Explaining adoption and use of payment instruments by U.S. consumers

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Abstract

This paper develops and estimates a structural model of adoption and use of payment instruments by U.S. consumers. We utilize a cross-section from the Survey of Consumer Payment Choice, a new survey of consumer behavior. Our empirical model combines the elements of a discrete-continuous model, where a consumer first picks a product and then chooses how much to use it, with a bundled choice model, in which consumers can choose multiple products that may affect the utility derived from one another. We consider how changes in the costs of adoption and use may differentially affect substitution patterns. We also evaluate how substitution differs across income levels. These results are particularly relevant for bank pricing of debit card services in response to the regulation of interchange fees on debit cards enacted by the Durbin Amendment to the Dodd-Frank Act, which became effective on October 1, 2011.

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1 Introduction

During the past three decades, the U.S. payments system has been undergoing a transformation from paper to electronic means of payment. Innovations include ATM machines, debit and prepaid cards, online banking, and even mobile payments via cell phone. A notable by-product of this transformation has been an increase in the number of payment instruments held and used by consumers. By 2008, the average consumer held 5.1 of the nine common payment instruments and used 4.2 of them during a typical month Foster, Meijer, Schuh, and Zabek (2009). In our dataset, consumers overall held more than 100 different portfolios of payment instruments and their patterns of payment use varied widely—even after conditioning on their portfolio of payment instruments. This striking range of variety in consumer payment behavior is not fully explained in the economics literature.

This paper develops and estimates a structural model of adoption and use of payment instruments by U.S. consumers. In our two-stage model, consumers first adopt a portfolio of payment instruments, such as debit, credit, cash and check. Then, consumers choose how much to use each instrument in different contexts, such as online, essential retail, and nonessential retail. We separately identify the effect of explanatory variables on adoption and use. We compute elasticities of substitution across different instruments, focusing on how these differ in response to changes in the costs of adoption and use. Our paper makes use of a new public dataset, the Survey of Consumer Payment Choice Foster, Meijer, Schuh, and Zabek (SCPC, described in 2009) specifically designed to address these topics.

Our paper also is motivated by recent research and policy actions aimed at interchange fees for debit and credit card systems. Interchange fees are the subject of regulatory and antitrust activity in a growing number of countries Bradford and Hayashi (2008); Weiner and Wright (2005). In the United States, recent legislation requires the Federal Reserve to regulate the interchange fees of debit cards.[1] Australia has regulated credit card interchange fees since 2001, and the European Union is studying this issue as well.

As banks respond, consumers may face different charges for adoption and use of payment cards. For example, in the United States, some banks have responded to the debit interchange regulation by eliminating rewards programs, a change in the use cost. Some banks have proposed fixed monthly charges on holding or using a debit card, a change in the adoption cost. For instance, Bank of America proposed a fee of $5 per month in which a debit card was used. This well-publicized initiative was eventually abandoned, but alter-

[1] This regulation is part of the Dodd-Frank Wall Street Reform and Consumer Protection Act, signed into law in July, 2010. The specific section referring to debit interchange fees is often referred to as the Durbin Amendment. It requires the Federal Reserve to regulate the interchange fees on debit cards based on bank variable costs. The current policy, which became effective on October 1, 2011, sets the fee substantially below previously observed interchange fees. See the Board of Governors' final rule, Regulation II, Debit Card Interchange Fees and Routing (http://www.federalreserve.gov/newsevents/press/bcreg/20110629a.htm)

natives, such as monthly fees on checking accounts, can be regarded in a similar way. Note that it is possible that banks will not adjust pricing to consumers in response to interchange regulation. Bank pricing is an important issue that we do not study in this paper. Rather, we consider how consumers would respond towards debit cards if banks did make changes in their fee structures.

Understanding how consumers substitute between payment instruments following such changes is important for evaluating these regulations. For instance, consumers may respond to an increase in the cost of using debit cards either by switching to cash or by switching to credit cards. As a digital mechanism, credit cards are often considered more efficient than cash, but since they rely on consumer credit, some view a switch to increased credit card use as undesirable. Furthermore, substitution patterns in response to adoption charges likely differ from substitution patterns in response to use charges, so it is important to employ an approach that recognizes these differences. Moreover, payment substitution is especially important because consumers rarely face explicit costs of using an instrument, and so they may receive poor signals about the social cost of their choice.

Our model incorporates features from several literatures. As our model allows consumers to make separate decisions about adoption and use, it is related to the "discrete-continuous" (or "discrete-discrete") literature of Dubin and McFadden (1984) and Hendel (1999). The discrete-continuous literature typically allows the researcher to structurally estimate the effect of the use value on adoption. These methods typically assume that the consumer has only a limited amount of information at the time of the adoption decision—no more information than the econometrician. These models are also related to the two-step selection model of Heckman (1979). The Heckman selection model can be interpreted as assuming that the consumer knows perfectly the outcome of the use decision at the time of adoption, and therefore knows more than the econometrician has. However, the Heckman selection model does not allow for the identification of the effect of the use decision on the adoption decision. Our model combines both of these features in a single model, allowing agents to know more than the econometrician about use at the time of adoption while at the same time identifying the structural effect of the use value on adoption. We discuss this further below.[2]

Also, because consumers make choices over bundles of goods (for instance, consumers may choose debit, credit, both or neither), our model is related to the bundled choice literature such as Gentzkow (2007) and Crawford and Yurukoglu (2009). In this environment, it is difficult to distinguish between complementary products and correlated preferences. While this problem has typically been approached by using excluded variables Gentzkow

[2]As discussed below, other models such as structural labor models and some models in environmental economics and trade have similar features, although they do not highlight these issues.

(as in 2007) we exploit the fact that we observe use to pin down the substitutability (or complementarity) and allow correlation only in the adoption stage Crawford and Yurukoglu (which is similar to the approach of 2009).

There is a substantial literature on consumer payment choice, such as that reviewed in Rysman (2007, 2010). A related paper is Schuh and Stavins (2010), which uses an earlier, smaller but similar dataset with a Heckman selection model of each payment instrument separately to study adoption and use. Our paper improves upon that study by using a new dataset and a more complete model of the joint adoption and use decision, along with the focus on elasticities in the context of regulatory intervention into pricing in payments markets. Our paper is closely related to the work of Borzekowski, Kiser, and Ahmed (2008) and Borzekowski and Kiser (2008), which use survey data to study adoption and use of debit, although they do not study substitution patterns across payment instruments. Arango, Huynh, and Sabetti (2011) also study payment choice, in this case using diary data.

Our paper is relevant for the literature on two-sided markets as well Rochet and Tirole (see 2006); Rysman (see 2009); Hagiu and Wright (see 2011). While we do not model two-sidedness in the sense that we do not consider the response of merchants to consumer decisions, the payments context that we study is an important motivator for the two-sided markets literature. Also, the distinctions between adoption and use decisions that we focus on are often important in that literature. Examples are Rochet and Tirole (2006) and Weyl (2009).

The SCPC enables us to study a number of important payment *instruments*: cash, check, credit and debit, prepaid cards, online banking, direct bank account deductions, and direct income deductions. In addition, we see use in different payment *contexts*, such as traditional retail, online retail and bill pay. We find that income and age are important determinants of payment choice, with older, wealthier households more likely to use credit cards than other households. The survey asks respondents to evaluate instruments along several dimensions, such as security, ease of use, and set-up cost, on a numerical scale. These are important predictors of choice. In particular, ease of use is highly valued. The security that consumers perceive in each payment instrument is less important. While surprising, this result is consistent with a number of other studies Rysman (discussed in 2010).

To evaluate substitution patterns, we consider changes to consumers' perceived costs of using debit cards. We consider cases in which consumers can and cannot adjust their bundle of payment instruments, which we view as long-run and short-run scenarios. We also distinguish between responses to use costs and adoption costs. We find responses heavily weighted towards paper products, that is, cash and check. We find relatively similar responses across use and adoption costs, both in the short and long run. However, we find substantially heterogeneous responses based on income and education differences. We find that high-income and high-education households substitute towards credit cards much more than low-income and low-education households, which tend to move towards paper products. This effect is in part due to adoption patterns, since poorer households tend not to hold credit cards. In evaluating these results, keep in mind that our paper addresses only some of the issues associated with interchange regulation. We do not incorporate the merchant response to such regulation either in terms of acceptance or pricing, the ways in which it will affect bank pricing or consumer banking choices or other changes associated with recent policies, such as changes in policies towards discounting by merchants for particular payment instruments. Any of these developments could have countervailing effects to those we describe here.

2 Model Comparison and Identification

Our model fits into a general literature in which agents first make a discrete choice and then an ordered or continuous choice over intensity of use. Important early citations are Dubin and McFadden (1984) and Hanemann (1984). More recently, Hendel (1999), Burda, Harding, and Hausman (2012) and Dube (2004) also fit in this area. There is also a similarity to the Heckman (1979) selection model, in which an initial discrete choice determines whether we observe a continuous outcome variable. As a general example of a Heckman model, consider a discrete choice $Y \in \{0,1\}$, where we observe w if $Y = 1$. A standard approach would be to model a latent variable Y^* where $Y = 1$ if $Y^* > 0$ and $Y = 0$ otherwise, with:

$$
\begin{aligned}
Y^* &= z\beta_z + \varepsilon_y \\
w &= x\beta_x + \varepsilon_w \ .
\end{aligned}
$$

The standard approach to estimate the Heckman selection model is to estimate the discrete choice model in a first step and then address correlation between ε_y and ε_w with a control function approach that includes a function of the first-stage results in the linear second stage. This is also the approach followed by Dubin and McFadden (1984) in the context of electricity use and the adoption of electric appliances. However, note that w is not allowed to influence the discrete choice directly. We typically assume that $x \in z$, and we could further assume that $\varepsilon_y = \varepsilon_w + u_y$, that is, that ε_y equals ε_w plus some further noise. Then, the agent observes all of the elements of w when making the discrete decision, and so has perfect foresight. However, the effect of w on Y is captured in reduced form. The weakness of this approach from our perspective is it does not identify the causal effect of w on Y.

The discrete-continuous literature has taken the opposite approach. For instance, Hendel

(1999) allows the analog of $x\beta_x$ to enter as an element of z and thus structurally identifies the effect of the use decision on the adoption decision. However, Hendel (1999) assumes that ε_w does not enter the adoption decision, so it is as if the consumer cannot predict the use decision at the time of adoption. Burda, Harding, and Hausman (2012) are similar. From our perspective, this is restrictive. One might rationalize this set-up by saying that the consumers predict their use with error, but the implicit assumption is that consumers predict their use no better than the econometrician. Dube (2004) does allow for the consumer to have perfect information over use, but he does not model adoption costs, as he studies supermarket food purchases.

In contrast, our model allows both for the structural identification of the effect of use on adoption, and for the consumer to know use at the time of adoption better than the econometrician. The former is attractive since we are specifically interested in distinguishing the effect of changes in adoption costs from use costs. The latter is attractive because it is a realistic and flexible approach.[3,4]

Whereas the Heckman selection model is often estimated in two steps, our model with use directly affecting adoption is akin to a simultaneous equations model in which the equations must be estimated jointly. This leads us to another point: Whereas identification in the Heckman selection model requires an excluded variable in the first equation, our simultaneous equations approach requires excluded variables in both equations. We use consumer ratings of topics that should be relevant for only adoption or only use, such as ratings of the ease of set-up and the speed of use.

In addition to the identification issues associated with the discrete-continuous element of the model, we also face identification issues associated with bundled choice. Importantly, we model the value of a bundle as additively separable in adoption costs. That is, adopting one payment method does not raise or lower the costs of adopting another payment method. An important issue in estimating the demand for bundles of goods is how one distinguishes between the causal effect that adopting one element of a bundle has on the value of adopting other elements, and correlation in the utility of elements. If we observe only a positive correlation, we cannot tell whether the elements of the bundle are truly complements or whether consumers who like one element also tend to like the other. The

[3] To be clear, while we believe our model is more appropriate to our context than previous models, these other models take on a series of complex issues that we need not address. For instance, Hendel (1999), Dube (2004), and Burda, Harding, and Hausman (2012) model ordered choice for the intensity of use, an issue that we abstract from. Hendel (1999) infers the number of choices an agent makes, Dube (2004) infers consumption opportunities from purchase data and Burda, Harding, and Hausman (2012) use a flexible Bayesian method with a non-parametric interpretation.

[4] We are not aware of a similar discussion of the role of consumer information and structural modeling in the discrete-continuous demand literature. However, our model is not the first structural model to have the feature that the decisionmaker predicts the second stage of a two-stage model better than the econometrician. Some examples appear in structural labor and environmental economics.

distinction is important: an exogenous change in the price of one payment affects the use of other payments in different ways depending on these assumptions.

We address this identification issue by assuming that payment methods are substitutes only through use. That is, adopting a debit card does not make it harder or easier to adopt a credit card. However, a person who adopts a debit card may be less likely to adopt a credit card because he expects to use a credit card less often. Our model still accommodates high joint adoption of credit and debit cards by allowing people that have low adoption costs for debit to also have low adoption costs for credit. Thus, we expect the logit use model to capture the extent to which payment methods, such as debit and credit, are substitutes. Correlation will be captured in the covariance matrix governing unobserved elements of use utility and adoption cost. Other papers that have similarly employed use to identify substitution and adoption to identify correlation, are Ryan and Tucker (2009) and Crawford and Yurukoglu (2009). This approach differs from Gentzkow (2007), who uses an instrumenting strategy to separate these issues. Note that our model rules out the possibility that payment methods are complements. We believe this is realistic and consistent with our data.

3 Data

Our paper relies on the Survey of Consumer Payment Choice (SCPC). This dataset is designed by the Consumer Payments Research Center at the Federal Reserve Bank of Boston and collected by the RAND Corporation. The SCPC uses the RAND American Life Panel, a pool of individuals who are frequently surveyed on a variety of topics. The respondents complete Internet surveys, with special provisions for respondents without Internet access. Several preliminary surveys have been administered, but the first installment of the annual survey was administered in 2008. The results are publicly available.

The SCPC focuses on adoption and use of different payment instruments in retail and billing environments, as well as cash holdings and online banking. In addition, the survey collects consumer attitudes towards different features of payment instruments, as well as demographic information. A more complete description of the dataset as well as a useful set of summary variables appears in Foster et al. (2009). Below, we present a few tables that help to explain what we do in this paper. The SCPC provides survey weights for obtaining a nationally representative sample. We use the weights to construct the tables in this section and the summary statistics in Section 6.2, but not to estimate the model parameters, as reported in Section 6.1.[5]

[5] If our model of heterogeneity is well specified, there will be no difference between estimates with and without the weights. As we include many interactions with demographics, weighted results can be difficult to interpret.

To restrict heterogeneity, we drop from our sample consumers who do not have checking accounts, leaving 997 observations. For this reason, the weighted national estimates reported here will not match exactly the published SCPC results in Foster et al. (2009). The survey asks consumers about adoption and use of eight payment instruments: cash, checks, debit cards, credit cards, prepaid cards, online banking bill payment, direct bank account deduction, and direct deduction from income.[6] Prepaid cards allow a consumer to load a dollar value of money (prefunded by cash, a demand deposit account, or even a credit card) and then make payments wherever the card is accepted. A prepaid card does not tap into a consumer's bank (checking) account as a debit card does, but it deducts money from the balance stored electronically on the card. Online banking bill payments are initiated by a consumer, using the consumer's bank website to authorize the bank to pay (credit) a third party from the account electronically. Bank account deductions are initiated by a consumer when the consumer gives his bank account and routing numbers to a third party (other than the bank) and authorizes the third party to withdraw (debit) the payment from the customer's bank account.[7] Thus, bank account deduction differs from online banking bill payment primarily by the initiation and authorization of the payment through disclosure of the account and routing numbers, which may be a security concern, and by the entity given authorization to make the electronic payment (bank versus third party). Both of these electronic payments are functionally similar except that online banking bill payment must occur on the bank's website while bank account deductions can be made on the website of a billing company such as a utility or an online retailer such as Amazon.[8] Both of these electronic methods can be used to set up automatic payments for recurring bills, such as mortgages or to make discretionary payments as needed. Direct deduction from income designates payments that come directly out of a consumer's paycheck and must be organized with the employer. Health insurance payments are a common example of direct deduction from income. Table 1 reports adoption rates for each payment type in our sample. Adoption of cash and check is 100 percent by assumption due to sample selection of bank account holders.

In addition to adoption of payment mechanisms, the survey collects data on their use. The survey asks participants how many transactions they complete in a typical month with each payment instrument in seven payment contexts. The contexts are: essential retail,

[6]The SCPC also includes data on money orders and travelers checks. However, it does not include characteristics of these instruments and they are used relatively infrequently, so we do not include them in our analysis.

[7]The official term in the 2008 SCPC is "electronic bank account deduction" but we suppress "electronic" for simplicity. In the 2009 and later SCPC, the official terminology changed to "bank account number payment."

[8]Note that the 2008 SCPC did not allow consumers to choose that they used online banking to do automatic bill pay. This combination will be allowed in future versions of the survey.

Table 1: Adoption Rates, by Payment Instrument

Category	Payment instrument	Adoption rate (%)
Paper	Cash	100*
	Check	100*
Card	Debit	80
	Credit	78
	Prepaid	17
Electronic	Online banking	52
	Bank account deduction	73
	Income deduction	18

*By construction

Table 2: Number of Transactions Per Month, by Payment Context

Category	Payment context	Mean	Std
Bills	Automatic	6.0	11.2
	Online	6.5	10.5
	In person	7.6	12.8
Retail	Online	6.8	11.4
	Essential	19.1	23.5
	Nonessential	9.8	15.7
Other		12.8	15.0

nonessential retail, online retail, automatic bills, online bills, bills by check or in-person, and other non-retail. The distinction between essential and nonessential retail is similar to the distinction between necessities and luxury goods.[9] Automatic bills involve a consumer's agreeing with a merchant to pay some amount on a regular basis. For example, many consumers pay their mortgage and utility bills this way. Online bills involve a consumer's going to a website (other than the consumer's online banking site) to pay a bill. Bills by mail or in person involve a consumer's paying a bill by mailing a check or card information or by visiting the merchant in person. Other nonretail includes payments to household help, such as baby-sitters, and similar transactions not included in aforementioned categories. Table 2 reports the average number of transactions by context in our sample.

[9]Formal definitions of contexts appear in Foster et al. (2009). An essential payment is a payment made in person to buy basic goods from retail outlets, including: grocery stores, supermarkets, food stores, restaurants, bars, coffee shops, superstores, warehouses, club stores, drug or convenience stores, and gas stations. A nonessential retail payment is a payment made in person to buy other goods from retailers, including: general merchandise, department stores, electronics and appliances stores, home goods, hardware stores, furniture stores, office supply stores, and other miscellaneous and specialty stores.

Table 3: Number of Transactions Per Month by Payment Instrument and Context

	Bills			Retail			Other
Payment Instrument	Automatic	Online	Mail/In person	Online	Essential	Nonessential	
Cash			1.1		6.2	3.1	3.8
Check			4.0	1.6	1.0	0.7	2.8
Debit	1.6	1.6	1.3	2.1	7.5	3.6	3.3
Credit	1.4	1.1	1.2	1.6	4.2	2.2	2.8
Stored value				0.1	0.2	0.1	0.1
Online banking		2.1					
Bank account deduction	2.3	1.7		1.3			
Income deduction	0.8						

Naturally, not every payment instrument is available in every payment context; for instance, one cannot shop online with cash. Table 3 shows the average number of transactions in each instrument-context combination in our dataset. Blank entries indicate entries that were ruled out by the survey itself. Our empirical model provides predictions of the outcomes in Table 1 and Table 3. Note that we will treat these outcomes as continuous variables. Although some outcomes appear sufficiently low enough that discreteness might matter, in most cases the numbers in each cell are reasonably large.

Importantly for our purposes, the SCPC asks participants about how they evaluate payment mechanisms in several dimensions on a scale of 1 to 5. Averages appear in Table 4. Higher numbers mean that the participant has a more favorable view. For instance, cash does poorly in “security” and “records” (the ease of tracking use) but well in “set-up” (the cost of setting up a payment instrument), “cost” (the cost of use) and “acceptance” (the level of merchant acceptance). The rest of the table is also consistent with conventional wisdom. For instance, checks score low on speed but high on record keeping. Debit and credit look similar to each other, except for “cost” where debit is better. Previous discussion alludes to the fact that our model requires variables that can affect use but not adoption, and vice versa. We assume that ease and speed affect use but not adoption, whereas setup affects adoption but not use.

The SCPC provides sampling weights chosen to match the March *Current Population Survey* (CPS), so that weighted aggregate SCPC data (used in other tables of the paper) are representative of the U.S. population.

Table 4: Average Ratings of Payment Instruments

Payment instrument	Security	Setup	Acceptance	Cost	Control	Records	Speed	Ease
Cash	2.6	4.3	4.6	4.3	3.9	2.5	4.3	4.1
Check	2.9	3.7	3.6	3.7	3.2	4.1	2.9	3.4
Debit	2.9	3.9	4.3	3.8	3.6	4.0	4.0	4.2
Credit	3.0	3.7	4.5	2.7	3.5	4.2	4.0	4.3
Prepaid	2.7	3.4	3.8	3.3	3.3	2.9	3.7	3.7
Bank account deduction*	3.3	3.4	3.2	3.7	3.6	3.9	3.8	3.6

*This rating is the same for online banking bill payment and bank account deduction.

4 Model

In this section, we present a model of consumer payment choice of adoption and use of payment instruments in payment contexts. Our model proceeds in two stages. In stage 1, the consumer picks which payment instruments to adopt. In stage 2, the consumer faces payment opportunities and decides to which adopted instrument and context to allocate those opportunities. That is, the consumer first picks adoption, and then use.

In stage 1, consumer i chooses among J payment instruments. Examples of instruments $j = 1, \cdots, J$ are cash, credit card, and debit card. The consumer adopts any combination of instruments. The consumer selects bundle $b_i \in B$, where b_i is a set of payment instruments, and B is the set of all possible sets of payment instruments. In our case, we observe eight instruments, but we assume that consumers always adopt cash and check (and we select our sample on this criteria), so there are only six choices; thus, B has 64 elements (2^6). Also, every bundle b_i contains option $j = 0$, the option not make a purchase. Before further describing the choice in stage 1, we describe stage 2.

In stage 2, consumer i faces a sequence of L payment opportunities, indexed by l. A payment opportunity is bestowed exogenously and gives a consumer the opportunity to make a purchase or pay a bill. One can think of payment opportunities as time periods in the month, such as hours, as if the consumer could make one payment per hour. At each opportunity, the consumer selects which payment instrument to use and to which context to allocate the opportunity. For the instrument, the consumer selects one element $j \in b_i$. For the context, the consumers faces C contexts. Examples of contexts, $c = 1, \cdots, C$ are online purchases, essential retail, and nonessential retail. The consumer can also choose not to use an opportunity, and thus make no payment.

As an example, consider a single day in which a consumer is endowed with 12 payment opportunities. The consumer may choose to skip the first two, buy an essential retail good with cash for the third, skip the next one, pay a bill by check with the fourth, skip the next three, buy a product online with a credit card with the next (assuming the consumer has adopted a credit card), and skip the remaining three opportunities in the day. Since we observe only transactions per month, we do not dwell on the ordering of transactions or how opportunities are spread over the day or month, and we assume that all payment opportunities are identical. Our set-up accommodates consumers who make different numbers of transactions in a month, either because of their income, their preferences, or their portfolio of payment instruments (such as holding a credit card). Also, our model allows consumers to substitute across contexts based on payment instruments. For instance, a consumer with a credit or debit card may choose to make online purchases, while a consumer with only cash and check may not do so. As a result, a consumer with a card may choose fewer nonessential retail payments. In practice, we assume that the number of payment opportunities is 400 per month, about 13 per day, constant across all consumers. This number is well above what we observe for any consumer in the dataset.

At opportunity l, the utility to consumer i from using payment method $j \in b_i$ and context c is:

$$u_{ijcl} = \delta_{ijc} + \varepsilon^u_{ijcl} \ .$$

The consumer observes both δ_{ijc} and ε^u_{ijcl} when choosing j and c, but observes only δ_{ijc} at the time of adopting j. Discussion of econometrics is delayed until the following section, but we note that the econometrician may not perfectly observe δ_{ijc}. For each opportunity l, consumer i chooses j and c such that $u_{ijcl} \geq u_{ij'c'l} \forall j' \in b_i, c' = 1, \ldots, C$.

We denote $v_{il}(b)$ as the indirect utility from holding bundle b_i for opportunity l:

$$v_{il}(b) = \max_{j \in b_i, c \in \{1,\ldots,C\}} u_{ijcl} \ . \tag{1}$$

At the time of adoption, the consumer is concerned with the expected indirect utility, averaged over ε^u_{ijcl}. One can think of this as the average over payment opportunities l:

$$v_i(b) = E[v_{il}(b)] \ .$$

Now consider stage 1, the adoption stage. The consumer knows δ_{ijc} and the distribution of ε^u_{ijcl} but not the realizations. Thus, the consumer knows $v_i(b)$ for each possible bundle $b \in B$. The value to consumer i of adopting bundle b is:

$$V_{ib} = \overline{V}_{ib} + \varepsilon^a_{ib} = \sum_{j \in b} \lambda_{ij} + \alpha v_i(b) + \varepsilon^a_{ib}. \tag{2}$$

The parameters λ_{ij} represent a payment instrument-specific utility term in excess of any utility from use. It could be an explicit cost such as an annual fee, or represent the cost of learning or paperwork. We think of it as the adoption cost, whereas $v_i(b)$ represents the use benefit, although λ_{ij} is not restricted to be negative and could be an "adoption benefit." The parameter α moderates the value of use utility relative to the adoption cost. The variable ε^a_{ib} represents utility that is idiosyncratic to the consumer and the bundle (the superscript "a" refers to adoption). The consumer picks b such that $V_{ib} \geq V_{ib'} \forall b' \in B$.

Thus, consumers select a bundle of payment instruments in anticipation of their use preferences in the second period. We do not model the fact that some payments "must be paid" (such as food purchases or bills). Whatever desire the consumer has to make a payment is captured by δ_{ijc}, the consumer utility from allocating a payment opportunity to that context and instrument. This approach captures the issues we hope to address.

Note that in our model the adoption cost of a bundle of payment instruments is simply the sum of the adoption costs of the individual instruments. There are no "economies of scope" or other such causal effects of adoption of one instrument on the other payment instruments. Rather, we match joint adoption patterns by allowing for correlated preferences through the unobserved elements of λ_{ij} (discussed below). It is difficult to separate these effects, and we feel that our assumptions are reasonable. Of course, we allow for a negative causal effect of adoption of one payment instrument on the value of the others through use—for instance, adopting a credit card will make adopting a debit card less valuable since those instruments are substitutes in use. Our assumption is that adopting one has no effect on the adoption cost of the other.

5 Estimation

This section provides our parametric assumptions for purposes of estimation and our estimation strategy. In the second-stage problem (the use stage), we assume that ε^u_{ijcl} is distributed Type 1 Extreme Value (the superscript u refers to use). We normalize the value of no payment to zero, so $\delta_{i0} = 0$. Therefore, the probability (or expected share) of payment instrument j and context c by consumer i integrated across options l is:

$$s_{ijc} = \frac{\exp(\delta_{ijc})}{\sum_{k \in b_i} \sum_{d \in C} \exp(\delta_{ikd})} \quad .$$

The Extreme Value assumption implies that the distribution of the value of opportunity l when holding bundle b (from Equation 1) follows:

$$v_{il}(b) = \ln\left(\sum_{j\in b}\sum_{c\in C}\exp(\delta_{ijc})\right) + \varepsilon^u_{il} \ ,$$

where ε^u_{il} is also distributed Type 1 Extreme Value. The mean of a variable with this distribution is Euler's constant, γ. Therefore, the expected value of bundle b, now averaging across the L purchases is:

$$v_i(b) = E[v_{il}(b_i)] = \left(\ln\sum_{j\in b}\sum_{c\in C}\exp(\delta_{ijc}) + \gamma\right) \ . \tag{3}$$

In the first stage, we assume that ε^a_{ib} is distributed Type 1 Extreme Value and is *iid* across consumers and bundles. Therefore, the probability of picking bundle b_i is:

$$\Pr(b_i) = \frac{\exp(\overline{V}_{ib})}{\sum_{k\in B}\exp(\overline{V}_{ik})} \ .$$

Although we assume that the consumer knows both δ_{ijc} and λ_{ij}, we allow the econometrician to face uncertainty about these values. We assume that:

$$\delta_{ijc} = x_{ijc}\beta_\delta + \nu_{ijc} \ . \tag{4}$$

The vector x_{ijc} is a set of observable characteristics about the individual, the payment choice and the context, and possibly some interactions between these. The parameter ν_{ijc} represents the quality that consumer i perceives for method j in context c that is unobserved to the researcher.

We assume that:

$$\lambda_{ij} = z_{ij}\beta_\lambda + \omega_{ij} \ . \tag{5}$$

The vector z_{ij} represents payment instrument-specific observable characteristics. Let the vector $\nu_{\mathbf{i}}$ be the $C\times J$ vector of terms ν_{ijc}, which includes terms for products that are part of b_i and for those that are not.[10] Similarly, define $\omega_{\mathbf{i}}$ to be the $J-2$ vector of values of ω_{ij}. The "-2" reflects the fact that we assume that consumers always adopt check and cash, so we do not model those adoption choices. We assume that the unobservable terms are distributed multivariate normal, possibly with correlation. Thus, $\{\nu_{\mathbf{i}}, \omega_{\mathbf{i}}\} \sim \mathbb{N}(0,\Sigma)$, with

[10] In fact, not every instrument can be used in every context in our survey (as reflected in Table 3), and we restrict our consumers to be unable to make such a choice. Because of this issue, we will never observe the full set of $C\times J$ market shares. We ignore this issue in our notation for this section.

joint CDF Φ and joint PDF ϕ. The set of parameters to estimate is $\theta = \{\beta_\delta, \beta_\lambda, \alpha, \Sigma\}$.

In order to construct the likelihood function, let y^*_{ijc} be the observed number of transactions that i allocates to instrument j and context c, and b^*_i be the observed bundle. That is, the "*" symbol indicates data. Let $\mathbf{y^*_i}$ be the vector made up of elements y^*_{ijc}. Then, the likelihood function is:

$$\mathcal{L}_i(\mathbf{y^*_i}, b^*_i|\theta) = \int_{\nu_\mathbf{i}} \int_{\omega_i} \Pr(\mathbf{y^*_i}, b^*_i|\theta, \nu_i, \omega_i) f(\nu_i, \omega_i) d\omega_i d\nu_i \ .$$

That is, we integrate out the unobserved terms ν_i and ω_i to construct our likelihood function. Because this is an integral over a high-dimensional multivariate normal distribution, we turn to simulation techniques to compute our likelihood. In what follows, we present computational details of our algorithm for interested readers.

The elements of Σ affect the substitution patterns, and the correlation between first and second-stage choices. We can potentially allow for arbitrary correlation among the elements of ν_{ijc} and ω_{ij} through the parameter matrix Σ. In practice, we restrict the elements of Σ but allow it to have the flexibility to address several issues. In particular, we allow consumers to have correlated values for the use utility of using an instrument in different contexts, as well as correlated values for the use utility of different instruments in the same context. For example, a consumer may have an idiosyncratic preference to pay by credit card or to shop online. In addition, we allow for the instrument preference in use to also enter the adoption value of that instrument. This feature introduces a selection effect, so that consumers who value an instrument for unobserved reasons also have different adoption costs for that instrument.

In particular, let ε^1_{ijc} be distributed standard normal, independent across i, j, and c. Let ε^2_{ij} be standard normal and independent across i and j, but be constant across c. Let ε^3_{ic} be defined analogously. Then we define:

$$\begin{aligned} \nu_{ijc} &= \sigma_1 \varepsilon^1_{ijc} + \sigma_j \varepsilon^2_{ij} + \sigma_c \varepsilon^3_{ic} \\ \omega_{ij} &= \sigma_2 \varepsilon^2_{ij} \ . \end{aligned} \tag{6}$$

Thus, σ_1, σ_j, and σ_c determine correlation within use, and σ_2 determines correlation across the two stages. We draw the elements $\{\varepsilon^1_{ijc}, \varepsilon^2_{ij}, \varepsilon^3_{ic}\}$ from an independent standard normal distribution ns times for each individual i. The parameters $\{\sigma_1, \sigma_2, \sigma_j, \sigma_c\}$ determine Σ and are to be estimated.

It is straightforward to add further shocks. We experiment with several extensions. Since we are particularly motivated by public policy towards debit cards, we are interested in allowing rich substitution patterns for debit. Debit cards are close to credit because they are both card based, and close to cash since payment is immediate. Therefore, we add a shock to use (ν_{ijc}) that affects both debit and credit, and a separate use shock for debit and cash. In addition, we allow for a shock that is constant for debit and credit in adoption.

We begin our algorithm by generating values of ε (in practice, from a Halton sequence as opposed to a pseudo-random number generator). Based on parameters, we use the values of ε to construct values ν^s_{ijc} and ω^s_{ij} according to Equation 6. The are used to construct δ^s_{ijc} using Equation 4 and values of λ^s_{ij} using Equation 5. Based on δ^s_{ijc}, we construct $v^s_i(b)$ from Equation 3 (the values from use of each bundle, consumer, and draw). With v^s_{ib} and λ^s_{ij}, we construct $\overline{V}^s_{ib}$ from Equation 2 (the value of adoption). Using δ^s_{ijc} and $\overline{V}^s_{ib}$ we can construct our simulated likelihood function:

$$\widehat{\mathcal{L}}_i(\mathbf{y_i^*}, b_i^*; \theta) = \frac{1}{ns} \sum_{s=1}^{ns} \Pr\left(\mathbf{y_i^*} | b_i^*, \nu_i^s, \omega_i^s, \theta\right) \Pr\left(b_i^* | \nu_i^s, \omega_i^s, \theta\right) \quad ,$$

where:

$$\begin{aligned}
\Pr(\mathbf{y_i^*} | b_i^*, \nu_i^s, \omega_i^s, \theta) &= \Pi_{j \in b_i^*} \Pi_{c \in C} \left(\frac{\exp(\delta^s_{ijc})}{\sum_{k \in b_i^*} \sum_{d \in C} \exp(\delta^s_{ikd})} \right)^{y^*_{ijc}} \\
\Pr\left(b_i^* | \nu_i^s, \omega_i^s, \theta\right) &= \frac{\exp(\overline{V}^s_{ib^*})}{\sum_{k \in B} \exp(\overline{V}^s_{ik})}.
\end{aligned}$$

As in any approach that relies on maximum simulated likelihood, bias is introduced since $\mathcal{L}_i$ is approximated with simulation error, which enters nonlinearly (since we actually maximize the logarithm of the simulated likelihood) into our objective function. See Pakes and Pollard (1989) and Gourieroux and Montfort (1996). Maximum simulated likelihood is consistent only as ns goes to ∞. Fortunately, our objective function is not difficult to compute, and so we set ns very high, such that we expect this problem is minimized.

Several issues with our model and estimation deserve discussion. First, in our model, consumers know the values ν_{ijc} perfectly, so they predict their use pattern very accurately at the time of adoption. However, this notion does not need to be taken literally. It is possible that consumers predict use with some error. For instance, suppose that consumers get a signal of the use value of a bundle denoted as $\widehat{v(b_i)}$, where $\widehat{v(b_i)} = v(b_i) + \xi_{ib}$, where ξ_{ib} is some white noise. As long as $\xi_{ib} + \epsilon^a_{ib}$ is distributed Extreme Value, our model of adoption (in Equation 2) is the same. In this case, one can interpret the parameter α as measuring the accuracy of the consumer's knowledge about final use. In either case, an attractive feature of the model is that it allows the consumer to have better knowledge than the econometrician has about use.[11]

[11] A perhaps more realistic model would build prediction error into δ_{ijc}, so that prediction error for one instrument would affect all bundles to which it was a part. We view this as difficult to identify separately

A more complicated issue is that adoption is dynamic, whereas we model it as being static. In practice, a consumer may adopt an instrument, experiment with it and learn different ways in which it might be used, and perhaps build up a comfort level with it that affects her propensity to substitute newer technologies, such as debit or prepaid cards. We ignore these issues—one would need a panel in order to study dynamic adoption and particularly one would need detailed use data to study learning—but we regard them as interesting and potentially important.

A third issue is that our model is a partial equilibrium model in the sense that we hold fixed the decisions of merchants. For instance, if higher bank fees on debit cards cause consumers to reduce the use of debit cards, merchants may be less likely to accept debit cards. However, reduced interchange fees should cause more attractive pricing to merchants by banks, and this should increase merchant participation. The overall effect is unknown, and it could impact consumer decisionmaking. While these effects are potentially interesting, they are outside the scope of this paper.

An important issue is that we rely heavily on consumer ratings of payment instruments. These ratings are self-reported evaluations and may be problematic. Reporting may vary across consumers, and there may be bias in how the ratings are determined—for instance, consumers may assign high ratings to their own choices ex post that they would not have assigned ex ante. We can experiment without these ratings, but they provide an important source of variation in our approach. Schuh and Stavins (2010) also find them to be important. We found the results of the ratings consistent with our expectations, both in the simple statistics and the estimation results.

Lastly, we discuss standard errors. We compute standard errors using the outer product of the gradient to compute the information matrix. Our standard errors appear very small, particularly for the use parameters. In part, this is because we have many observations for this part of the model. Our effective number of observations is the number of consumers (997) times the number of use choices per consumer, which we set at 400, plus an adoption choice for each consumer (a further 997 observations). Furthermore, we have not corrected for misspecification (that is, we have not used a sandwich estimator of the variance that utilizes both the information matrix and the Hessian, or "robust" standard errors) and we have not corrected for extra variance due to simulation approximation. We are currently exploring these issues, including the use of the bootstrap.

from the model we consider, but it might be possible.

6 Results

In addition to using the full dataset, we consider two variants for robustness purposes. The first alternative model uses only "retail" payment instruments and contexts: that is, the instruments are cash, check, credit cards, debit cards, and prepaid cards, and the contexts are online retail, essential retail, nonessential retail, and other. This specification rules out the bill pay options, which eliminates some of the heterogeneity in choices and makes some variables easier to interpret, especially the ratings of the different instruments. Second, we consider the full model but restricted to the "no debt" subsample, meaning people who report not carrying a balance on their credit card. This restriction eliminates heterogeneity in the data and makes some results easier to interpret. That model is restricted to consumers who have adopted a credit card. In addition to the "full model" described above, we also provide estimates of the use stage alone, ignoring the adoption stage. These estimates use only observed choices and so do not address the selection inherent in the adoption decision.

For explanatory variables in the use equation (the elements of x), we include payment context-instrument fixed effects, consumer ratings of the payment instrument, demographics (age, gender, race, marital status, employment status, and education level) and payment instrument-income interactions for each payment instrument. For the debit and credit card equations, we include measures of debt and interactions of debt with income. For explanatory variables in the adoption equation (the elements of z), we include payment instrument dummies and demographics, as well as the consumer rating of the set-up experience and a measure of internet access.

6.1 Parameter results

Table 5 provides the average utility of each payment instrument-context combination in the use equation. For essential retail, cash and debit are the most popular instruments, followed by credit cards. Check is further back, with prepaid cards being the least popular. For nonessential retail, debit and cash are the most popular, but credit cards are more popular than in the essential retail context. For online retail, the results are very similar for all payment instruments except for prepaid cards, which are less popular than any other payment instrument. In the bill pay contexts, check is far more popular than cash, debit, or credit, although online payments and automatic deductions are close to check in popularity.

Table 6 contains results for demographic variables. In order to constrain the number of parameters, we do not include every demographic variable in every payment instrument equation. Instead, we limit the potential demographic variables based on previous studies (for example, Mann 2011). As seen in Table 6, we allow age to affect check, debit, and credit; we allow gender to affect only debit and credit; and we allow education to affect

Table 5: Average Utilities by Context and Payment Instrument in Use Equation

	Bills			Retail			Other
Payment Instrument	Automatic	Online	Mail/In person	Online	Essential	Nonessential	
Cash			-6.18		-3.80	-4.83	-4.24
			(0.02)		(0.01)	(0.02)	(0.01)
Check			-4.27	-5.52	-5.72	-6.30	-4.64
			(0.01)	(0.02)	(0.03)	(0.03)	(0.01)
Debit	-5.60	-5.55	-5.88	-5.36	-3.74	-4.59	-4.37
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Credit	-5.98	-6.11	-6.20	-5.54	-4.31	-5.10	-4.66
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Stored value			-8.30	-7.07	-5.99	-7.06	-6.97
			(0.20)	(0.10)	(0.07)	(0.11)	(0.09)
Online banking		-4.44					
		(0.02)					
Bank account deduction	-4.65	-4.86		-5.33			
	(0.02)	(0.01)		(0.02)			
Income deduction	-4.37						
	(0.04)						

Standard errors in parenthesis.

debit, credit, online bill pay, and automatic income deduction. We allow effects on credit and debit use for every demographic variable, as these payment instruments are of high policy interest. The "full model" column of the table shows that older consumers use credit and check more often than younger consumers do, that men are more likely than women to use debit and credit, and that more highly educated people favor credit cards. Employed people are less likely to use credit cards, presumably because they do not need access to credit.

The different specifications in Table 6 provide interesting comparisons. For instance, age has a positive effect on debit in the "use only" model, but a negative effect in the full model, suggesting a strong selection effect whereby older people who adopt debit cards are particularly likely to make heavy use of them.[12] Similarly, males and blacks appear to use debit very little in the use-only model, but this appears to be due to a selection effect. Also, the fact that males use debit and credit cards more than females is driven by those who carry credit card debt, since thrse parameters are negative in the no-debt sample. There is a similar effect for black consumers.

Table 7 presents the effect of income on each payment instrument in the use equation. Higher income affects the use of most instruments positively and significantly. The only negative and significant coefficient on income is for prepaid cards. This is not surprising, since prepaid cards can be seen as inferior substitutes to other cards, and they tend to be popular with consumers who are less likely to use traditional bank cards. Income has the smallest positive effect on cash, and its effect actually negative (and insignificant) on automatic income deduction. In the retail-only specification, we see that income has the largest effect on credit card use. Check has a relatively large coefficient in the full model because of its heavy use in bill pay contexts.

Next in Table 8, we consider the role of consumer ratings. Overall, consumer ratings are important, explaining about the same amount of variation in use as the demographic variables, although they account for far fewer parameters. All of the ratings variables have a positive effect on payment use, as expected. Ease of use is the most important determinant of use, followed by cost of use. These results are generally consistent with those in Schuh and Stavins (2010). Perhaps surprisingly, security is relatively unimportant, although it is still positive and statistically significant. This result appears in other settings as well (see Rysman 2010, for an overview). Interestingly, the effect of ease of use is not as strong in the retail model, suggesting that ease of use is particularly important in the bill pay context.

Finally, we consider the role of debt in determining use. Table 9 contains results. Row 1 reports the effect of a dummy for overdrawing a checking account in the last 12 months,

[12] Conversations with bank executives suggests that customers who decline the debit feature of their ATM card are likely to be elderly.

Table 6: Demographics in use.

Independent variable	Dependent variable	Use	Full	Retail	No debt
Age	Check	1.12	1.14	0.48	1.48
		(0.02)	(0.02)	(0.03)	(0.03)
	Debit	0.28	-0.43	0.05	-0.45
		(0.02)	(0.02)	(0.03)	(0.02)
	Credit	0.63	0.24	0.01	0.33
		(0.02)	(0.02)	(0.03)	(0.02)
Male	Debit	-0.22	0.21	-0.32	-0.53
		(0.01)	(0.01)	(0.02)	(0.02)
	Credit	0.11	0.09	0.27	-0.14
		(0.01)	(0.01)	(0.02)	(0.01)
Black	Debit	-0.07	0.27	0.24	-0.98
		(0.03)	(0.03)	(0.04)	(0.04)
	Credit	0.3	0.38	-0.05	-1.07
		(0.03)	(0.03)	(0.05)	(0.15)
Married	Debit	-0.12	-0.16	0.03	-0.52
		(0.01)	(0.01)	(0.02)	(0.02)
	Credit	0.0	0.31	-0.02	0.22
		(0.01)	(0.01)	(0.02)	(0.02)
Employed	Debit	0.02	-0.06	0.26	-0.56
		(0.01)	(0.01)	(0.02)	(0.02)
	Credit	-0.16	-0.3	-0.08	0.06
		(0.01)	(0.01)	(0.02)	(0.02)
Education	Debit	-0.08	-0.11	-0.11	-0.2
		(0.01)	(0.01)	(0.01)	(0.01)
	Credit	0.22	0.35	0.26	0.16
		(0.01)	(0.01)	(0.01)	(0.01)
	Online banking	0.07	0.01		0.21
		(0.01)	(0.01)		(0.02)
	Bank account deduction	0.08	0.1		0.06
		(0.01)	(0.01)		(0.01)

Standard errors in parenthesis.

The “use” specification refers to the model in which adoption is not taken into account.

“Full” refers to the complete model described earlier. The “retail” specification refers to the specification where the only instruments used are cash, check, credit, debit, and stored value, and the only contexts are online, essential, nonessential, and other.

“No debt” refers to restricting the sample to consumers who do not report carrying credit card debt.

Table 7: Effect of Income of Each Instrument on Use

Payment instrument	Use	Full	Retail	No debt
Cash	0.13	0.11	-0.03	-0.004
	(0.01)	(0.02)	(0.02)	(0.02)
Check	0.54	0.61	0.07	0.27
	(0.02)	(0.02)	(0.02)	(0.02)
Debit	0.69	0.54	0.08	0.32
	(0.02)	(0.02)	(0.03)	(0.02)
Credit	-0.01	0.16	0.30	0.66
	(0.02)	(0.02)	(0.02)	(0.02)
Stored value	-0.61	-0.62		-0.57
	(0.06)	(0.06)		(0.13)
Online banking	0.49	0.53	-0.18	0.44
	(0.05)	(0.05)	(0.03)	(0.05)
Bank account deduction	0.23	0.23		0.23
	(0.02)	(0.02)		(0.02)
Income deduction	-0.01	-0.03		0.57)
	(0.11)	(0.13)		(0.09)

Standard errors in parenthesis.

Table 8: Effect of Consumer Ratings of Payment Instruments on Use

Variable	Use	Full	Retail	No debt
Security	0.014	0.014	0.023	0.020
	(0.002)	(0.002)	(0.003)	(0.003)
Acceptance	0.007	0.017	0.042	0.003
	(0.003)	(0.003)	(0.006)	(0.005)
Cost	0.100	0.084	0.054	0.034
	(0.003)	(0.003)	(0.004)	(0.003)
Control	0.029	0.015	0.035	0.030
	(0.002)	(0.002)	(0.004)	(0.003)
Record	0.039	0.012	0.042	0.168
	(0.003)	(0.003)	(0.005)	(0.004)
Speed	0.028	0.033	0.059	0.041
	(0.004)	(0.004)	(0.006)	(0.004)
Ease	0.106	0.129	0.089	0.117
	(0.004)	(0.004)	(0.006)	(0.004)

Standard errors in parenthesis.

Table 9: Effect of Debt Characteristics on Debit and Credit Card Use

Independent variable	Dependent variable	Use	Full	Retail	No debt
Overdraft	Debit	0.25	0.49	0.21	0.82
		(0.01)	(0.01)	(0.02)	(0.02)
	Credit	-0.15	-0.18	-0.22	-0.42
		(0.01)	(0.01)	(0.02)	(0.02)
Debt revolver	Debit	0.96	1.05	0.55	
		(0.01)	(0.02)	(0.02)	
	Credit	-0.6	-0.55	-0.26	
		(0.01)	(0.01)	(0.02)	
Debt amount	Debit	-0.09	-0.08	-0.2	
		(0.01)	(0.02)	(0.02)	
	Credit	-0.07	-0.03	-0.02	
		(0.01)	(0.01)	(0.02)	
Debt $\times$ Income	Debit	0.02	0.02	0.06	
		(0.01)	(0.01)	(0.01)	
	Credit	0.05	0.036	0.03	
		(0.00)	(0.00)	(0.01)	
Debt $\times$ Education	Debit	0.006	0.004	0.0008	
		(0.00)	(0.00)	(0.00)	
	Credit	-0.015	-0.013	-0.014	
		(0.00)	(0.00)	(0.00)	

Standard errors in parenthesis.

and it predicts higher debit use, suggesting that households that engage in overdrawing do not have credit lines or have exhausted them. A dummy for having revolved a credit card in the last 12 months also predicts higher debit use, either because the cost of using a credit card increases or because credit card revolvers use debit cards more than other consumers, in order to curb their spending. The size of the revolving balance actually has a negative effect on debit use, although the economic magnitude is not large.

Now we turn to results from the adoption equation. The payment instrument dummy coefficients appear in Table 10. These represent costs, so high coefficients imply an instrument that is more costly to adopt. Since all consumers hold cash and check by assumption, we do not estimate costs for these variables. We see that credit cards are the least costly to adopt, followed by debit. The difference is statistically significant, and the differences are smaller in the no-debt and retail-only specifications. Prepaid cards are more costly than other card options. Interestingly, bank account deduction is regarded as very inexperience to adopt, although not quite as inexperience as payment cards. Online bill pay is more expensive.

Table 10: Effect of Payment Instrument Dummy Variables on the Cost of Adoption

Category	Payment instrument	Full	No debt	Retail
Card	Debit	-1.29	-0.82	-1.41
		(0.10)	(0.10)	(0.13)
	Credit	-1.84	-0.44	-1.79
		(0.13)	(0.13)	(0.13)
	Stored value	1.39	0.62	1.47
		(0.09)	(0.10)	(0.09)
Electronic	Online banking	0.26	-0.59	
		(0.09)	(0.10)	
	Bank account deduction	-0.99	1.40	
		(0.10)	(0.09)	
	Income deduction	1.43	1.59	
		(0.09)	(0.11)	

Standard errors in parenthesis.

We include several additional variables in the adoption decision. The results are presented in Table 11. Again, a negative coefficient indicates higher adoption and vice versa. In particular, a higher rating of set-up cost leads to increased adoption of that instrument, as expected. Note that even though there is a separate equation for each payment instrument, some coefficients on explanatory variables were constrained to be the same in each equation (for example, no higher school degree) in order to reduce the number of estimated parameters. Overall, adoption costs vary with income and payment instrument. We graph this result in Figure 1. Notice that the adoption cost of all of the instruments (except for prepaid cards) drops with income, but that the adoption cost of credit drops at the highest rate. This result may be explained in part by credit checks and selective offers by banks.

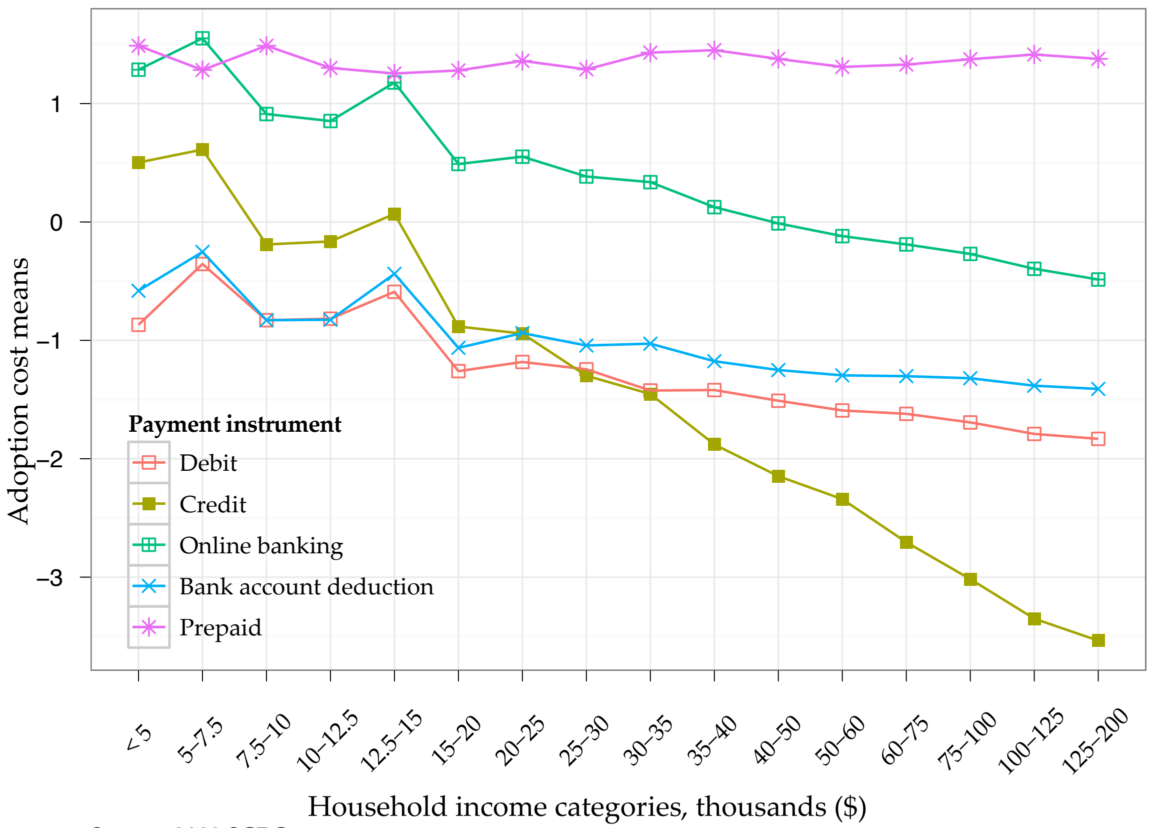
With respect to credit cards, the correlation between adoption cost and income may reflect both consumer preferences and the willingness of card companies to grant the credit line. We cannot separate the effect of income through these two channels, particularly because we do not observe application behavior. We think of our specification as a reduced-form equation for the more complicated simultaneous equations model of consumer and bank decision-making. Therefore, to interpret our counterfactual changes in the costs of debit cards, we must maintain an assumption that the reduced-form relationship between income (and other explanatory variables) and credit-card adoption remains constant. We believe this is a reasonable assumption.

Finally, we consider the elements of the Σ matrix. In the full model, this accounts for 30 parameters. Rather than presenting each parameter, we provide the correlation coefficients for the unobserved elements of adoption and use, which differ by context. That is, we

Table 11: Effect of Personal Characteristics on the Cost of Payment Instrument Adoption

Demographic variable	Payment instrument(s)	Full	Retail	No debt
Income	D	-0.02	-0.07	-0.02
		(0.03)	(0.03)	(0.03)
	C	-0.21	-0.21	-0.21
		(0.04)	(0.03)	(0.04)
	O	-0.1	-0.05	0.1
		(0.02)	(0.02)	(0.03)
	B	-0.01		0.02
		(0.03)		(0.02)
No high school degree	D, C, O, B	1.24	1.63	1.51
		(0.24)	(0.46)	(0.25)
Education × High school degree	D, C, O, B	-0.18	-0.16	-0.19
		(0.04)	(0.09)	(0.04)
Employed	D	0.5	-0.53	-0.83
		(0.19)	(0.22)	(0.2)
	C	0.27	0.33	0.69
		(0.26)	(0.27)	(0.28)
Dial-up internet	O, B	0.54		0.6
		(0.18)		(0.18)
Setup	All	-0.32	-0.44	-0.32
		(0.04)	(0.06)	(0.04)
Bank interest rate	C	1.47	1.35	2.63
		(0.24)	(0.24)	(0.29)

D = debit, C = credit, O = online banking, B = bank account deduction
All = debit, credit, online banking, bank account deduction, and income deduction
Standard errors in parenthesis.



Source: 2008 SCPC

Figure 1: Adoption costs by income categories

Table 12: Correlation Coefficients for Unobserved Terms in Use and Adoption

	Bills			Retail			Other
Payment Instrument	Automatic	Online	Mail/In Person	Online	Essential	Nonessential	
Debit	0.702	0.779	0.738	0.652	0.844	0.794	0.844
	(0.064)	(0.071)	(0.068)	(0.060)	(0.077)	(0.073)	(0.077)
Credit	0.663	0.771	0.712	0.601	0.874	0.793	0.874
	(0.108)	(0.126)	(0.116)	(0.098)	(0.143)	(0.129)	(0.143)
Stored value			0.820	0.721	0.942	0.884	0.942
			(0.171)	(0.150)	(0.197)	(0.185)	(0.197)
Online banking		0.876					
		(0.029)					
Bank account deduction	0.0001	0.0001		0.0001			
	(0.0001)	(0.0002)		(0.0001)			
Income deduction	0.438						
	(0.032)						

Standard errors in parenthesis.

provide $\rho(\nu_{ijc}, \omega_{ij})$ in Table 12. Although it is possible to estimate negative parameters, all of our parameters are positive, which implies positive selection into use. Debit and credit cards exhibit very high selection, particularly in retail contexts, suggesting that consumers who adopt for unobserved reasons tend also to be surprisingly frequent users. As we saw in comparisons of the use-only and full models, this selection effect can change parameters substantially.

6.2 Summary of net benefits

How do use benefits compare with adoption costs? Figure 2 presents our estimates of expected costs and benefits of adoption of debit card for different income levels. Since the benefit of adopting any payment instrument depends on the composition of the bundle of payment instruments, we choose full bundle as the target bundle, and the initial bundle is full minus debit card. The benefit of debit card adoption for a given consumer is the difference between the expected values of the two bundles, based on their use in future transactions. We compute such a benefit for every observation in the sample within a given income category and take an average, using survey weights. The lines are not smooth, since these consumers differ in other dimensions besides income. We conduct a similar exercise for the costs of adoption. To give these values a meaningful interpretation, we plot costs and benefits relative to the net benefit of adoption by the baseline category: consumers

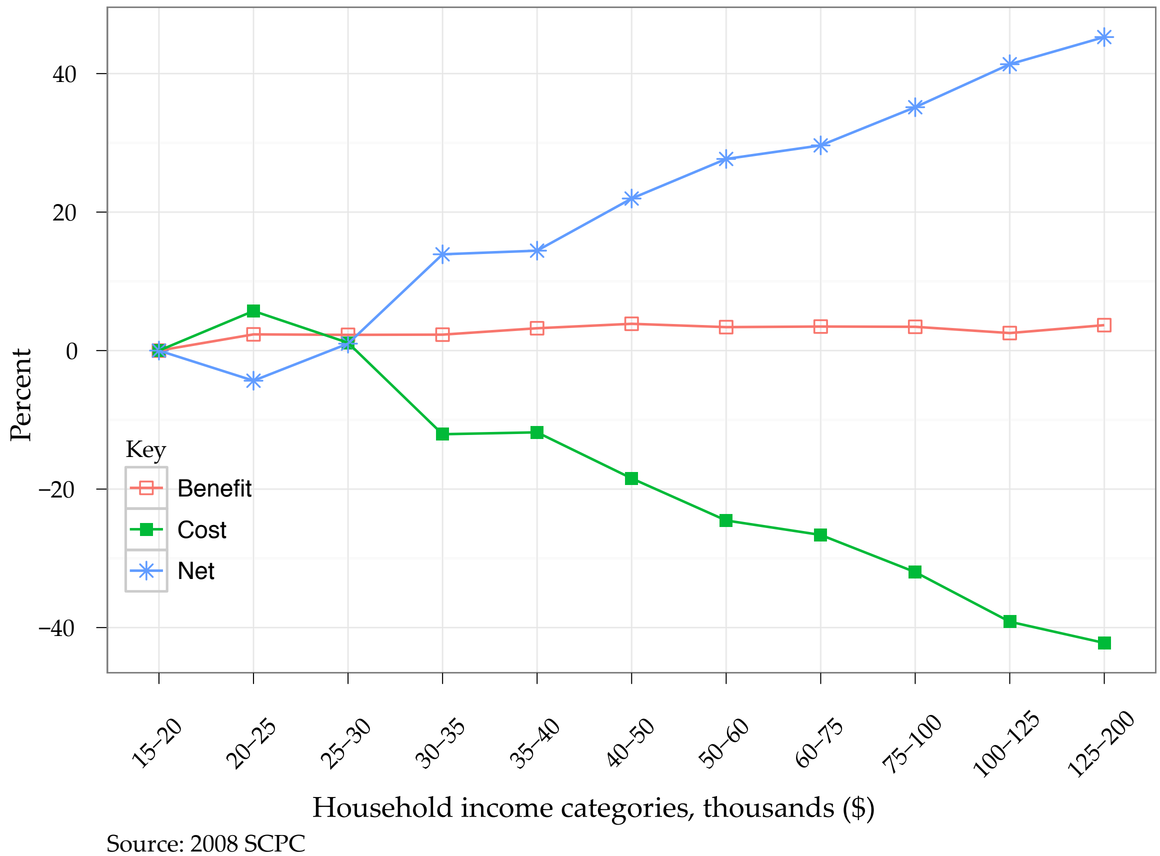


Figure 2: Use benefit and adopt cost for debit cards by income.

with the lowest income (less than $15,000 per year).

For example, the average consumer with income between $35,000 and $40,000 per year enjoys about a 3 percent higher benefit from debit than the average consumer from the baseline category ($15,000 per year or less). However, costs decrease by about 11 percent, and so the net benefit increases by about 14 percent. As income grows, the benefit stays fairly constant, while adoption costs decrease, reaching −40 percent.

Thus, the results of policies affecting debit cards are likely to be heterogeneous in the population, particularly when we study instrument adoption and holdings. This result plays an important role in our results below.

6.3 Counterfactual experiments

We used our estimated model to assess consumers' potential payment choice responses to pricing decisions that banks may make following the Federal Reserve's action to cap debit card interchange fees. Indeed, some banks announced their intention to institute monthly debit card fees for some customers just prior to the implementation of Regulation

II on October 1, 2011.[13] The counterfactual experiments that we focus on compute how consumers respond to a change in the cost of debit cards or cost of bank account products by substituting from debit cards to other types of payments.

The first set of counterfactuals concerns changes in two types of cost of debit cards: the cost of use and the cost of adoption. To simulate an increase in the use cost of debit, such as a monthly fee or reduction in rewards paid, we downgrade consumers' assessments of the "cost of use" characteristic of debit cards by enough to reduce debit's share of payments by 1 percentage point.[14] To simulate an increase in the adoption cost of debit, rather than the use cost, we compute a change in the adoption cost estimate that would induce a 1 percentage point decrease in debit's market share. Note that this change produces a larger decline in welfare than the increase in the use cost of debit, because adoption costs are harder to avoid, but in our simulation it generates a comparable change in market share of debit. We also measure the responses of consumers to higher costs in terms of use only, holding payment instrument adoption fixed (the "short run"), and allowing adoption to change (the "long run").

Figure 3 plots the estimated changes in the market shares (use) of payment instruments other than debit cards in response to increases in the cost of debit cards.[15] For each counterfactual simulation, the decline in debit market share (not plotted in the figure) is normalized to −100 percent, so the changes in other market shares sum to +100 percent. Thus, one can view the market share changes as analogous to cross-price elasticities of demand for the use of other payment instruments.

The model predicts that, in the short run, consumers would shift most (about three-fifths) of their payment use from debit cards to traditional paper payment substitutes in response to an increase in the use cost of debit (top bars in Figure 3). Cash use increases by 34 percentage points and check by 25. Credit cards are the next highest, with a 20 percentage point increase. The rest of the payment options fill out the remaining 21 percentage points, with bank account deduction receiving the largest share of that.

What if we consider the "long run," in which consumers are allowed to adjust their adoption decisions to the change in the use cost of debit (middle bars in Figure 3)? In this case, the results are quite similar to the short-run results with cash, check, and credit cards gaining 34, 26, and 21 points, respectively. This result implies that the change in the use

[13] See "Banks to Make Customers Pay Fee for Using Debit Cards," by Tara Siegel Bernard and Ben Protess, *New York Times*, September 29, 2011.

[14] In the 2008 SCPC, the debit card share of consumer payments was 31 percent, so this experiment reduces consumer debit use to 30 percent.

[15] To compute these results, we compute choices for each consumer in our dataset and use the survey weights to construct a nationally representative result. We assume consumers cannot switch to the outside option, both because this assumption makes it easy to interpret substitution patterns and because we observe little about the outside option.

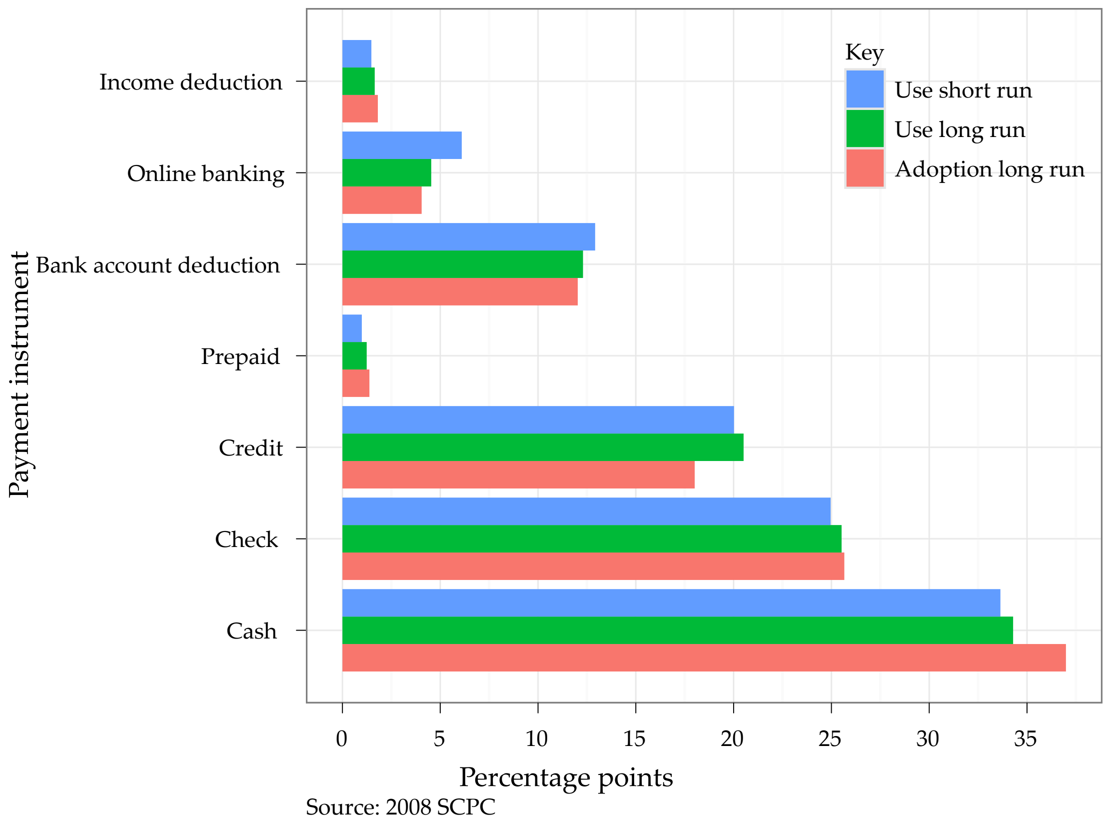


Figure 3: Changes in market shares in response to increases in debit card use cost and adoption cost, by adoption adjustment (short run or long run)

cost of debit (such as monthly fees) does not induce much increase in the adoption of credit cards by consumers who would not have done so otherwise. This outcome stems largely from the fact that it is mainly consumers with low incomes who are affected by the change and those consumers are unlikely to adopt credit cards.

We also want to examine the response of market shares to an increase in the adoption cost of debit, for comparison with an increase in use cost of debit. For changes in the cost of adoption, it only makes sense to view the long-run responses (bottom bars of Figure 3). In response to an increase in the cost of debit adoption, cash use gains by even more than in response to an increase in cost of debit use, this time gaining 37 percent of the loss to debit share. Credit cards do slightly worse than cash, gaining only 18 percentage points. This result follows from the fact that low income households respond to adoption costs more than high-income households do, and they are likely to switch to paper products. Still, we find that the results of the experiments in Figure 3 are fairly similar. We find bigger differences below, when we compare the decisions of high and low-income households.

The second set of counterfactuals recognizes that banks are multi-product firms selling bundled products and that recouping lost revenues only by raising costs (fees) on debit cards may not be optimal for bank profits. An alternative response to regulatory changes might be for banks to raise the cost of demand deposit accounts, leading to a higher cost of all payment instruments tied to a bank account. To simulate an increase in the cost of a bank account, we consider a change of -0.072 (the amount used in Figure 3) to the value of δ_{ijc} (the mean use utility) for each product related to a consumer's bank (checking) account: cash, check, debit card, online banking bill pay, and bank account deduction.[16] In this case, the sum of the market share declines in bank products will equal the sum of the market share increases of the other payment instruments. We allow adoption behavior to adjust, so the changes are long run, but the reader should keep in mind that our model assumes consumers always hold a checking account.

As one would expect, the market shares of the bank products all decline in response to an increase in the cost of a bank account, as shown in Figure 4. The use (market share) of cash, checks, and debit cards each declines by more than 20 percentage points. By far, credit cards account for most of the increase in use by other payment instruments. Income deduction and prepaid cards also increase but by much less. Therefore, it would seem that banks' decision to increase the cost of a checking account (rather than to increase the cost of a debit card) would depend on the magnitude of the revenue stream banks receive from credit card use (relative to bank account products) and the extent to which their customers

[16] Although banks also provide credit card services, we do not include credit cards in this simulation because the credit card account is not explicitly linked to a consumer's checking account. In fact, many consumers hold credit cards that were issued by banks other than the bank where they have their primary checking account.

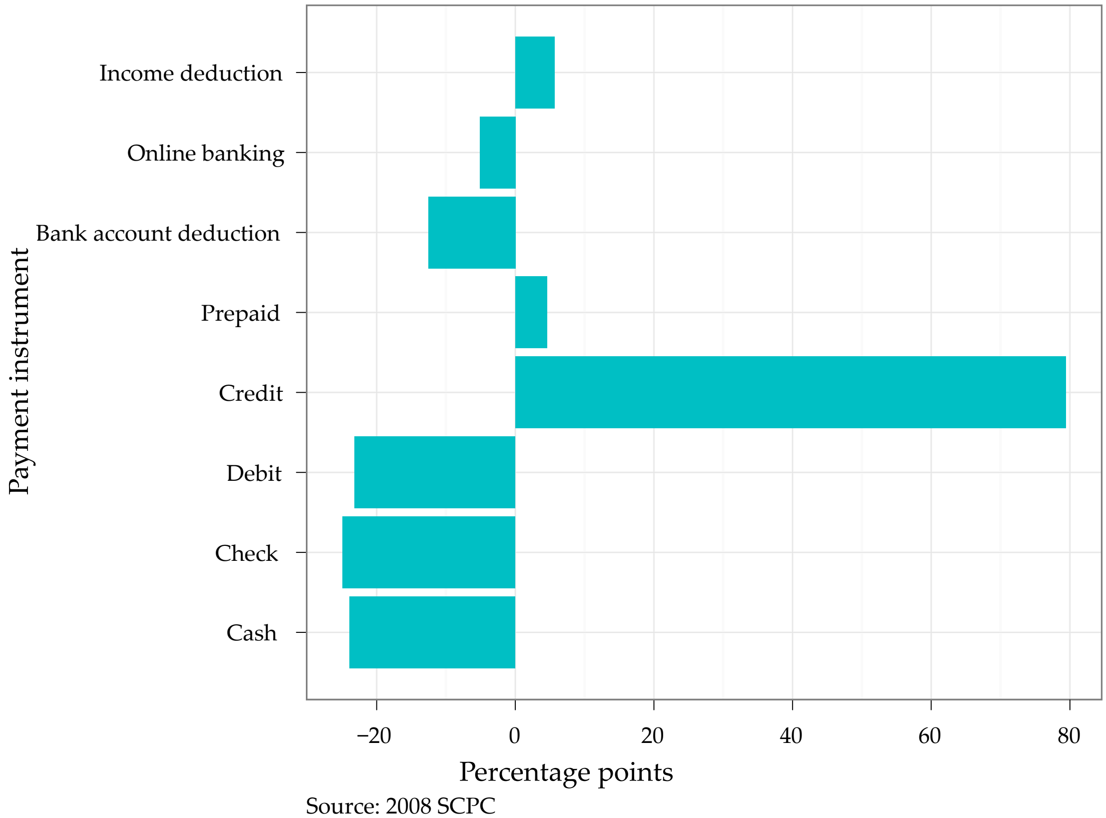


Figure 4: Changes in market share in response to an increase in the cost of bank account products, allowing adoption to adjust (long run)

would switch to a credit card with another bank, among other factors.

Next, we consider how responses differ across income groups. We consider two hypothetical consumers, a high-income consumer and a low-income consumer. The high-income consumer is a college graduate and has an annual income of $80,000. The low-income consumer has a high school degree and an annual income of $30,000. Otherwise, they are identical. We begin by assuming that they each hold every instrument, and graph the response to an increase in the use cost of debit. We see very large differences in Figure 5, with the high-income household shifting market share to credit card by almost 10 percentage points more than the low-income household, and making less use of cash and stored value cards.

Figure 5 suppresses the issue of adoption. In order to focus on adoption effects, we consider the case in which each household holds only cash, check, and debit. Naturally in this case, all of the substitution from debit is to cash and check. In Figure 6, we see that substitution patterns are similar for high and low-income households. However, in

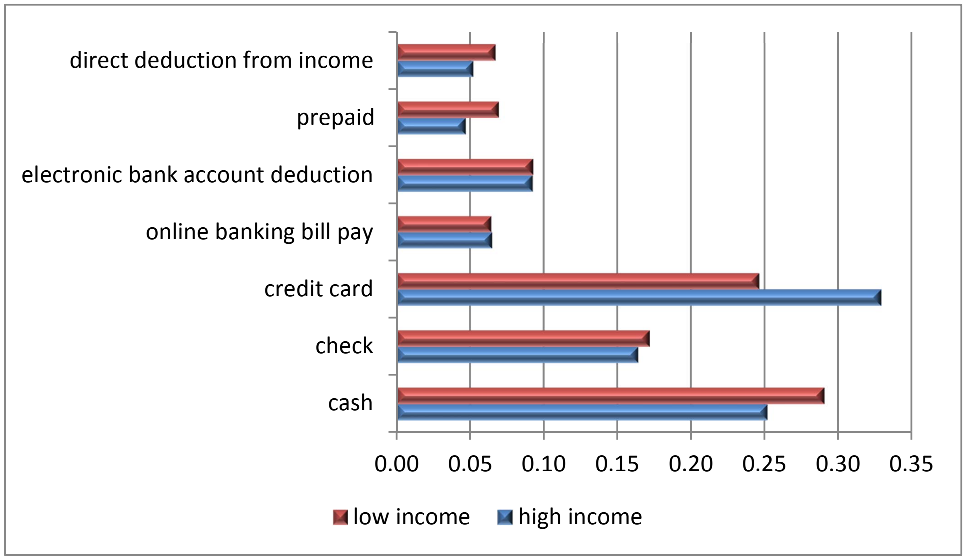


Figure 5: Changes in market share in response to an increase in the use cost of debit, assuming consumers hold all instruments.

Figure 7, we allow these consumers to adjust their holdings of instruments. Here we see large differences, with the high-income household moving a much larger share of payments to credit and the low-income household favoring cash and, to a lesser extent, check. Naturally, the reality is that many high-income households already hold credit cards, which would exacerbate these differences.

Finally, we consider consumer welfare from these interventions, graphed in Figure 8. The long-run welfare cost of the policy is estimated to be between -2.8 percent and -1.3 percent of the initial welfare level, depending on the income. In the short run, before adoption choices can respond, the welfare loss is substantially larger, about 7 percent to 30 percent larger, depending on income. The difference over the income range is striking, with welfare falling more than twice as much for consumers from low-income households than consumers from the wealthiest households in the long run, and 2.5 times as much in the short run. Consumers in wealthy households fare better because they typically have adopted larger bundles to begin with, so it is easier for them to substitute in the short run, and because there is less adjustment (and, because they are wealthy, less costly adjustment) in the long run.

7 Conclusion

In this paper, we specify a new model of adoption and use of payment instruments, such as credit cards, debit cards, and prepaid cards. Our model addresses features of the discrete-

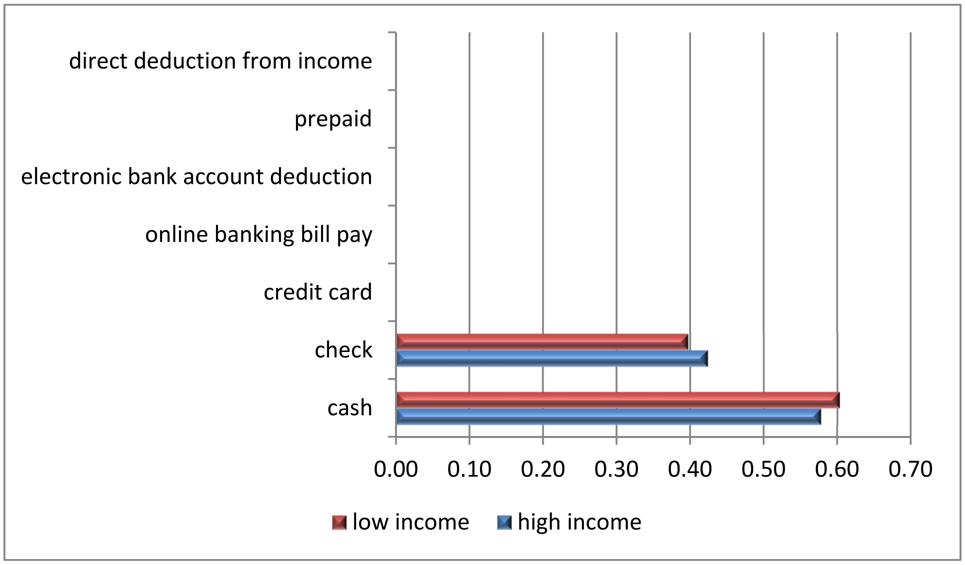


Figure 6: Changes in market shares in response to an increase in the use cost of debit, assuming consumers hold only cash, check, and debit.

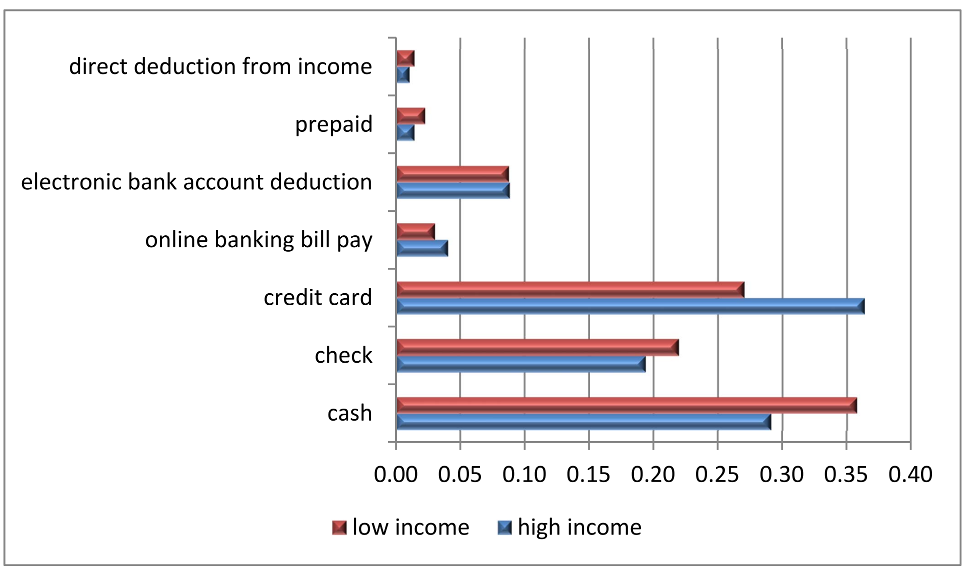
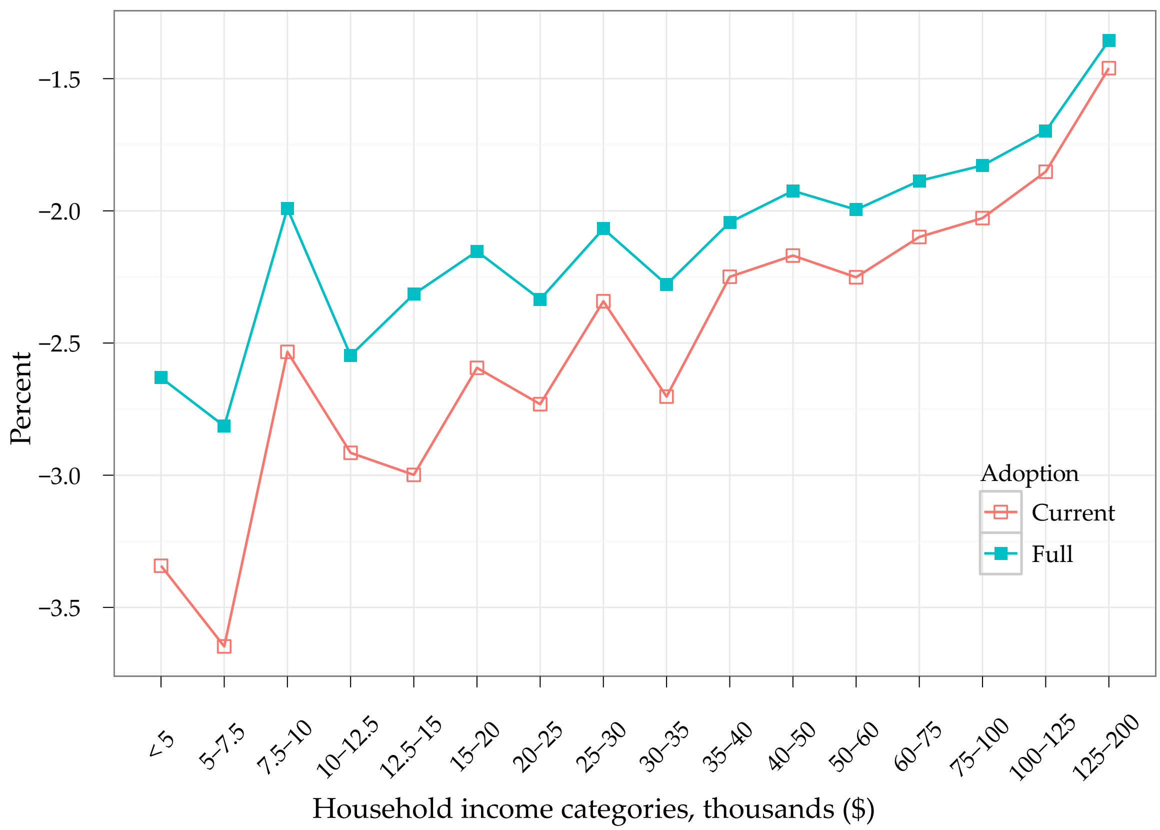


Figure 7: Changes in market shares in response to an increase in the use cost of debit, assuming consumers hold only cash, check, and debit, but can adjust their instrument holdings.



Source: 2008 SCPC

Figure 8: Welfare change from a change in the use cost of debit, by income category

continuous nature of the problem in a way that is much more rigorous than the previous literature. We also discuss identification of the bundled nature of the problem.

Using new data available from the Federal Reserve Bank of Boston, we estimate the model. We find a number of interesting results about the determinants of payment choice. We compute demand elasticities to the cost of debit cards and find substantial switching of payment methods resulting from a simulated increase in the cost of debit cards, particularly to paper-based methods such as cash and check, but also to credit cards. We show that responses vary with demographics, particularly income and education.

Our study provides perspective on one feature of the potential response to interchange fee regulation, and thus serves to inform future policy in this area. The limited nature of our study means that, by itself, it cannot argue for or against interchange fee regulation, or whether the regulated rate is too high or low. Interchange fee regulation can be evaluated along several dimensions not considered in this paper, and thus provides a complex policy question towards which we wish to contribute.

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