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

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October 4, 2013

Abstract

The way that consumers make payments is changing rapidly and attracts important current policy interest. 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. We evaluate substitution and income effects. Our simulations shed light on consumer response to the recent government interventions into payment markets.

*We thank Wilko Bolt, Beth Kiser, Ariel Pakes and Bob Triest for insightful comments on the paper. We also thank Mingli Chen, Vikram Jambulapati, Sarojini Rao, and Hanbing Zhang for excellent research assistance. 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

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, and online banking. 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 data set, consumers overall hold more than 50 different portfolios of payment instruments and their patterns of payment use vary 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 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 data set, the Survey of Consumer Payment Choice (SCPC, described in Foster et al. 2009) specifically designed to address these topics. 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. The coverage of bill payments is unusual for data sets in the payments area, and we find that accounting for bill payments is important. The data set also includes information about household demographics such as age, income and education. The survey asks respondents to evaluate instruments, on a numerical scale, along several dimensions, such as security, ease of use, and set-up cost. These are important predictors of choice. In particular, ease of use is highly valued.

Our econometric model allows us to separately identify the effect of explanatory variables on adoption and use, and to identify the value of usage on adoption. Because
adoption and usage represent a set of simultaneous equations, we rely on exclusion restrictions to obtain identification. In particular, we specify that some consumer ratings, such as the rating of ease of use, affect usage but not adoption, whereas others, such as the rating of set-up cost, affect adoption but not usage. In estimation, we use Maximum Simulated Likelihood to account for correlations within and across instruments in adoption and usage, which thus allows for a selection effect: consumers that adopt an instrument for unobserved reasons may also have high usage of that instrument for unobserved reasons. An attractive feature of our model is that consumers anticipate a shock to usage at the time of adoption, so our model allows consumers to know more than the researcher about the consumers’ usage when they make their adoption decision. We believe this is a realistic feature in the adoption of payments instruments.

We focus on substitution patterns around debit and credit cards. To evaluate substitution patterns for debit cards, we separately consider changes to the use value and adoption cost of debit cards, and look at how that affects market shares for other instruments. 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 find substitution heavily weighted towards paper products, that is, cash and check. The popularity of check as a substitute to debit might be surprising, but we show that this result is driven by the heavy use of debit in bill-pay contexts in our data, where check is also very popular. Thus, accounting for bill payments impacts our results in important ways.

We further find relatively similar responses across use and adoption costs, both in the short and long run. In contrast, 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. We also consider the effect of a change in the usage cost of credit cards. Similar to debit, we find substantial substitution to paper products, although less so than in the case of debit. We find that wealthy consumers suffer relatively more, as they are more likely to be credit card users.

Understanding consumers substitution patterns between payment instruments is
an important policy issue. Consumers rarely face explicit costs of using an instrument, and so consumers may receive poor signals about the social cost of their choice. For this reason, and a variety of others, government intervention is common in these markets, and understanding substitution patterns is important for designing and evaluating these policies. For example, central banks typically consider credit cards to be more efficient than cash, since credit cards are a digital mechanism. Thus, the efficiency implications of a regulation that impacts the cost of debit cards depends on whether consumers switch from debit to cash or to credit cards. Furthermore, substitution patterns may depend on whether the regulation affects the adoption or use cost of debit cards, so it is important to employ an approach that recognizes these differences.

Our emphasis on debit and credit cards is in part motivated by two recent research and policy actions in the payments market. First, in the United States, recent legislation requires the Federal Reserve to regulate the interchange fees of debit cards.\(^1\) Also, regulation is common internationally: Australia has regulated credit card interchange fees since 2003, the European Union is studying this issue, and a number of other countries are at various stages of regulation (Bradford and Hayashi 2008; Weiner and Wright 2005). As banks respond to this regulation, consumers may face different charges for adoption and use of payment instruments.\(^2\) We do not study bank pricing in this paper. Rather, we consider how consumers would respond to different potential changes in the fee structure of banks. In particular, we use our model to simulate how consumers respond to a change in the usage cost and to a change in the adoption cost of debit cards.

A second policy development is the move towards allowing merchants to surcharge

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\(^1\)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)

\(^2\)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 in each month in which a debit card was used. This well-publicized initiative was eventually abandoned, but alternatives, such as monthly fees on checking accounts, can be regarded in a similar way.
or discount payment instruments. Previously, merchant contracts with card companies prohibited merchants from steering consumers among card products, although merchants have always been allowed to offer discounts for cash use. A series of recent antitrust and regulatory initiatives allow for merchants to discount particular card products. Also, surcharging is currently allowed in some countries, such as Australia and the United Kingdom, and appears to impact card usage. Since discounting and/or surcharging appears to be likely in the United States in the near future, we are interested in how consumers will respond. Thus, we interpret our experiments with the usage value of credit cards in this light.

Discussing policy brings us to several caveats. Keep in mind that our paper addresses only some of the issues associated with interchange and surcharging regulation. We do not incorporate the merchant response to such regulation either in terms of acceptance or pricing, and we do not study the ways in which it will affect bank pricing or consumer banking choices. Also, other recent policy changes, such as changes in the ability of merchants to steer payments over different networks, also affect these outcomes. Conditional on these factors, our model is able to provide an estimate of substitution patterns.

Our paper contributes to several literatures, both in terms of modeling and in its application. As our econometric 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. A particularly unattractive feature of these models for the payments context is that the models typically assume that the consumer has only a limited amount of information about usage at the time of the adoption decision—no more information than the econometrician has. In contrast, our allows consumers to know more than the econometrician about usage.

These models are also related to the two-step selection model of Heckman (1979).

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3 A July, 2011 settlement between the Department of Justice and Visa and MasterCard (effective January, 2013) allows merchants to discount card products at the point of sale, so a merchant could offer a discount to a consumer for using a debit or credit card that sets low merchant fees. A separate settlement proposed in July, 2012 between merchants and Visa and MasterCard would allow merchants to surcharge different card products, rather than offer a discount (there is little difference between surcharging and discounting in standard economic models, but the difference appears important to industry participants.). Furthermore, under the Durbin Amendment (see footnote 1) also allows for discounting.
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. 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.\(^4\)

One aspect of our model is the choice between bundles of payments instruments (for instance, consumers may choose debit, credit, both, or neither), so our model is related to the bundled choice literature such as Gentzkow (2007) and Crawford and Yurukoglu (2012). When observing choices over bundles, it is difficult to distinguish between complementary products and correlated preferences. Gentzkow (2007) addresses this issue using an instrumental variables approach. In contrast, we exploit the fact that we observe usage to pin down the substitutability (or complementarity) and allow for correlation only in the adoption stage (which is similar to the approach of Crawford and Yurukoglu 2012).

There is a substantial literature on consumer payment choice, such as that reviewed in Rysman (2007; 2010). Schuh and Stavins (2010; 2013) are related to our paper in that they use a Heckman selection model of each payment instrument separately to study adoption and use. Our paper uses a more structural 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. Ching and Hayashi (2010) measure how payment choice responds to reward programs. Like, Schuh and Stavins (2010; 2013), Ching and Hayashi (2010) precedes our paper in the use of self-reported preference data to account for heterogeneity in consumer preferences. 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. Arango, Huynh, and Sabetti (2011) also study payment choice, in this case using diary data. Amromin and Chakravorti (2009) study cash use across different countries. Klee (2008) and Cohen and Rysman (2012) study payment choice in grocery setting using scanner data. As in Yang and Ching (2013), the adoption of payment instruments

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\(^4\)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.
can be seen as a form of technology adoption. Numerous central banks now collect data similar to ours, so a further contribution of our paper is to provide a method for analyzing this kind of data.

Our paper is relevant for the literature on two-sided markets as well (see Rochet and Tirole 2006; Rysman 2009; Hagiu and Wright 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 distinction between adoption and use decisions that we focus on is often important in that literature. Examples are Rochet and Tirole (2006) and Weyl (2010). There is a substantial literature studying interchange fees, such as Rochet and Tirole (2002). See Verdier (2011) and Rysman and Wright (2012) for recent surveys. As we are motivated by regulatory and antitrust intervention into payment markets, our research is related to a group of papers that observe such interventions directly and estimate the impact. These papers typically have less detailed data or modeling of the consumer side, but a more complete treatment of the merchant side and thus, the two-sided effect. Examples from the Spanish banking market are Carbo-Valverde, Chakravorti, and Rodriguez-Fernandez (2013) and Carbo-Valverde, Linares-Zegarra, and Rodriguez-Fernandez (2012).

2 Data

Our paper relies on the Survey of Consumer Payment Choice (SCPC). This data set 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 data 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 data set as well as a useful set of summary variables appears in Foster et al. (2009). Below, we
present a few tables that are relevant to our goals. 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 7, but not to estimate the model parameters, as reported in Section 6.\(^5\)

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, bank account deduction, and income deduction.\(^6\) 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

\(^5\)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.

\(^6\)The SCPC also includes data on money orders and travelers checks. However, it does not include characteristics of these instruments and households use them 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
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.9

In addition to average adoption numbers, it will be important to analyze which instruments are typically held together. Table 2 reports the top 15 most popular bundles of instruments. The first column reports the share of the population that holds that bundle (making use of the population weights in the data set). Each column has a “1” or a “0” for whether that instrument is in the bundle or not. For example, the most popular bundle, held by 23% of the population, includes cash, check, debit, credit, on-line banking and bank account deduction, missing only prepaid and income deduction, for a total of six payment instruments. The fourth most popular bundle, held by 6% of the population, has cash and check and no other instruments. Near the bottom of the table, we see households that hold either debit or credit, but not both. This table covers 85% of the population.

In addition to the 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, nonessential retail, online retail, automatic bills, online bills, bills by check or in-person, and other nonretail. The distinction between essential

d0 automatic bill-pay. This combination will be allowed in future versions of the survey.

9Note that adoption of debit is only 80%, although banks seek to distribute ATM cards with debit payment features. Thus, after opening an account, there is rarely any further “adoption” action that must take place to obtain a debit card. This number is below 100% because some people tell their bank that they do not want a debit card. Also, some people may not recognize that they have a debit card and misreport. Interestingly, the 80% number is consistent with our discussion with bank executives, who have access to administrative data. Overall, we expect debit cards to have low adoption costs, and we ultimately find that they have the lowest adoption costs of all of our instruments for low income consumers.
Table 2: Population holdings of the top 15 bundles of payment instruments.

<table>
<thead>
<tr>
<th>Population</th>
<th>cash</th>
<th>check</th>
<th>debit</th>
<th>credit</th>
<th>prepaid</th>
<th>online</th>
<th>bank acct</th>
<th>income</th>
<th>deduction</th>
<th>total</th>
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<td>23%</td>
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<td>0</td>
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A "1" indicates population holds that instrument.

and nonessential retail is similar to the distinction between necessities and luxury goods.\textsuperscript{10} 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 3 reports the average number of transactions by context in our sample, as well as by instrument and context. We see that cash and debit are popular for essential retail, whereas credit is relatively more popular for non-essential retail. Checks have a higher share of its use in bill-pay relative to credit and debit. But debit, credit and bank account deduction are also popular in bill-pay, with numbers of transactions close to check. Check dominates the mail-in and in-person context, whereas bank

\textsuperscript{10}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.
account deduction is the most popular method for automatic and on-line bill-pay. As we will see below, these features of the data play an important role in our results. Naturally, not every payment instrument is available in every payment context; for instance, one cannot shop online with cash. Blank entries in Table 3 indicate entries that were ruled out by the survey itself, such as using cash to shop on-line. Our econometric model provides predictions of the outcomes in Table 1 and Table 3.

It is important to recognize that the SCPC records only the number of transactions with each instrument, not the value of those transactions. Clearly, the value of transactions is also of interest. However, it is outside of the scope of this paper. Much of the private and social costs of using a payment instrument are at a per transaction level, not a per dollar level. For evidence, see Garcia Swartz and Hahn (2006). Thus, we view the transaction level with great interest.

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.

Our model simultaneously predicts the adoption and usage, which raises an identification problem. For example, we may observe that consumers with high usage
value are likely to adopt an instrument, but it will be difficult to say whether high usage value causes consumers to adopt an instrument or is instead correlated with adoption preference. In order to resolve this, our econometric model requires variables that can affect use but not adoption, and vice versa. We assume the rating of set-up cost affects adoption, but does not otherwise affect usage. We assume that the rest of the characteristics affect usage but not otherwise adoption. Thus, if we see that consumers who find an instrument easy to use are particularly likely to adopt, than our exclusion restriction imposes that usage has a causal effect on adoption.

In practice, ease of use and cost of use, turn out to be important in predicting usage. In order for these variables to be useful instruments, one requirement is that they vary substantially across the population. The significant results in the final tables confirm this, but for exploratory purposes, we also provide Table 5. In this table, we calculate the covariance matrix for the ratings of debit cards. The diagonal provides the variance, whereas the off-diagonals are correlation coefficients (thus, they are between -1 and 1). Looking at the diagonal, we see substantial variance in ratings. Several have variances above 1 (on a 5 point scale) and all have variances above 0.5. In addition, the table indicates that none of the variables have correlations above 0.5, which suggests substantial heterogeneity in these ratings across the population. Tables for other payment instruments look similar.

### 3 Model

In this section, we present a model of consumer choice of adoption of payment instruments and use 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...
Table 5: Covariance matrix for ratings of debit cards.

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 \( j = 1, \ldots, J \) are cash, credit card, and debit card. The consumer can adopt 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 to 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 consumer faces \( C \) contexts. Examples of contexts, \( c = 1, \ldots, C \) are online purchases, essential retail, and nonessential retail, for a total of seven \( (C = 7) \) possible contexts. 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 (one per hour). 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 approach has several advantages. Our set-up makes use of the total number of payments to infer demand for payments relative to the outside option, which may be affected by 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 can choose to make online purchases, while a consumer with only cash and check cannot do so. As a result, a consumer with a card may choose fewer nonessential retail payments and more on-line payments. In practice, we assume that the number of payment opportunities \( L \) is 436 per month, about 14 per day, constant across all consumers. This number is above what we observe for any consumer in the data set, and well above the average number of transactions.

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

\[
\begin{align*}
    u_{ijcl} &= \delta_{ijc} + \varepsilon^u_{ijcl}.
\end{align*}
\]

The consumer observes both \( \delta_{ijc} \) and \( \varepsilon^u_{ijcl} \) when choosing \( j \) and \( c \), but observes only \( \delta_{ijc} \) at the time of adopting \( j \). Thus, \( \varepsilon^u_{ijcl} \) can be interpreted as prediction error in usage at the time of adoption. Discussion of econometrics is delayed until the following section, but we note that the econometrician may not perfectly observe \( \delta_{ijc} \), so the consumer still knows more about usage than the econometrician at the time of adoption. For each opportunity \( l \), consumer \( i \) chooses \( j \) and \( c \) such that

\[
    u_{ijd} \geq u_{ij'c'l}
\]

\( \forall j' \in b_i, c' = 1, \ldots, C \).

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

\[
    v_{il}(b) = \max_{j \in b_i, c \in \{1, \ldots, C\}} u_{ijd}.
\]

At the time of adoption, the consumer is concerned with the expected indirect utility, averaged over \( \varepsilon^u_{ijd} \). One can think of this as the average over payment opportunities
Now consider stage 1, the adoption stage. The consumer knows $\delta_{ijc}$ and the distribution of $\varepsilon_{ijcl}$ 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:

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

The parameters $\lambda_{ij}$ 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 $\lambda_{ij}$ is not restricted to be negative and could be an “adoption benefit.” The variable $\varepsilon^a_{ib}$ 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 $\delta_{ijc}$, the consumer utility from allocating a payment opportunity to that context and instrument. This approach captures the issues we hope to address, namely substitution across contexts and instruments in response to demographics, preferences and the instrument portfolio.

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 $\lambda_{ij}$ (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, even though such effects might be important in a more general model.
4 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 $\varepsilon_{ijcl}^u$ is distributed Type 1 Extreme Value (the superscript $u$ refers to use). We normalize the value of no payment to zero, so $\delta_{ij0} = 0$.

Therefore, the probability (or expected share) of payment instrument $j$ and context $c$ by consumer $i$ integrated across options $l$ is:

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

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

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

where $\varepsilon_{il}^u$ is also distributed Type 1 Extreme Value. The mean of a variable with this distribution is Euler’s constant, $\gamma$. Therefore, the expected value of bundle $b$, now averaging across the $L$ purchases is:

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

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

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

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

$$\delta_{ijc} = x_{ijc}\beta + \nu_{ijc} . \quad (4)$$

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

---

11 Here, the subscripting of $\delta_{i0}$ refers to the option $j = 0$, which implies there is no context chosen.
\( \nu_{ijc} \) represents the quality that consumer \( i \) perceives for method \( j \) in context \( c \) that is unobserved to the researcher.

For the instruments besides cash and check, 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 \( \nu_i \) be the \( C \times J \) vector of terms \( \nu_{ijc} \), which includes terms for products that are part of \( b_i \) and for those that are not.\(^\text{12}\) Similarly, define \( \omega_i \) to be the \( J - 2 \) vector of values of \( \omega_{ij} \). 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, \( \{\nu_i, \omega_i\} \sim \mathcal{N}(0, \Sigma) \), with joint CDF \( \Phi \) and joint PDF \( \phi \). The set of parameters to estimate is \( \theta = \{\beta_{\delta}, \beta_{\lambda}, \Sigma\} \).

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 \( y_i^* \) be the vector made up of elements \( y_{ijc}^* \). Then, the likelihood function is:

\[
\mathcal{L}_i(y_i^*, b_i^*|\theta) = \int_{\nu_i} \int_{\omega_i} \Pr(y_i^*, b_i^*|\theta, \nu_i, \omega_i) f(\nu_i, \omega_i) d\omega_i d\nu_i.
\]

That is, we integrate out the unobserved terms \( \nu_i \) and \( \omega_i \) 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 \( \Sigma \) affect the substitution patterns, and the correlation between first and second-stage choices. We can potentially allow for arbitrary correlation among the elements of \( \nu_{ijc} \) and \( \omega_{ij} \) through the parameter matrix \( \Sigma \). In practice, we restrict the elements of \( \Sigma \) 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

\(^{12}\)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.
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 $\varepsilon_{ijc}^1$ be distributed standard normal, independent across $i$, $j$, and $c$. Let $\varepsilon_{ij}^2$ be standard normal and independent across $i$ and $j$, but be constant across $c$. Let $\varepsilon_{ic}^3$ be defined analogously. Then we define:

$$
\nu_{ijc} = \sigma^1 \varepsilon_{ijc}^1 + \sigma^2_j \varepsilon_{ij}^2 + \sigma^3_c \varepsilon_{ic}^3
$$

$$
\omega_{ij} = \sigma^1_j \varepsilon_{ij}^1 + \sigma^2_j \varepsilon_{ij}^2.
$$

Thus, $\sigma^1$, $\sigma^2_j$, and $\sigma^3_c$ determine the variance of use utility, with $\sigma^2_j$ measuring instrument correlation and $\sigma^3_c$ measuring context correlation. For adoption, $\sigma^2_j$ and $\sigma^5_j$ determine the variance. Together, $\sigma^2_j$ and $\sigma^5_j$ determine the correlation between unobserved adoption and use. That is, they determine the selection effect. Note that the selection effect could be negative if they have opposite signs.

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 cards. Debit cards are close to credit because they are both card based, and close to cash since payment is immediate. Check is also an important potential substitute. Therefore, the results that we present below come from a specification in which we have added three further shocks. Each shock enters the use value of two instruments, debit-cash, debit-check and debit-credit. We add 6 parameters to the model to govern the effect of each shock in each instrument. Thus, we allow for further (possibly negative) correlation between these three pairs of payment instruments.

Our algorithm proceeds by first generating values of $\varepsilon$ (in practice, from a Halton sequence as opposed to a pseudo-random number generator). Based on $\Sigma$ parameters, we use the values of $\varepsilon$ to construct values $\nu_{ijc}^s$ and $\omega_{ij}^s$ according to Equation 6. They are used to construct $\delta_{ijc}^s$ using Equation 4 and values of $\lambda_{ij}^s$ using Equation 5. Based on $\delta_{ijc}^s$, we construct $v_{ib}^s(b)$ from Equation 3 (the values from use of each bundle, consumer, and draw). With $v_{ib}^s$ and $\lambda_{ij}^s$, we construct $V_{ib}^s$ from Equation 2 (the value
of adoption). Using $\delta_{ijc}^s$ and $V_{ib}^s$ we can construct our simulated likelihood function:

$$\hat{L}_i(y^*_i, b^*_i; \theta) = \frac{1}{n_s} \sum_{s=1}^{n_s} \Pr(y^*_i | b^*_i, \nu^*_i, \omega^*_i, \theta) \Pr(b^*_i | \nu^*_i, \omega^*_i, \theta),$$

where:

$$\Pr(y^*_i | b^*_i, \nu^*_i, \omega^*_i, \theta) = \prod_{j \in b^*_i} \prod_{c \in C} \left( \frac{\exp(\delta_{ijc}^s)}{\sum_{k \in b^*_i} \sum_{d \in C} \exp(\delta_{ikd}^s)} \right)^{v^*_ijc},$$

$$\Pr(b^*_i | \nu^*_i, \omega^*_i, \theta) = \frac{\exp(V_{ib}^s)}{\sum_{k \in B} \exp(V_{ik}^s)}.$$

As in any approach that relies on maximum simulated likelihood, bias is introduced since $L_i$ 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 $n_s$ goes to $\infty$. Fortunately, our objective function is not difficult to compute, and so we set $n_s$ high, equal to 200 in what we present below, such that we expect this problem is minimized. Raising this value does not importantly impact our results.

Several issues deserve discussion. In reality, 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 to 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 second issue is that we rely heavily on consumer ratings of payment instruments. These ratings are self-reported evaluations and therefore 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; 2013) also find them to be important. We found the results of the ratings consistent with our expectations, in both 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. We adjust upwards the inverse of the information matrix to account for simulation error, as in Pakes and Pollard (1989). In practice, we follow the discussion in Train (2003) on addressing the issue of simulation. The household-level shocks at the level of the context and instrument (the latter which affects both adoption and usage) can be interpreted as a form of clustering in the sense of Moulton (1990), who advocates for household-level shocks to address standard errors in a panel data context. The estimates of our use parameters are more precise than our adoption parameters because we observe each household make many use choices but only one adoption choice (although in computing standard errors, we always treat the number of observations as the number of households, not the number of households time the number of use choices).

5 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. In this study, we highlight the contribution of our model to the existing literature. 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 $Y = 1$.\(^{13}\) A standard approach would be to model a latent variable $Y^* \equiv z \beta_z + \varepsilon_y$ where $Y = 1$ if $Y^* > 0$ and $Y = 0$ otherwise, with:

\[
\begin{align*}
Y^* &= z \beta_z + \varepsilon_y \\
w &= x \beta_x + \varepsilon_w.
\end{align*}
\]

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 $\varepsilon_y$ and $\epsilon_w$.\(^{13}\)Note that the notation in this section is meant to convey the Heckman model, and is unrelated to the structural model we develop for this paper.
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 in this approach, \( w \) 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 \( \varepsilon_y \) equals \( \varepsilon_w \) 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 \( \varepsilon_w \) 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.\(^{14,15}\)

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

\(^{14}\)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) 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.

\(^{15}\)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.
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 set-up cost and the ease 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 a positive correlation in the adoption of two instruments, we cannot tell whether the instruments are truly complements or whether consumers who like one instrument also tend to like the other. The distinction is important: an exogenous change in the price of one payment instrument affects the use of the 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 who 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 have similarly employed use to identify substitution and adoption to identify correlation, such as Ryan and Tucker (2012) and Crawford and Yurukoglu (2012). 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.
6 Results

In addition to the “full model” described above, we also provide estimates of the use stage alone, ignoring the adoption stage. These results provide a useful comparison because they do not address the selection inherent in the adoption decision.

For explanatory variables in the use equation (the elements of $x$), we include context-instrument fixed effects, consumer ratings of the payment instrument, demographics (age, income, gender, marital status, employment status, and education level) separately for cash, check, debit and credit. We do not include demographics for the other instruments in order to preserve degrees of freedom. For explanatory variables in the adoption equation (the elements of $z$), we include payment instrument dummies and demographics (income, education and employment status), as well as the consumer rating of the set-up experience.\footnote{We also experimented with a sample that was restricted to consumers who do not carry a balance. However, results were similar, both for parameters and counterfactual experiments.}

Table 6 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 relatively 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 7 presents the effect of each demographic variable on each payment instrument in the use equation. Wealthier households prefer credit cards. The “use-only” column indicates that less wealthy households use cash more than wealthy households. However, the “full” column indicates that this effect is due to selection. In the full model, the effect of income on cash use is close to zero and insignificant (although we will see that there is an important adoption effect of income). Similarly, the less wealthy households use prepaid cards more than wealthy households, but this effect is substantially reduced when accounting for selection. Education has a large positive effect on credit card use, and a significant negative effect on cash, check and debit, perhaps because educated households are better able to manage a credit line.
Table 6: Average Utilities by Context and Payment Instrument in Use Equation.

Older people use cash and check more than younger households. Employment causes households to use debit and not credit, perhaps because they do not need the credit feature.

Next in Table 8, we consider the role of consumer ratings. Overall, consumer ratings are important, as they explain 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 control and cost of use. These results are generally consistent with those in Schuh and Stavins (2010), who found that characteristics explain more of the variation in use than do demographics. 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).

Now we turn to results from the adoption equation. The payment instrument dummy coefficients appear in Table 9. These represent costs, so high coefficients imply an instrument that is more costly to adopt. Since all consumers hold cash and check, we do not estimate costs for these variables. We see that credit cards are the least costly to adopt, followed by debit. Prepaid cards are more costly than other

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17 We compute this statistic by calculating the variance generated by demographic variables and payment characteristics in the prediction of mean utilities.
<table>
<thead>
<tr>
<th></th>
<th>use only</th>
<th>full</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Household income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.04 (0.003)</td>
<td>0.002 (0.003)</td>
</tr>
<tr>
<td>cash</td>
<td>-0.07 (0.004)</td>
<td>0.001 (0.004)</td>
</tr>
<tr>
<td>check</td>
<td>0.01 (0.004)</td>
<td>-0.01 (0.006)</td>
</tr>
<tr>
<td>debit</td>
<td>0.02 (0.005)</td>
<td>0.02 (0.006)</td>
</tr>
<tr>
<td>credit</td>
<td>0.04 (0.006)</td>
<td>0.05 (0.006)</td>
</tr>
<tr>
<td>prepaid</td>
<td>-0.25 (0.076)</td>
<td>-0.11 (0.026)</td>
</tr>
<tr>
<td><strong>Education: college degree or higher</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.14 (0.02)</td>
<td>0.22 (0.02)</td>
</tr>
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<td>cash</td>
<td>-0.05 (0.02)</td>
<td>-0.16 (0.03)</td>
</tr>
<tr>
<td>check</td>
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<td>-0.21 (0.03)</td>
</tr>
<tr>
<td>debit</td>
<td>-0.96 (0.02)</td>
<td>-0.58 (0.02)</td>
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<tr>
<td>credit</td>
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<td>0.51 (0.03)</td>
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<tr>
<td>prepaid</td>
<td>0.21 (0.29)</td>
<td>0.06 (0.17)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-0.005 (0.01)</td>
<td>-0.02 (0.01)</td>
</tr>
<tr>
<td>cash</td>
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<td>0.08 (0.01)</td>
</tr>
<tr>
<td>check</td>
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<td>0.07 (0.01)</td>
</tr>
<tr>
<td>credit</td>
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<td>0.08 (0.01)</td>
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<tr>
<td>prepaid</td>
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<td>-0.10 (0.04)</td>
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<tr>
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<td>0.19 (0.02)</td>
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<td>-0.59 (0.03)</td>
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<td>0.06 (0.03)</td>
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<tr>
<td>prepaid</td>
<td>1.01 (0.37)</td>
<td>-0.60 (0.16)</td>
</tr>
<tr>
<td><strong>Employed</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.08 (0.02)</td>
<td>0.19 (0.02)</td>
</tr>
<tr>
<td>cash</td>
<td>0.06 (0.03)</td>
<td>-0.03 (0.03)</td>
</tr>
<tr>
<td>check</td>
<td>-0.25 (0.03)</td>
<td>-0.13 (0.03)</td>
</tr>
<tr>
<td>debit</td>
<td>0.48 (0.03)</td>
<td>0.28 (0.03)</td>
</tr>
<tr>
<td>credit</td>
<td>-0.35 (0.03)</td>
<td>-0.29 (0.03)</td>
</tr>
<tr>
<td>prepaid</td>
<td>-1.96 (0.25)</td>
<td>-0.26 (0.15)</td>
</tr>
</tbody>
</table>

Notes: 997 observations. Standard errors are in parenthesis. The "use only" model does include the adoption stage.

Table 7: Partial effect of socio-economic status on value of usage.
Table 8: Effect of Payment Characteristics on Use.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Coef</th>
<th>std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>debit card</td>
<td>-1.42</td>
<td>(0.61)</td>
</tr>
<tr>
<td>credit card</td>
<td>-1.77</td>
<td>(0.70)</td>
</tr>
<tr>
<td>online banking bill pay</td>
<td>0.05</td>
<td>(0.31)</td>
</tr>
<tr>
<td>bank account deduction</td>
<td>-1.08</td>
<td>(0.31)</td>
</tr>
<tr>
<td>store value card</td>
<td>1.49</td>
<td>(0.82)</td>
</tr>
<tr>
<td>direct deduction from income</td>
<td>1.61</td>
<td>(0.26)</td>
</tr>
</tbody>
</table>

Notes: 997 observations.

Table 9: Mean values of adoption by instrument.

Card options. Interestingly, bank account deduction (which is often facilitated by employers and mortgage companies) is regarded as very cheap to adopt, although not quite as inexpensive as credit or debit cards. Online bill-pay, which tends to require more initiative on the part of consumers, is more expensive.

We include several additional variables in the adoption decision. The results are presented in Table 10. 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. Overall, adoption costs vary with income and payment instrument. 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.

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
Table 10: Effect of Personal Characteristics on the Cost of Payment-Instrument Adoption.

specification as a reduced form 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.

The correlation matrix $\Sigma$ contains 19 parameters and generates a rich set of correlations. We defer a complete discussion to the Appendix. Overall, we find substantial correlation in unobserved utility across instruments and contexts in usage, and we find strong correlation between adoption and usage unobserved terms, generating an important selection effect into usage.

7 Counterfactual experiments

7.1 Debit cards

We use our estimated model to assess consumer response to a change in the cost of using debit cards: the cost of use and the cost of adoption. In addition to our policy motivation, these experiments provide magnitudes, in the sense of cross-elasticities, to the parameters in the previous sub-section. To calculate a change in the usage
value, we lower the mean utility of usage of debit cards ($\delta_{ijc}$ for $j = \text{debit}$ for each context $c$) by the same level amount, enough to reduce debit’s overall share of usage by 1 percentage point, from 31% to 30% of the market.\(^{18}\) We also distinguish between the responses of consumers holding payment instrument adoption fixed (the “short run”), and allowing adoption to change (the “long run”). To simulate an increase in the adoption cost of debit, rather than the use cost, we compute the change in the adoption cost ($\lambda_{ij}$) that would induce a 1 percentage point decrease in debit’s use market share.\(^{19}\) Changing adoption costs has no effect in the short-run, so we provide results for this experiment for the long-run only.\(^{20}\)

Figure 1 plots the estimated changes in the market shares in usage of payment instruments other than debit cards in response to a reduction in the use value of debit cards. To compute these results, we compute choices for each consumer 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 allows us to focus on substitution issues.\(^{21}\) 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 three experiments predict that cash will pick up between 32 and 34% of debit’s loss, with checks gaining about 25% and credit cards gaining 21%. Thus, our model predicts that paper products (cash and check) dominate as substitutes to debit. Our model predicts only small differences across the three experiments. There is slightly higher substitution towards cash in response to the usage cost than

\(^{18}\)Given our linear utility functions, reducing $\delta_{ijc}$ is equivalent to lowering a rating such as ease of use by the the same amount, scaled by the coefficient on the rating. In this interpretation, our experiment could potentially lower some ratings below zero. However, we do not regard this issue as particularly problematic.

\(^{19}\)Adoption of debit cards is different from other payment instruments, because dual ATM/debit cards are typically given automatically to checking account holders. One way to interpret the cost of debit card adoption is to think about the cost of opening a checking account, although surprisingly debit card adoption is much lower than checking account adoption. See footnote 9.

\(^{20}\)Note that our change in adoption produces a larger decline in welfare than the increase in the use cost of debit, because taking away an option has larger welfare consequences and it takes a substantial utility change to induce a consumer to drop an option.

\(^{21}\)We do not study substitution to the outside option since the results will depend highly on how we set the potential market ($L$), which is somewhat arbitrary. However, our results for substitution between payment instruments should be useful regardless of how we set $L$. 

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in response to the adoption cost. This result occurs because it is primarily wealthy people who stop using debit in response to adoption costs, and they have more options in their portfolio than low income consumers, and are more likely to use check. We explore income differences further below. But overall, we found little difference in the response to use and adoption costs, perhaps as one would expect if consumers are rational decision-makers.

Also, despite the importance of selection, our model predicts that the long-run and short-run effects of a change in the usage value of debit are very similar. There is a slightly higher substitution towards cash in the long-run, as consumers drop their debit card. This similarity between long and short-run results follows from the fact that some consumers already hold substitute products and those that do not face large adoption costs. That does not mean that adoption is unimportant. We show in what follows that adoption is central for understanding several results.

A perhaps surprising result of Figure 1 is that paper products do so well, and in particular that checks emerge as a stronger substitute than credit cards. Bank account deduction as a substitute to debit is also surprising (bank account deduction gains 13-14% in each experiment). In order to understand this further, we look at
the contexts in which these instruments are used. Figure 2 breaks up the short-run response to a change in the usage value of debit cards into the change in the retail context (summing over on-line, essential and non-essential retail, as well as “other”) and the change in the bill-pay context (summing over the automatic, on-line and in-person/mail bill-pay contexts). In this figure, the two bars for each instrument sum to the short-run line in Figure 1. Thus, the sum of all the lines in Figure 2 is one.

We find that the strength of check as a substitute to debit cards is driven by the bill-pay sector. Recall from Table 6 that our data shows substantial use of debit cards to pay bills. We see here that while check is only a mediocre substitute to debit in retail transactions, check dominates in the bill pay sector, and bank account deduction does well also. In Figure 2, we see that retail follows the expected pattern. Cash is by far the strongest substitute to debit cards, followed by credit cards and then by checks. The check use stems in part from households that do not hold credit cards, as we show below. However, we see that in bill-pay, check is the leading substitute in the bill-pay sector, along with bank account deduction. Credit card does poorly here, in part because it is low income households that use debit cards to pay bills, and these households do not hold credit cards, and also because credit cards face strong substitutes (checks or bank account deduction) in each bill-pay context. Keep in mind that check is the only bill-pay option that all consumers hold. The popularity of check in the bill-pay sector means that overall, it is a stronger substitute to debit than credit cards. This analysis highlights the importance of our study design and data set, which incorporates both adoption and usage, and recognizes different contexts for usage, particularly bill-pay.

Note that there is some substitution from retail to bill-pay in our counterfactual. Since debit is primarily a retail instrument, consumers in our model find retail less attractive as debit declines in value. Allowing this sort of substitution is an important element of our model, since in some cases, households may choose to pay for something in a retail or bill-pay format based on their payment instrument. For example, a consumer without a credit card may purchase an item or subscription via installments. Still, we wish to explore the role of this substitution in our results. First, we estimated a nested logit version of our model, in which bill-pay and retail are separate nests. In this specification, the importance of the nests (the inclusive parameter) is identified by the extent to which consumers maintain a constant level of bill and retail payments, despite different preferences and holdings. Remarkably, we found that the nesting
Figure 2: Short-run changes in market share percentage points in response to increases in debit card use cost, by bill-pay and retail contexts.

was unimportant, and results were very close to our original logit specification. This may be a result of the rich correlation matrix that we specify. We also estimated a model in which consumers could not substitute between bill-pay and retail. This model found that the decline in the utility of debit affected bill-pay more strongly than what we found in our original specification, such that even without bill-retail substitution, the results were almost identical to Figure 1. Thus, we view the results on the importance of check as a substitute to debit as robust to several modeling approaches.

We find substantial heterogeneity across socio-economic class. 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, with average values in the data for other variables. We assume that they each hold every instrument, and we graph the response to an

Note that the specification in which consumers could not substitute between bill-pay and retail is difficult to interpret since it requires two assumptions about the potential number of transactions, the number for bill-pay and the number for retail. Similarly, normalizing the outside option to bill-pay and retail to zero assumes that the outside options to both categories are equal to each other. This matters for our counterfactual, since our experiment consists of altering the value of debit relative to the outside option. Given the similarity in results to our favored specification, we did not further pursue these issues.
increase in the use cost of debit. We see very large differences in Figure 3, with the high-income household shifting market share to credit card by almost 16 percentage points more than the low-income household. The low-income household uses cash more than the high-income household by 9 percentage points, and cash and check together by 15 percentage points. Note also that, different from Figure 1, credit cards are more popular than check for both households. The explanation is that we have assumed that both households hold each payment instrument, whereas the differences in Figure 1 were in part due to different holdings. Naturally, the differences would be even larger if we started with a more realistic scenario, where the wealthy household held more instruments than the poorer one.

Finally, we consider the effect on consumer welfare from these interventions, graphed in Figure 4 for annual incomes greater than $7,500. The long-run welfare cost of the policy is estimated to be between $-2.8$ percent and $-1.3$ percent, compared to 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 for 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. As stated above, we do not incorporate the merchant response to recent regulation either in terms of acceptance or pricing, and we do not study the ways in which the regulation will affect bank pricing or consumer banking choices.

7.2 Credit cards

Now we turn to credit cards, motivated by the recent policy action that would allow for merchant surcharging of card products. Because surcharging acts as a usage fee, we study only changes to usage values for credit cards. Similar to our study of debit cards, we alter the usage utility of credit cards enough to change the market share for credit card by one percentage point, and then calculate changes in market shares for the other products assuming consumers do not switch to the outside option. The result appears in Figure 5. Among all credit card holders, substitution appears

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23We focus on credit cards, but note that the legal implications of these policies apply to credit and debit cards equally. Merchants can surcharge either type. However, since credit cards typically carry higher merchant fees, we expect that these developments will lead primarily towards making credit more expensive than other payment instruments.
about evenly split between cash, check and debit, each with between 25 and 27% market share, with bank account deduction capturing 15%. When we look only at those that also hold a debit card, debit does substantially better, gaining 30%, more than 6 percentage points better than cash or check. Again, check’s strong showing mostly comes from bill-pay. Bill-pay accounts for 43% of check’s market share change, whereas bill-pay accounts for only 23% of debit’s market share change.

Substitution patterns may be broadly similar for debit and credit cards, but welfare calculations exhibit important differences. We present the percentage change in welfare by income category for the change in the use value of credit cards. In Figure 6, we see welfare changes between 1.5 and 3% in the short-run, with long-run high around 2.5%. However, the pattern is different from the debit card case because the welfare decrease is proportionally larger for wealthy people. Whereas households with incomes less than $40,000 experience decreases less than 1.5% in the long-run, we find that households above $125,000 face decreases close to 2.5%. Naturally, this arises because wealthy people are more likely to hold and use credit cards.
Figure 6: Welfare change from a change in the use cost of credit, by income category.

8 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-continuous nature of the problem in a way that is more rigorous and flexible (in that we allow for the agent to know more than the econometrician, and we identify the structural effect of the continuous choice on the discrete choices) than the previous literature. We achieve identification by through exclusion restrictions on which consumer preferences affect only usage or adoption. 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, particularly to paper-based methods such as cash and check. We show that responses vary with demographics, particularly income and education, and by context such as bill-pay and retail.

Our study provides perspective on one feature of the potential response to interchange fee and surcharging regulation, and thus serves to inform future policy in this area. There are several other dimensions of response to these policies, so these interventions provide a complex policy question towards which we contribute.
References


Appendix

This section presents the estimates from the covariance matrix $\Sigma$. Table 11 presents the coefficients on the standard normal shocks for usage that we draw. The coefficients on instrument shocks are comparable in size to those on context shocks. The bottom panel presents the extra shocks that we built around the debit choice. The fact that the debit and credit coefficients in the debit-credit shock are of opposite sign implies a negative covariance in the use of these instruments, suggesting that heavy users of one rarely switch to the other. Cash and debit appear as close substitutes here.

Table 12 presents that standard deviation in usage for each context and instrument. The entries in this table are made up of the coefficients in Table 11. Note that this is the variance due to the terms $\nu$ and $\omega$ in our model. That is, this is the information known to the consumer that is not observed by the researcher. All of the magnitudes are comparable in size, so no one entry in the table stands out. However, it appears that the on-line retail context has the most heterogeneity and that cash use has the least, which seems reasonable.

In addition, we allow for correlation between the adoption and usage stage. Rather than present the underlying parameters, we present the correlations in Table 13. Although the parameters that generate the selection effect vary only by instrument, the resulting correlation differs by context as well since context-level variance affects the correlation between instrument adoption and instrument usage. Thus, Table 13 presents correlation terms by context and instrument. We see that there are important selection effects, particularly for debit. Selection is very high for prepaid cards, which indeed serve a specialized population.
Instrument-specific shock

<table>
<thead>
<tr>
<th></th>
<th>use</th>
<th>full</th>
</tr>
</thead>
<tbody>
<tr>
<td>cash</td>
<td>0.60 (0.01)</td>
<td>0.001 (0.00)</td>
</tr>
<tr>
<td>check</td>
<td>0.26 (0.01)</td>
<td>0.13 (0.01)</td>
</tr>
<tr>
<td>debit card</td>
<td>1.04 (0.01)</td>
<td>0.96 (0.01)</td>
</tr>
<tr>
<td>credit card</td>
<td>1.00 (0.01)</td>
<td>0.89 (0.01)</td>
</tr>
<tr>
<td>prepaid card</td>
<td>0.78 (0.03)</td>
<td>0.81 (0.03)</td>
</tr>
<tr>
<td>online banking</td>
<td>0.07 (0.02)</td>
<td>0.45 (0.01)</td>
</tr>
<tr>
<td>bank acct. deduct</td>
<td>5.19 (0.46)</td>
<td>1.10 (0.11)</td>
</tr>
<tr>
<td>income deduction</td>
<td>0.03 (0.17)</td>
<td>0.30 (0.04)</td>
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</table>

Context-specific shocks

<table>
<thead>
<tr>
<th></th>
<th>use</th>
<th>full</th>
</tr>
</thead>
<tbody>
<tr>
<td>automatic bill pay</td>
<td>0.76 (0.01)</td>
<td>0.87 (0.02)</td>
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<tr>
<td>online bill pay</td>
<td>0.71 (0.02)</td>
<td>0.72 (0.01)</td>
</tr>
<tr>
<td>in person/mail bill pay</td>
<td>0.82 (0.02)</td>
<td>0.64 (0.01)</td>
</tr>
<tr>
<td>online retail</td>
<td>1.03 (0.02)</td>
<td>1.01 (0.02)</td>
</tr>
<tr>
<td>essential retail</td>
<td>0.10 (0.01)</td>
<td>0.16 (0.01)</td>
</tr>
<tr>
<td>non-essential retail</td>
<td>0.47 (0.01)</td>
<td>0.56 (0.01)</td>
</tr>
<tr>
<td>other</td>
<td>0.07 (0.01)</td>
<td>0.04 (0.01)</td>
</tr>
</tbody>
</table>

Common shocks (coefs)

<table>
<thead>
<tr>
<th></th>
<th>use</th>
<th>full</th>
</tr>
</thead>
<tbody>
<tr>
<td>cash (debit - cash)</td>
<td>-0.78 (0.01)</td>
<td>0.89 (0.01)</td>
</tr>
<tr>
<td>debit card (debit - cash)</td>
<td>-0.32 (0.01)</td>
<td>0.62 (0.01)</td>
</tr>
<tr>
<td>debit card (debit - credit)</td>
<td>-0.73 (0.01)</td>
<td>0.14 (0.01)</td>
</tr>
<tr>
<td>credit card (debit - credit)</td>
<td>-0.01 (0.01)</td>
<td>-0.67 (0.01)</td>
</tr>
<tr>
<td>check (debit - check)</td>
<td>0.90 (0.01)</td>
<td>1.00 (0.01)</td>
</tr>
<tr>
<td>debit card (debit - check)</td>
<td>0.34 (0.01)</td>
<td>-0.02 (0.01)</td>
</tr>
</tbody>
</table>

Table 11: Coefficients on shocks that govern the correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>Bill Pay</th>
<th>Retail</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Automatic</td>
<td>Online Mail</td>
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<tr>
<td>cash</td>
<td>1.10</td>
<td>(0.01) 0.91</td>
</tr>
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<td>check</td>
<td>1.43</td>
<td>(0.01) 1.02</td>
</tr>
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<td>debit card</td>
<td>1.44</td>
<td>(0.01) 1.35</td>
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<tr>
<td>credit card</td>
<td>1.41</td>
<td>(0.01) 1.32</td>
</tr>
<tr>
<td>prepaid card</td>
<td>1.28</td>
<td>(0.01) 1.50</td>
</tr>
<tr>
<td>online banking</td>
<td>1.08</td>
<td>(0.08) 1.12</td>
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<tr>
<td>bank acct. deduct.</td>
<td>0.98</td>
<td>0.85 (0.01)</td>
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<tr>
<td>income deduction</td>
<td>0.92</td>
<td>0.10      (0.02)</td>
</tr>
</tbody>
</table>

Table 12: Coefficients on shocks that govern the correlation matrix
Table 13: Correlation between instrument adoption and usage, by instrument and context.

<table>
<thead>
<tr>
<th>Instrument</th>
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<th></th>
<th>Retail</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
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<td>Automatic</td>
<td>Online</td>
<td>Mail/In person</td>
<td>Online</td>
<td>Essential</td>
<td>Non-essential</td>
<td>Other</td>
<td></td>
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<tr>
<td>debit card</td>
<td>0.73</td>
<td>0.83</td>
<td>0.75</td>
<td>0.83</td>
<td>(0.44)</td>
<td>(0.49)</td>
<td>(0.45)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>credit card</td>
<td>0.69</td>
<td>0.59</td>
<td>0.79</td>
<td>0.71</td>
<td>0.80</td>
<td>(0.49)</td>
<td>(0.42)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>online banking</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
<td>(0.49)</td>
<td>(0.42)</td>
<td>(0.56)</td>
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<td>0.86</td>
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<td>0.41</td>
<td>(0.44)</td>
<td>(0.50)</td>
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<td></td>
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<tr>
<td>income deduction</td>
<td>0.32</td>
<td></td>
<td></td>
<td></td>
<td>(0.32)</td>
<td>(0.30)</td>
<td>(0.38)</td>
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