Explaining adoption and use of payment instruments by US consumers

Sergei Koulayev*

Marc Rysman**

Scott Schuh***

and

Joanna Stavins***

Motivated by recent policy intervention into payments markets, we develop and estimate a structural model of adoption and use of payment instruments by U.S. consumers. Our structural model differentiates between the adoption and use of payment instruments. We evaluate substitution among payment instruments and welfare implications. Cash is the most significant substitute to debit cards in retail settings, whereas checks are the most significant in bill-pay settings. Furthermore, low income consumers lose proportionally more than high income consumers when debit cards become more expensive, whereas the reverse is true when credit cards do.

1. Introduction

■ We use the Survey of Consumer Payment Choice to estimate the effect of payment policies on payment use and on social welfare.

The goal of this article is to estimate substitution patterns between payment instruments for US consumers. We analyze substitution in response to change in the value of usage and the cost of adoption of payment instruments. This issue is important because, during the past three decades, the US payments system has been undergoing a transformation from article to electronic means of payment. Modern consumers have access to ATM machines, debit and prepaid cards, and online banking. Because governments have a responsibility to deliver a safe and efficient payments system, understanding substitution patterns is important. More

specifically, our research is motivated by recent regulation of the debit card interchange fee, further described below, that has the potential to make debit cards less attractive to consumers, either via bank-imposed usage charges or adoption charges. Recent regulation also allows merchants to surcharge for cards. Understanding how consumers will substitute in response to these changes is important for evaluating the impact of these policies.

Our article makes use of a new public data set, the Survey of Consumer Payment Choice (SCPC, described in Foster, Meijer, Schuh, and Zabek, 2009) specifically designed to address these topics. In the SCPC, participants report their number of transactions that month by payment *instrument*: cash, check, credit and debit, prepaid cards, online banking, direct bank account deductions, and direct income deductions. In addition, for each instrument, the participant indicates how many transactions were used in each payment *context*, such as traditional retail, online retail, and bill-pay. The data set also includes information about participant 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 setup cost, which turn out to be important predictors of choice. A drawback of the SCPC is that it does not track transaction values, so our model studies only the number of transactions, not the values.

To estimate substitution patterns, this article develops and estimates a new structural model of adoption and use of payment instruments. 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. The model has several important technical features. A strength of our model is that it allows for flexible substitution patterns. Our model allows for correlation in unobserved terms across instruments and contexts, so for instance, one consumer may prefer to use a credit card in online and retail payments, whereas another may prefer to shop online, whether it be with a credit card or a debit card. We further allow for correlation to affect adoption and usage for a given instrument, which thus allows for a selection effect: consumers who adopt an instrument for unobserved reasons may also have high usage of that instrument for unobserved reasons. Because consumers in the adoption stage perceive a portion of the terms in usage that are unobserved to the researcher, our model allows consumers to know more than the researcher about their usage when the consumers make their adoption decisions. We believe this is an attractive and realistic feature in the adoption of payments instruments. As usage value and adoption cost are modelled in a simultaneous equations framework, we use exclusion restrictions based on consumer ratings of instruments to achieve identification. Our model generates a computationally complex likelihood function, which we address with simulation techniques.

Our counterfactual analysis considers what would happen if debit cards became more expensive to use or adopt. We find that cash and check are significant substitutes for debit cards, more so than credit cards. These results differ by context—cash is a popular substitute in retail, whereas checks are a popular substitute in bill-pay contexts. The coverage of bill payments is unusual for data sets in the payments area, and we find that accounting for bill payments is important. Overall, we find regulation that makes debit cards less attractive to consumers, either to adopt or to use, moves consumers away from digital payment products such as credit cards. This effect differs across demographics: we find that making debit cards less attractive causes high-income and high-education consumers to substitute toward credit cards relatively more than low-income and low-education consumers, who tend to move toward paper products, such as cash and check. Similar to debit, we find that making credit cards less attractive causes substantial substitution to paper products, though less so than in the case of debit.

We also perform welfare calculations. We find that when debit becomes less attractive, less wealthy consumers suffer relatively more, as they use debit more intensively and may not have access to as many alternative instruments. In contrast, making credit cards less attractive causes wealthy consumers to suffer relatively more, as they are more likely to hold and use credit cards.

These results are important for the Board of Governors of the Federal Reserve System, which was mandated by the Financial Reform Act of 2010 to regulate debit card interchange

fees, leading to a substantial reduction in the overall fee level. Because we find that making debit cards less attractive to consumers causes substitution toward paper products, the regulation may increase the cost of the payments system. Furthermore, our result that regulating credit and debit cards have different effects for different income groups implies that these policies have distributional implications, and thus adds a further concern to policy intervention. Note that we do not provide a full welfare calculation of all of the implications of these regulations, such as how banks will pass through changes in the interchange fee or how merchants will respond. Although we do not evaluate the policies overall, our article contributes to this evaluation.

Section 2 addresses that though there is a substantial body of literature on consumer payments, this is the first article with a structural model of payment adoption and use that allows us to estimate the effects of regulatory changes. Section 3 uses the 2008 Survey of Consumer Payment Choice, a representative survey of adult consumers in the U.S. that collects data on payment method adoption, use, and assessments of payment instruments. Section 4 develops a structural model of consumer adoption and use of payment instruments, where consumers pick payment instruments to adopt in stage 1, and then decide on how to use them in stage 2. Section 5 provides our parametric assumptions and our estimation strategy. Section 6 shows how our model extends a general literature in which agents first make a discrete choice about adoption and then adopters make an ordered or continuous choice over intensity of use, by allowing for the structural identification of the effect of use on adoption. Section 7 presents the estimation results, where the demographic attributes and consumer ratings affect the use and adoption of payment instruments, both individually and as bundles. Section 8 shows how introducing a fee on debit card use, resulting from a regulatory change, would affect consumer holding and use of payment instruments, including how consumers would substitute away from debit cards and how the reduction in debit card use would lower consumer welfare, especially for lower-income consumers. Section 9 provides perspective on the effect of introducing interchange fees or surcharges on payment cards, and thus serves to inform future policy in this area, thus contributing to the analysis of this complex policy question.

2. Policy setting and literature review

■ Although there is a substantial body of literature on consumer payments, this is the first paper with a structural model of payment adoption and use that allows us to estimate the effects of regulatory changes.

Understanding consumer substitution patterns between payment instruments is an important policy issue. Consumers face few 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 payment cards to be more efficient than cash or check, as payment cards are a digital mechanism. In this light, the effect of regulation that lowers the value of debit cards depends on whether consumers switch to cash or to credit cards. Furthermore, substitution patterns may depend on whether the regulation affects the adoption cost or usage value 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 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] Note that regulation is common internationally:

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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, particularly for signature debit cards. See the Board of Governors' final rule, Regulation II, Debit Card Interchange Fees and Routing (www.federalreserve.gov/newsevents/press/bcreg/20110629a.htm).

Australia has regulated credit card interchange fees since 2003, the European Union has recently implemented caps on some interchange fees, 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 article. 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 value and to a change in the adoption cost of debit cards. These simulations are meant to represent cases in which banks pass their reductions in interchange revenue through to consumers either via lowering usage value (such as eliminating rewards programs) or via increased adoption costs (such as fixed fees for holding a debit card).

A second policy development is the move toward allowing merchants to surcharge 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.[3] Also, surcharging is currently allowed in some countries, such as Australia and the United Kingdom, and appears to impact card usage. As 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 article 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 regulation 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 card networks, also affect these outcomes. In addition, our model and data study the number of transactions rather than their value, so it is difficult to say how different outcomes would be if banks utilized value-based fees rather than per transaction fees.[4] Conditional on these factors, our model is able to provide an estimate of substitution patterns, which has an important role in welfare outcomes.

Our article contributes to several literatures, in terms of modelling 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), as well as the selection literature of Heckman (1979). Relative to these models, our model combines two desirable features. As in the selection literature, our model allows consumers to know more than the econometrician about usage at the time of adoption. We implement this by allowing for correlation between the unobserved terms in usage and adoption. As in the structural discrete-continuous literature, we structurally estimate the

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[2] In the United States, some banks have responded to the debit interchange regulation by eliminating rewards programs, a change in the usage value. 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.

[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 might be important from a behavioral perspective and appears to be important to industry participants). Furthermore, the Durbin Amendment (see footnote 1) also allows for discounting. For some discussion, see Schuh, Shy, Stavins, and Triest (2012).

[4] Perhaps value-based fees would have lower effects on the number of transactions, which is what we study, but a larger effect on value-weighted transactions.

effect of the usage value on adoption. Our model incorporates both of these features in a single model, which we discuss further below.[5]

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 by assuming that usage pins down the substitutability (or complementarity) between payment instruments, and we allow for only correlation 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 article in that they use a Heckman selection model of each payment instrument separately to study adoption and use. Our article 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 rewards programs. Like Schuh and Stavins (2010, 2013), Ching and Hayashi (2010) precedes our article in the use of self-reported preference data to account for heterogeneity in consumer preferences. Our article 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 (2015) 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 a grocery setting, using scanner data. Wang and Wolman (2014) study payment card use with data collected from the registers of a large retailer. As in Yang and Ching (2014), Hayashi and Klee (2003) study the adoption of payment instruments as a form of technology adoption. Bolt, Jonker, and Van Renselaar (2010) study payments in the context of surcharging. Our model is distinguished from other work in that we consider the joint adoption and usage of multiple instruments simultaneously. Numerous central banks now collect data similar to ours, so a further contribution of our article is to provide a method for analyzing this kind of data.

Our article is relevant for the literature on two-sided markets as well (see Rochet and Tirole, 2006; Rysman, 2009; Hagiu and Wright, 2015). Although 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 (2014) for recent surveys. As we are motivated by regulatory and antitrust intervention into payments markets, our research is related to a group of articles that observe such interventions directly and estimate the impact. These articles typically have less detailed data or modelling 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 (2015) and Carbo-Valverde, Linares-Zegarra, and Rodriguez-Fernandez (2012). Schuh, Stavins, and Shy (2010) model the welfare implications of an interchange fee system that rewards card users relative to noncard users.

3. Data

■　　We use the 2008 Survey of Consumer Payment Choice, a representative survey of adult consumers in the U.S. that collects data on payment method adoption, use, and assessments of payment instruments.

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

Our article 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 we use the first installment of the annual survey, which 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 toward 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 8 but not to estimate the model parameters, as reported in Section 7.[6] 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.[7] Table A4 in the Appendix provides a detailed explanation of each payment instrument. Briefly, *debit cards* draw payment immediately from the consumer's bank account. *Credit cards* draw from a consumer credit line that can be paid monthly or rolled over to future months with some finance charge. In our classification system, credit cards include charge cards, which are cards for which the balance must be paid monthly, and do not have the month-to-month credit feature. *Prepaid cards* allow a consumer to load a dollar value of money (prefunded by cash, a demand deposit account, or even another payment card) and then make payments wherever the card is accepted, up to the amount that is preloaded on to the card. Some prepaid cards work only with a particular merchant, or just for transportation, whereas others can be used as general purpose payment cards. With *online banking bill-pay*, the consumer uses her bank website to direct a payment to a service provider or an individual. With *bank account deduction*, the consumer provides her bank account information to a service provider, and the service provider communicates with the bank to collect the fee.[8] 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 vs. third party). Both of these electronic payments are functionally similar except that online banking bill-payment must occur on the bank's website, whereas bank account deductions can be made on the website of a billing company such as a utility or an online retailer such as Amazon.[9] Both of these electronic methods can be used to set up automatic payments for recurring bills, such as mortgages, or to make discretionary payments as needed. *Direct deduction from income* designates payments that come directly out of a consumer's paycheck and must be organized with the employer. Health insurance payments are a common example of direct deduction from

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[6] 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.

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

[8] 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."

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

TABLE 1   Adoption Rates by Payment Instruments

Instrument	Adoption rate
Cash	1.00
Check	1.00
Debit card	0.80
Credit card	0.78
Prepaid card	0.17
Online banking	0.52
Bank account deduction	0.73
Income deduction	0.18

Note: weighted averages across sample

TABLE 2   Population Holdings of the Top 15 Bundles of Payment Instruments

Population	Cash	Check	Debit	Credit	Prepaid	Online banking	Bank account deduction	Income deduction
23%	1	1	1	1	0	1	1	0
12%	1	1	1	1	0	0	1	0
8%	1	1	1	1	0	1	1	1
6%	1	1	0	0	0	0	0	0
5%	1	1	1	1	1	1	1	0
4%	1	1	1	1	0	1	0	0
4%	1	1	1	1	0	0	0	0
3%	1	1	1	0	0	0	0	0
3%	1	1	1	1	1	0	1	0
3%	1	1	1	1	0	0	1	1
3%	1	1	0	1	0	0	0	0
3%	1	1	0	1	0	0	1	0
2%	1	1	1	0	0	1	1	0
2%	1	1	1	0	0	1	0	0
2%	1	1	1	0	0	0	0	0

Notes: A "1" indicates population holds that instrument. Percentages are unweighted. Number of observations: 997.

income. Table 1 reports adoption rates for each payment type in our sample. Adoption of cash and check is 100% by assumption due to sample selection of bank account holders.[10]

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, online 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 consumers that hold either debit or credit, but not both. This table covers 84.7% of the population.

In addition to the adoption of payment mechanisms, the survey collects data on the use of payment instruments. The survey asks participants how many transactions they complete in a

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[10] Note that adoption of debit is only 80%, though 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 (note that we consider only households that have a bank account).

TABLE 3   Average Number of Transactions Per Typical Month, by Instrument and Context

	Bill-pay			Retail					
	Automatic	Online	In person/mail	Online	Essential	Nonessential	Other	Total	Share
Cash			1.1		6.2	3.1	3.8	14.2	21%
Check			4.0	1.6	1.0	0.7	2.8	10.1	15%
Debit card	1.6	1.6	1.3	2.1	7.5	3.6	3.3	21.0	31%
Credit card	1.4	1.1	1.2	1.6	4.2	2.2	2.8	14.5	21%
Prepaid card				0.1	0.2	0.1	0.1	0.5	1%
Online banking		2.1						2.1	3%
Bank account deduction	2.3	1.7		1.3				5.4	8%
Income deduction	0.8							0.8	1%
Total	6.0	6.5	7.6	6.8	19.1	9.8	12.8	68.6	

Notes: 997 Observations, adjusted by population weights. Share is the Total column divided by 68.6.

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. *Essential retail* and *nonessential retail* goods refer to in-person shopping only. All online purchases are captured by *online retail*. *Automatic bills* involve a consumer 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 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 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 babysitters, person-to-person gifts and loans, and similar transactions not included in the aforementioned categories.

    It is worth taking a moment to understand the definitions of the essential and nonessential retail contexts. Although these are meant to be similar to the distinction between necessities and luxury goods, the survey operates at the level of the transaction, not the product, and so the survey asks about the type of store rather than the product purchased. The survey in fact does not use the essential/nonessential terminology. The survey asks participants to determine how many payments they make for *retail basic* goods in-person. The survey lists a set of examples, which are grocery stores, supermarkets, food stores, restaurants, bars, coffee shops, superstores, warehouses, club stores, drug or convenience stores, and gas stations. The survey then asks the participant to determine how many payments they make for *other retail* goods in-person. The examples for this case are general merchandise, department stores, electronics and appliances stores, home goods, hardware stores, furniture stores, office supply stores, and other miscellaneous and specialty stores. We term these two sets of payments as essential and nonessential, but it is not perfect terminology.[11]

    Table 3 reports the average number of transactions by context in our sample, as well as by instrument and context. Blank entries in Table 3 indicate entries that were ruled out by the survey itself, such as using cash to shop online. We see that cash and debit are popular for essential retail, whereas credit is relatively more popular for nonessential retail. Check use is concentrated in bill-pay, relative to credit and debit. However, 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 account deduction is the most popular method for automatic and online 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;

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    [11] In particular, we do not mean to take a position on what products are considered essential for modern life. We might view a cellular phone purchased at an electronics store as essential, or a bottle of wine purchased as part of a grocery shop as nonessential. However, if consumers pay for the phone as they would for a nonessential payment and the grocery shop with wine as they would for an essential payment, it causes little problem for us.

TABLE 4   Average Ratings of Payment Instruments

	Security	Setup	Acceptance	Cost	Control	Records	Speed	Ease
Cash	2.6	4.3	4.6	4.3	3.9	2.5	4.3	4.1
Check	2.9	3.7	3.6	3.7	3.2	4.1	2.9	3.4
Debit 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
Prepaid card	2.7	3.4	3.8	3.3	3.3	2.9	3.7	3.7
Bank account deduction	3.3	3.4	3.2	3.7	3.6	3.9	3.8	3.6

Notes: 997 observations, adjusted by population weights. The survey does not distinguish between online banking bill-payment and automatic bank account deduction for this part.

for instance, one cannot shop online with cash. Our econometric model provides predictions of the outcomes in Table 1 and Table 3.[12]

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 article. 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, Hahn, and Layne-Farrar (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 *setup* (the cost of obtaining or 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.[13]

Our model simultaneously predicts 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. Thus, there is a simultaneous equations problem, which we resolve with exclusion restrictions—variables that can affect use but not adoption, and vice versa. We assume the rating of setup 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, then 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. 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 has correlations above 0.5, which suggests substantial heterogeneity in these ratings across the population. Tables for other payment instruments look similar.

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[12] Table 3 implies that the total number of transactions in a month is 68.6. This number is difficult to verify in other data sets. Interestingly, a recent diary-based survey of payment habits administered to the same population found a similar total number of transactions. For more on the Diary of Consumer Payment Choices, see Shy and Stavins (2014).

[13] For consumers that revolve a credit card balance, they begin interest payments as soon as they make a purchase, so credit is indeed more costly for them. According to the Survey of Consumer Finances of 2013, 38.1% of households revolve credit card balances.

TABLE 5   Covariance Matrix for Ratings of Debit Cards

	Security	Setup	Acceptance	Cost	Control	Records	Speed	Ease
Security	1.35							
Setup	0.16	0.69						
Acceptance	0.14	0.38	0.68					
Cost	0.22	0.34	0.26	1.02				
Control	0.11	0.24	0.25	0.22	1.36			
Records	0.23	0.31	0.35	0.27	0.23	0.85		
Speed	0.15	0.37	0.37	0.30	0.25	0.32	0.68	
Ease of use	0.17	0.45	0.47	0.38	0.26	0.38	0.50	0.74

Notes: Diagonal reports variance. Off-diagonals report correlation coefficient. Results are unweighted.

4. Model

■   We develop a structural model of consumer adoption and use of payment instruments, where consumers pick payment instruments to adopt in stage 1, and then decide on how to use them in stage 2.

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

In stage 1, consumer i chooses among J payment instruments. Examples of instruments $j = 1, \cdots, J$ are cash, credit card, and debit card. The consumer 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 $j = 0$, which gives the consumer the option to not make a payment in the usage stage (stage 2). 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. At each payment opportunity ℓ, the consumer chooses from b_i which payment instrument to use, which may be the choice to forgo the payment opportunity. 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, $c = 1, \cdots, C$ are online purchases, essential retail, and nonessential retail, for a total of seven ($C = 7$) possible contexts. At each payment opportunity, each consumer selects from one of the seven contexts—all contexts are always available. The consumer can also choose not to use an opportunity, and thus make no payment, denoted as choosing $j = 0$.

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. Because we observe only the number of transactions in a 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 setup 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). For example, if income affects each instrument in a positive way, that tells us that high-income consumers make more payments than low-income consumers. An important issue is that credit cards have a credit function that can allow consumers to have more transactions relative to their income. Our model can match this by finding a large coefficient on a dummy variable for credit cards in the usage equation.

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, whereas 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 online payments. In practice, we assume that the number of payment opportunities L is 390 per month, about 13 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. Thus, if we observe a consumer that makes 100 transactions in a month, we assume they chose not to make a transaction 290 times.[14] Our model predicts the probability of transacting, as well as the probability of each instrument-context combination for each transaction.

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

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

The consumer observes δ_{ijc} and ε_{ijcl}^u when choosing j and c but observes only δ_{ijc} at the time of adopting j. Thus, ε_{ijcl}^u can be interpreted as prediction error in usage at the time of adoption (the superscript u refers to use). Discussion of econometrics is delayed until the following section, but we note that the econometrician may not perfectly observe δ_{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 $u_{ijcl} \geq u_{ij'c'l} \ \forall j' \in b_i, c' = 1, \ldots, C$. Throughout the article, we refer to δ_{ijc} as the *usage value* of instrument j to consumer i in context c.

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

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

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

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

Now consider stage 1, the adoption stage. The consumer knows δ_{ijc} and the distribution of ε_{ijcl}^u, 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:

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

The parameters λ_{ij} represent a payment instrument-specific utility term in excess of any utility from use. It could be an explicit cost such as an annual fee, or represent the cost of learning or paperwork. We refer λ_{ij} as the *adoption cost* of j to i, although λ_{ij} is not restricted to be negative and could be an "adoption benefit." The variable ε_{ib}^a 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.

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[14] The choice of L is analogous to selecting the size of the potential market in typical discrete-choice models, such as Berry, Levinsohn, and Pakes (1995) and Nevo (2001). In many data sets, we observe market shares among the available products, but we do not observe how many people might have purchased but selected not to. To model the choice not to purchase, we must make an assumption on the size of the potential market. In practice, the assumption on the potential market primarily affects the constant term, but not the other parameters.

We do not observe variation in prices of usage and adoption, but we assume those to be captured in the usage value δ_{ijc} and the adoption cost λ_{ij}. Thus, a change in fees can be modelled as a change in one of these values. An increased usage fee lowers δ_{ijc}, whereas an increase in an adoption fee raises λ_{ij}. Similarly, we model a reduction in a rewards program as a reduction in δ_{ijc}. In practice, consumers may not treat pecuniary benefits and costs symmetrically. For instance, consumers may value a dollar surcharge to using a card asymmetrically to a dollar subsidy to using a card. We do not observe fees or subsidies, so this is not an issue for us in estimation. Rather, we look at how demographic variables predict adoption and usage, so we capture the extent to which demographic variables, such as education, affect how consumers make choices. In our counterfactual analysis, we adjust δ_{ijc} and λ_{ij} directly, so it may be interpreted either as a reduction in rewards or an increase in an explicit cost.

We do not model the fact that some payments "must be paid" (such as food purchases or bills). Whatever desire the consumer has to make a payment is captured by δ_{ijc}, the consumer utility from allocating a payment opportunity to that context and instrument. This approach captures the issues we hope to address, 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 λ_{ij} (discussed below). It is difficult to separate causal and correlated 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 because those instruments are substitutes in use. Our assumption is that adopting one has no effect on the adoption cost of the other.

5. Estimation

■ This section provides our parametric assumptions and our estimation strategy. In the second-stage problem (the use stage), we assume that ε^u_{ijcl} is distributed Type 1 Extreme Value. We normalize the value of no payment to zero, so $\delta_{i0} = 0$.[15] 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:

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

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

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

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[15] Here, the subscripting of δ_{i0} refers to the option $j = 0$, which implies there is no context chosen.

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

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

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

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

The vector x_{ijc} is a set of observable characteristics about the individual, the payment choice, and the context, and possibly some interactions between these. The variable ν_{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 $\nu_{\mathbf{i}}$ be the $C \times J$ vector of terms ν_{ijc}, which includes terms for products that are part of b_i, and for those that are not.[16] Similarly, define $\omega_{\mathbf{i}}$ to be the $J - 2$ vector of values of ω_{ij}. The "-2" reflects the fact that we assume that consumers always adopt check and cash, so we do not model those adoption choices. We assume that the unobservable terms are distributed multivariate normal, possibly with correlation. Thus, $\{\nu_{\mathbf{i}}, \omega_{\mathbf{i}}\} \sim \mathbb{N}(0, \Sigma)$, with joint CDF Φ and joint PDF ϕ. The set of parameters to estimate is $\theta = \{\beta_\delta, \beta_\lambda, \Sigma\}$.

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

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

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

The elements of Σ affect the substitution patterns, and the correlation between first- and second-stage choices. We can potentially allow for arbitrary correlation among the elements of ν_{ijc} and ω_{ij} through the parameter matrix Σ. In practice, we restrict the elements of Σ but allow it to have the flexibility to address several issues. In particular, we allow consumers to have correlated unobserved usage values for using an instrument in different contexts, as well as correlated unobserved usage values for 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 correlation between ν_{ijc} and ω_j when they refer to the same instrument. This feature introduces a selection effect, so that consumers who value an instrument for unobserved reasons also have different unobserved adoption costs for that instrument.

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

$$\nu_{ijc} = \sigma^1 \varepsilon_{ijc}^1 + \sigma_j^2 \varepsilon_{ij}^2 + \sigma_c^3 \varepsilon_{ic}^3 \tag{6}$$

$$\omega_{ij} = \sigma_j^4 \varepsilon_{ij}^4 + \sigma_j^5 \varepsilon_{ij}^2.$$

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[16] 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.

Thus, σ^1, σ_j^2, and σ_c^3 determine the variance of use utility, with σ_j^2 measuring instrument correlation and σ_c^3 measuring context correlation. For adoption, σ_j^4 and σ_j^5 determine the variance. Together, σ_j^2 and σ_j^5 determine the correlation between unobserved adoption and use. That is, they determine the selection effect. Note that the selection effect could be negative if σ_j^2 and σ_j^5 have opposite signs.

It is straightforward to add further shocks. We experiment with several extensions. As we are particularly motivated by public policy toward debit cards, we are interested in allowing rich substitution patterns for debit cards. Debit cards are close to credit because they are card based and close to cash because 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 six 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 ns draws of the vector of values $\{\bar{\varepsilon}^1, \bar{\varepsilon}^2, \bar{\varepsilon}^3, \bar{\varepsilon}^4\}$ (in practice, from a Halton sequence as opposed to a pseudo random number generator), where ns is the number of draws we use in our simulation estimator. Based on the current guess of parameters in Σ, we use these draws to construct values of ν_{ijc}^s and ω_{ij}^s according to equation (6), where superscript s refers to the simulation draw, $s = 1, \ldots, ns$. We use the values of ν_{ijc}^s and ω_{ij}^s to construct δ_{ijc}^s, using equation (4) and values of λ_{ij}^s using equation (5). Based on δ_{ijc}^s, we construct $\nu_i^s(b)$ from equation (3) (the values from use of each bundle, consumer, and draw). With ν_{ib}^s and λ_{ij}^s, we construct $\bar{V}_{ib}^s$ from equation (2) (the value of adoption). Using δ_{ijc}^s and $\bar{V}_{ib}^s$, we can construct our simulated likelihood function:

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

where:

$$\Pr(\mathbf{y_i^*}|b_i^*, \nu_i^s, \omega_i^s, \theta) = \Pi_{j \in b_i^*} \Pi_{c \in C} \left(\frac{\exp(\delta_{ijc}^s)}{\sum_{k \in b_i^*} \sum_{d \in C} \exp(\delta_{ikd}^s)} \right)^{y_{ijc}^*}$$

$$\Pr\left(b_i^*|\nu_i^s, \omega_i^s, \theta\right) = \frac{\exp(\overline{V}_{ib^*}^s)}{\sum_{k \in B} \exp(\overline{V}_{ik}^s)}.$$

As in any approach that relies on maximum simulated likelihood, bias is introduced because $\mathcal{L}_i$ is approximated with simulation error, which enters nonlinearly (because we actually maximize the logarithm of the simulated likelihood) into our objective function. See Pakes and Pollard (1989) and Gourieroux and Montfort (1996). Maximum simulated likelihood is consistent only as ns goes to ∞. Fortunately, our objective function is not difficult to compute, and so we set ns 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 to study dynamic adoption and particularly one would need detailed use data to study learning—but we regard this issue 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*. However, we

found the results of the ratings consistent with our expectations, in the simple statistics and the estimation results. Schuh and Stavins (2010, 2013) also find them to be important.

Last, we discuss standard errors. We compute standard errors using the outer product of the gradient to compute the information matrix. We adjust the inverse of information matrix upward 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 consumer-level shocks at the level of the context and instrument (the latter, which affects adoption and usage) can be interpreted as a form of clustering in the sense of Moulton (1990), who advocates for consumer-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 consumer make many use choices but only one adoption choice (though in computing standard errors, we always treat the number of observations as the number of consumers, not the number of consumers times the number of use choices).

6. Model comparison and identification

■ This section shows how our model extends a general literature in which agents first make a discrete choice about adoption and then adopters make an ordered or continuous choice over intensity of use, by allowing for the structural identification of the effect of use on adoption.

Our model fits into a general literature in which agents first make a discrete choice about adoption and then adopters make an ordered or continuous choice over intensity of use. In this section, 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 $Y = 1$.[17] A standard approach would be to model a latent variable Y^* where $Y = 1$ if $Y^* > 0$ and $Y = 0$ otherwise, with:

$$Y^* = z\beta_z + \varepsilon_y$$

$$w = x\beta_x + \varepsilon_w.$$

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

In contrast, our model allows for the structural identification of the effect of use on adoption. Furthermore, like the Heckman model, our model allows for the consumer in the adoption stage to predict usage better than the econometrician. The former is attractive because we are specifically interested in distinguishing the effect of changes in adoption costs from the effect of changes in use values. The latter is attractive because it is a realistic and flexible approach.[18]

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[17] 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 article.

[18] This feature distinguishes our model from several models that model discrete and multiple choices, such as Burda, Harding, and Hausman (2012). We are not aware of a similar discussion to ours of the role of consumer information and structural modelling 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.

Although the Heckman selection model is often estimated as a two-step model, our model with use directly affecting adoption is akin to a simultaneous equations model. 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 categories that should be relevant only for adoption or only for use, such as ratings of setup 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 being 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 through use only. 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 articles have similarly employed use to identify substitution in an adoption context, 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.[19] We believe this is realistic and consistent with our data.

7. Results

■ This section presents the estimation results, where the demographic attributes and consumer ratings affect the use and adoption of payment instruments, both individually and as bundles.

In addition to the "full model" described above (the model of usage and adoption), we also provide estimates of a "use-only" model, which is the use stage alone, ignoring the adoption stage. In the use-only model, we estimate the part of the model that predicts the number of transactions for each context-instrument, taking the portfolio of instruments as given, and we do not include the part of the model that predicts the portfolio of instruments. These results provide a useful comparison because they do not address the selection inherent in the adoption decision. The results of the use-only model tend to be closer to the raw data, and comparing them to the full model highlights when we can rely on raw data and when we cannot.

For explanatory variables in the use equation (the elements of x), we include context-instrument fixed effects, consumer ratings (except for the rating of setup cost) 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 to preserve degrees of freedom. For explanatory variables in the adoption equation

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[19] Our approach would be more problematic if we were also modelling the adoption of bank accounts. Naturally, adopting a bank account makes it easier to adopt a credit card (as consumers typically pay a credit card bill out of a bank account), a debit card, online bill-pay, and others. However, we study only consumers that hold bank accounts.

TABLE 6   Average Utilities by Context and Payment Instrument in Use Equation

	Bill-pay			Retail			
	Automatic	Online	In-person	Online	Essential	Nonessential	Other
Cash			−6.87		−4.45	−5.55	−4.89
			(0.11)		(0.11)	(0.11)	(0.11)
Check			−4.81	−6.04	−6.27	−6.86	−5.20
			(0.12)	(0.12)	(0.12)	(0.13)	(0.12)
Debit card	−6.10	−6.25	−6.48	−5.82	−4.31	−5.27	−4.99
	(0.13)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)
Credit card	−6.45	−6.74	−6.68	−6.01	−4.82	−5.54	−5.17
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Prepaid card			−8.66	−8.07	−6.74	−7.69	−7.60
			(0.49)	(0.40)	(0.41)	(0.47)	(0.46)
Online banking		−4.95					
		(0.08)					
Bank account deduction	−5.14	−5.51		−5.82			
	(0.09)	(0.09)		(0.09)			
Income deduction	−5.06						
	(0.07)						

Notes: Standard errors are in parentheses. 997 observations, unweighted.

(the elements of z), we include payment instrument dummies and demographics (income, education, and employment status), as well as the consumer rating of the setup experience.[20]

Table 6 provides the average utility of each payment instrument-context combination in the use equation. Table 6 presents the average across all consumers, whether they hold the instrument or not. 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. The dominance of cash and debit card in this context can also be seen from Table 3, which presents the average number of transactions per instrument and context. For nonessential retail, debit and cash are still dominant, but credit cards are relatively more popular than in the essential retail context. That may reflect the fact that credit cards enable nonessential purchases via their credit function and enable consumers to smooth payments for larger purchases. Notably, this latter result is not directly observed from the raw data: in Table 3, credit card still lags behind cash in terms of transaction counts. This is because the average transaction count by credit card depends not only on the average utility of that instrument, but also on a host of other factors, such as the rates of adoption of credit cards, the sociodemographic composition of credit card users, and so on. The structural model accounts for all of these extra factors and delivers the base utility of each instrument in each context. For online retail, the results are very similar for all payment instruments except for prepaid cards, which are more seldom used to make purchases on the Internet. In fact, the only context where the prepaid card has any meaningful utility is essential retail: even though the average transaction count is just 0.1 and the average for checks is much higher at 1 transaction per typical month (Table 3), our model finds that prepaid is almost as valuable as checks. This gap between the model's prediction and raw data is explained by the sparse adoption of prepaid cards (see Table 1), in contrast to universal adoption of checks.

In the bill-pay contexts, checks are much preferred to cash, debit, or credit, provided that checks are accepted (mail/in-person bill-pay). In the area of electronic bill-pay, such methods as online banking and automatic deductions are popular. These patterns follow the data averages found in Table 3.

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[20] We also experimented with a sample that was restricted to consumers who do not carry a balance. Results were similar, for parameters and counterfactual experiments.

TABLE 7   Partial effect of Socioeconomic Status on Value of Usage

	Use-only model	Full model
Household Income		
Intercept	0.04 (0.003)	0.002 (0.003)
Cash	−0.07 (0.004)	0.001 (0.004)
Check	0.01 (0.004)	−0.01 (0.006)
Debit	0.02 (0.005)	0.02 (0.006)
Credit	0.04 (0.006)	0.05 (0.006)
Prepaid	−0.25 (0.076)	−0.11 (0.026)
Education: College Degree or Higher		
Intercept	0.14 (0.02)	0.22 (0.02)
Cash	−0.05 (0.02)	−0.16 (0.03)
Check	−0.18 (0.02)	−0.21 (0.03)
Debit	−0.96 (0.02)	−0.58 (0.02)
Credit	0.46 (0.03)	0.51 (0.03)
Prepaid	0.21 (0.29)	0.06 (0.17)
Age		
Intercept	−0.005 (0.01)	−0.02 (0.01)
Cash	−0.02 (0.01)	0.08 (0.01)
Check	0.13 (0.01)	0.25 (0.01)
Debit	−0.06 (0.01)	0.07 (0.01)
Credit	−0.02 (0.01)	0.08 (0.01)
Prepaid	0.29 (0.09)	−0.10 (0.04)
Male		
Intercept	0.02 (0.02)	−0.05 (0.02)
Cash	−0.10 (0.02)	0.20 (0.03)
Check	−0.17 (0.02)	−0.36 (0.03)
Debit	−0.22 (0.02)	−0.12 (0.03)
Credit	0.08 (0.03)	−0.01 (0.03)
Prepaid	−3.32 (0.40)	−0.29 (0.18)
Married		
Intercept	0.05 (0.02)	0.19 (0.02)
Cash	0.04 (0.03)	−0.18 (0.03)
Check	0.11 (0.03)	0.19 (0.03)
Debit	−0.59 (0.03)	−0.59 (0.03)
Credit	0.33 (0.03)	0.06 (0.03)
Prepaid	1.01 (0.37)	−0.60 (0.16)
Employed		
Intercept	0.08 (0.02)	0.19 (0.02)
Cash	0.06 (0.03)	−0.03 (0.03)
Check	−0.25 (0.03)	−0.13 (0.03)
Debit	0.48 (0.03)	0.28 (0.03)
Credit	−0.35 (0.03)	−0.29 (0.03)
Prepaid	−1.96 (0.25)	−0.26 (0.15)

Notes: 997 observations, unweighted. Standard errors are in parentheses. The use-only model does not include the adoption stage.

Table 7 presents the effect of each demographic variable on each payment instrument in the use equation. The coefficients represent the extra preference (positive or negative) that a particular demographic group places on a particular payment instrument. In interpreting this table, keep in mind that the parameters are relative to the outside option of not making a transaction. So for instance, consider the variable *age*. If all the coefficients were positive and of the same size, that

would tell us that older consumers make more transactions, but that they prefer all instruments with the same relative proportions as younger consumers. That is, a positive coefficient on age for one instrument does not mean that older consumers use that instrument more than other instruments. The size of the coefficient must be compared to the coefficient on age for other instruments.

In fact, from the "Full model" column, we find that the coefficient on check is higher than the coefficients on cash, credit, and debit, and all of them are positive. Together, these results tell us that older consumers make more transactions, and that they place more preference on checks than do younger consumers. This result is not surprising and is similar to previous research. The surprise is that age coefficients on cash, credit, and debit are of similar magnitude, indicating that older consumers do not place a higher preference on cash relative to credit and debit. It is notable that we find this result only in our full model, that is, when we account for the fact that older consumers hold relatively more payment instruments. The use-only model, which takes the adoption decisions as given, predicts that debit card use declines with age, just as in Borzekowski, Kiser, and Ahmed (2008). This difference in results between the full and the use-only models emphasizes the observed frequencies of use of payment instruments is a noisy indicator of preferences, due to its dependence on the bundle of available choices.

Analyzing the results, we find that wealthier consumers prefer credit cards. The "Use-only" column indicates that less wealthy consumers use cash more than wealthy consumers, similar to the literature (see, e.g., Wang and Wolman, 2014). However, the "Full" column indicates that this effect is due in part to selection. In the full model, the coefficient of income on cash use is higher, being close to zero and insignificant. Still, the coefficient on income for cash is lower than for other instruments, telling us that the share of cash use declines with income. Similarly, the less wealthy consumers use prepaid cards more than wealthy consumers, 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. The positive relationship of education with credit use and the negative one with debit use are largely supported by the existing studies. Using scanner data, Klee (2008) finds that education is positively associated with the use of credit cards and negatively with cash and checks. Borzekowski and Kiser (2008) report that survey respondents with a bachelor or graduate degree show disutility from spending from liquidity, meaning a debit card. One limitation of the existing results is that the literature typically does not emphasize separate effects of education on usage and on adoption. Using our two-stage model, we find that with respect to credit, education is associated with lower adoption costs and higher utility of usage (see Table 7 for usage and Table 10, discussed below, for adoption results). A similar result, but with the opposite sign, holds for debit.

The effects we find here could result from an inherent preference by high-income or high-education consumers for credit over debit use but presumably also reflect that these groups are likely to have higher rewards cards, have higher limits, higher lifetime income, and are better at managing balances and fees.

Even though we find that higher-income consumers prefer credit cards, the relationship between employment and credit card use is the opposite: employed consumers use credit cards less than unemployed ones. This finding comes through in the raw data and in the estimation. Perhaps these results reflect the conflicting roles that credit cards play in household finance; whereas income and employment makes credit cards more attractive and easier to manage, they also make the credit feature less necessary. We also find that males prefer cash and particularly credit card relative to debit or check.

Next in Table 8, we consider the role of consumer ratings. Similar ratings variables were consistently found to be important in other studies that rely on surveys, such as Schuh and Stavins (2010), Borzekowski and Kiser (2008), Arango, Huynh, and Sabetti (2015), Klee (2008), and Ching and Hayashi (2010). Overall, our results find that consumer ratings are important predictors of payment choice, as they explain about the same amount of variation in use as the demographic

TABLE 8   Estimates of Tastes for Payment Characteristics

	Use-only model	Full model
Security	−0.01 (0.003)	0.04 (0.003)
Acceptance	0.01 (0.005)	0.02 (0.005)
Cost of use	0.10 (0.004)	0.08 (0.005)
Control of pay time	0.03 (0.004)	0.08 (0.004)
Record keeping	0.08 (0.005)	0.002 (0.005)
Speed	0.01 (0.005)	0.04 (0.005)
Ease of use	0.12 (0.006)	0.10 (0.006)

Notes: 997 observations, unweighted. Standard errors are in parentheses. The use-only model does not include the adoption stage.

TABLE 9   Mean Values of Adoption by Instrument

	Coefficient	Standard Error
Debit card	−1.42	(0.61)
Credit card	−1.77	(0.70)
Online banking bill-pay	0.05	(0.31)
Prepaid	1.49	(0.82)
Bank account deduction	−1.08	(0.31)
Income deduction	1.61	(0.26)

Notes: 997 observations, weighted by population. Standard errors are in parentheses.

variables, although they account for far fewer parameters.[21] 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. Perhaps surprisingly, we find that though the coefficient on security is positive and statistically significant, it is smaller than for a number of the other ratings. This result appears in other settings as well. For instance, Arango, Huynh, and Sabetti (2015) find that security has an insignificant, and even a slightly negative, effect on the propensity to use credit cards. Ching and Hayashi (2010) also find safety to be insignificant in some specifications. We do not interpret these results as implying that security of a payment instrument is not important. It is possible that the security is important for new payment products but is less important for relatively established payment instruments, such as those in our study (see Rysman, 2010).

Now we turn to results from the adoption equation. Table 9 shows the average adoption costs (which are not restricted to be positive, as discussed previously), by instrument. Higher values imply that an instrument is more costly to adopt. Because all consumers hold cash and check, we do not estimate costs for these variables. We see that credit cards and debit cards are the least costly to adopt. Prepaid cards are more costly than other card options, and indeed, prepaid cards have high fees in most cases. 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 costly.

We include several additional covariates in the adoption decision: setup cost, household income, education, and employment status. The results are presented in Table 10. Again, a negative coefficient indicates lower adoption cost and vice versa. We find that a higher rating of setup cost (which means the consumer believes setup costs are low) leads to lower adoption cost 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. The inverse

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[21] We compute this statistic by calculating the variance generated by demographic variables and payment characteristics in the prediction of mean utilities. Schuh and Stavins (2010) find a similar result.

TABLE 10   **Effect of Personal Characteristics on the Cost of Payment-Instrument Adoption**

	Coefficient	Standard Error
Setup Cost	−0.33	(0.04)
Household Income		
Intercept	−0.06	(0.01)
Debit	−0.01	(0.04)
Credit	−0.17	(0.05)
Prepaid	0.03	(0.05)
Education: College Degree or Higher		
Intercept	−0.22	(0.09)
Debit	0.25	(0.25)
Credit	−0.98	(0.32)
Prepaid	0.05	(0.24)
Employed		
Intercept	−0.08	(0.10)
Debit	−0.34	(0.25)
Credit	0.48	(0.31)
Prepaid	−0.27	(0.24)

Notes: 997 observations, unweighted. Standard errors are in parentheses.

relationship between adoption rates and income is also found in Hayashi and Klee (2003) in two separate surveys (see Table 3 in their study). With respect to education, Hayashi and Klee (2003) find a generally positive association with the adoption of debit, though the relationship is statistically insignificant in most specifications.

With respect to credit cards, the negative correlation between adoption cost and income may reflect consumer preferences and the willingness of card companies to grant the credit line. We cannot separate the effect of income through these two channels, particularly because we do not observe application behavior. We think of our specification as a reduced form for the more complicated simultaneous equations model of consumer and bank decision making. Therefore, to interpret our counterfactual changes in the usage value and adoption cost 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 Σ 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 usage utility across instruments and contexts, and we find a strong correlation between adoption and usage unobserved terms, generating an important selection effect into usage.

We find that the level of fit of the model is good, with an R^2 statistic of 50.5% when looking at the predictions of "market shares" of payment instrument, by context, in the usage stage. With 13,356 nonzero market-share observations and only 102 parameters related to the usage equation, there is little danger of overfitting. On a set of 100 randomly selected subsamples, the distribution R^2 statistics has a median of 50.4% and a standard deviation of 2.04%.

It is worthwhile to contrast our results with the findings of Schuh and Stavins (2013), who use the same survey data as we do but take a reduced-form approach to explaining adoption and use. Specifically, they estimate a separate Heckman equation for each of the seven payment instruments.[22] Because the same data is used in both studies, the difference in results will mostly reflect the impact of restrictions imposed by the modelling approach. The most notable of these differences are that Schuh and Stavins (2013) do not allow for a structural effect of use

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[22] The approach of Heckman (1979) is mathematically similar to the treatment of intensive and extensive margins in Dubin and McFadden (1984), except that the latter use a multinomial first stage.

on adoption, and they treat each instrument separately, rather than allowing for correlation or substitution in use and adoption. For the sake of brevity, we restrict our discussion to instruments that are actively adopted, for example, other than cash and checks.

Overall, the results are similar, which we take as support for the general modelling approach. There are some interesting differences. Contrary to our results, Schuh and Stavins (2013) do not find a significant effect of income either on usage or on the adoption of credit and debit cards (except for households with under $25,000 yearly income, which are much less likely to adopt both cards but represent only 11% of the population). In particular, our results suggest that higher-income consumers have lower costs of adoption of a credit card. A possible explanation is that to see that high-income households use plastic more, the researcher must condition on the fact that high-income households also hold many instruments. Also, we find the size of the selection effect (that is, the correlation between the unobserved elements of adoption and usage) are substantially larger than Schuh and Stavins (2013).[23]

8. Counterfactual experiments

■　We show how introducing a fee on debit card use, resulting from a regulatory change, would affect consumer holding and use of payment instruments, including how consumers would substitute away from debit cards and how the reduction in debit card use would lower consumer welfare, especially for lower-income consumers.

We first discuss counterfactual experiments that focus on debit cards and then turn to credit cards. Our goal is to evaluate outcomes if consumers face per-use fees or adoption fees on card products.

To simulate a bank imposing a per-use fee (or eliminating a rewards program) on a debit card, we use our model at the estimated parameters to assess the consumer response to a reduction in the usage value of a debit card. To consider the effect of a bank imposing a fixed fee, such as a monthly fee on debit cards, we simulate the effect of an increase in the adoption cost. In addition to our policy motivation, these experiments provide magnitudes, in the sense of cross-elasticities, to the parameters in the previous subsection.

Formally, let $\overrightarrow{\delta}$ be the $J \times C$ vector of average usage values. That is, element jc is the average of δ_{ijc}, averaged over i. Analogously, let $\overrightarrow{\lambda}$ be the $J-2$ vector of average adoption costs. Let $s^d(\overrightarrow{\delta}, \overrightarrow{\lambda})$ be the overall usage share of debit cards (a scalar value) among payment instruments (not including the outside option). For instance, at the estimated values $\overrightarrow{\delta}$ and $\overrightarrow{\lambda}$, we have that $s^d(\overrightarrow{\delta}, \overrightarrow{\lambda}) = 0.31$, the observed market share of transactions in the data (see Table 3). Let $\overrightarrow{\Delta}$ be a $J \times C$ vector of elements Δ_{jc}, where Δ_{jc} takes on only two values, Δ or 0. That is, $\Delta_{jc} = \Delta$ if j refers to a debit card, and $\Delta_{jc} = 0$ otherwise. Thus, we adjust all of the values of δ_{ijc} for debit cards. We find Δ such that $s^d(\overrightarrow{\delta}, \overrightarrow{\lambda}) - s^d(\overrightarrow{\delta} - \overrightarrow{\Delta}, \overrightarrow{\lambda}) = 0.01$.[24] Our focus is on how the market shares of other payment instruments respond to this change. We can similarly consider adjustments to $\overrightarrow{\lambda}$ that reduce debit market shares among transactions by 0.01. In this case, $\overrightarrow{\Delta}$ is $J-2 \times 1$ and has only one nonzero element. We choose 0.01 because we want a small value to approximate an elasticity.

We also distinguish between the responses of consumers holding payment instrument adoption fixed (the "short run"), and allowing adoption to change (the "long run"). Changing adoption costs has no effect in the short run, so we provide results for this experiment for the long run only.

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[23] One difference with the existing literature is that with respect to employment, our results imply that employed individuals derive lower benefit from credit cards in the usage and in the adoption stage, whereas Schuh and Stavins (2013) conclude that employment is associated with a higher rate of credit card adoption but does not bring an extra benefit from credit at the usage stage. Note that the effect of employment is subtle and operates through income as well.

[24] Given our linear utility functions, reducing δ_{ijc} is equivalent to lowering a rating such as *ease of use* by 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.

FIGURE 1

CHANGES IN USE OF EACH PAYMENT INSTRUMENT, MEASURED AS MARKET SHARE PERCENTAGE POINTS, IN RESPONSE TO A DECREASE IN DEBIT CARD USAGE VALUE AND AN INCREASE IN ADOPTION COST, BY ADOPTION ADJUSTMENT (SHORT RUN OR LONG RUN)
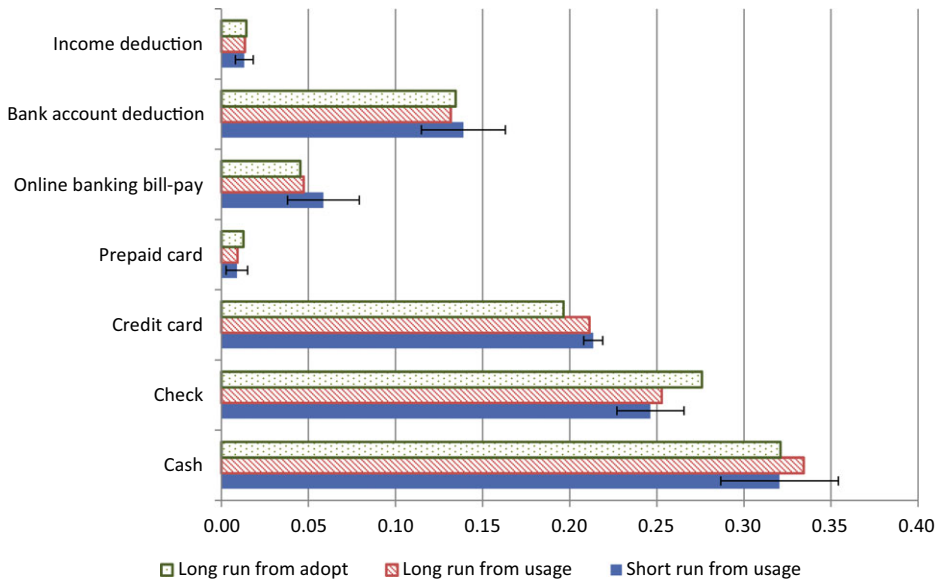

Figure 1 plots the estimated changes in the transactions market shares in usage of payment instruments other than debit cards in response to the reduction in the usage value of debit cards. To compute these results, we compute choices for each consumer in our data set and use the survey weights to construct a nationally representative result. We assume consumers cannot switch to the outside option (the option of not making a payment), which allows us to focus on substitution issues.[25] For each counterfactual simulation, the decline in debit market share (not plotted in the figure) is one percentage point, so the increases in other market shares sum to one. Thus, one can view the market share changes as analogous to cross-price elasticities of demand for the use of other payment instruments. Figure 1 also graphs the 95% confidence interval for the first experiment, calculated from the variance of the underlying parameters via the delta method. The confidence intervals for the other experiments look similar. We do not include them to make the figure less cluttered.

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 toward cash in response to the change in usage value than in response to the change in 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. However, overall, we find little difference in the response to usage value and adoption costs.

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 toward cash in the long run, as consumers drop their debit card. This similarity

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[25] We do not study substitution to the outside option because 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 robust to different values of L.

FIGURE 2

SHORT-RUN CHANGES IN MARKET SHARE PERCENTAGE POINTS IN RESPONSE TO AN INCREASE IN DEBIT CARD USE COST, BY BILL-PAY AND RETAIL CONTEXTS
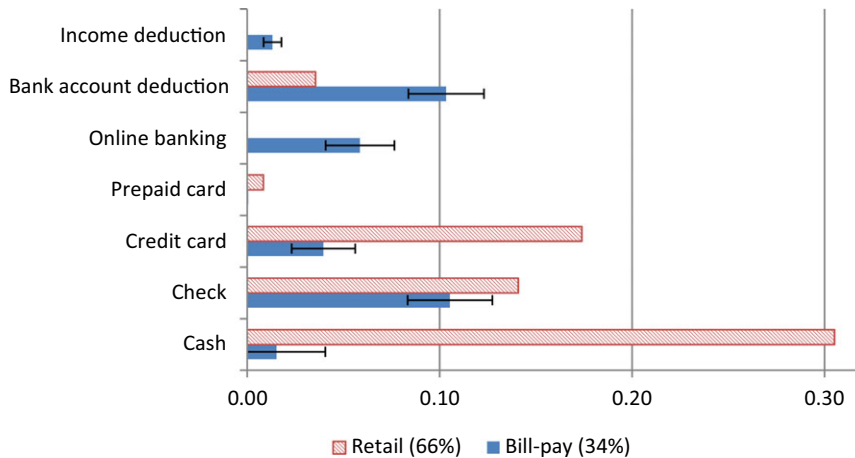
between long- and short-run results follows from the fact that some consumers already hold substitute products and those that do not face large adoption costs. That is, the long-run response is concentrated on those who already hold other instruments, and those consumers can also respond in the short run. That does not mean that adoption is unimportant. We show in what follows that adoption is central for understanding several results.

Thus, the main results of Figure 1 are that a change in the usage value of debit leads to a substantial substitution toward paper products, and that this result differs little in the long and short run. A change in adoption costs finds similar results.

It is perhaps surprising that paper products do so well, and in particular that checks emerge as a stronger substitute to debit cards than credit cards. However, other studies of payment choice also provide evidence that debit cards and paper instruments are closely related. Garcia Swartz, Hahn, and Layne-Farrar (2006) consider the evolution of usage of debit, credit, cash, and check in a nationwide grocery store chain and find that debit cards pick up a large portion of the decline in cash and check that happened in the recent years (see Figure 2 in their study). More direct evidence comes from Borzekowski and Kiser (2008), who report that 48.5% of respondents in a nationally representative survey indicated that for them debit serves as a substitute for cash, and about 32% of respondents said they used debit instead of checks. In a European survey, as reported by Bolt, Jonker, and Van Renselaar (2010), respondents were asked about their reaction to a transaction fee on debit card use, and 65% indicated they would pay with cash instead (there was no checks option).

What explains this result in our data? Although part of the substitutability of check and debit might be that they have similar liquidity characteristics, we find that an important element of the explanation is how payment instruments are used in different contexts. In particular, check dominates as a substitute in bill-pay contexts, whereas credit cards are a stronger substitute in retail contexts.

To make this point, 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 online, essential and nonessential retail, as well as other) and the change in the bill-pay context (summing over the automatic, online, 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 lines in Figure 2 is one.

In Figure 2, we see that retail follows the expected pattern. Cash is, again, by far the strongest substitute to debit cards, but credit cards now take the second place, followed by checks. The rank reversal of credit and checks in the retail sector is intuitive. Furthermore, as we show below,

the check use in retail stems in part from consumers that do not hold credit cards, or else check use would be even lower. Also Ching and Hayashi (2010) consider the effect of removing reward programs on debit (analogous to our increase in disutility of debit) and find that in the retail context, credit card shows a stronger response than paper products (cash and checks combined).

Although credit card is a stronger substitute to debit than check in the retail sector, we see that check is the leading substitute in the bill-pay sector. Bank account deduction is also important. Credit card does poorly here, in part because it is low-income consumers that use debit cards to pay bills, and these consumers do not hold credit cards, and also because credit cards face strong substitutes (checks or bank account deduction) in each bill-pay context. Indeed, Hayashi and Klee (2003) use a different survey to point out a large reduction in the share of credit card between retail and bill-pay contexts (see Tables 2(a) and 2(b) in their study).

In interpreting retail and bill-pay results, it is important to keep in mind that check is the only bill-pay option that all consumers hold, whereas the adoption of other instruments varies. Recall from Table 3 that our data show substantial use of debit cards to pay bills. The popularity of check in the bill-pay sector means that overall, it is a stronger substitute to debit than credit cards. Bill-pay also explains the otherwise surprising result that bank account deduction is a substitute to debit. Bank account deduction gains 13%–14% in each experiment in Figure 1, and similarly Hayashi and Klee (2003) also report a strong relationship between direct deposit and debit in bill-pay contexts. This analysis highlights the importance of our study design and data set, which incorporates adoption and usage, and recognizes that the substitution between payment options may change across retail and bill-pay contexts.

Note that in our counterfactual analysis, we see some substitution of payments from retail to bill-pay. As 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, as in some cases, consumers 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. However, some readers may find such substitution unrealistic, so we wish to explore the role of this substitution in our results. First, we estimated our model with a nested logit version of the usage stage, 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-pay and retail payments, despite different preferences and holdings.

Remarkably, we found that the nesting 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, so the nested logit specification adds little new explanatory power to the model. We also estimated a model in which consumers could not substitute between bill-pay and retail. The results were almost identical to Figure 1.[26] Thus, we view the results on the importance of check as a substitute to debit as robust to several modelling approaches.

We now turn to the heterogeneity of our results across socioeconomic class, which we find is substantial. To show this, we predict outcomes from our model for different consumers. 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 a decrease in the usage value of debit.

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[26] Note that the specification in which consumers could not substitute between bill-pay, and retail is difficult to interpret because 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, because 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.

FIGURE 3

CHANGES IN MARKET SHARE PERCENTAGE POINTS IN RESPONSE TO A DECREASE IN THE USAGE VALUE OF DEBIT, ASSUMING CONSUMERS HOLD ALL INSTRUMENTS.
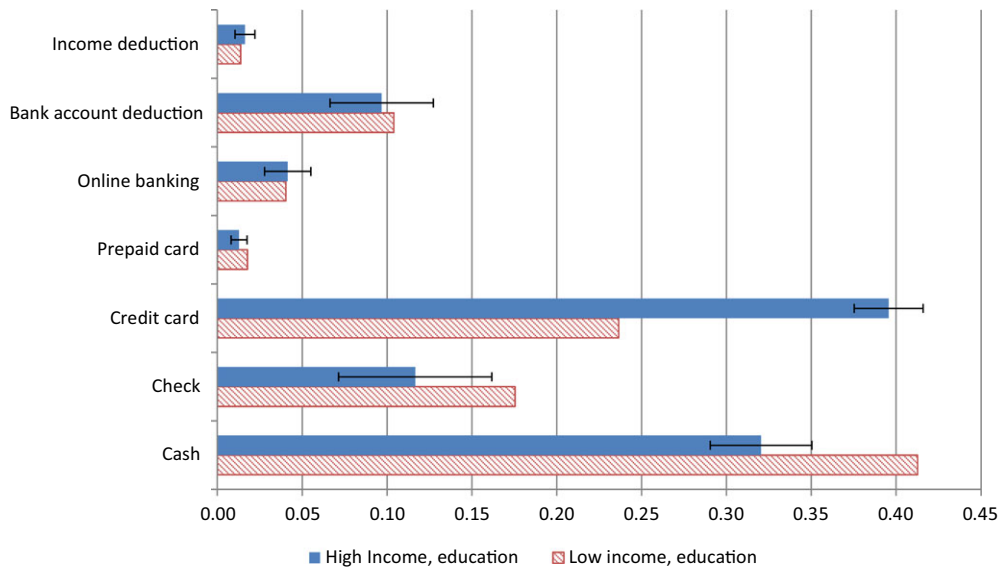
We see very large differences in Figure 3, with the high-income consumer shifting market share to credit card by almost 16 percentage points more than the low-income consumer. The low-income consumer shifts to cash more than the high-income consumer by 9 percentage points, and cash and check together by 15 percentage points. Note also that, different from Figure 1, credit cards are more popular than check for both consumers. The explanation is that we have assumed that both consumers hold each payment instrument, whereas the differences in Figure 1 were in part due to different holdings. Naturally, the differences in Figure 3 would be even larger if we started with a more realistic scenario, where the wealthy consumer 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 change in the usage value of debit is estimated to be between -2.8% and -1.3%, 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% to 30% larger, with larger effects for low-income consumers. The difference over the income range is striking, with welfare falling more than twice as much for consumers from low-income consumers than for consumers from the wealthiest consumers in the long run, and 2.5 times as much in the short run. Wealthy consumers 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.[27]

Interestingly, our estimated model requires a substantially larger change in adoption cost than usage value to implement the same change in the share of debit cards. Although even a small change in usage value causes a change in share, a change in adoption cost does not affect market shares unless it induces consumers to drop their debit card entirely. If we compare small changes in usage value and adoption cost that have the same welfare effect, the change in adoption cost has a more even effect across income as it induces little change in behavior.

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[27] 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 regulation will affect bank pricing or consumer banking choices.

FIGURE 4

WELFARE CHANGE FROM A DECREASE IN THE USAGE VALUE OF DEBIT, BY INCOME CATEGORY
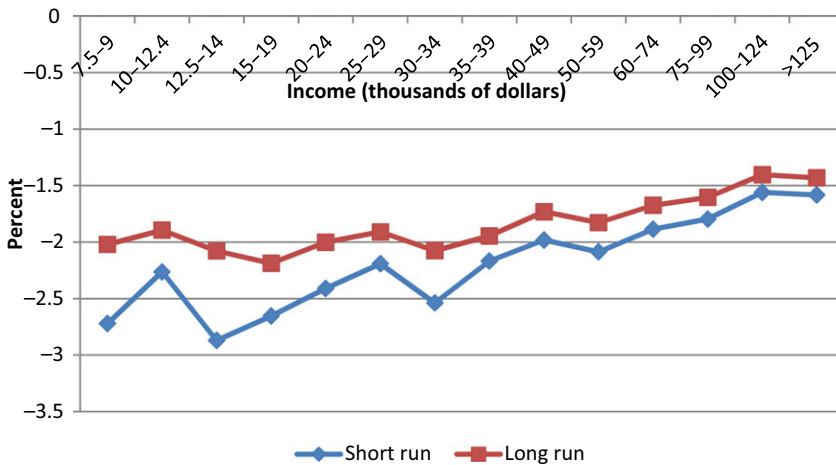
We are interested in placing a dollar value on these changes in utility. Because our survey data does not offer any variation in an explicit price of use for payment instruments, we turn to estimates made by other studies. Two studies offer evidence on the own-price semielasticity of debit, one at 3.9¢ and another at 3.6¢. Such is the per-transaction fee on debit use that will reduce the share of debit by one percentage point.[28] Taking the latter estimate, our welfare results imply that a 3.6 cent per-transaction fee on debit leads to a 1%–3% drop in the welfare.

By making some further assumptions, we can place a dollar value on the welfare drop. In particular, suppose we model the usage value δ_{ijc} as linear in the price of using instrument j, so for instance, $\delta_{ijc} = \tilde{\delta}_{ijc} - \beta_p p_j$, where p_j is the price of instrument j, β_p is the price coefficient, and $\tilde{\delta}_{ijc}$ is whatever part of δ_{ijc} does not depend on price. Although we observe no variation in p_j, we can interpret Borzekowski, Kiser, and Ahmed (2008) to say that Δ (which we have computed) corresponds to a change in p_j of 3.6¢, and thus $\beta_p = \Delta/3.6$. With this marginal utility of income, we divide welfare by β_p to get a welfare estimate in dollars. Among consumers that hold debit cards, we find that an increase in price of 3.6¢ per transaction leads to a decline in welfare of 0.2008¢ per payment opportunity, which corresponds to a welfare decrease of 78.3¢ per month.

Now we turn to credit cards, motivated by recent policy actions that would allow for merchant surcharging of card products.[29] Because surcharging acts as a usage fee, we study changes to usage values for credit cards. Similar to our study of debit cards, we alter the usage value 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 about evenly split between cash, check, and debit, each with between 25% and 27% market share, with bank account deduction capturing 15%. The strong showing of paper products is surprising and is at odds with results by Arango, Huynh, and Sabetti (2015), who find the effect on cash to

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[28] Bolt, Jonker, and Van Renselaar (2010) present an estimate of the own-price semielasticity of debit card use: 3 euro cents, or $3 \times 1.3 = 3.9$¢, for one percentage point change in the market share of debit. In the US context, Borzekowski, Kiser, and Ahmed (2008) offer a remarkably similar estimate: 75¢ drives the share of debit down by 21 percentage points, or 3.6¢ for one percentage point.

[29] We 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, because credit cards typically carry higher merchant fees, we expect that these developments will lead primarily toward making credit more expensive than other payment instruments.

FIGURE 5

CHANGES IN MARKET SHARE PERCENTAGE POINTS IN RESPONSE TO A DECREASE IN THE USAGE VALUE OF CREDIT CARDS
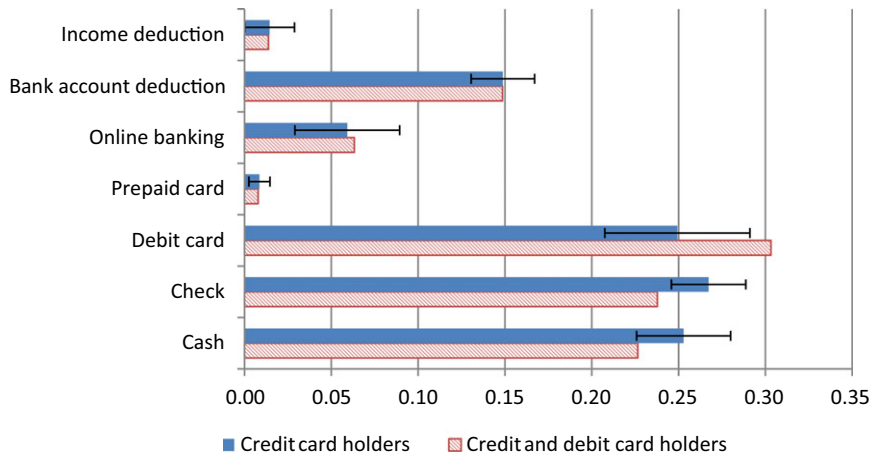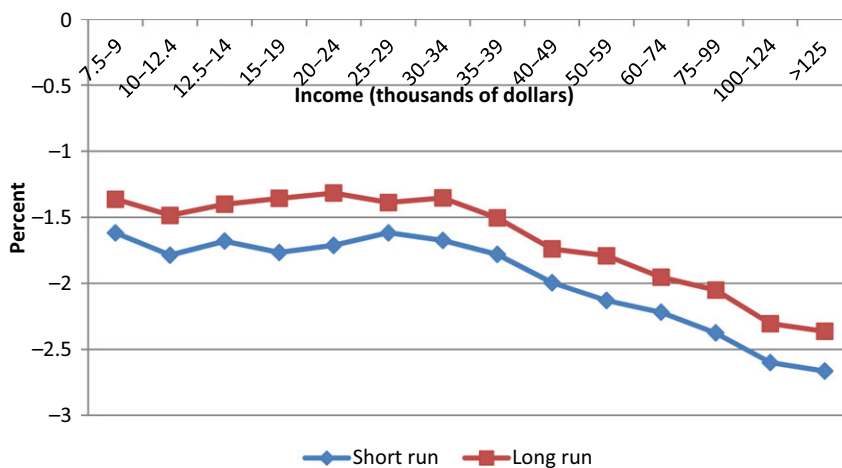

FIGURE 6

WELFARE CHANGE FROM A CHANGE IN THE USAGE VALUE OF CREDIT, BY INCOME CATEGORY

be small, with debit picking up most of the decline in credit (though they do not present results on checks). In part, this result highlights the importance of accounting for bill-pay contexts. However, Ching and Hayashi (2010) consider the effect of removing credit card rewards in a retail context and find results that are similar to ours: the shares of debit and of paper products (checks and cash combined) increase to a similar magnitude.

When we look only at those consumers that also hold a debit card, debit does substantially better. Debit gains 30%, more than six percentage points better than cash or check. Again, check's strong showing mostly comes from bill-pay contexts. In separate calculations, we find that 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. In Figure 6, we see that welfare decreases between 1.5% and 3% in the short

run, with a 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. Although consumers with incomes less than $40,000 experience decreases less than 1.5% in the long run, we find that consumers above $125,000 face decreases close to 2.5%. Naturally, this arises because wealthy people are more likely to hold and use credit cards.

9. Conclusion

■ Our study provides perspective on the effect of introducing interchange fees or surcharges on payment cards, and thus serves to inform future policy in this area, thus contributing to the analysis of this complex policy question.

In this article, 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 through exclusion restrictions on which consumer preferences affect usage and 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, such as the role of age and income. 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. We find that the welfare effects of reducing the usage value of debit cards are larger for low-income, low-education consumers, whereas reducing the value of credit cards hurts wealthy consumers more than poorer ones.

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 toward which we contribute.

Appendix

This section presents the estimates from the covariance matrix Σ. Table A1 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 A2 presents the standard deviation in usage for each context and instrument. The entries in this table are made up of the coefficients in Table A1. Note that this is the variance due to the terms v and ω 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 online 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 A3. Although the parameters that generate the selection effect vary only by instrument, the resulting correlations differ by context as well because context-level variance affects the correlation between instrument adoption and instrument usage. Thus, Table A3 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.

TABLE A1   Coefficients on Shocks that Govern the Correlation Matrix

	Use-only model	Full model
Instrument-Specific Shock		
Cash	0.60 (0.01)	0.001 (0.00)
Check	0.26 (0.01)	0.13 (0.01)
Debit card	1.04 (0.01)	0.96 (0.01)
Credit card	1.00 (0.01)	0.89 (0.01)
Prepaid card	0.78 (0.03)	0.81 (0.03)
Online banking	0.07 (0.02)	0.45 (0.01)
Bank account deduction	5.19 (0.46)	1.10 (0.11)
Income deduction	0.03 (0.17)	0.30 (0.04)
Context-Specific Shocks		
Automatic bill-pay	0.76 (0.01)	0.87 (0.02)
Online bill-pay	0.71 (0.02)	0.72 (0.01)
In-person/mail bill-pay	0.82 (0.02)	0.64 (0.01)
Online retail	1.03 (0.02)	1.01 (0.02)
Essential retail	0.10 (0.01)	0.16 (0.01)
Nonessential retail	0.47 (0.01)	0.56 (0.01)
Other	0.07 (0.01)	0.04 (0.01)
Common Shocks (Coefficients)		
Cash (debit - cash)	−0.78 (0.01)	0.89 (0.01)
Debit card (debit - cash)	−0.32 (0.01)	0.62 (0.01)
Debit card (debit - credit)	−0.73 (0.01)	0.14 (0.01)
Credit card (debit - credit)	−0.01 (0.01)	−0.67 (0.01)
Check (debit - check)	0.90 (0.01)	1.00 (0.01)
Debit card (debit - check)	0.34 (0.01)	−0.02 (0.01)

TABLE A2   Standard Deviation of Correlation Matrix $\sum$, by Instrument and Context

	Bill-pay			Retail			
	Automatic	Online	Mail/in-person	Online	Essential	Nonessential	Other
Cash			1.10 (0.01)		0.91 (0.01)	1.05 (0.01)	0.89 (0.01)
Check			1.20 (0.01)	1.43 (0.01)	1.02 (0.01)	1.15 (0.01)	1.01 (0.01)
Debit card	1.44 (0.01)	1.35 (0.01)	1.32 (0.01)	1.53 (0.01)	1.16 (0.01)	1.28 (0.01)	1.15 (0.01)
Credit card	1.41 (0.01)	1.32 (0.01)	1.29 (0.01)	1.51 (0.01)	1.13 (0.01)	1.25 (0.01)	1.12 (0.01)
Prepaid card			1.28 (0.10)	1.50 (0.08)	1.12 (0.11)	1.24 (0.10)	1.10 (0.11)
Online banking		1.08 (0.03)					
Bank account deduction	0.98 (0.02)	0.85 (0.01)		1.11 (0.02)			
Income deduction	0.92 (0.02)						

TABLE A3   Correlation between Instrument Adoption and Usage, by Instrument and Context

	Bill-pay			Retail			
	Automatic	Online	Mail/in-person	Online	Essential	Nonessential	Other
Debit card			0.73		0.83	0.75	0.83
			(0.44)		(0.49)	(0.45)	(0.50)
Credit card			0.69	0.59	0.79	0.71	0.80
			(0.49)	(0.42)	(0.56)	(0.50)	(0.56)
Online banking		0.75					
		(0.55)					
Prepaid card			0.86	0.74	0.99	0.89	1.00
			(0.59)	(0.50)	(0.67)	(0.61)	(0.68)
Bank account deduction	0.46	0.54		0.41			
	(0.44)	(0.50)		(0.38)			
Income deduction	0.32						
	(0.33)						

Note: Although covariance doesn't vary by context, the correlation does, because variance of instruments does.

TABLE A4   Definitions of Payment Instruments

Cash	Also called **currency**. Includes coins, Federal Reserve notes, and other paper bills.
Check	A draft piece of paper directing a bank or other financial institution to pay a specific amount of money from a demand deposit account as instructed to a person or business.
Debit card	Also called a **check card**. A type of card that allows the cardholder to make a payment that is deducted directly from a bank account at the time of purchase or bill-payment. Often these cards have a Visa or MasterCard logo, but they are not a credit card. A debit card also works as an ATM card.
Credit card	Also called a **charge card**. A type of card that authorizes the cardholder to make a purchase by granting a line of credit that will be paid back to the card company at a later date, possibly in installments. Examples include: Visa, MasterCard, Discover, American Express, and cards branded by retail, gasoline, or other companies.
Prepaid card	Also called a **stored value card** or **gift card**. A type of card that can be used for payments up to the amount of money stored (or loaded) on the card. Often these cards will have a Visa or MasterCard logo, but they are not a credit card or debit card. Examples include: general purpose, specific purpose (retailers, telephone, public transportation, etc.), payroll cards, and electronic benefits transfer (EBT).
Electronic bank account deduction (EBAD)	An electronic payment made directly from a bank account and initiated by a consumer who provides a bank account number and bank routing number to a nonbank third party via the Internet, verbally, or in writing. This payment is made *without* using a paper check or payment card, and can be automatic or processed as needed. Examples include: automatic bill-payment, bill-payment made online at a company's web-site (but not using online banking bill-payment), other online payment, or payment made directly from income.
Online banking bill-pay (OBBP)	A bill payment made directly from a bank account and initiated by a consumer using the bank's online banking bill-payment function on the bank's website via the Internet or a mobile banking application. This payment is made *without* using a paper check or payment card, and can be automatic or processed as needed.
Money order	A draft piece of paper issued by a bank, post office, or telegraph office authorizing payment of a specified amount of cash from the issuing institution to the individual named on the order.
Travelers check	A draft piece of paper issued by a bank or company and directing the issuer to pay a specific amount of money in cash as instructed to a person or business. It is similar to a check but works like cash and is protected against forgery, loss, or theft.

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