3.5675**	0.1958	**1.2762**	0.4338	**1.8895**	0.2457
TV	**0.8172**	0.1023	**1.0749**	0.1065	**1.3615**	0.1678
TV sq	**-0.1400**	0.0403	**-0.2242**	0.0537	**-0.2832**	0.0648
Less than $5	**-3.1921**	0.4493	**-1.2917**	0.1846	**-3.4816**	0.5343
Less than $10	**-2.9933**	0.3666	**-1.3868**	0.1729	**-2.5528**	0.3903
Grocery Store	**0.5807**	0.1432	**0.5748**	0.1249	**0.8743**	0.1947
Entertainment	**-1.1524**	0.2475	**-0.4254**	0.1441	**-1.0243**	0.2734
Age	**-3.8548**	0.2946	**-2.1717**	0.2712	**-3.5558**	0.3947
Income	**-1.2672**	0.1929	**-0.8009**	0.1777	**-1.3882**	0.2832
Ease of Use	**0.1708**	0.0194	**0.1595**	0.0656	**0.2283**	0.0458
Record Keeping	0.2036	0.1156	0.2708	0.1603	0.2956	0.2694
Num. of DC	-0.3539	0.1721	0.2548	0.3328	0.5346	0.3807
RC for TV	–	–	**0.4337**	0.1619	0.3723	0.2217
RC for Ease	–	–	-0.1539	0.1284	–	–
RC for Record	–	–	**-0.6375**	0.2422	**-1.7222**	0.3034
RC for Num DCs	–	–	**2.0838**	0.1927	**2.1846**	0.3294
Scale for DC	**-0.6707**	0.0389			**-0.7431**	0.0570
Summary Statistics						
No. of Param.	28		36		35	
Log Likelihood	-4071.2		-3972.1		-3948.6	
AIC	8198.5		8016.1		7967.3	
BIC	8346.3		8206.2		8152.1	

Note: The bold numbers in the estimates columns are statistically significant at the 5% level.

Table 7: Model Fit - Overall Fitness

	Data	Model Prediction			
		Model (iii)	Model (iv)	Model (v)	Model (vi)
Frequency Share					
Cash	57.20%	56.21%	56.72%	56.55%	56.48%
Credit	18.61%	18.61%	19.01%	19.37%	19.17%
Debit	24.19%	25.18%	24.27%	24.07%	24.35%
Value Share					
Cash	30.48%	30.27%	32.24%	31.56%	31.27%
Credit	34.83%	34.51%	34.85%	35.25%	35.00%
Debit	34.69%	35.22%	32.92%	33.19%	33.73%

Note: As indicated in Table 4, Model (iii) does not include any individual heterogeneity, whereas Model (iv) includes scale coefficients and Model (v) includes random coefficients. Model (vi) includes both random and scale coefficients. Indicated numbers are frequency and volume shares of each payment method.

Table 8: Model Fit - By Merchants' Acceptance

	Data	Model Prediction			
		Model (iii)	Model (iv)	Model (v)	Model (vi)
Merchants Accepting Cash and Credit					
Frequency Share					
Cash	66.36%	73.53%	74.92%	74.97%	74.86%
Credit	33.64%	26.47%	25.08%	25.03%	25.14%
Value Share					
Cash	26.81%	40.84%	43.60%	44.22%	41.99%
Credit	73.19%	59.16%	56.40%	55.78%	58.01%
Merchants Accepting Cash and Debit					
Frequency Share					
Cash	64.22%	59.81%	60.70%	62.53%	61.91%
Debit	35.78%	40.19%	39.30%	37.47%	38.09%
Value Share					
Cash	37.39%	33.97%	37.59%	40.90%	39.57%
Debit	62.61%	66.03%	62.41%	59.10%	60.43%

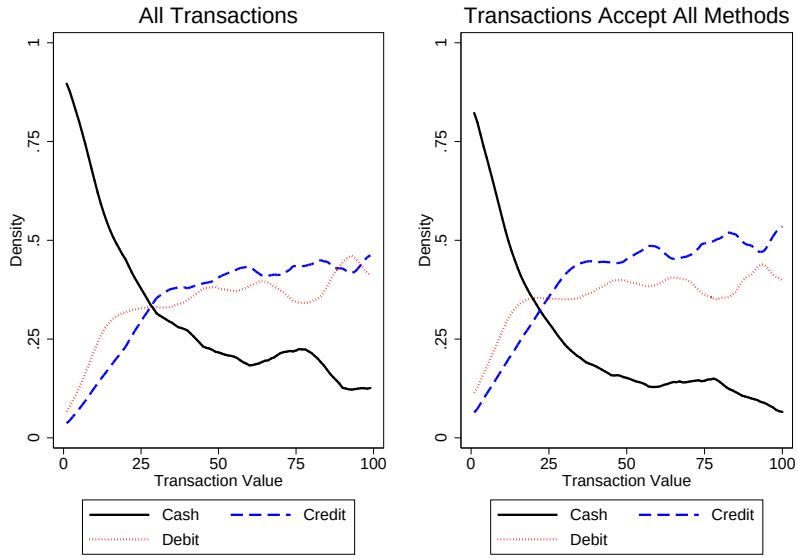
Note: As indicated in Table 4, Model (iii) does not include any individual heterogeneity, whereas Model (iv) includes scale coefficients and Model (v) includes random coefficients. Model (vi) includes both random and scale coefficients. Indicated numbers are frequency and volume shares of each payment method.

Table 9: Simulation results for overall effects

	Data	Model Prediction			
		Model (iii)	Model (iv)	Model (v)	Model (vi)
Frequency Share					
Cash	56.99%	-6.86%	-7.58%	-7.98%	-7.70%
Credit	18.91%	3.69%	4.17%	4.76%	4.38%
Debit	24.10%	3.18%	3.41%	3.22%	3.32%
Value Share					
Cash	30.06%	-6.93%	-7.55%	-7.86%	-7.53%
Credit	36.01%	4.34%	5.57%	5.87%	5.21%
Debit	33.93%	2.58%	1.98%	1.99%	2.33%

Note: The displayed numbers in 'Model Prediction' columns are percentage point changes which are calculated as the difference between the predicted market share under the current choice sets and the predicted market share under the counterfactual choice sets.

Figure 6: Method of Payment Choices by Acceptance



Note: The left panel shows the three methods' frequency by transaction values for all transactions (it is identical to Figure 1), whereas the right panel shows the three methods' frequency for transactions that accept all three methods.

Table 10: Simulation Results - By Merchants' Acceptance

	Data	Model Prediction			
		Model (iii)	Model (iv)	Model (v)	Model (vi)
Merchants Accepting Cash					
Frequency Share					
Cash	100.00%	-32.85%	-34.64%	-34.39%	-34.31%
Credit	0.00%	14.51%	15.36%	16.49%	15.87%
Debit	0.00%	18.35%	19.28%	17.90%	18.45%
Value Share					
Cash	100.00%	-67.66%	-66.77%	-67.71%	-67.70%
Credit	0.00%	33.08%	34.57%	35.96%	34.64%
Debit	0.00%	34.58%	32.20%	31.74%	33.06%
Merchants Accepting Cash and Credit					
Frequency Share					
Cash	68.55%	-11.49%	-15.27%	-14.38%	-13.96%
Credit	31.45%	-5.21%	-3.81%	-2.68%	-3.61%
Debit	0.00%	16.69%	19.08%	17.06%	17.58%
Value Share					
Cash	28.88%	-7.61%	-13.38%	-12.38%	-9.61%
Credit	71.12%	-12.86%	-10.17%	-9.91%	-12.18%
Debit	0.00%	20.47%	23.55%	22.29%	21.79%
Merchants Accepting Cash and Debit					
Frequency Share					
Cash	65.42%	-4.80%	-6.67%	-7.39%	-6.92%
Credit	0.00%	8.55%	10.23%	10.60%	10.09%
Debit	34.58%	-3.76%	-3.55%	-3.21%	-3.17%
Value Share					
Cash	39.74%	-4.59%	-8.82%	-11.01%	-10.08%
Credit	0.00%	14.64%	20.58%	22.20%	20.67%
Debit	60.26%	-10.05%	-11.76%	-11.20%	-10.59%
Merchants Accepting Every Method					
Frequency Share					
Cash	42.24%	-0.23%	-0.11%	-0.69%	-0.41%
Credit	28.70%	-0.04%	-0.07%	0.41%	0.17%
Debit	29.05%	0.26%	0.18%	0.27%	0.24%
Value Share					
Cash	19.43%	-0.01%	0.19%	0.32%	0.46%
Credit	47.01%	-0.77%	-0.67%	-0.80%	-1.13%
Debit	33.56%	0.78%	0.48%	0.48%	0.67%

Note: The displayed numbers in 'Model Prediction' columns are percentage point changes which are calculated as the difference between the predicted market share under the current choice sets and the predicted market share under the counterfactual choice sets.

Table 11: Simulation Results - By Transaction Values

	Data	Model Prediction			
		Model (iii)	Model (iv)	Model (v)	Model (vi)
Less Than $10					
Frequency Share					
Cash	85.44%	-6.19%	-7.29%	-8.11%	-7.46%
Credit	4.68%	2.87%	3.53%	4.32%	3.79%
Debit	9.88%	3.33%	3.76%	3.79%	3.68%
Value Share					
Cash	79.04%	-6.31%	-6.96%	-7.85%	-7.34%
Credit	7.05%	3.21%	3.62%	4.48%	3.96%
Debit	13.91%	3.10%	3.33%	3.38%	3.38%
Between $10 and $25					
Frequency Share					
Cash	52.34%	-9.04%	-9.53%	-9.73%	-9.77%
Credit	17.20%	4.90%	4.45%	5.57%	5.32%
Debit	30.46%	4.14%	5.08%	4.16%	4.45%
Value Share					
Cash	50.65%	-8.36%	-8.76%	-8.98%	-9.02%
Credit	18.00%	4.58%	4.21%	5.23%	5.01%
Debit	31.34%	3.78%	4.55%	3.75%	4.01%
More than $25					
Frequency Share					
Cash	26.95%	-6.00%	-6.45%	-6.52%	-6.42%
Credit	37.00%	3.73%	4.71%	4.68%	4.37%
Debit	36.05%	2.27%	1.74%	1.84%	2.04%
Value Share					
Cash	22.49%	-6.72%	-7.38%	-7.66%	-7.28%
Credit	41.55%	4.39%	5.97%	6.10%	5.34%
Debit	35.96%	2.33%	1.40%	1.56%	1.94%

Note: The displayed numbers in 'Model Prediction' columns are percentage point changes which are calculated as the difference between the predicted market share under the current choice sets and the predicted market share under the counterfactual choice sets.

Appendix: Sample Construction

Originally, the number of individuals who completed the diary survey instrument (DSI) is 3,253. To construct the estimation samples, we first drop 348 individuals who did not answer some attitudinal questions or who were missing some important demographic variables. These operations leave 2,905 individuals with 16,135 transactions.

As a second step, we drop some transactions if missing transaction values (1,674 transactions), if missing decision (54 transactions), if using multiple transaction methods (161 transactions), if using checks or store-value cards (300 transactions), if missing perceived acceptance (4,111 transactions), if inconsistent with decision and choice sets (299 transactions), if unable to use cash (208 transactions), if transaction value is more than $300 (103 transactions). These operations leave 2,336 individuals with 9,220 transactions.[26]

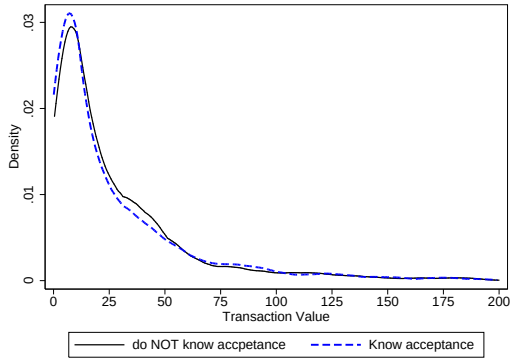
Along the process, the biggest drop has occurred as a result of missing perceived acceptance. One potential concern is that those who do not report the perceived acceptance might be correlated with transaction values, which is the most important determinant in payment choices economically and statistically. As we can easily imagine, for small-value transactions, respondents might not know their acceptance and might more likely answer 'I do not know.' If this is true, this process would create some problems. However, as Figure 7 indicates, the distributions of transaction values look similar. We might be able to impute the acceptance based on transaction values, the number of cashiers at each merchant, and shopping type. However, we will not take this approach as this perceived acceptance is one of the key variables and it seems there is no systematic correlation at least for transaction values.

Finally, for identification purposes, we drop 884 individuals with 1,312 transactions, since they had only one or two shopping records. This final operation yields 1,452 individuals with 7,908 transactions. Again, we also show two distributions for transaction values, which stay

[26] 569 respondents have been dropped during these operations, as they have zero transactions which can be used for the estimation.

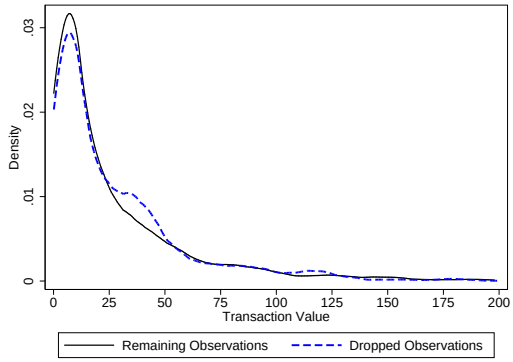
in the sample and are dropped from the sample in Figure 8. These two kernel density estimates suggest that both distributions are similar and we can estimate the models with 1,452 individuals without any problems, since they are representative.

Figure 7: Transaction Value Distributions



Note: The black solid line shows the distribution of transaction values when consumers answer 'I know the acceptance' and the blue dotted line shows the distribution of transaction values when consumers report 'I do NOT know the acceptance,' which we drop from our estimation sample.

Figure 8: Transaction Value Distributions



Note: The black solid line shows the distribution of transaction values that we use for this paper and the blue dotted line shows the distribution of transaction values that we drop from our estimation samples.