Explaining adoption and use of payment instruments by US consumers

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September 16, 2011

Strictly Preliminary.
Do not cite or quote.

Abstract

This paper estimates a structural model of adoption and usage of payment instruments by US 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 first a consumer 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 each other. We consider how changes in the costs of adoption and usage may differentially affect substitution patterns. These results are relevant for current regulation of interchange fees.

*The views presented here are those of the authors only and do not necessarily represent the views of the Federal Reserve Bank of Boston or the Federal Reserve System.

1 Introduction

Interchange fees are the subject of regulatory and antitrust activity in a growing number of countries (Bradford & Hayashi, Bradford & Hayashi; Weiner & Wright, 2005). In the US, recent legislation requires the Federal Reserve Bank to regulate the interchange fee for debit cards.[1] As banks respond, consumers will face different charges for adoption and usage. Similarly, Australia has regulated credit card interchange fees since 2001, and an antitrust proceeding in Europe led last year to the regulation of cross-border interchange fees for credit cards. As these changes affect bank pricing, consumers will face different costs and benefits of card use, and understanding how consumers substitute between payment instruments under these changes is important for evaluating these regulations. This 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. 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. A social planner may evaluate these outcomes very differently if, for example, the social planner has an interest either in encouraging digital payment mechanisms or discouraging the use of credit.

Evaluating the elasticities between payment instruments is particularly challenging because payment mechanisms have both an adoption and a use component. For example, in the U.S., some banks appear to have plans to respond to the debit interchange regulation by eliminating rewards programs, where others have proposed fixed monthly or annual charges on holding a debit card. Substitution patterns in response to adoption charges likely differ from substitution patterns in response to usage charges, and understanding these differences is important for evaluating the policy.

This paper estimates a structural model of adoption and usage of payment instruments by US 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 on-line, essential retail and non-essential retail. We separately identify the effect of explanatory variables on adoption and

[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 Bank to set the interchange fee for debit cards based on bank variable costs. The current proposal, due to go into effect in July 2011, sets the fee substantially below currently observed interchange fees.

usage behavior. We compute elasticities of substitution across different instruments, focusing on how these differ in response to changes in adoption and usage costs. Our paper makes use a of a new public data set, the Survey of Consumer Payment Choice (SCPC, described in Foster, Meijer, Schuh & Zabek, 2010) specifically designed to address these topics.

Our model incorporates features from several literatures. As our model allows consumers to make separate adoption and usage decisions, it is related to the "discrete-continuous" (or "discrete-discrete") literature of Dubin & 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 require the consumer to have 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 allowing the agent to know perfectly the outcome of the usage decision at the time of adoption, and in this sense know more than the econometrician. However, the selection model does not allow for the identification of the effect of the usage decision on the adoption decision. Our model is combines both of these features in a single model, which we discuss 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 & Yurukoglu (2009). In this environment, it is difficult to distinguish between complementarily products and correlated preferences. While this problem has typically been approached with the use of excluded variables (as in Gentzkow, 2007) we use the fact that we observe usage to pin down the complementarity (or substitutability), and allow only for correlation in the adoption stage (which is similar to Crawford & Yurukoglu, 2009).

There is a substantial literature on consumer payment choice, such as reviewed in Rysman (2007, 2010). The closest paper is perhaps Schuh & Stavins (2010), which uses an earlier, smaller but similar data set with a Heckman selection model of each payment instrument separately to study adoption and use. Our paper is distinguished by its use of a new data set and the careful treatment of the joint adoption and usage decision, along with the focus on elasticities in the context of regulatory intervention into pricing in payments markets.

[2] As discussed below, other models have similar features, such as more structural labor models and some models in environmental economics and trade.

Our paper is relevant for the literature on two-sided markets as well (see Rochet & Tirole, 2006; Rysman, 2009). 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 usage decisions that we focus on are often important in that literature. Examples are Rochet & Tirole (2006) and Weyl (2009).

The SCPC allows us to study a number of important payment *instruments*: cash, check, credit and debit, stored value cards, on-line banking, direct bank account deductions and direct income deductions. In addition, we see usage in different payment *contexts*, such as traditional retail, on-line 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. The survey includes respondent valuations of the features of different mechanisms, and these are important predictors of choice. In particular, ease of use is highly valued. The security that households perceive in each instrument is relatively less important. While surprising, this result is consistent with a number of other studies (discussed in Rysman, 2010).

In order 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 of instruments, which we view as long-run and short-run scenarios. We also distinguish between responses to usage costs and adoption costs. We find that the short-run response to usage costs is largely towards the paper instruments, cash and check. This is in part driven by less wealthy people who do not hold credit cards. In the long-run, credit cards become a more important substitutes as more households adopt them. The long-run response to adoption costs is more heavily tilted towards paper products, as we find that less wealthy people respond relatively more to adoption costs, and they tend to avoid credit cards. Overall, we find that less wealthy people are hurt relatively more from an increase in the cost of debit since they hold smaller bundles of payment instruments, and tend to favor debit.

2 Data

Our paper relies on the Survey of Consumer Payment Choice (SCPC). This data set is collected by the Consumer Payments Research Center at the Boston Federal Reserve Bank, joint with the RAND Corporation. The SCPC uses the RAND American Life Panel, a set of 1,500 households that are frequently surveyed on a variety of topics. The respondents complete Internet surveys, with special provisions for households without Internet access. RAND has response rates that are typically around 80% of panelists. Several preliminary surveys have been administered but the first installment of what will be an annual survey was administered in 2008. The results are publicly available. The SCPC focuses on adoption and usage of different payment instruments in retail and billing environments, as well as cash holdings and on-line 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 data set as well as a useful set of summary variables appears in Foster et al. (2010). Below, we present a few tables that are helpful for understanding what we do in this paper. The SCPC provides survey weights for obtaining a nationally representative sample. We use the weights to construct that 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.[3]

In order to restrict heterogeneity, we drop from our sample households that do not have checking accounts. Thus, we use 997 households. The survey asks consumers about adoption and usage of 8 payment instruments: cash, checks, debit cards, credit cards, stored value cards, on-line banking bill payment, direct bank account deduction, and direct deduction from income. Stored value cards are cards on which a consumer pre-pays money and then may use in a way similar to a credit card. A stored value card does not tap into a consumer's account. On-line banking bill payment is when a consumer pays a bill through the consumer's bank's web site. Direct bank account deduction is when a when a consumer purchases directly out of a bank account. Doing so requires providing the seller with a bank account number. Bank account deduction is often used for recurring bills, particularly mortgages, or it is used through a merchant web site. Direct deduction from income are payments that come directly out of a consumer's paycheck and must be organized with the employer. Health insurance is a common example. Table 1 reports adoption rates for each payment type in our sample.

In addition to payment mechanisms, the survey collects data on usage. The survey asks participants how many transactions they complete in a typical month with each payment instrument in seven payment *contexts*. The

[3] 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.

paper		card			bill pay		
cash	check	debit	credit	stored value	on-line banking	direct bank accnt deduct	income deduction
100%	100%	80%	78%	17%	52%	73%	18%

Table 1: Adoption rates by payment instrument.

	Bill Pay			Retail			
	Automatic	Online	In person	Online	Essential	Non-essential	Other
mean	6.0	6.5	7.6	6.8	19.1	9.8	12.8
std dev	11.2	10.5	12.8	11.4	23.5	15.7	15.0

Table 2: Number of transactions per month, by payment context

contexts are essential retail, non-essential retail, on-line retail, automatic bills, on-line bills, bills by check or in-person, and other non-retail. Automatic bills are when a consumer agrees with a merchant to pay some amount on a regular basis. Many households pay their mortgage this way. On-line bills are when a household goes to a web site to pay a bill, and bills by check or in-person are when a household pays a bill by mailing a check or card information, or visiting the merchant in person. "Other non-retail" includes payments to household help, such as baby-sitters, and similar issues. Table 2 reports the average number of transactions by context in our sample.

Naturally, not every payment instrument is available in every payment context; for instance, one cannot shop on-line with cash. Table 3 shows the average number of transactions in each instrument-context combination in our data set. Blank entries indicate entries that were ruled out by the survey itself. Our empirical model will provide predictions of the outcomes in Table 1 and Table 3. Note that we will treat these outcomes as continuous variables. Although some appear 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. Averages appear in Table 4. Higher numbers mean the participant has a more favorable view. For instance, cash does poorly in "security" and "records" (the ease of tracking usage) but well in "set-up" (the cost of setting up a payment instrument), "cost" (the cost of usage) and "acceptance" (the level of merchant acceptance. The rest of the table also is in line with conventional wisdom. For instance, checks score low on speed but high on record keeping. Debit and credit look similar to each other. Previous discussion alluded

	Bill Pay			Retail			
	Automatic	Online	In person	Online	Essential	Non-essential	Other
cash			1.1		6.2	3.1	3.8
check			4.0	1.6	1.0	0.7	2.8
debit card	1.6	1.6	1.3	2.1	7.5	3.6	3.3
credit card	1.4	1.1	1.2	1.6	4.2	2.2	2.8
store value card				0.1	0.2	0.1	0.1
online bank bill pay		2.1					
direct bank deduct	2.3	1.7		1.3			
income deduction	0.8						

Notes: 997 Observations.

Table 3: Number of transactions per month by instrument and context.

	security	setup	accept	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 card	2.9	3.9	4.3	3.8	3.6	4.0	4.0	4.2
credit card	3.0	3.7	4.5	2.7	3.5	4.2	4.0	4.3
stored value cd	2.7	3.4	3.8	3.3	3.3	2.9	3.7	3.7
bank bill pay	3.3	3.4	3.2	3.7	3.6	3.9	3.8	3.6

Table 4: Average ratings of payment instruments

to the fact that our model will require variables that can affect usage but not adoption, and *vice versa*. We will assume that ease and speed affect usage but not otherwise adoption, whereas setup affects adoption but not usage.

Table 2 displays demographic data for our sample. These roughly conform to other survey data, although we have a high number of people with a post-graduate education.

3 Model

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

In stage 1, consumer i faces J payment instruments. Examples of instruments $j = 1, \cdots, J$ are cash, credit card and debit card. The consumer

var	min	mean	med	max	std
age	16	48.68	49	85	14.15
male	0	0.44	0	1	0.50
citizen	0	0.98	1	1	0.14
hh-size	0	1.13	1	9	1.40
white	0	0.89	1	1	0.32
black	0	0.07	0	1	0.25
asian	0	0.03	0	1	0.17
latino	0	0.04	0	1	0.20
married	0	0.65	1	1	0.48
single	0	0.15	0	1	0.35
edu-hs	0	0.14	0	1	0.35
edu-sc	0	0.34	0	1	0.47
edu-c	0	0.28	0	1	0.45
edu-pgs	0	0.22	0	1	0.41

Table 5: Demographic data

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 8 instruments but we assume that consumers always adopt cash and check (and we select our sample on this criteria) so there are only 6 choices, thus B has 64 elements (2^6). 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. At each opportunity, the consumer selects which payment instrument to use and 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 on-line purchases, essential retail and non-essential retail. At each opportunity, the consumer can choose not to pay.

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

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

where we assume that ε^u_{ijcl} is distributed Type 1 Extreme Value (the superscript "u" refers to *usage*). Every bundle b_i includes the option $j = 0$, the option not to pay, and we normalize $\delta_{i0} = 0$. Thus, the probability (or expected share) of instrument j and context c by consumer i is:

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

The Extreme Value assumption implies that the distribution of the value of opportunity l when holding bundle b follows:

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

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

$$v_i(b) = E[v_{il}(b_i)] = \left(\ln \sum_{j \in b} \sum_{c \in C} \exp(\delta_{ijc}) + \gamma \right) \tag{1}$$

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

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

The parameters λ_{ij} represents an instrument-specific utility term in excess of any utility from usage. We think of it as the adoption cost, whereas $v_i(b)$ represents the usage benefit, although λ_{ij} is not restricted to be negative and could be an "adoption benefit." The parameter α moderates the value of usage utility relative to the adoption cost. The variable ε^a_{ib} is distributed Type 1 Extreme Value and is *iid* across consumers and bundles (the superscript "a" refers to *adoption*). The consumer picks b such that $V_{ib} \geq V_{ib'} \forall b' \in B$. Thus, the probability of picking bundle b_i is:

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

Note that in our model, the adoption cost of a bundle of 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 instruments. Rather, we match joint adoption patters 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 instrument on the value of the other through usage — for instance, adopting a credit card will make adopting a debit card less valuable since they are substitutes in usage. Our assumption is that adopting one has no effect on the *adoption cost* of the other.

4 Estimation

We assume that:

$$\delta_{ijc} = x_{ijc}\beta_\delta + \nu_{ijc}. \tag{3}$$

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 normalize the choice of no purchase to have value $\delta_{ijc} = 0$. We assume the number of potential payments that a household may make is 400, and experiment with alternative choices.

We assume that:

$$\lambda_{ij} = z_{ij}\beta_\lambda + \omega_{ij}. \tag{4}$$

The vector z_{ij} represents 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 those that are not.[4] Similarly, define $\omega_\mathbf{i}$ to be the $J-2$ vector of values of ω_{ij}. The "-2" reflects the fact that we assume 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 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 $\overrightarrow{y}^*_i$ be the vector made up of elements y^*_{ijc}.Then, the likelihood function is:

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

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.

[4]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.

Our model allows for correlation across instruments in usage, contexts in usage, and for correlation between adoption and usage of instruments. The latter generates the selection effect in the two-stage model. 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:

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

Thus, σ_1, σ_j and σ_c determine correlation within usage, 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.

Specifically, 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 of δ^s_{ijc} using Equation 3 and values of λ^s_{ij} using Equation 4. Based on δ^s_{ijc}, we construct v^s_{ib} from Equation 1 (the values from usage for each bundle, consumer and draw). With v^s_{ib} and λ^s_{ij}, we construct V^s_{ib} from Equation 2 (the value of adoption). Using δ^s_{ijc} and V^s_{ib} we can construct our simulated likelihood function:

$$\widehat{\mathcal{L}}_i(\overrightarrow{y}^*_i, b^*_i; \theta) = \frac{1}{ns} \sum_{s=1}^{ns} \Pr\left(\overrightarrow{y}^*_i | b^*_i, \nu^s_i, \omega^s_i, \theta\right) \Pr\left(b^*_i | \nu^s_i, \omega^s_i, \theta\right)$$

where:

$$\begin{aligned} \Pr(\overrightarrow{y}^*_i | b^*_i, \nu^s_i, \omega^s_i, \theta) &= \sum_{j \in b^*_i} \sum_{c \in C} \left(\frac{\delta^s_{ijc}}{\sum_{k \in b^*_i} \sum_{d \in C} \delta^s_{ikd}} \right)^{y^*_{ijc}} \\ \Pr\left(b^*_i | \nu^s_i, \omega^s_i, \theta\right) &= \frac{\exp(V^s_{ib^*})}{\sum_{k \in B} \exp(V^s_{ik})}. \end{aligned}$$

As in any approach that relies on maximum simulated likelihood, bias is introduced since $\mathcal{L}_i$ is approximated with simulation error, which enters non-linearly (since we actually maximize the logarithm of the simulated likelihood) into our objective function. See Pakes & Pollard (1989) and Gourieroux & 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.

5 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 usage. Important early citations are Dubin & McFadden (1984) and Hanemann (1984). More recently, Hendel (1999), Burda, Harding & Hausman (2010) 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 the outcome of a continuous choice. 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 & McFadden (1984) in the context of electricity usage 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 a the discrete decision, and so has perfect foresight. However, the effect of w on the Y is captures in reduced-form. This approach does not identify the effect of w on Y.

The discrete-continuous literature has taken the opposite approach. For instance, Hendel (1999) allows the equivalent $x\beta_x$ to enter as an element of z, and thus structurally identifies the effect of the output decision on the adoption decision. However, Hendel (1999) assumes that ε_w does not enter the adoption decision, so it as if the consumer cannot predict the output decision at the time of adoption. Burda et al. (2010) are similar. From our perspective, this is restrictive. One might rationalize this set-up by saying the consumers predict their usage with error, but the implicit assumption is that consumers predict their usage no better than the econometrician. Dube (2004) does allow for the consumer to have perfect information over usage, but he does not model adoption costs, as he studies super-market food purchases.

In contrast, our model allows both for the structural identification of the effect of usage on adoption, as well as for the consumer to know usage 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 usage costs. The latter is attractive because it is a realistic and flexible approach.[5][6]

Whereas the Heckman selection model is often estimated in two steps, our model with usage directly affecting adoption is akin to a simultaneous equations model, and 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. As stated above, we use consumer ratings of topics that should be relevant for only adoption or usage, 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 have written the model so that the value of a bundle is additively separable in adoption costs λ_{ij}. 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 for elements. If we only observe a positive correlation, we cannot tell whether the elements of the bundle are truly complements or whether consumers that like one element tend to like the other. The 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 usage. Thus, we expect the logit usage model

[5] 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 et al. (2010) model ordered choice for the intensity of usage, an issue that we abstract away from. Hendel (1999) infers the number of choices an agent makes, Dube (2004) infers consumption opportunities from purchase data and Burda et al. (2010) use a flexible Bayesian method with a non-parametric interpretation.

[6] 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 decision-maker predicts the second-stage of a two-stage model better than the econometrician. Some examples appear in structural labor and environmental economics [get some cites].

to capture the extent to which payment methods, such as debit and credit, are substitutes. Correlation will be captured in the covariance matrix governing δ_{ijt} and λ_{ij}. Other papers that have similarly used usage to identify substitution and adoption to identify correlation are Ryan & Tucker (2009) and Crawford & Yurukoglu (2009). This approach differs from Gentzkow (2007), who uses an instrumenting strategy to separate these issues. Note that our model rules out that payment methods are complements. We believe this is realistic, but we plan to pursue this issue further if it appears to be an important issue in our results.

There are several issues with our model and estimation that deserve discussion. First, in our model, consumers know the values ν_{ijc} perfectly, so they predict their usage pattern very accurately at the time of adoption. However, this notion does not need to be taken literally. It is possible that consumers predict usage with some error. For instance, suppose that consumers get a signal of the usage 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 knowledge that the consumer has about final usage. In either case, the attractive feature of the model is that it allows the consumer to have better knowledge than the econometrician about usage.[7]

A more complicated issue is that adoption is dynamic whereas we model it as 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 the consumer's propensity to substitute to newer technologies, such as debit or stored-value cards. We ignore these issues — one would need a panel to study dynamic adoption and particularly detailed usage 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 that decisions of merchants fixed. For instance, if interchange fees 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, which should increase merchant participation. The overall effect is unknown, but could impact

[7] A perhaps more realistic model would build prediction error into ν_i, so that prediction error for one instrument would affect all bundles that it was a part of. We view this as difficult to identify separately from the model we consider, but it would perhaps be possible.

consumer decision-making. While these effects are potentially interesting, they are outside of the scope of this paper.

An important issue is that we rely heavily on consumer ratings of instruments. These are self-reported evaluations, and may be problematic. Consumers can report them differently, and there may be bias in how they are determined – for instance, consumers may assign high ratings to their own choices ex post that they would not have assigned ex ante. We found the results of the ratings very sensible, both in the simple statistics and the estimation results, which we found supportive of their use.

6 Results

In addition to using the full data set, 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 stored value cards, and the contexts are on-line retail, essential retail, non-essential 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" sub-sample, people that report not carrying a balance on their credit card. While this rules out some heterogeneity, it also introduces an element of selection since the data set is restricted to households that have adopted a credit card. Also, in addition to considering the "full model" described above, we also provide estimates of the usage stage alone, ignoring the adoption stage. These estimates use only observed choices and so do not address the selection that is inherent in the adoption decision.

For explanatory variables in the usage equation (the elements of x), we include context-instrument fixed effects, consumer ratings of instrument, demographics (age, gender, black, married, employed and education level) and instrument-income interactions for each instrument. For the debit and credit 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 instrument dummies and demographics, as well as the consumer rating of the set-up and also a measure of internet access.

6.1 Parameter results

Table 6 provides the average utility of each instrument-context combination in the usage equation. For essential retail, cash and debit are the most

	Bill Pay			Retail			
	Automatic	Online	In person	Online	Essential	Non-essential	Other
cash			-6.25		-3.83	-4.85	-4.28
			(0.02)		(0.01)	(0.02)	(0.01)
check			-4.31	-5.60	-5.74	-6.31	-4.68
			(0.01)	(0.02)	(0.02)	(0.03)	(0.01)
debit card	-5.47	-5.49	-5.78	-5.25	-3.61	-4.47	-4.25
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
credit card	-6.06	-6.29	-6.22	-5.68	-4.40	-5.14	-4.75
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
store value card			-8.44	-7.44	-6.24	-7.31	-7.28
			(0.19)	(0.10)	(0.07)	(0.12)	(0.09)
online bank bill pay		-4.38					
		(0.02)					
bank accnt deduct	-4.72	-4.97		-5.43			
	(0.02)	(0.02)		(0.02)			
income deduction	-4.47						
	(0.04)						

Notes: Standard errors are in parenthesis. 997 observations.

Table 6: Average utilities by context and instrument in usage equation.

popular, followed at some distance by credit cards. Check is further back, with stored value cards being the least popular. For non-essential retail, debit and cash are still the most popular, but credit cards are almost as popular. In the bill pay contexts, check is by far more popular than cash, debit or credit, although online payments and automatic deductions are close to check in popularity.

Table 7 contains results for demographic variables. In order to constrain the number of parameters, we do not include every demographic variable in every instrument equation. As seen in Table 7, we allow age to affect check, debit and credit, we allow gender to affect only debit and credit, and we allow education to affect debit, credit, on-line bill pay and automatic income deduction. We allow effects on credit and debit usage for every demographic variable, as these instruments are of high policy interest. The “full model” column of the table shows that older consumers use credit and check more often, that men are more likely than women to use debit and credit, and that higher 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 7 provide interesting comparisons. For instance, age has a positive effect in the “usage only” model, but negative in the full model, suggesting a strong selection effect whereby older people that adopt debit cards are particularly likely to make heavy use of

variable	instrument	usage only	full	retail only	no debt sample
age	check	1.12 (0.02)	1.14 (0.02)	0.48 (0.03)	1.48 (0.03)
	debit	0.28 (0.02)	-0.43 (0.02)	0.05 (0.03)	-0.45 (0.02)
	credit	0.63 (0.02)	0.24 (0.02)	0.01 (0.03)	0.33 (0.02)
male	debit	-0.22 (0.01)	0.21 (0.01)	-0.32 (0.02)	-0.53 (0.02)
	credit	0.11 (0.01)	0.09 (0.01)	0.27 (0.02)	-0.14 (0.01)
black	debit	-0.07 (0.03)	0.27 (0.03)	0.24 (0.04)	-0.98 (0.04)
	credit	0.30 (0.03)	0.38 (0.03)	-0.05 (0.05)	-1.07 (0.15)
married	debit	-0.12 (0.01)	-0.16 (0.01)	0.03 (0.02)	-0.52 (0.02)
	credit	0.00 (0.01)	0.31 (0.01)	-0.02 (0.02)	0.22 (0.02)
employed	debit	0.02 (0.01)	-0.06 (0.01)	0.26 (0.02)	-0.56 (0.02)
	credit	-0.16 (0.01)	-0.30 (0.01)	-0.08 (0.02)	0.06 (0.02)
education	debit	-0.08 (0.01)	-0.11 (0.01)	-0.11 (0.01)	-0.20 (0.01)
	credit	0.22 (0.01)	0.35 (0.01)	0.26 (0.01)	0.16 (0.01)
	bank bill pay	0.07 (0.01)	0.01 (0.01)		0.21 (0.02)
	bank ded.	0.08 (0.01)	0.10 (0.01)		0.06 (0.01)

Notes: Standard errors are in parenthesis. 997 observations.

Table 7: Demographics in usage.

it.[8] Similarly, males and blacks appear to use debit very little in the usage-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 that carry debts, since those parameters are negative in the no-debt sample. There is a similar effect for black households.

Table 8 presents the effect of income on each payment instrument in the usage equation. Higher income affects most instrument positively and significantly. Only stored value cards have a negative coefficient for income. This is not surprising, since stored value cards can be seen as inferior substitutes to other cards that are popular with households that have difficulty with bank products. Income has the smallest positive effect on cash and debit use. In the retail-only specification, we see that income has the largest effect on credit. Check has a relatively larger coefficient in the full model because wealthier households use bill-pay contexts more often.

Next, we consider the role of consumer ratings in Table 9. Overall, consumer ratings are important, explaining about the same amount of variation in usage as the demographic variables, although they account for far fewer parameters. All of the ratings variables as viewed positively, as we expected (although *speed* is negative and insignificant in the retail-only specification). *Ease of use* is the most important determinant of usage, followed by cost of use. Perhaps surprisingly, *security* is relatively unimportant, although it is still positive and statistically significant. This results appears in other set-

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

	usage only	full	retail only	no debt sample
cash	0.12 (0.02)	0.05 (0.01)	-0.07 (0.02)	-0.004 (0.02)
check	0.45 (0.02)	0.45 (0.02)	0.19 (0.03)	0.27 (0.02)
debit card	0.64 (0.02)	0.07 (0.02)	0.03 (0.02)	0.32 (0.02)
credit card	0.12 (0.02)	0.18 (0.02)	0.25 (0.03)	0.66 (0.02)
store value card	-1.17 (0.07)	-0.68 (0.05)		-0.57 (0.13)
online bank bill pay	0.60 (0.04)	0.75 (0.03)	-0.16 (0.03)	0.44 (0.05)
bank accnt deduct	0.24 (0.02)	0.31 (0.02)		0.23 (0.02)
income deduct	0.27 (0.09)	0.19 (0.10)		0.57 (0.09)

Notes: Standard errors are in parenthesis. 997 observations.

Table 8: The effect of income for each instrument, in usage equation.

	usage only	full	retail only	no debt sample
security	0.011 (0.002)	0.015 (0.002)	0.016 (0.003)	0.020 (0.003)
acceptance	0.013 (0.003)	0.001 (0.003)	0.0001 (0.006)	0.003 (0.005)
cost of use	0.115 (0.003)	0.097 (0.003)	0.055 (0.005)	0.034 (0.003)
control of pay time	0.040 (0.002)	0.050 (0.002)	0.033 (0.004)	0.030 (0.003)
record keeping	0.062 (0.003)	0.032 (0.003)	0.064 (0.005)	0.168 (0.004)
speed	-0.020 (0.003)	0.009 (0.004)	-0.004 (0.006)	0.041 (0.004)
ease of use	0.113 (0.003)	0.149 (0.004)	0.066 (0.006)	0.117 (0.004)

Notes: Standard errors are in parenthesis. 997 observations.

Table 9: Effect of consumer ratings of payment instruments on usage.

tings 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 sector.

Finally, for usage, we consider the role of debt in determining usage. Table 10 contains results. Row 1 reports the effect of a dummy for overdrawing a checking account in the last 12 months, and it predicts higher debit usage. Also, a dummy for having revolved credit card in the last 12 months also predicts debit usage, presumably because the cost of using a credit card is particularly high now. The size of the revolving balance does not have a significant effect, although it is possibly measured with error as it is self-reported.

Now we turn to results from the adoption equation. The instrument dummy coefficients appear in Table 11. These are costs, so high coefficients imply an instrument that is more costly to adopt. Since all households 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. Stored value cards are more costly than other card options, which may affect the fee structure associated with

variable	instrument	usage only	full	retail only	no debt sample
overdraft	debit	0.44 (0.09)	0.44 (0.09)	0.24 (0.08)	0.50 (0.12)
	credit	-0.04 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.04 (0.13)
debt revolver	debit	0.45 (0.10)	0.45 (0.11)	0.34 (0.09)	
	credit	-0.58 (0.09)	-0.56 (0.09)	-0.34 (0.09)	
debt amount	debit	-0.08 (0.08)	-0.09 (0.08)	-0.06 (0.09)	
	credit	0.02 (0.07)	0.02 (0.07)	0.03 (0.07)	
debt X income	debit	0.02 (0.03)	0.03 (0.03)	0.01 (0.04)	
	credit	0.00 (0.03)	0.001 (0.03)	-0.01 (0.03)	
debt X edu	debit	0.003 (0.01)	0.002 (0.01)	0.004 (0.01)	
	credit	-0.004 (0.01)	-0.005 (0.01)	-0.003 (0.01)	

Notes: Standard errors are in parenthesis. 997 observations.

Table 10: The effect of debt characteristics on debit and credit card usage.

	card			bill pay		
	debit	credit	stored value	on-line banking	direct bank accnt deduct	income deduction
full	-1.29	-1.84	1.39	0.26	-0.99	1.43
	(0.10)	(0.13)	(0.09)	(0.09)	(0.10)	(0.09)
no debt sample	-0.82	-0.44	0.62	-0.59	1.40	1.59
	(0.10)	(0.13)	(0.10)	(0.10)	(0.09)	(0.11)
retail only	-1.41	-1.79	1.47			
	(0.13)	(0.13)	(0.09)			

Notes: Standard errors are in parenthesis. 997 observations.

Table 11: The effect of instrument dummy variables on adoption.

these cards. Interestingly, automatic bank account deduction is regarded as very cheap, perhaps because many people pay their mortgage in this way at no charge. On-line bill pay is more expensive.

We include several more variables in the adoption decision, which are presented in Figure 12. In particular, the set-up cost rating leads to increased adoption of that instrument, as expected. Overall, adoption costs vary with income and instrument. We graph this in Figure 1. Notice that the adoption costs of all of the instruments (but stored value cards) drops with income, but that the adoption cost of credit drops most precipitously. This result could be explained in part due to credit checks and selective offers by banks.

Finally, we consider the elements of the Σ matrix. In the full model, this accounts for 27 parameters. Rather than presenting each parameter, we provide the correlation coefficients for the unobserved elements of adoption and usage, which differ by context. That is, we provide $\rho(\nu_{ijc}, \omega_{ij})$ in Table 13. We see almost exclusively positive parameters, which implies positive selection into usage. Bank account deduction exhibits negative selection – that

Variable	Instrument	full		retail only		no debt sample	
income	debit	-0.02	(0.03)	-0.07	(0.03)	-0.02	(0.03)
	credit	-0.21	(0.04)	-0.21	(0.03)	-0.21	(0.04)
	bank bill pay	-0.10	(0.02)	-0.05	(0.02)	-0.10	(0.03)
	bank account deduction	-0.01	(0.03)			-0.02	(0.02)
no HS degree	dc,cc,bank bill pay, bank accnt	1.24	(0.24)	1.63	(0.46)	1.51	(0.25)
edu X (HS deg)	dc,cc,bank bill pay, bank accnt	-0.18	(0.04)	-0.16	(0.09)	-0.19	(0.04)
employed	debit	-0.50	(0.19)	-0.53	(0.22)	-0.83	(0.20)
	credit	0.27	(0.26)	0.33	(0.27)	0.69	(0.28)
dialup	bank bill pay, bank account	0.54	(0.18)			0.60	(0.18)
setup cost	all	-0.32	(0.04)	-0.44	(0.06)	-0.32	(0.04)
bank int. rate	credit	1.47	(0.24)	1.35	(0.24)	2.63	(0.29)

Notes: Standard errors are in parenthesis. 997 observations.

Table 12: The effect personal characteristics on instrument adoption.

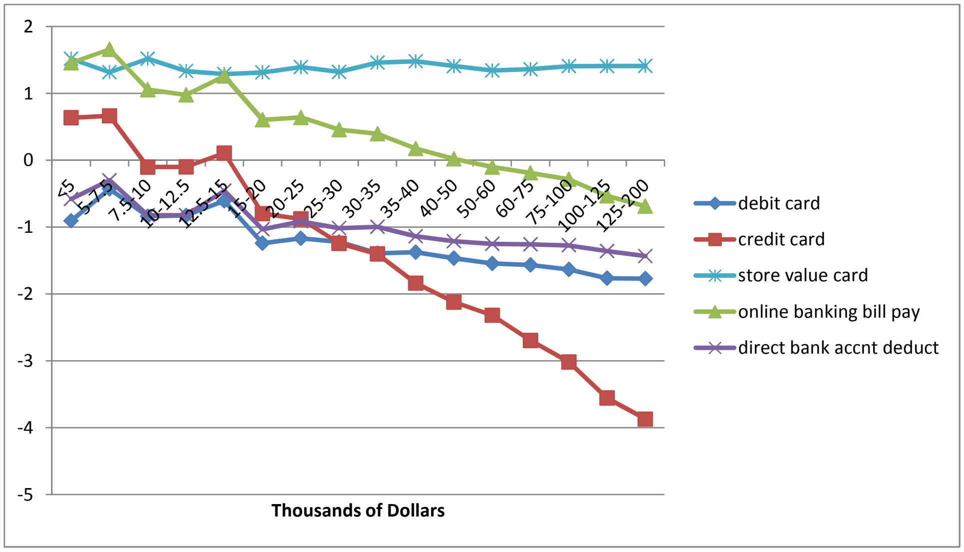

Figure 1: Adoption costs by income.

	Bill Pay			Retail			
	Automatic	Online	In person	Online	Essential	Non-essential	Other
debit card	0.74	0.81	0.79	0.68	0.96	0.88	0.95
	(0.06)	(0.06)	(0.06)	(0.05)	(0.08)	(0.07)	(0.08)
credit card	0.59	0.65	0.63	0.54	0.79	0.71	0.78
	(0.25)	(0.28)	(0.27)	(0.23)	(0.34)	(0.31)	(0.33)
store value card			0.02	0.01	0.17	0.03	0.09
			(0.06)	(0.04)	(0.66)	(0.10)	(0.34)
online bank bill pay		0.79					
		(0.13)					
bank accnt deduct	-0.45	-0.50		-0.41			
	(0.30)	(0.33)		(0.27)			
income deduction	0.001						
	(0.01)						

Table 13: Correlation coefficients for unobserved terms in usage and adoption.

is, households that adopt for unobservable reasons tend to use it little – this may be driven by mortgage issues. In contrast, debit and credit cards exhibit very high selection, particularly in retail contexts, suggesting that households that adopt for unobserved reasons tend also to be surprisingly high users. As we saw in comparisons of the use-only and full models, this selection effect can change parameters substantially.

6.2 Summary statistics and counterfactuals

How do usage benefits compare to 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 instrument depends on the composition of the bundle, we choose full bundle as a target one, 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 both bundles, stemming from their use in future transactions. We compute such benefit for every observation in the sample that falls 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 with the lowest income (less than 15K per year).

For example, the average consumer with income between 35K to 40K per year) enjoys about the same benefits of debit as the average consumer

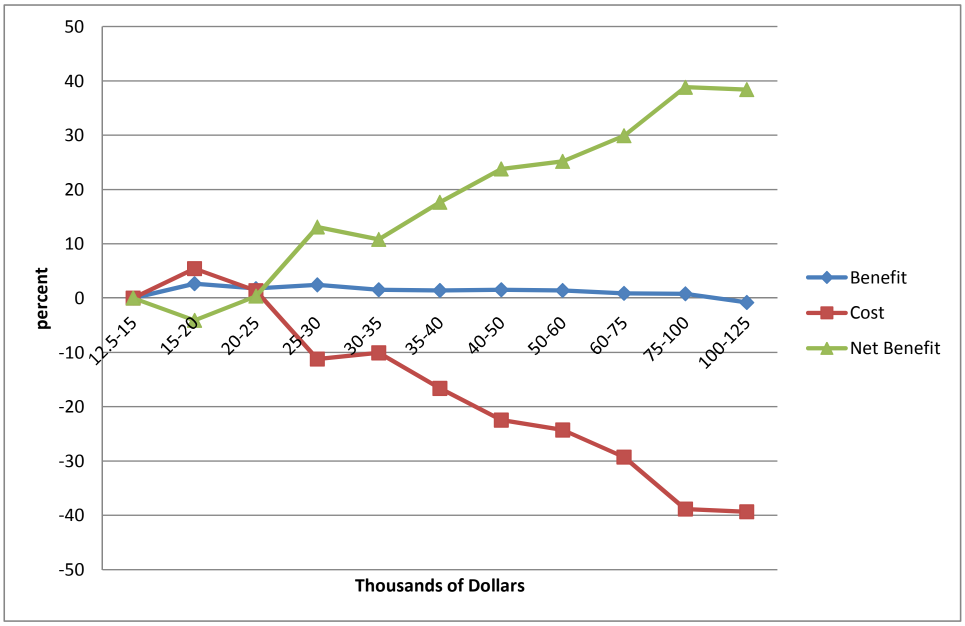

Figure 2: Usage benefit and adopt cost for debit cards by income.

from the baseline category (15K per year or less). However, costs decrease by only 20%, and so net benefit increases by that amount. As income grows, the net benefit stays fairly constant, while adoption costs decrease, reaching -40%.

Two conclusions can be made from these results: a) effects of policies directed at debit cards are likely to be very heterogeneous in the population; b) higher income people will be more sensitive to usage-side interventions, while lower income people would react more to adoption side interventions. These conclusions play an important role in our results below.

The counterfactual that we focus on, as motivated by the Durbin Amendment, is how consumers respond to a change in the cost of debit. We simulate the change in cost by downgrading consumer's reports on the "cost of use" characteristic of debit, by enough to reduce debit's share by 1%. In order to compute these results, we compute choices for each household in our data set and use the survey weights to construct a nationally representative result. We assume consumers cannot switch to the outside option, which makes substitution patterns easy to interpret, and because we observe little about the outside option. In our first experiment, we hold adoption fixed and look only at changes in usage. Figure 3 illustrates changes in the market shares

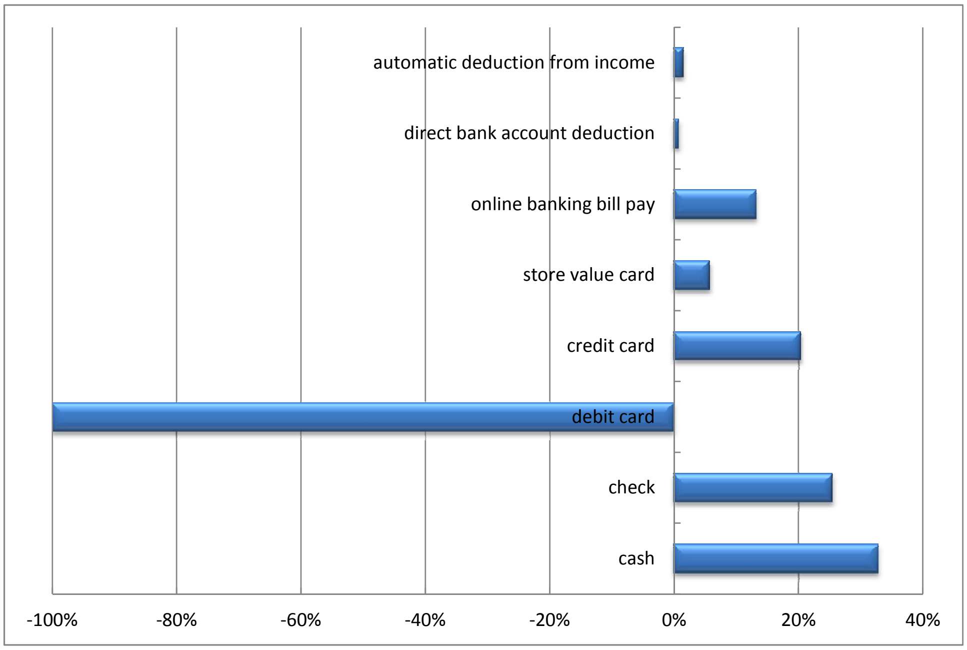

Figure 3: Change in market share for a change in the cost of debit, holding adoption fixed.

of payment instruments for this "short-run" experiment. Most of the substitution is to paper products: cash increases by 33 percentage points and check by 26. Credit cards are the next highest, with 20 percentage points. The rest of the options fill out the remaining 21 percentage points, with direct bank account deduction getting the largest share of that.

What if we consider the "long run," in which we allow adoption decisions to adjust to the change in the usage cost of debit? The outcome appears in Figure 4. Again, we consider a change in debit utility that reduces debit market share by 1%, but this time in the long-run. The change is the top line of each pair in the figure. We do not exhibit debit in this case, as it is again -1. In this case, results are similar to short-run, with credit cards gaining 21 points as opposed to 20. Thus, the change in debit fees causes only a few people to adopt credit cards that would not have otherwise. This outcome results from the fact that it is primary low-income households that are affected by the change, who are unlikely to adopt credit.

The figure also considers a change in the adoption cost of debit, rather than the usage cost. We compute a change in the adoption cost that would

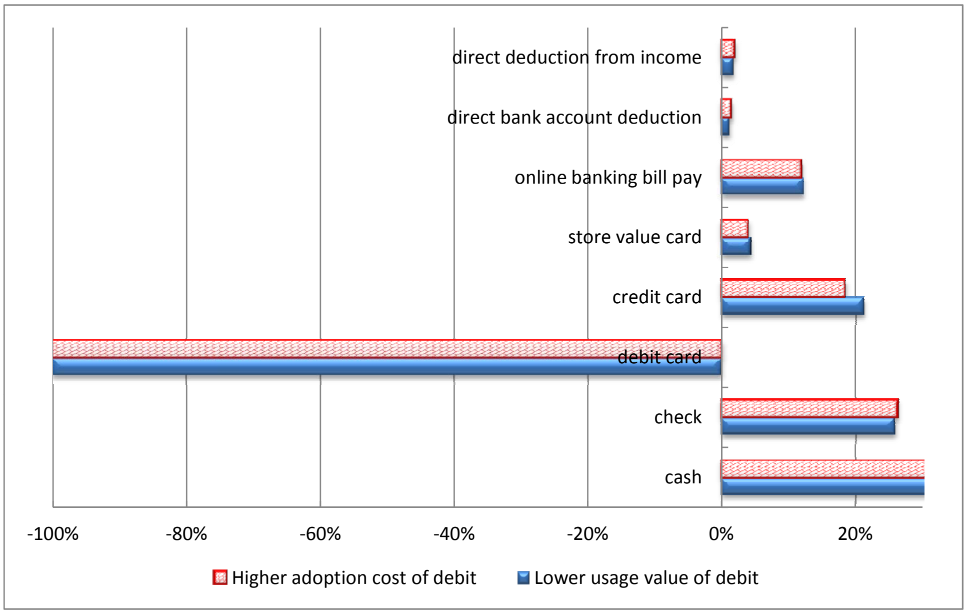

Figure 4: Change in market share for debit-reducing equivalent changes in adoption and usage costs of debit.

induce a 1% decrease in debit market share. Note that this is a much larger welfare decrease in the previous case because adoption costs are hard to avoid. However, it generates a comparable market share change. Resulting changes in market share for other instruments are the bottom lines of Figure 4. In response to adoption costs, cash gains by even more, gaining 36% of the loss to debit. Credit cards do worse, gaining only 18 percentage points. This is a result of the fact that adoption costs target low income households, and so causes a bigger switch to cash than usage costs.

Banks are multi-product firms and recognize that recouping costs just through debit fees may be non-optimal. An alternative might be for banks to spread costs across their different products. In Figure 5, we consider a change of -0.072 to the value of δ_{ijc} (the mean usage utility) for each bank related product: cash, check, debit, on-line bill pay, and auto-deduction bill pay. We allow adoption behavior to adjust, but keep in mind that our model assumes consumers always hold a checking account. As one would expect, market shares for the bank products declines, and credit cards become much more popular. Stored value cards also do relatively well.

Finally, we consider welfare from these interventions, graphed in Figure 6

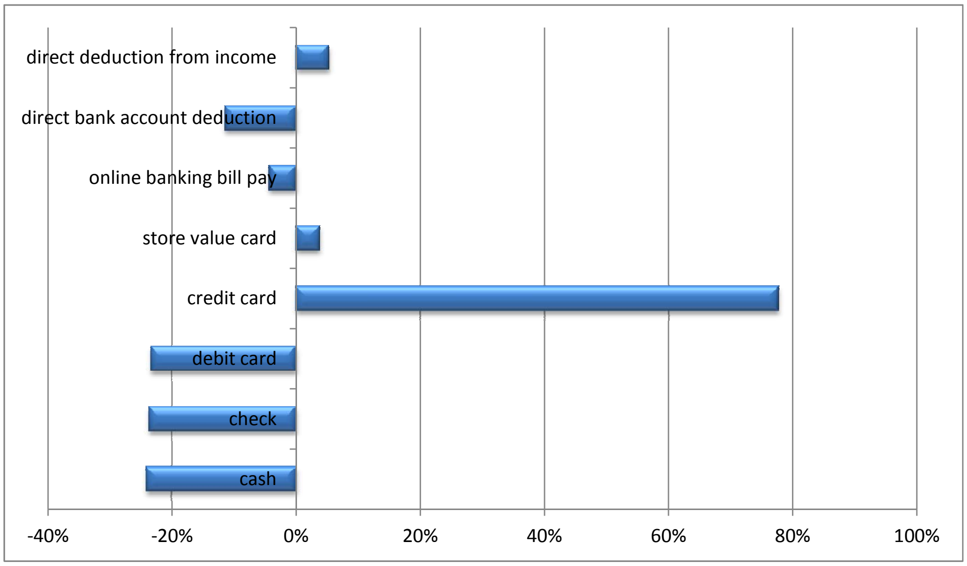

Figure 5: Change in market share for a change in the cost of bank products, allowing adoption to adjust.

The long-run welfare cost of the policy is estimated to be between -2.8 and -1.3% 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 8% to 30% larger depending on income. The difference over the income range is striking, with low income welfare falling losing more than twice the amount (as a percent of their income drop) than the wealthiest in the long run, and 2.5 times more in the short-run. Wealthy households fare better because they typically have adopted larger bundles to begin with, so it is easier to substitute in the short-run and 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 usage of payment instruments, such as credit cards, debit cards and stored value cards. Our model addresses features of the discrete-continuous nature of the problem in a way that is more attractive than the previous literature. We also discuss identification of the bundled nature of the problem.

Using a new data available from the Federal Reserve Bank of Boston,

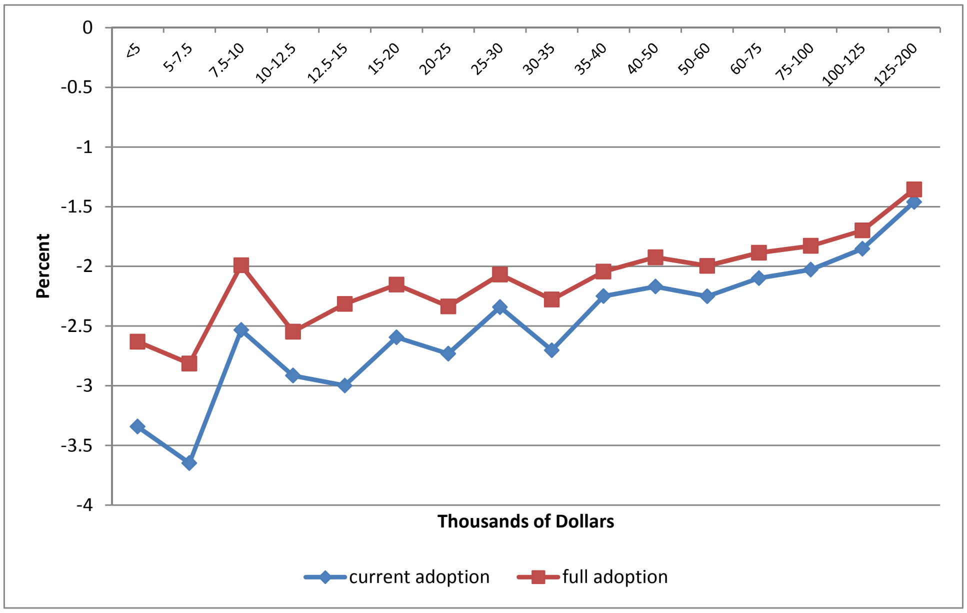

Figure 6: Welfare change from a change in the usage cost of debit, income category.

we estimate the model. We find a number of interesting results about the determinants of payment choice. We compute elasticities to the cost of debit and find substantial switching, particular to paper-based methods such as cash and check.

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