This Is "What's in Your Wallet"...and Here's How You Use It*

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Abstract

U.S. consumer wallets have many more means of payment so why is cash still used so often? We develop a dynamic structural model blending cash inventory management and payment instrument choice. For each expenditure, consumers endogenously choose cash, debit card, or credit card with an option to withdraw cash beforehand. The model is estimated with transaction-level data from a daily consumer payment diary and reveals that utility from payment services far exceeds cash management costs. Card owners' optimal cash holdings are about $50 and determined jointly with cash payment shares. Eliminating cash would reduce the welfare of consumers holding debit and credit cards about as much as eliminating either card because even card-holding consumers value cash transactions. This result understates total welfare from cash by excluding consumers who rely most heavily on it (e.g., lower income) and has implications for monetary policy and consumption financing.

Keywords: Money demand; cash inventory management; payment demand; debit cards; credit cards; structural estimation; discrete-continuous choice; Diary of Consumer Payment Choice

JEL Classification: E41, E42, D12, D14

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1 Introduction

A popular advertising campaign for a U.S. bank asks, "What's in *your* wallet?" For years the answer was "cash and checks," plus maybe one credit card for high-income consumers. Today, U.S. consumer wallets are thick and diverse following a quarter-century transformation of payments from paper to cards and electronic means of payment.[1] Most consumers have five or six types of payment instruments; the average wallet holds nearly a dozen (two per type). Now, three-fourths of consumers have at least one credit card and the average consumer has 3-1/2. Yet the average (median) wallet still has $70 ($30) of currency despite a widespread "War on Cash" to eliminate it. For reasons not fully understood, U.S.consumers still use a lot of cash—27 percent of all payments, and 58 percent for low-income, low-education black consumers (see Stavins 2016)—yet they have adopted new instruments without discarding older ones.[2] And there is no representative wallet—more than 100 unique portfolios of instruments exist. Only one in seven consumers holds the most popular wallet: cash, check, debit card, credit card, and two types of electronic bank payments.

Thicker wallets reflect heterogeneous utility from payment services and no instrument emerging as "one size fits all." U.S. consumers make about three-quarters of their payments (volume, not value) with cash, debit cards, and credit cards, mainly for retail and other low-value payments; consumers often turn to electronic instruments for bills and other higher-value payments (see Greene and Schuh 2017). Some consumers rely heavily on one type of payment card (debit, credit, or prepaid) for their card payments, a practice called "single-homing" by Rysman (2007) and Shy (2013). But scant few consumers single-home for all payments, and even less report never using cash (see Briglevics, Schuh, and Zhang 2016). Klee (2008) found that instrument choices are correlated with the dollar values of payments—cash for low values and debit or credit cards for higher values. Non-acceptance of payment instruments occurs, but it is too rare to explain the U.S. di-

[1] This transformation is being measured by the Federal Reserve Payment Study and the Survey and Diary of Consumer Payment Choice from the Federal Reserve Bank of Atlanta. Unless noted otherwise, statistics cited in this paper are from Greene, Schuh, and Stavins (2016) and Greene and Schuh (2016).

[2] The exception is checks, which most consumers still have but are using less often. See Gerdes and Walton (2002), Benton et al. (2007), Schuh and Stavins (2010), and Gerdes et al. (2019).

versity choices. However, new data from the Diary of Consumer Payment Choice (DCPC) shows the probability of cash use is roughly constant around 50 percent for most payments (i.e., less than \$100) when consumers have sufficient cash in their wallets at the point of sale. Hence, the unconditional negative correlation between payment values and the probability of choosing cash is an artifact of failure to condition on consumers' cash management policies. Thus, analyzing payment choices independently of cash holdings leads to incorrect inferences about consumers' preferences for payment services.

The "Transformation of Payments" from paper to electronic means may seem mundane but, like Chodorow-Reich et al. (2019), we find "cash continues to serve an essential role in facilitating economic activity" (p. 60) because consumers get utility from cash transactions—not just in India but also the United States. Our model with deeper microfoundations and individual transactions but partial equilibrium framework shows that eliminating cash would reduced the welfare of consumers holding debit and credit cards about the same as eliminating either card. This finding understates the full welfare of cash by abstracting from the most cash-intensive consumers (lower income and education) and has broad implications for monetary policy and consumption financing. The welfare value of cash to consumers sets a high bar for proposals to reform monetary policy by eliminating currency and taxing demand deposits, or to "fight crime" (Rogoff 2016). Given that neither debit cards nor private cryptocurrency (e.g., Bitcoin) have supplanted cash use by U.S. consumers, our results and Huynh et al. (2020) together raise questions about the value of a central bank digitial currency (CBDC) for retail payments. The value of cash to consumers also suggests that consumer expenditures and household financial management are jointly determined and need to be modeled as such. Evidently, the choice of payment instrument is not innocuous but reveals complex, heterogeneous optimizing behavior that links consumption-saving decisions with portfolio management (see also Fulford and Schuh 2017).

Theoretical models generally have not kept pace with the remarkable scope of transformation in money and payments because two strands of literature have not been fully connected. One strand is the demand for money, where prototypical models of cash inventory management are Alvarez and Lippi (2009, 2017).[3] This research includes a few means of payment—cash, debit cards, and credit cards—but the adoption, characteristics, and suitability for expenditure of payment instruments are not central to the problem. Instead, these models impose *a priori* temporal orderings on the use of assets and liabilities, which are not consistent with transactions-level data. The other strand is the demand for payment instruments, where a protoypical model is Koulayev et al. (2016).[4] This research examines a wide range of payment instruments, modeling their adoption and use based on a rich array of instrument characteristics and payment conditions, including dollar value, that yield utility and influence endogenous choices at the point of sale. However, these models tend to be static, ignore cash inventory management, and abstract from consumption-saving and portfolio allocation decisions that are central to monetary models.

To better understand simultaneous demand for money and payments, we propose a dynamic optimizing model of cash management and payment choice that blends the theoretical approaches of these two literatures. As in monetary models, consumers manage cash inventories to fund current and future payments.[5] As in payments models, agents endogenously choose an instrument for each transaction to maximize utility from payment services. This way the model can replicate empirically observed orderings and substitution patterns among instruments across transaction values, and provide a framework for evaluating the relative importance of cash management costs and utility from payment services for consumer welfare. A key feature of the model is its ability to assess whether reluctance to withdraw cash primarily reflects the costs of cash management or consumers' inherent preferences for using cash to pay for transactions—especially those with low values. This feature enables better estimation of consumer welfare and evaluation of monetary and other public policies.

[3]Other research examining money demand with an option for credit payments includes Telyukova (2013), Briglevics and Schuh (2013), Fulford and Schuh (2017), and Alvarez and Argente (2019).

[4]Other research examining payment choice includes Schuh and Stavins (2010), Wakamori and Welte (2017) and Hunyh, Nicholls, and Shcherbakov (2019).

[5]Limited data availability prevents the inclusion of similar management tasks for other liquid assets and liabilities, such as checking accounts and credit card accounts. The potential benefits of doing so are illustrated in Samphantharak, Schuh, and Townsend (2018).

The model is estimated with transactions-level longitudinal micro data that tracks each consumer payment and cash management decision. The data are from the DCPC, the U.S. version of daily diary surveys developed by central banks and other researchers to record consumer cash management and payment activity in industrial countries documented in Bagnall et al. (2016). In addition to capturing the richness of cash management and payment choices, diary surveys have less error than recall-based survey data used in previous research, and diaries provide relatively accurate estimates of aggregate consumer expenditures (see Schuh (2018)). Although the theoretical model does not yield closed-form solutions, its structural parameters can be estimated using the method described in Bajari, Benkard, and Levin (2007).

The estimated model reveals at least two new insights that extend the money demand and payment choice literatures. First, there is statistically and economically significant evidence that consumers jointly determine cash demand and payment choice: the probability of observing a withdrawal almost triples when people do not have enough cash on them to fund their next transaction even if they have a debit and a credit card to make that purchase. Estimated cash management behavior is qualitatively similar to existing models with fixed or exogenous cash payments except that now the share of cash payments fluctuates due to substitution among payment instruments. Likewise, estimated payments behavior is qualitatively similar to existing models without cash management except now instrument choice probabilities depend on cash holdings and the costs of withdrawals. The probability of cash use declines much faster with payment value when cash holdings are smaller because consumers try to postpone withdrawals until a favorable opportunity is available. Conversely, with optimal cash holdings estimated to be around \$50, consumers with much larger amounts of cash in their wallets are much *more likely* to use cash. Alvarez and Lippi (2017) describe this phenomenon as "cash burns" in a model where cash is assumed to be used first; our model exhibits this behavior when consumers are not constrained to order their use of assets and liabilities and consumers make optimal dynamic choices. The key implication of these results is that models focusing on either cash management or payment choice, and taking the other as fixed or exogenous, are incompletely specified.

A second, perhaps more important, insight is that utility gains from payment choices are an order of magnitude larger than utility losses from cash management costs. This finding has been hidden by the relative disconnectedness of the monetary and payment literatures, but it is not surprising in retrospect. The average U.S. consumer makes only five cash withdrawals per month but nearly 60 payments, so the opportunities to reap utility from optimal payment choices far exceed the relatively low incidence of cash management costs. The monetary literature's focus on minimizing the costs of managing cash, rather than on maximizing the net benefits of using cash, appears to have led to an underappreciation of the larger welfare value of cash use for consumption expenditures. This finding has even broader implications. The consumption literature likewise generally has abstracted from payment choices, but the estimated model suggests that consumer decisions to fund consumption expenditures have non-trivial welfare implications. For examples, using a credit card to get rewards like "cash back" (without using revolving debt) or using cash to get price discounts can reduce consumption costs and increases utility. Revealed preferences inferred by the estimated model show that consumers reap positive utility from optimal payment choices, and this dimension of consumer decision making largely has been overlooked.

Finally, counterfactual model simulations provide three new insights and implications for consumer welfare. First, the welfare cost of inflation is higher than previously estimated. When inflation increases, not only do opportunity and withdrawal costs rise but the cash share of payments also falls, lowering utility from cash payment services. Second, technological changes like ATMs and cash back from debit cards have yielded welfare gains roughly similar to gains from reducing inflation. However, most cash withdrawals already are relatively low cost due to consumer optimization, so the scope for further welfare gains from technological changes in cash withdrawals is modest. Finally, and most importantly, monetary or other policies that restrict consumer payment choices (or merchant acceptance of payments) would adversely affect consumer welfare far more than inflation or technological changes. Policies that would eliminate (or prevent acceptance of) cash would reduce consumer relative welfare from payments about an order of magnitude more than changes in inflation or technology, and about the same amount as would eliminating *either* debit or credit cards. Eliminating *both* debit and credit cards, however, would reduce welfare much more than eliminating just cash. Therefore, cash still contributes significantly to consumer welfare despite criticisms and calls for its removal by Rogoff (2016) and others.

2 Literature review

This section provides a brief overview of two literatures, monetary and payments, that are inherently related but remain largely disconnected. This paper is part of an emerging research program that is attempting to more fully integrate them.

2.1 Demand for money and credit

Modeling money demand as the optimal solution of an inventory management problem has a long tradition in monetary economics starting with Allais (1947) and popularized by Baumol (1952) and Tobin (1956). The core objective of this problem, the minimization of opportunity and transactions costs, remains central to the current literature. Changes in transactions costs are most often specified as improvements in withdrawal technologies such as ATMs (for examples, see Lippi and Secchi 2009; Alvarez and Lippi 2009; Amromin and Chakravorti 2009). Opportunity costs arise from interest-differentials between liquid assets serving as a medium of exchange without bearing interest, like currency, and interest-bearing assets that cannot be used for payment.

The opportunity cost distinction has been evolving as the number of assets serving as a medium of exchange and the number bearing interest both have increased over time. Whitesell (1989) extended the Baumol-Tobin model to allow payments from currency and debitable (checkable) demand deposits that do not pay interest but have a fee differential. The elimination of Regulation Q in the early 1980s permitted interest payments on demand deposits, but still only about half of consumers have an interest-bearing checking account. Mulligan and Sala-i-Martin (2000) show that failure to adopt interest-bearing transaction accounts affects the interest-elasticity of money demand. Subsequent financial innovations increased the variety of interest-bearing liquid assets available to settle payments. For example, Ball (2012) and Lucas and Nicolini (2015) argue that money market deposit accounts (MMDA), which now are used as a medium of exchange, can be added to transactions balances to mitigate the historical destabilization of M1 velocity.[6]

Other theoretical approaches to modeling the demand for money go beyond the framework proposed in this paper. One approach is the shopping-time model in which money balances produce utility by saving time or energy in the shopping process (see McCallum and Goodfriend 1987),which is similar to a money-in-utility function specification. A related, but deeper, approach is search-theoretic models in the New Monetarist Economics (NME) tradition, which motivate demand for cash balances because they facilitate exchange (see Lagos, Rocheteau, and Wright 2017).

Demand for transactions balances to fund consumer expenditures also includes short-term (revolving) credit. Sastry (1970), Bar-Ilan (1990), and Alvarez and Lippi (2017) offer models that allow consumers to pay with credit *after* they run out of cash. Microeconometric studies similar to this paper estimate more stable money demand by controlling for adoption of credit cards (Duca and Whitesell 1995; Reynard 2004; Briglevics and Schuh 2013). Fulford and Schuh (2017) build a model with endogenous payment choices that embodies the relative net benefits of money and credit and links them to consumption expenditures and debt accumulation. Alternatively, studies like Townsend (1989), Telyukova and Wright (2008) and Telyukova (2013) started to address the need for transaction-specific endogenous demand for money and credit using NME style models, in which consumers hold cash balances because they are unable to buy certain goods using credit. Nosal and Rocheteau (2011, Chapter 8) presents a tractable model in which consumers endogenously choose between credit and cash and can reset their cash holdings at a fixed cost. From this line of research, Chiu and Molico (2010) is closest to our work; their calibrated general equilibrium model features cash withdrawal decisions resulting

[6]Also, Hester (1972) accurately predicted that money velocity would be affected by the introduction of electronic funds transfers (Automated Clearing House network).

from a stochastic dynamic optimization problem.

Models of demand for money and credit often assume a temporal ordering of use based on *a priori* beliefs about the relative costs and benefits—lowest net cost funds are used first—rather than allowing transaction-specific variation in net benefits. Strict temporal orderings of settlement funds are inconsistent with empirical evidence found in daily payment diaries where the choice of money or credit varies by transaction.[7] NME models that allow non-acceptance of money or credit by sellers can generate alternating use of funds in environments where exchange opportunities and outcomes are random. But payment choices become more systematic when acceptance is universal or agents have foreknowledge of acceptance and preferences for household financial decisions, especially cash management.

In general, the monetary literature has abstracted from details about the choice of instrument used to authorize payment. Tobin (2008) defined payment instruments as "derivative media" linked to monetary assets (currency, demand deposits, etc.) and to liabilities (such as credit card limits). For currency, the instrument and asset are the same, but multiple instruments can be used to access demand deposits (checks, debit cards, prepaid cards, and online banking payments). Simpson Prescott and Weinberg (2003) show that non-pecuniary characteristics of payment instruments, such as communication and commitment, also can be important determinants of their use. This decision has become more complex as payment instruments once limited to demand deposits now can be used to make payments directly from more favorable liquid assets, like MMDAs, or from liquid liabilities, like a home equity line of credit (HELOC). And, of course, not all credit cards are alike in terms of their fees, rewards and rates paid to revolve balances—prompting a bank to ask which card is in our wallets. Thus, studying payment choices jointly with demand for money and credit may expand our ability to understand and explain the payments transformation and financial innovations in assets and liabilities.[8]

[7]Table 1 in Huynh, Schmidt-Dengler, and Stix (2014) details the predictions of some models that are not borne out in Canadian and Austrian data.

[8]The advent of new technologies such as e-money and mobile payments also may have similar implications. Recent technology has even altered the concept of "money" itself, with Bitcoin and M-PESA (Jack, Suri, and Townsend 2010) serving jointly as an electronic payment network and private money in the form of "virtual currency." For extended definitions and discussions of "e-money," see ECB (2012,

2.2 Demand for payments

A key segment of the payments literature is modeling consumer demand for instruments to authorize retail payments.[9] An early innovation is Stavins (2001), which investigated slow *adoption* of electronic payments methods by heterogeneous consumers using the limited data on payments in the Survey of Consumer Finances. Subsequent research by Borzekowski, Kiser, and Ahmed (2008) and Schuh and Stavins (2010), as well as references therein, also modeled the *use* of payment instruments (number of payments) as a function of technology and instrument-specific characteristics like cost, convenience, security, and record-keeping using better-suited recall-based survey data. This research relies on two-step discrete-continuous models of adoption and use of individual payment instruments. Koulayev et al. (2016) extended this approach by simultaneously modeling adoption of a bundle of instruments (the wallet), and including random utility from the use of payment instruments in various payment contexts. This model focuses primarily on costs and benefits of instruments used to make heterogeneous payments by a cross-section of consumers, but abstracts from consumer demand for money and credit needed to settle payments.

An alternative approach is to model consumer demand for payments at the point of sale (POS) over time. Starting with Klee (2008), and followed by Cohen and Rysman (2013) and Wang and Wolman (2016), researchers used scanner data from retail stores to document instrument choices at checkout to estimate multinomial logit models. These studies found notable correlation between the dollar values of individual transactions and the choice of payment instruments, with cash being far more likely to be used for payments of small dollar values.[10] This result added a new perspective unavailable from survey data, which generally do not contain individual payments or dollar values. However,

2015) and Committee on Payments and Market Infrastructure and Markets Committee (2018).

[9]Research on supply of payment services—provision of payment networks and the acceptance of payment instruments by merchants—also is important in general equilibrium. Humphrey, Kim, and Vale (2001) argue that adoption of electronic methods lowers the social costs of payment systems. See Hunyh, Nicholls, and Shcherbakov (2019) for an estimated model of merchant acceptance. We exclude this part of the literature because it goes beyond the scope of our partial equilibrium consumer model, and because acceptance is not measured well in the DCPC.

[10]Arango, Hogg, and Lee (2015), Eschelbach and Schmidt (2013), Briglevics and Schuh (2014), and Huynh, Schmidt-Dengler, and Stix (2014) also provide evidence that cash holdings are correlated with payment instrument choices.

except for Cohen and Rysman (2013), scanner data do not provide information about the demographics of each consumer, their options at the time of payment (cash in their wallet or instrument adoption), or the longitudinal behavior of individual consumers. In particular, scanner data do not reveal single-homing behavior by individual consumers (see Rysman 2007; Shy 2013), which (Briglevics, Schuh, and Zhang 2016) show is obscured by the aggregate correlation between payment values and instrument choices across all consumers.

Shortcomings of recall-based surveys and scanner data motivated development of daily consumer payment diaries used in the cross-country study by Bagnall et al. (2016). In real time, payment diaries track the dollar value of each transaction, the payment instrument used, and information about the consumer and merchant involved in each payment.[11] Recent research uses payment diary data to estimate POS choice probability models for various countries and non-retail transactions.[12] Wakamori and Welte (2017) extended this research using the Canadian data to estimate a random coefficients model where not all respondents switch from cash to a debit or credit card at the same transaction value. They found the dominance of cash for low-value transactions is primarily driven by consumer preferences for cash. A limitation of econometric models applied to diary data thus far is they are not derived from a dynamic optimizing framework for consumers' joint payment and cash management choices that provides cash-flow accounting of money holdings (stock) and payments, withdrawals, and deposits (flows).

2.3 Joint demand for money, credit, and payments

The unique role of payment instruments offers the potential to better connect demand for money and credit, on one had, with the demand for specific consumer expenditures. An early example is Prescott (1987), which enhances cash-in-advance constraints by jointly

[11] Cohen and Rysman (2013) resolved the scanner data anonymity problem by surveying participating consumers and asking them to re-scan their products. This strategy produces data similar to a payment diary but requires *ex post* recall of real-time POS conditions.

[12] See Fung, Huynh, and Sabetti (2012) and Arango, Hogg, and Lee (2015) for Canada; van der Cruijsen, Hernandez, and Jonker (2015) for The Netherlands; Bounie and Bouhdaoui (2012) for France; von Kalckreuth, Schmidt, and Stix (2009) and Eschelbach and Schmidt (2013) for Germany, and Briglevics and Schuh (2014) for the United States.

modeling the choice of payment instruments (currency and interest-bearing bank drafts). Fulford and Schuh (2017) jointly models credit card spending, revolving debt, and payments settled with money over the life-cycle. Alvarez and Argente (2019) models the cash-credit card tradeoff for consumers paying for Uber rides. And Stokey (2019) develops an extensive general equilibrium model that includes banks and a monetary authority to assess the macroeconomic impact of payment choices. In each case, however, the models only determine the aggregate shares of expenditures and funding paid for with each instrument type during a period of time, not the choice of payment instrument and settlement funds for individual payment opportunities.

We model each sequential payment choice for individual consumer expenditures while tracking consumer cash management and the corresponding cash-flow for currency. To our knowledge, this is the first attempt to use longitudinal panel data with individual transactions from payment diaries to estimate a dynamic optimizing model that jointly explains consumer payment instrument use and cash management linked by the accounting cash-flow identity at the transaction level. Samphantharak, Schuh, and Townsend (2018) illustrate the empirical potential of this approach using the 2012 DCPC data to demonstrate how household financial statements can track exact cash-flows connecting the payment instrument used to authorize a specific consumer expenditure directly to the monetary asset or credit liability (balance sheet) used to settle the exchange.

3 Data

This section provides a brief overview of the primary data sources for this paper, the 2012 Diary of Consumer Payment Choice (DCPC) and corresponding 2012 Survey of Consumer Payment Choice. More details can be found in Schuh (2018) and Appendix A.

The SCPC and DCPC are complementary surveys that measure detailed payment choices and cash management of U.S. consumers. SCPC respondents complete an online survey and *recall* from memory their adoption of financial acccounts and payment instruments, cash management, and (not used in this paper) frequency of use of payment instruments. DCPC respondents *record* their payment transactions and cash management for three consecutive days. We use SCPC consumer data on adoption of accounts and payment instruments plus DCPC transactions data on: 1) payment values, instrument used, location, and type and 2) cash holdings, deposits, and withdrawals by location. Time of day information in the DCPC is used to recreate the sequence of transactions.

DCPC data are a balanced longitudinal panel of a representative sample of about 2,500 U.S. consumers during October 1-31, 2012. Respondents were selected from the RAND *American Life Panel* to match the population of U.S. adults (ages 18 years and older). After completing their SCPC, respondents were assigned to complete their DCPC on randomly selected days throughout the month so panel entry and exit is deterministic and fixed. This diary design produces representative samples for each day of the month as well as for the entire month.

The DCPC panel data mimic the transaction records of monthly statements for checking and credit card accounts. Thus, they are essentially the same as transactions data from banks and financial institutions also found in the kinds of personal financial management (PFM) services and applications used by Baker (2018), Olafsson and Pagel (2018), and Gelman et al. (2018). Data from financial institutions may have less measurement and reporting error than consumer diary data, but the DCPC data are superior in other respects. For example, the DCPC tracks what consumers do with cash withdrawn from banks, not just how much they withdrew. The DCPC also collects additional relevant information at the time of transaction, such as cash held in wallet. And, importantly, the DCPC data are based on sampling and implementation methods that are designed to produce representative samples of U.S. consumers whereas PFM data are not.

We restrict the sample for model estimation to *in-person* POS transactions, including person-to-person (P2P) payments, by consumers who had *both* a debit card (hence checking account) and credit card. The restricted sample represents the bulk of cash use because online payments don't accept cash and few bill payments are made with cash. Wallet restrictions are made to sidestep the theoretical complication of modeling adoption; in practice, respondents are unlikely to adopt or discard payment cards during

Variable	DCPC Sample Full	DCPC Sample Estimation
Adoption rates (share of respondents)		
Cash	1.00	1.00
Debit card	.78	1.00
Credit card	.69	1.00
Debit and credit card	.57	1.00
Neither debit nor credit card	.10	0.00
Payment use (share of transactions)		
Cash	.51	.44
Debit	.28	.31
Credit	.21	.24
Transactions at POS with cash, debit, credit (#)		
Total	10,822	6,707
When CIA binds	2,803	2,044
When $m < \$2$	1,206	850
Values at POS with cash, debit, credit ($)		
Median	12.60	13.41
Average	27.99	29.66
Standard deviation	66.66	73.89

NOTE: The number of respondents is 2,468 in the full DCPC sample and 1,272 in the estimation sample.

Table 1: Payment instruments and transactions, 2012

the three diary days. The restricted sample accounts for 62 percent of POS transactions and 57 percent of respondents, who are not quite representative of the U.S. population. However, payment card adopters rely on cash relatively less than other consumers, so our results likely serve as a lower bound on the usefulness of cash.

4 Empirical evidence

This section provides evidence on consumer payment choices and cash management to motivate the model and enhance understanding of the estimation results.[13]

4.1 Payment adoption and use

The first two panels of Table 1 report statistics on consumer adoption and use of payment instruments for the DCPC ("full sample") and sub-sample used in estimation ("estimation sample"). In the full sample, all respondents adopted cash, 78 percent had a debit card, 69 percent had a credit card, 57 percent had both payment cards, and only 10 percent had neither card.[14] In the estimation sample, respondents have all three payment instruments by construction. Despite thicker consumer wallets, cash is still king at the point of sale. In the full sample, cash accounted for half (51 percent) of POS payments by volume (number of transactions). Even in the estimation sample, where respondents have both payment cards, cash accounted for a higher share (44 percent) than either debit cards (31 percent) or credit cards (24 percent). Thus, the estimation subsample understates the full use and value of cash.

Ching and Hayashi (2010) showed that consumer use of payment cards can be influenced by monetary incentives, such as cash back or airline mileage, that entice consumers to use payment cards more often. "Convenience users" who pay off their credit card charges in full each month receive the full benefit of rewards, but "revolvers" who carry high-interest unpaid balances on their cards have an offsetting cost. Table 2 shows consumer payment choices broken down by credit card use (convenience or revolving) and type (with rewards or not) in the estimation sample. Not surprisingly, consumers with a rewards card are more likely to pay with a credit card—convenience users are nearly twice as likely (40.0 versus 23.1 percent), and revolvers more than three times (19.6 versus 5.8).

However, adoption of a rewards card has little effect on cash activity because higher credit card use is largely offset by lower debit card use. Table 2 shows that revolvers use cash 3-5 percentage points more often than convenience users, but cash shares are essentially the same for consumers with and without rewards. Although rewards card

[13]Reported sample moments are unweighted because the structural model is estimated without weights. The DCPC data are collected using stratified random sampling, so weighted sample means are required to estimate population moments for all U.S. consumers, which can be found in Schuh and Stavins (2014) and Greene, Schuh, and Stavins (2018).

[14]The weighted population estimates are quite similar: 100 percent for cash, 79 for debit card, and 72 percent credit card. Cash "adoption" actually is measured in the SCPC and DCPC questionnaires rather than assumed. It is defined as having or using cash at some point during the year.

Credit card type	Number of transactions	Percentage of transactions (%)			
		Cash	Debit	Credit	Preceded by withdrawals
Convenience users					
Rewards	1,661	42.6	17.5	40.0	7.5
No rewards	2,582	42.6	34.3	23.1	9.3
Revolvers					
Rewards	1,860	46.0	34.4	19.6	8.3
No rewards	604	47.9	46.4	5.8	9.1
All types	6,707	44.0	31.2	24.8	8.5

Table 2: Payment choices by credit card type, 2012

holders are less likely to withdraw cash before a transaction, the differences are less than 2 percentage points.[15] These results are fortuitous because the DCPC data do not track whether specific card payments were made with a rewards card or not. Therefore, the model and estimation can focus on cash management without specifying separate decision rules for different types of debit and credit card adopters and users.

4.2 Transactions

The remaining two panels of Table 1 report statistics on the volume and values of transactions for which consumers made payments. Nearly 11,000 POS transactions are recorded in the diary. The estimation sample includes 57 percent of all DCPC respondents who account for a slightly disproportionate amount of payments at 62 percent ($\sim$ 6707/10822). For close to one-third of transactions ($\sim$ 2044/6707), cash is not an option because the consumer does not have enough in their wallet to fund the payment and hence the cash-in-advance (CIA) constraint is binding. For almost one in eight transactions ($\sim$ 850/6707), consumers have essentially no cash in their wallet ($<$ \$2).

Table 1 also shows the frequency and value of POS transactions. In the estimation sample, a consumers made an average of 1.8 payments per day ($\sim 6707/(1272 * 3)$) or 5.3 per three-day diary period.[16] Daily transactions by respondents in the estimation sample

[15] Using SCPC data, Briglevics and Schuh (2013) found no effect of credit card rewards or debt on average cash holdings but showed that cash demand of revolvers is less interest sensitive than cash demand of convenience users.

[16] These estimates are slightly higher than the full sample (1.5 and 4.4, respectively).

are relatively smooth over time. Six of seven respondents (84 percent) made at least one payment on two or all three of their diary days; no respondents had zero transactions for all three days. Transactions per day ranged from 0 (zero) to 11; 74 percent of days have 1-5 transactions, although 24 percent of days have none. Most POS transactions are relatively low-value. The median consumer payment was $13, so half of all recorded POS transaction values do not require consumers to hold large amounts of cash. Some merchants impose minimum values (typically $10) for credit card transactions, which also helps cash to compare favorably. Even the average transaction value was only slightly more than double the median (about $30) despite large variation (standard deviations). However, the left panel of Figure 1 shows that the full distribution of POS transaction values is skewed to the right by much larger amounts, even after excluding bill payments.

As noted in Section 2, transaction values are good predictors of the payment instruments consumers choose. Following the literature, we estimated a multinomial logit model of payment choice and plot the unconditional probabilities of each instrument as a function of transaction value in the right panel of Figure 1. Like the scanner data, DCPC data reflect a negative correlation between cash use and transaction values. Payment cards are used more often for larger values, with debit cards slightly higher than credit.[17] These payment choice probabilities are central to estimation of the structural model, which adds controls for consumer-level cash management.

To preview later results showing the sensitivity of cash use to cash holdings, the right panel of Figure 1 also includes the estimated probability of cash use for the subset of transactions that were unconstrained by the amount of cash in their wallets (dotted black line).[18] When consumers had enough cash to pay for their next transaction in full with cash, the probability of using cash was remarkably stable at just under 50 percent for transaction values up to $100. Thus, the overall negative correlation between cash use

[17]The modest dominance of debit differs from prior estimates using retail-store scanner data that showed credit more common than debit. The reason is that scanner data combines signature debit and credit card payments, which run on the same networks, and could not be identified separately due to technical limitations. Instead, the DCPC measures signature and PIN debit card payments separately, so debit and credit use are identified accurately.

[18]The multinomial logit of payment choice simply adds an indicator variable for a binding CIA constraint to the variables in the utility functions (a constant, an indicator variable for transaction values under $10, and a linear term in the transaction value).

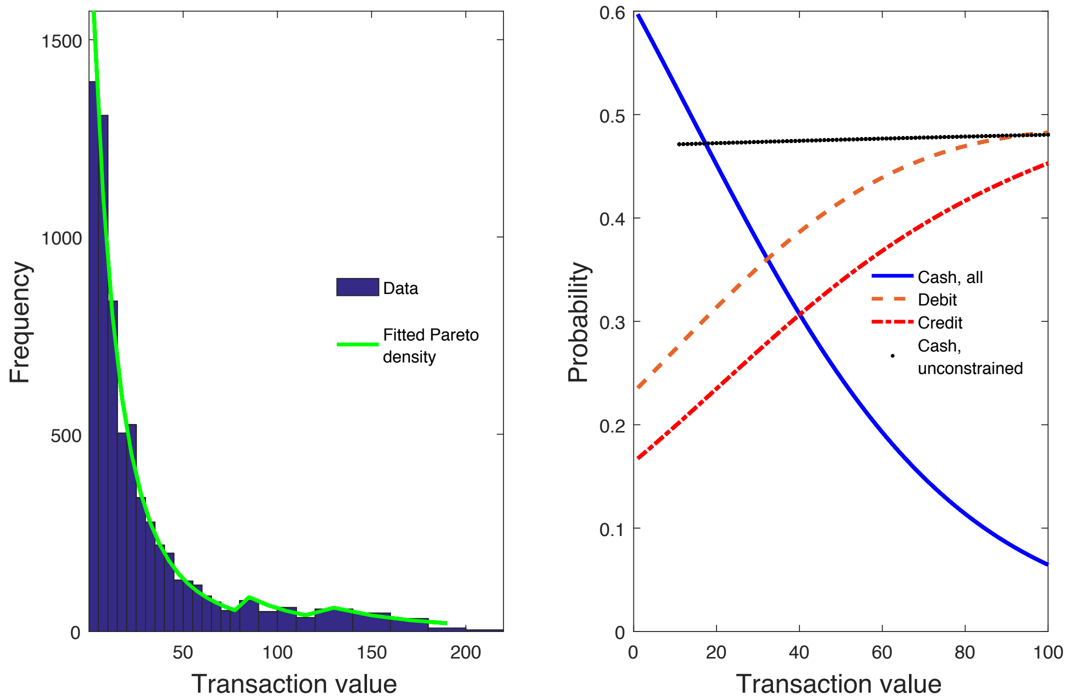

Figure 1: Distribution of POS transaction values (left) and payment probabilities (right)

and transaction values, observed in the data and noted in the literature, is explained by cash holding behavior. Indirectly, however, the occurrence of payment values that exceed the amount of cash held in wallet reflects consumers' endogenous decision to forego cash withdrawals that would have removed their cash-in-advance constraint.

4.3 Cash management

Table 3 reports statistics on cash holdings and withdrawals. In addition to providing context for model estimation, these statistics suggest how well cash demand models in prior research could explain the DCPC data.

4.3.1 Cash holdings

Most consumers hold low amounts of cash, but some hold relatively large amounts (first two panels of Table 3). The median consumer in the estimation sample only has \$20 stored at home (first panel) compared with \$36 in the median consumer's wallet before a transaction (second panel). However, average cash held at home is \$202, whereas the average held in a wallet is only \$76. Thus, while most consumers would require a cash

Variable	DCPC Sample Full	Estimation
Cash held at home ($)*		
Median	20.00	20.00
Average	234.23	202.02
Standard deviation	583.15	466.62
Cash in wallet		
Before POS transaction ($)		
Median	40.00	36.00
Average	80.98	75.57
Standard deviation	145.40	130.58
*Before card transactions (ratio)****		
Median debit card	.61	.61
Median credit card	1.37	1.10
Average debit card	3.68	3.62
Average credit card	6.02	4.77
Before withdrawal ($)		
Median	10.00	11.00
Average	41.32	43.09
Standard deviation	107.63	114.10
*Cash withdrawals***		
Number (#)	1,024	573
Median amount ($)	40.00	40.00
Average amount ($)	81.30	77.27

NOTES: *Excludes observations above $5,000. **Excludes observations above $1,100. Outliers are excluded because they significantly influence estimated moments. ***Value of cash in wallet relative to value of the current card transaction.

Table 3: Cash holdings and withdrawals, 2012

withdrawal to pay for a large-value transaction, some have a large stash of cash they can tap to replenish their cash-in-wallet holdings.[19] The average cash in a wallet can fund 2-1/2 average-sized transactions ($\sim$ 75.57/29.66) and 6 median-sized transactions ($\sim$ 75.57/12.60), but median cash in wallet can fund less than 2 median transactions ($\sim$ 20/13).

[19]As explained in Appendix A, these cash-at-home stocks are used to handle cases where the cash-flow identity does not hold. We construct a withdrawal location category (not reported in the diary but derived from the data) called "cash at home" to explain the beginning-of-day adjustments necessary to correct cash-flow errors in the stock of cash in wallet. These withdrawals from cash at home account for one-fifth of all withdrawals, but dropping them does not cause economically significant changes in the model estimates, as explained in Section 7.

4.3.2 Payments and cash holdings

Although most consumers have non-trivial amounts of cash in their wallets, many pay with a debit or credit card instead of using their available cash. The third panel of Table 3 quantifies this fact by reporting the ratios of cash in wallet to the value of the next card payment; ratios of 1.0 or greater indicate transactions where the CIA constraint was not binding and vice versa for ratios below 1.0. For most credit card payments, the CIA constraint was not binding (median ratio $>$ 1.0), but for most debit card payments it was (ratio of .61). The average ratios of cash to debit and cash to credit payment values are much higher (3.62 and 4.77, respectively), which indicates that even consumers with very large amounts of cash in their wallets still make card payments for some reason.

The relationship between cash-in-wallet and POS transaction values (including card payments) appears in their joint distribution depicted in Figure 2. Both axes are in logs and the transaction value axis is inverted; the heat map denotes the number of transactions. The diagonal between the northwest corner (low transaction values and cash holdings) and southeast corner (high transaction values and cash holdings) demarcates the feasible region for cash payments. Above the diagonal, consumers held sufficient cash to pay for the transaction; below the diagonal, consumers faced a CIA constraint and paid with a card. The key fact in Figure 2 is that most transactions occurred when the CIA constraint was *not* binding. A non-trivial mass of transactions also exists where consumers had very low cash balances (orange-yellow region along the left vertical axis) and thus had to use a payment card.

Narrowing the focus to cash payments only, Figure 3 displays the shares of cash payments for combinations of transaction values and cash on hand. The flat portion of the floor is the infeasible region where the CIA constraint binds. Two important facts are evident. First, cash shares generally decline as transaction values increase for essentially all levels of cash on hand but bottom out at around 0.4, even for large transactions by consumers with enough cash in their wallet (see also right side of Figure 1). Second, the cash share for each transaction value increases slightly with the level of cash on hand. This finding is consistent with consumers worrying about running out of cash and trying

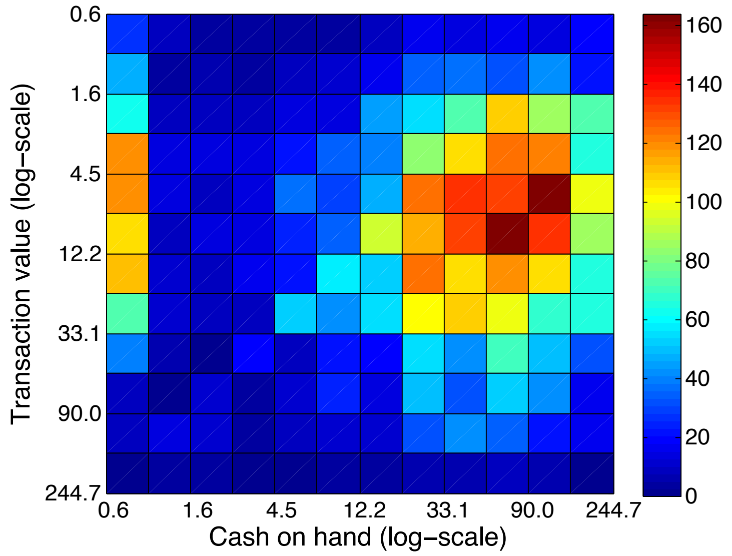

Figure 2: Joint distribution of POS transaction values and cash holdings

to conserve their holdings.

Overall, this subsection provides evidence against the hypothesis that consumers follow a lexicographic ordering of payment instrument choices across their sequential transactions. Consumers make card payments under a variety of cash holding conditions, and vice versa, so models that assume ordering of assets and liabilities (hence payment instrument choices) miss a salient feature of the data. To fit the data, models of cash demand must introduce structure to motivate different payment choices for each transaction and amount of cash holding. The model in the next section does this by introducing instrument-specific random utility that varies across payment opportunities and transaction values.

4.3.3 Withdrawals

The last two panels of Table 3 report cash withdrawals and their relation to cash holdings. Unlike transactions, consumer withdrawals are relatively rare. The estimation sample contains only 573 withdrawals for October 2012, an average of less than one per month (.45) per consumer. In the estimation sample, the median cash withdrawal was \$40 and the average withdrawal amount was almost twice as much (\$77). Figure 4 shows that the full distribution of withdrawal amounts is not smooth. The global mode is \$20 and local modes occur at \$40, \$60, \$100, and \$200—all multiples of the two largest denominations.

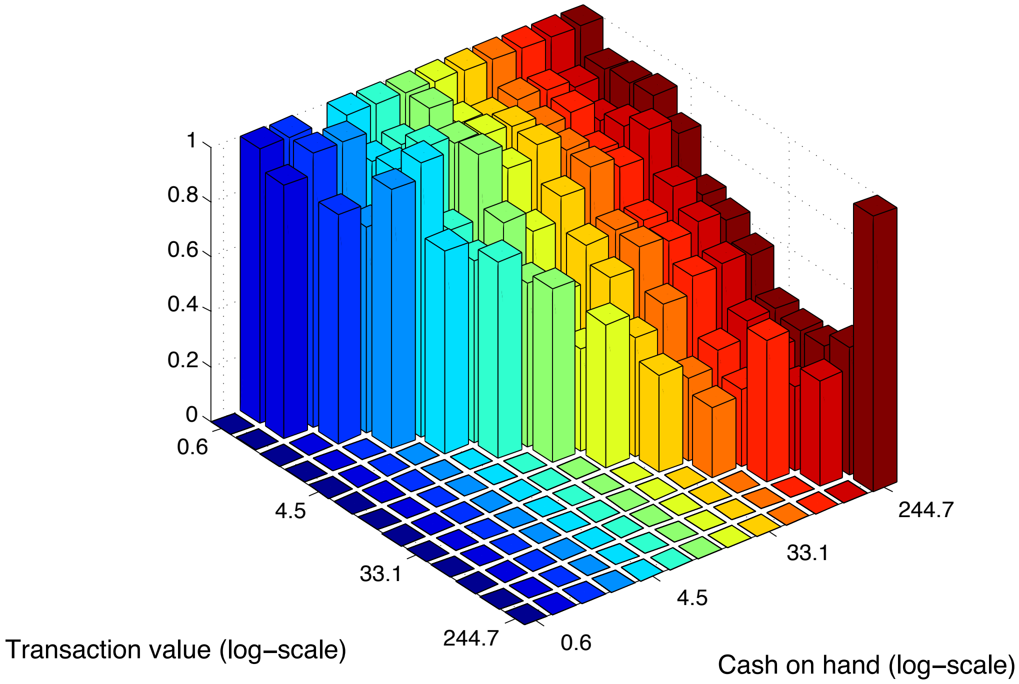

Figure 3: Shares of POS cash transactions

More than one in five withdrawals is less than $20.

An important feature of these withdrawal data is the heterogeneity of locations shown, in Table 4.[20] ATMs are most common, but obtaining cash from family and friends or from the beginning-of-day adjustment are tied for the second most frequent. These three locations account for nearly two-thirds of all withdrawals, while the remaining third represent a diverse range locations. The average withdrawal amount varies by more than $100 across locations, which may reflect heterogeneity in the cost of withdrawals at each location. Little evidence is available on the cost of withdrawals by location, but some (bank teller, check cashing store) may be higher cost than others (ATM or cash back). Because there are not enough observations to identify withdrawal costs for each location, our model incorporates this feature with an unobserved random cost.

The penultimate panel of Table 3 shows that most consumers held some cash when making a withdrawal (median of $11), while some had considerably more (average of $43 compared to average transaction of $30). This finding contrasts with the basic Baumol-

[20]Withdrawals are classified by generic categories, not specific geographic locations. Diary respondents are anonymous so addresses are unknown, and the DCPC does not contain names or locations of respondents' financial institutions. Thus, the data limit specification of withdrawal costs.

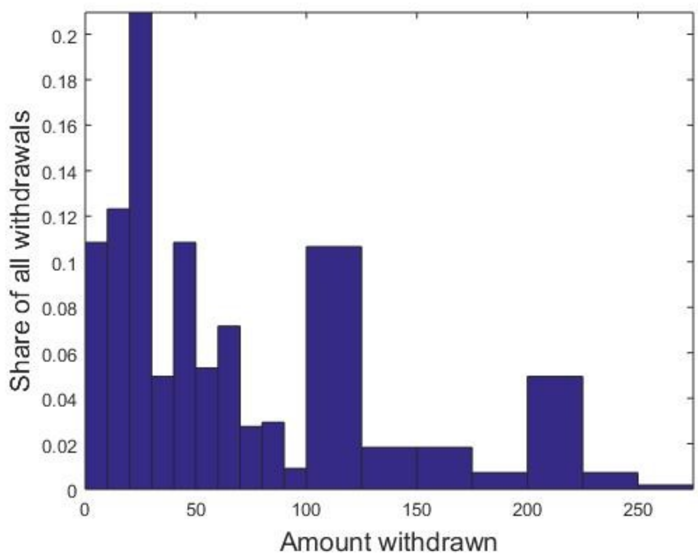

Figure 4: Distribution of withdrawal amounts, 2012

		Withdrawal amount ($)		
Location	Number	Average	Median	90th percentile
Bank teller	64	156	80	400
ATM	147	103	60	200
Cash back (retail store)	48	31	20	50
Cash refund (retail store)	7	30	21	75
Employer	25	104	70	200
Check cashing store	3	88	68	149
Family or friend	112	44	20	100
Cash at home	112	60	26	167
Other locations	55	53	25	112
Total	573	77	40	200

Table 4: Withdrawals by location, 2012

Tobin framework in which withdrawals only occur when cash holdings reach $0, but it is consistent with the models in Lippi and Secchi (2009) and Alvarez and Lippi (2009) that account for non-zero cash holdings at withdrawal by assuming random free withdrawals. However, the ratio of cash held before withdrawal ($41-43) to average cash in wallet ($76-81) is 0.5-0.6, notably higher in the 2012 DCPC than in Alvarez and Lippi (2009) for Italy (0.4) and the United States (0.3) in the 1980s. Lower interest rates and technological changes through 2012 may explain at least part of these differences.

A novel feature of the DCPC is that it shows how many POS transactions ahead consumers plan when making withdrawals. Figure 5 depicts the relationship between

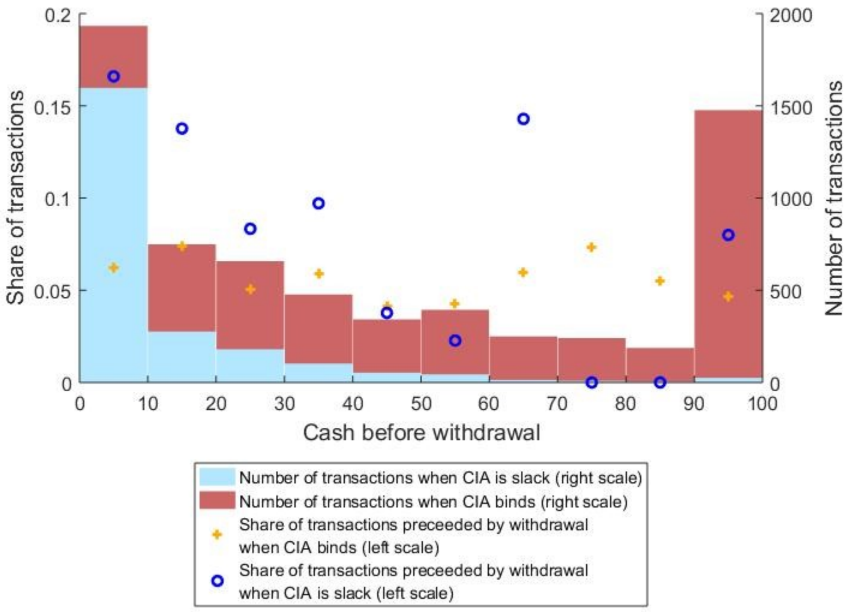

Figure 5: Share of withdrawals by amount of cash holdings

withdrawals and transactions by the amount of cash holdings. Symbols (+ and o) indicate the shares of POS transactions (left scale) preceded by a withdrawal when the CIA constraint was binding (+) or slack (o). Stacked bars represent the number of transactions (right scale) used to calculate these shares when the CIA constraint was binding or slack. Not surprisingly, consumers are much more likely to make a withdrawal when the CIA constraint is binding. For example, when cash holdings are $10 or less, cash-constrained consumers make a withdrawal for every six transactions whereas unconstrained consumers make one for every 16. When cash holdings reach $40, the effect of the CIA constraint on withdrawals disappears. Very few consumers with more than $50 face a binding CIA constraint, so the estimates of pre-transaction withdrawals are erratic in these small samples.

The evidence in this subsection, combined with the evidence in Figure 3 showing cash is used primarily for small transactions, suggests that short-term cash needs are an important driver of withdrawals. On the other hand, payment card holders can keep making purchases long after they run out of cash. These findings illustrate the simultaneity of cash management and payment choice, underscoring the importance of jointly modeling of these consumer decisions.

4.4 Intermediate summary

Given the extensive empirical evidence presented thus far, a brief summary may clarify key facts and motivate the model specification. Despite quantitative differences between the full and estimation samples, the latter does not exhibit any economically significant qualitative differences except for being relatively less cash intensive and excluding payments for which cash is rarely (bills) or never (online) used. Thus, the analysis likely understates the value of cash. A large majority of transactions are very small in dollar value (median of $13), and cash is much less likely to be used for large-value payments—but only when the CIA constraint is binding, so payment choices must be conditioned on cash holdings and withdrawal decisions. However, having sufficient cash in wallet does not necessitate a cash payment. Instead, consumers choose instruments that maximize transaction-specific utility, constrained by the cost of the pre-transaction withdrawal opportunities. For this reason, the source of financing of consumer payments (assets and liabilities) is not lexicographic (ordered) by presumed cost but rather is chosen optimally and endogenously.

5 Model

This section describes our model of cash management and payment instrument choice, which blends and builds on Alvarez and Lippi (2009, 2017) and Koulayev et al. (2016). Consumers finance a stream of transactions that have a stochastic value (p). Before each payment, consumers may withdraw cash; if so, they pay a stochastic withdrawal cost (b) along with the holding (opportunity) cost of cash between transactions (R). Then, at the point of sale, consumers choose cash, debit card, or credit card to make each payment based on transaction-specific random utility derived from the payment services provided by the payment instrument chosen.

As noted in Section 2, existing models tend to impose a temporal ordering of cash use based on *a priori* assumptions about its cost relative to other means of payment. However, the evidence in Section 4 shows that consumers do not follow lexicographic ordering of payment instrument use, suggesting that the utility of payment services varies across transactions and time. Instead of imposing *a priori* restrictions on instrument value and timing, we parameterize the utility functions and estimate them.

Using a random utility framework to model payment instrument choice means that, unlike traditional inventory management models of cash demand, the withdrawal and holding costs become parameters of a utility function and are not measured in units of money or interest rates. While this feature is important when interpreting the econometric estimates later, it nevertheless fits into the literature that usually interprets these costs broadly. For example, withdrawal costs are usually thought of as including shoe-leather costs of finding an ATM; holding costs capture the inconvenience associated with keeping a certain amount of cash in one's wallet, not just foregone interest.[21]

Currency payments are subject to a CIA constraint. If cash balances are insufficient to settle a transaction, consumers cannot take advantage of high utility opportunities associated with cash transactions.[22]. As a result, their expected utility from future transactions falls as they run out of cash. This change in expected utility is balanced against the costs of acquiring and holding cash associated with cash inventory management. Since the costs and benefits of holding cash accrue over multiple transactions, consumers take into account current and future costs and utility when making withdrawal and payment decisions. Importantly, in our blended model consumers can adjust their inflows and outflows of cash holdings *continually*, and thus have an extra margin on which to change cash holdings compared to other models of cash demand in the literature.

[21]Given that consumers in the estimation sample make 2.3 (2.0) transactions per day on average (median), the opportunity cost or risk of theft should be small and we interpret holding costs primarily as the "inconvenience" of carrying cash. A generous 2 percent annual rate for checking accounts interest translates into a 0.00002 ($\sim 1.02^{\frac{1}{2.3*365}} - 1$) percent interest rate over the average holding period.

[22]In reality, debit and credit card payments are subject to funding constraints as well (checking account balances have a zero minimum and credit card borrowing has an upper limit). Ideally, the model would incorporate these constraints too, but the DCPC does not provide data on them. However, the CIA constraint on currency is likely to bind most frequently at the point of sale because some consumers have overdraft protection on debit cards and some consumers can exceed their credit card limits.

5.1 The dynamic problem

The formal consumer's problem involves finding the optimal withdrawal and payment choices of a consumer who settles an infinite sequence of transactions with stochastic transaction values, p. Each transaction involves two sequential decisions: (1) a decision whether to withdraw cash before that transaction, followed by (2) a choice of payment instrument for that transaction.

Consider first the problem of choosing a payment instrument for a consumer who already made her withdrawal decision and holds m dollars of cash in her wallet. She can choose **c**redit, **d**ebit, or cas**h** (provided she has enough) to pay for the current transaction. Following Koulayev et al. (2016), the model contains a random utility framework where each payment method yields an indirect utility flow, $u^i(p) + \epsilon(i)$, associated with each instrument $i = \{c, d, h\}$. The stochastic part of utility, $\epsilon(i)$, is revealed to the consumer just before she chooses the payment instrument and captures the random value of each transaction that depends on payment choice but is unobservable to the econometrician.[23] The deterministic part of utility, $u^i(p)$, depends only on the current transaction value, p, which is assumed to be known by the consumer. The consumer does not know future realizations of p or $\epsilon(i)$, only the distributions from which they will be drawn. We discuss these assumption more after developing the full model.

At each point-of-sale, the consumer solves the Bellman equation

$$V(m; p) = \max_{i \in \{c,d,h\}} u^i(p) + \epsilon(i) + \beta E\left[W(m'; p', b')\right] \tag{1}$$

where $V(m; p)$ denotes the value of having m dollars of cash before making the current p-dollar transaction, and $E\left[W(m'; p', b')\right]$ denotes the expected continuation value of reaching the withdrawal decision before the next withdrawal decision with m' dollars of cash. $E[.]$ is the mathematical expectation operator taken over the realizations of all stochastic variables related to the next transaction. The $\epsilon(i)$'s are assumed to be inde-

[23] Examples of the random value may include non-acceptance of cash or card payments; discounts or surcharges associated with a payment instrument; unsafe environments where risk of theft is high for cash or where consumers prefer not to share their card information; and store clerks that are slow at dealing with cash.

pendently and identically distributed Type I extreme value. The law of motion for m is given by $m' = m - p \cdot \mathcal{I}(i = h)$, where $\mathcal{I}$ is an indicator function taking the value of 1 if cash is chosen $(i = h)$ and 0 otherwise. β is used to discount the utility from future transactions.

Prior to each transaction, the consumer decides whether to withdraw cash by solving another Bellman equation,

$$W(m; p, b) = \max_{m^* \geq m} -b \cdot \mathcal{I}(m^* \neq m) - R \cdot m^* + E\left[V(m^*; p)\right], \tag{2}$$

where $W(m; p, b)$ denotes the value of having m dollars of cash before making a withdrawal decision knowing that the next transaction to be financed is p dollars. The withdrawal cost, b, is drawn from a uniform distribution on the interval $[b_L, b_U]$ before each withdrawal decision, while the holding cost of each dollar of cash between transactions is fixed at R. The consumer will increase cash holdings from m to m^* by making a withdrawal $(m^* - m)$ if the expected value of having more cash at the next payment choice, $E\left[V(m^*; p)\right]$, exceeds the transaction and opportunity costs of withdrawal. In this case the indicator function $\mathcal{I}(m^* \neq m)$ will equal 1, otherwise it is 0. A unique feature of this model is that *the endogenous withdrawal decision and amount are time-varying* because they depend on the consumer's upcoming transaction value p and on the expected utility of using cash for that transaction.

This specification adds a new reason for not using cash: a decline in the continuation value, $E[W(m - p; p', b')]$, can induce consumers to choose cards, even if the current rewards $u^h(p) + \epsilon(h)$, are the highest for cash. Alas, unlike in the multinomial choice models, the declining cash usage for large transactions seen in the data might be the net effect of the increasing utility from cash payments being offset by the costs of carrying large quantities of cash or making frequent withdrawals. Only by estimating the structural parameters can we tell whether costs or preferences are responsible for the observed pattern in the data.

5.2 Discussion of assumptions

Specification of the consumer's transaction planning period relies on assumptions driven by challenges in model solution but do not qualitatively impact model estimation. Two assumptions merit further discussion. First, assuming consumers know the *exact* value of their next transaction when making withdrawal decisions is possibly strong but convenient, tractable, and necessary given the data: as Figure 5 shows the CIA constraint for the next transaction is a very strong predictor of withdrawals. While some consumers may be quite certain about their next payment (e.g., buying a regular morning cup of coffee for \$1.95 + tax), others may randomly encounter unexpected transactions (e.g., a last-minute lunch invitation) or unplanned purchases (e.g., a sale sign at a store for a new product) of unknown value. It would be preferable to introduce uncertainty about the next (current) transaction value, but there is no feasible way to infer the magnitude and variation of this uncertainty from the available data.

A second important assumption is that consumers only know the value of the upcoming transaction, but use the unconditional distribution of transaction values to plan for transactions beyond that one. Consumers may well plan on spending for multiple future transactions in reality, as is common when running errands or going on a day-long shopping trip. In that case the expected values of transaction in periods $t+1$ and beyond probably are not the unconditional mean of p. The primary concern for our estimation in this case is, that consumers manage their cash holdings smarter then what the model allows for. However, we find that the withdrawal probability for a slack CIA constraint (for the current transaction) does not increase significantly in the case when the consumer does not have enough cash to fund the current and the next transaction. Therefor, we believe that our assumption is a useful simplification that facilitates the estimation.

While these simplifying assumptions about the transaction planning period do not align with all consumers' actual behavior, they do not lead the model to overstate or overestimate the importance of cash payments. If the model consumer had better forecasts (or even perfect foresight) of transaction values in period $t + 1$ and beyond, there would be less uncertainty about future payment choices and she would be able to plan cash expenditures more accurately and lower both withdrawal and opportunity costs. Thus, the estimated model provides a lower bound on the value of cash.[24]

The specification of withdrawal costs extends the "random free withdrawals" approach in the models of Alvarez and Lippi (2009, 2017) where withdrawal costs were drawn from a two-element set $\{0, b\}$. Instead, we allow consumers to experience a range of withdrawal costs $b \in [b_L, b_U]$ that depend on the actual withdrawal made but are random from the perspective of the econometrician, which would appear as a Bernoulli distributed b. Table 4 shows numerous methods to obtain cash, which consumers are assumed to choose optimally and use to varying degrees. Although we know the type of withdrawal in the data (ATM, bank teller, etc.), there are not enough observations to estimate separate withdrawal costs. Also, we do not know the actual geographic location, type of institution, or other factors that determine the actual withdrawal cost. Specifying a continuous distribution for withdrawal costs, b, captures this variation in the data simply. The withdrawal cost only has first-order effects on whether consumers make a withdrawal, not how much they withdraw. Withdrawal amounts would vary even more if holding costs, R, also had a stochastic component, which would improve the fit of the estimated model. Unfortunately, the estimation method cannot handle errors in both b and R.[25]

5.3 Timing

Following is a summary of the timing structure of the model.

1. Before each transaction, a consumer with m dollars of cash in her wallet has the option to withdraw cash:

   (i) Random transaction value, p, and random withdrawal cost, b, are realized and observed by the consumer

[24] Counterfactual experiments where the variance of transaction values is reduced show similar behavior to the one reported in Section 7. The results from are available upon request.

[25] With an additional shock to R, the one-to-one mapping between the probability of making a withdrawal (observed in the data) and the percentiles of b (the unobserved structural shock) is broken. However, this mapping is crucial, as it allows us to link the observed behavior to the unobserved states of the model when forward-simulating the value functions. See Section 6 and (Ackerberg et al. 2007, , page 103) for more details.

(ii) Consumer decides how much cash (if any) to withdraw

- If withdrawing, consumer adjusts her holdings to m^* and incurs fixed withdrawal cost b and cash holding costs $R \cdot m^*$
- If not withdrawing, she incurs cash holding costs $R \cdot m$

2. After withdrawal decision, the consumer proceeds to the transaction:

   (i) Random components of utility for the current transaction, $\epsilon(i)$, are realized

   (ii) Payment instrument is chosen, $i = \{c, d, h\}$

   (iii) Cash on hand decreases by p, if consumer pays with cash

3. Return to step #1.

6 Estimation

To estimate the model, the deterministic part of the utility function for each payment instrument, $u^i(p)$, is parameterized as

$$u^i(p) = \gamma_0^i + \gamma_{p\leq 10}^i \mathcal{I}(p \leq 10) + \gamma_p^i p \qquad i \in \{c, d, h\},$$

which includes a constant, γ_0, an indicator variable for low-value transactions, $\mathcal{I}(p \leq 10)$, and a linear term in p. The dummy variable for transactions less than \$10 controls for the effects of potential supply-side constraints where vendors do not accept cards due to fees or other costs.[26] If the cash in advance constraint binds, $u^h(p) = -\infty$. These utility functions introduce separate channels for transaction values to influence payment choices that are independent of the effects of cash management costs (b and R).

In addition to computational ease, this parsimonious specification of utility is warranted for several reasons. First, Cohen and Rysman (2013) provide evidence from a large U.S. scanner data set that the effect of transaction values on payment instrument choice are not correlated with demographic variables or even individual fixed-effects. Second,

[26] We chose \$10 as the cutoff based on U.S. anecdotal evidence and the discrete drop in the probability of cash use at that transaction value seen in Figures 1 and 3.

although most prior studies use demographic variables as regressors, demographics tend to matter more for adoption of payment instruments than for use conditional on adoption, and our estimation is conditional on adoption of payment cards. Finally, we did not control for card rewards because Section 4.1 showed they had little effect on cash use.

The model is estimated using the methods described in Bajari, Benkard, and Levin (2007), or BBL, which is an extension of the Hotz and Miller (1993) conditional choice probability (CCP) estimator used in the empirical industrial organization literature to estimate dynamic structural models with discrete and continuous variables. This approach differs from the methodology used in prior studies of cash management or payment instrument choice. In the monetary literature, dynamic models typically are constructed to yield closed-form solutions for withdrawal policies that can be matched to data using GMM estimators. In the payments literature, static models typically are constructed for discrete choices where the likelihood functions have a closed-form that can be estimated or simulated as in Koulayev et al. (2016).

Like CCP estimators, the BBL procedure has two steps[27]. The first-step involves estimating reduced-form models for state transitions, which are used to characterize the expected value function $E[W(m;p,b)]$. As shown in BBL, the linearity of the utility functions (in structural parameters) and the error specifications imply that $E[W(m;p,b)]$ will be a product of the vector of structural parameters and some basis functions that are derived from the observed choices and state variables. The basis functions can be recovered with forward simulations. In our model, this means: 1) a Pareto-distribution is estimated for transaction amounts; 2) a nonparametric estimate describes payment instrument choice; and 3) the observed nonparametric distribution is used to describe withdrawals. In accordance with Figure 5, separate withdrawal functions are used for when the CIA constraint is binding and non-binding. These reduced-form policy functions are used to construct estimates of the basis functions of $E[W(m;p,b)]$ at a number of grid points in the state space. At each grid-point, we drew 10,000 paths of the stochastic variables with 7,200 transactions for each.[28]

[27] Appendix B contains more details of our estimation procedure.

[28] After about 7,200 transactions, the discount factor falls below machine precision so the present value

In the second stage of estimation, the structural parameters, $\theta = \{b_L\,,\, b_U\,,\, R,\, \gamma_0^h,\, \gamma_{p\leq 10}^h,\, \gamma_p^h,\, \gamma_0^d,\, \gamma_{p\leq 10}^d,\, \gamma_p^d,\, \gamma_0^c,\, \gamma_{p\leq 10}^c,\, \gamma_p^c\}$, are recovered using a simulated method of moments estimation as in Pakes, Ostrovsky, and Berry (2007), or POB. β is assumed to be fixed at .995. Cash management costs are restricted to be positive $(b, b_L, b_U, R > 0)$ because they enter equation (2) with negative signs. Using the basis functions from the first-stage simulations and a vector of structural parameters $\hat{\theta}$, the model's prediction is computed for each observation in the sample. As noted in POB, the maximum-likelihood (ML) estimator is not asymptotically efficient because the second stage uses the simulated value function (a function of the basis functions from the first-stage simulations) and not the true value function. Moreover, the ML estimate of the structural parameters can be very sensitive to this error if only a few withdrawals are observed in parts of the state space, resulting in poor small-sample performance. Figure 5 shows this is a realistic concern in the DCPC data.

In the estimation routine, six moments are simulated and matched to their data counterparts: the probabilities of withdrawal for low-value $(m \leq \$25)$ and high-value $(m > \$25)$ cash holdings; the probabilities of cash use for low-value $(p \leq 10)$ and high-value $(p > \$10)$ transactions; the average amount of cash purchases; and the average amount of cash withdrawn. Separating withdrawal probabilities for low and high values of cash holdings and transactions is important, as Figure 5 shows these could be quite different. Careful inspection of equation (1) reveals that when the CIA is binding the continuation value of the two remaining options (debit and credit) is the same since $m' = m$ regardless of which payment card is chosen. Therefore, a simple multinomial logit estimation will identify γ_0^d, $\gamma_{p\leq 10}^d$ and γ_p^d. Because the model only identifies utility differences and not the absolute level, we normalize utility from choosing a credit card to zero $(u^c(p) = 0)$. The six moment conditions are used to estimate the six remaining structural parameters $\{b_L, b_U, R, \gamma_0^h, \gamma_{p\leq 10}^h, \gamma_p^h\}$.

of additional transactions is zero.

b_L	b_U	R	γ_0^h	$\gamma_{p\leq10}^h$	γ_p^h	γ_0^d	$\gamma_{p\leq10}^d$	γ_p^d
0.0003	7.99	0.0049	2.20	0.79	-0.12	.57	.51	-.0037
(0.08)	(1.57)	(0.001)	(0.43)	(0.37)	(0.03)	(0.13)	(0.22)	(0.0016)

Table 5: Structural parameter estimates (standard errors)

7 Results

The estimated coefficients are supportive of the theoretical model, as shown in Table 5. All estimates are statistically significant at the 5-percent level or better except the lower bound on cash withdrawal costs (b_L), which is not significantly different from zero. The cash holding and opportunity cost parameters (b_L, b_U, and R) are restricted to plausible ranges, but the remaining unrestricted parameters have expected signs and plausible magnitudes. Relative utility declines with the transaction price for cash (γ_p^h) and debit card (γ_p^d) payments, although the latter is close to zero. Even after controlling for the costs of managing cash, consumers prefer cards for larger transaction values. Cash and debit card payments less than \$10 offer additional relative utility, suggesting that credit cards have lower acceptance or convenience for small-value payments.[29]

The estimates are parameters of a utility function that do not have natural units and thus can be hard to interpret beyond signs. For examples, b_U, b_L and R do not represent a dollar value or rate of interest, respectively, although R represents units of utility *per dollar* by virtue of multiplying cash holdings (m). Thus, the parameter estimates merit additional interpretation.

7.1 Parameter interpretation

A key result is the distribution of cash withdrawal costs $[b_L, b_U]$. Despite the relatively wide estimated range, in our simulations consumers never withdraw cash if withdrawal costs are greater than 4. That is, withdrawals only happen in the most favorable lower

[29]For robustness, we re-estimated the model without observations that required a beginning-of-day adjustment (withdrawal from cash at home) to correct the cash-flow identity. Estimates for R and debit-card utility parameters are essentially identical, and for cash utility parameters only moderately different ($\gamma_0 = 1.79$, $\gamma_{p<10} = 1.01$, and $\gamma_p = -.0757$. Naturally, the withdrawal cost estimates are economically different: $b_L = 2.0$ and $b_U = 5.2$. The change in estimated bounds suggests that withdrawals from cash at home are mainly very low-cost ($.0003 < b_L < 2.0$, as described in Section 7.3.2), but they don't influence optimal payment choices much.

half of the estimated distribution; the average withdrawal cost estimate, $\bar{\hat{b}} = 0.75$, reveals that consumers time most of their withdrawals strategically. One way to evaluate the economic magnitude of this relative utility estimate is to compare it with another estimated parameter of the inventory problem, such as the holding cost $(\hat{R})$. In that case, the fixed cost of withdrawals is roughly equal to the utility loss, or "inconvenience," of carrying \$153 $\left(= \bar{\hat{b}}/\hat{R}\right)$ between two transactions.

Another way to gauge the size of the withdrawal cost is to compare it with the benefit of a cash withdrawal that gives a consumer the option to pay with cash, which is particularly valuable for small-value transactions. We measure this benefit as the difference between expected instantaneous utility flow for a consumer who makes a transaction of size p with and without sufficient cash in her wallet. Formally, we calculate

$$\Delta E[u(p)] = \log\left[\sum_{i=\{c,d,\mathbf{h}\}} \exp(u^i(p))\right] - \log\left[\sum_{i=\{c,d\}} \exp(u^i(p))\right],$$

where the log-sum formula computes the expected utility derived from the payment choice. This formula abstracts from continuation values and thus reduces the problem to a multinomial choice model. Comparing this benefit to the fixed cost of withdrawals, it takes about two median-sized transactions to recoup the fixed cost of a withdrawal:

$$\frac{\bar{\hat{b}}}{\Delta E[u(p = 13.41)]} = 1.82$$

About 43 percent of POS payments were \$10 or less (see Figure 1), which explains the popularity of cash even though consumers receive relatively low payment-service utility from large-value cash transactions.

7.2 Cash holdings and use

Using the estimated model and data on cash holdings, Figure 6 illustrates the effects of CIA constraints on the probability of cash use by consumers. The four colored line types in Figure 6 plot the estimated probabilities of cash use for amounts of cash held in wallet

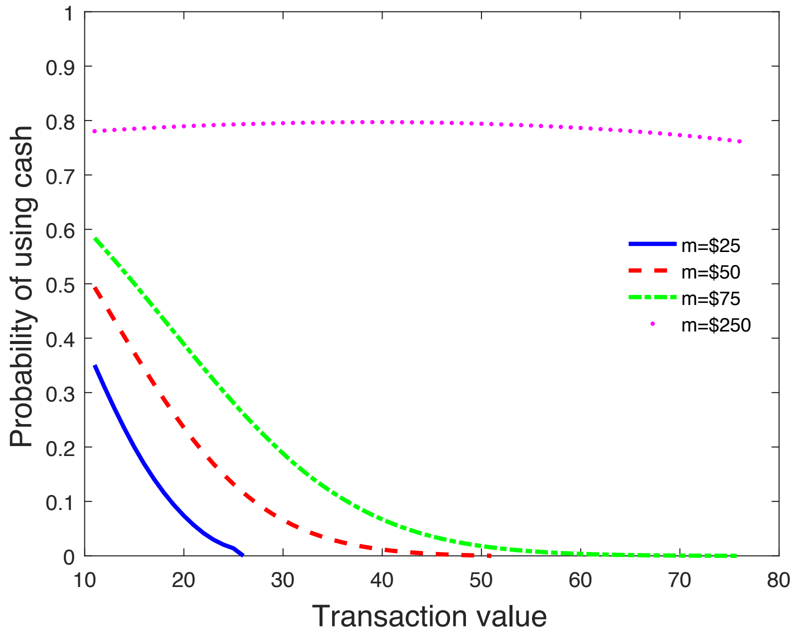

Figure 6: Probability of cash use by transaction value and cash holding

ranging from $25-250. When the CIA binds at the wallet amount, cash probabilities reach zero for larger transactions. Even with a roughly average amount of cash ($75), consumers are reluctant to use cash for larger transactions; less than 20 percent of purchases of $30 or more are made with cash. The tradeoff changes rapidly with cash holdings; consumers with $25 make only about one-third of their very small-value transactions with cash and less than 5 percent of $20 transactions. In contrast, for large cash holdings (e.g., $250), the probability of cash use is nearly 80 percent and stable up to $80.

The results in Figure 6 relate to other recent research. Eschelbach and Schmidt (2013) found that cash in wallets *after* transactions is strongly negatively correlated with the probability of cash use. However, cash holding and withdrawals are jointly determined (see Figure 5), so it is inappropriate to include cash holdings as an explanatory variable in a multinomial logit model without controlling for the endogeneity. Alvarez and Lippi (2017) assume credit card payments are more costly than cash payments on the margin so consumers spend cash as long as they have enough of it—a behavior they call "cash burns." Figure 6 shows this behavior arises even in a model where the relative value of cash payments fluctuates across transactions and consumers can substitute payment cards for cash at each transaction. Thus, consumers with $75 of cash and above are *more*

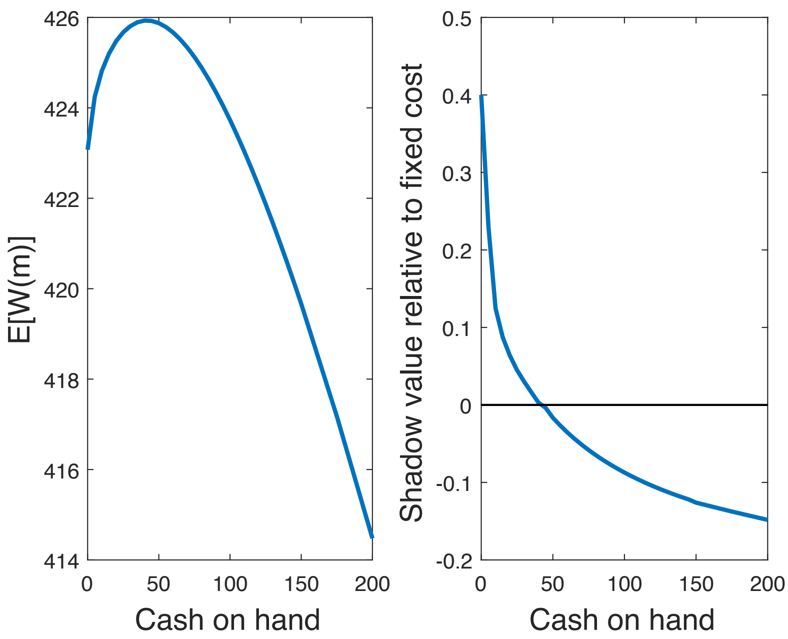

Figure 7: Expected continuation values before holding cost shocks and transaction values are drawn (left); shadow value of an additional dollar in cash (right)

likely (greater than 50 percent) to use cash for transactions under \$20 than consumers without a binding CIA constraint (see right panel of Figure 1, black dotted line).

The cash-burn result also is illustrated with the estimated model in Figure 7. To minimize withdrawal costs, consumers defer withdrawals and run down cash inventories until a favorable withdrawal opportunity arises, represented by low value of random cost $b \in [b_L, b_U]$. The intuition underlying this behavior appears in the continuation value, $E\left[W\left(m';p'\right)\right]$, plotted in the left panel of Figure 7 for each amount of cash held *after* a point of sale was made (and *before* the next withdrawal cost shock and transaction value are realized). The continuation value is hump-shaped with a maximum just below \$50. Consumers gladly make cash payments that decrease their holdings to around \$50 but tend to avoid cash purchases that reduce their holdings below \$50.

The shadow value of cash, shown in the right panel of Figure 7, is the marginal utility an extra unit of cash provides by relaxing the CIA constraint for current or future transactions. We compute the shadow value as the difference between the expected continuation values (before p and b are known) of holding $m+1$ and m dollars of cash,

$$\lambda(m) = E[W(m+1; p, b)] - E[W(m; p, b)],$$

where the expectation is taken over the realizations of p and b. The plotted shadow value (right panel) is the derivative of the continuation value (left panel) measured relative to the average cost of withdrawals ($\bar{\hat{b}} = .75$) for different values of m. The shadow value rises rapidly as cash falls below \$50, reaching about 40 percent of the average withdrawal cost when cash is depleted. But when cash rises above \$50 the shadow value turns negative and declines steadily because consumers are made worse off with more cash. Although having more cash relaxes the likelihood of a binding CIA constraint, consumers with more than \$50 in their wallet are not particularly worried about the constraint because most transactions are low value.

7.3 Consumer welfare

The welfare cost of inflation is a central concern in the monetary literature. Bailey (1956) measured the welfare cost of inflation in a static model with zero-interest money as the area under the interest-elastic money demand curve. More recently, Alvarez and Lippi (2009) computed welfare cost estimates in a dynamic stochastic model with a CIA constraint and inventory management, and Alvarez, Lippi, and Robatto (2019) showed the Bailey approach still is appropriate in a wide range of modern inventory theoretic models. However, few studies of money demand consider the effects of payment choice on welfare, so this subsection explores these effects in detail.

7.3.1 Holding costs with instrument choice

Another key result is the magnitude of the estimated cost of holding cash ($\hat{R} = .0049$), which includes the interest elasticity of cash demand among other factors. As holding costs increase, consumers should hold lower cash balances and make more withdrawals, thereby incurring more costs that are pure deadweight loss. However, in a model with non-

R	Cash holdings before transaction	withdrawal	Withdrawal amount	probability	Cash use share	Cash costs	Payment utility
.0025	36.59	15.57	43.94	.049	.35	26.5	465.5
.0030	33.36	14.01	40.48	.051	.34	28.7	464.1
.0035	30.76	13.21	37.25	.053	.33	30.4	462.7
.0040	28.31	11.28	36.22	.052	.33	31.8	461.1
.0045	26.50	11.03	33.23	.055	.32	33.2	459.9
.0049	25.49	10.68	31.90	.056	.32	34.6	459.0
.0055	23.58	9.69	29.71	.058	.31	35.9	457.4
.0060	22.71	9.43	28.77	.058	.31	37.2	456.5
.0065	21.33	8.65	27.68	.058	.30	37.6	454.5
.0070	20.04	8.23	26.14	.059	.30	38.2	453.0
.0075	19.47	7.79	25.77	.059	.30	39.5	452.4

Table 6: Cash management with different cash holding costs

cash means of payment consumers have an additional margin of response to changes in holding costs—substituting card payments for cash—that may have welfare implications. To gauge the importance of substitution among payment instruments, we simulated the estimated model for different values of the cash holding cost. Because R is a utility parameter, not the interest rate on an alternative asset, we do not know how much R would change if inflation rose one percentage point. Thus, we varied R by about half the estimated value and calculated implied elasticities.

The simulation results in Table 6 reveal the sensitivity of cash management to changes in the holding cost of cash.[30] A 50-percent decrease in the holding cost (.0049 to .0025) would raise cash holdings before a transaction about 44 percent ($25.49 to $36.59). This result implies a holding-cost elasticity of demand for cash of $-.85$, larger in absolute value than the prediction of -0.5 in the basic Baumol-Tobin model. Analogous elasticities for cash holdings before withdrawals and for withdrawal amounts are roughly similar. Table 6 also reveals a non-trivial asymmetry. A roughly 50-percent *increase* in holdings costs (.0049 to .0075) causes cash holdings before a transaction to decline about 24 percent ($25.49 to $19.47), an elasticity of $-.44$. The probability of making a withdrawal only falls about one-half of 1 percentage point.

The estimated model exhibits a novel sensitivity of payment choices to holding costs

[30]The reported figures are averages from simulating the choices of 2,000 consumers, who each start with zero cash, for 7,200 periods.

that differs from inventory theoretic models that assume no change in the cash share of payments. The decrease in holding costs induces a modest increase in the share of transactions made with cash from .32 to .35, or about 9 percent, an elasticity of $-.2$. Given the results in Figure 6, the magnitude of changes in cash holdings and cash share recorded in Table 6 would lead to non-trivial changes in the probabilities of choosing cash. These results reveal that cash holdings are more responsive to R than what standard inventory-theoretic models would predict. Table 6 shows that unless one can directly control for cash spending, estimates of the interest elasticity of cash demand will confound two effects: 1) a change in cash spending, and 2) a change in cash holdings to finance a constant stream of cash spending. Because there is little reason to believe that cash spending remains constant over time when alternative payment methods emerge, there is no reason to believe that the estimated interest elasticity of cash demand should stay constant over time either.

A reduction in holding costs ambiguously improves consumer welfare, defined as payment utility net of cash management costs, for two reasons. Total cash management costs decline (8.1 units of utility), naturally, in part due to a slight decline in the probability of withdrawal. At the same time, payment utility rises by almost the same amount in absolute terms as the reduction in costs (6.5 units of utility) as consumers take advantage of more cash payments. Cash costs fall much more in percentage terms (23.4 percent) than utility rises (1.4 percent), but the absolute changes in utility are similar and the change in net utility is small. In any case, these additional changes in consumer welfare due to changes in payment choices has been missing from previous research on the demand for money.

7.3.2 Withdrawal costs and technological change

As noted in Section 2, the literature widely acknowledges that considerable improvements in technology such as ATM networks and cash back withdrawals from retail stores have reduced the costs of cash management significantly. To measure the effects of technological change in our model, we ran counter-factual simulations with variation in the lower

	Cash holdings before		Withdrawal		Cash use	Cash	Payment
b_L	transaction	withdrawal	amount	probability	share	costs	utility
.0003	25.49	10.68	31.90	.056	.32	34.6	459.0
1	26.49	6.49	43.56	.038	.31	41.3	457.2
2	27.73	5.12	50.66	.031	.30	46.3	456.0
4	29.04	3.56	60.71	.023	.28	53.2	453.1

Table 7: Cash management with different withdrawal costs

bound of the cash withdrawal cost from the estimated value ($\hat{b}_L = .0003$) to the midpoint of the estimated range ($b_L = 4$) and compared the models' predicted changes in cash management.

Changing the lower bound of withdrawal costs affects withdrawals notably more than cash holdings or use, as shown in Table 7. The probability of a withdrawal more than doubles (.023 to .056) and the withdrawal amount nearly falls by half ($61 to $32). But cash holdings before a transaction decline less than 20 percent and the cash share only rises 4 percentage points (.28 to .32). As with holding costs, a reduction in cash withdrawal costs make consumers unequivocally better off. These changes primarily impact cash management costs, which fall by one-third (53.2 to 34.6), whereas payment utility rises by just over 1 percent. Collectively, these economically significant changes provide a quantitative guide to the potential effects of recent technological changes.

The estimated costs of withdrawal suggest the scope for additional cost-saving technology in cash withdrawals going forward may be modest. The distribution of simulated withdrawal costs decays rapidly from the lower bound, as shown in Figure 8, with a median cost $\hat{b} = .58 < \bar{\hat{b}} = .75$. Apparently, consumers strategically make the most of withdrawal opportunities at the plentiful number of relatively favorable (low-cost) opportunities available to them. Roughly three-quarters of withdrawals are relatively low cost (between 0-1), presumably including the roughly 20 percent of withdrawals from stocks of cash at home that may be essentially "free," but also including many opportunities from other locations that have positive but relatively low costs. A modest share of withdrawals still are made at relatively high cost, and these might benefit from further technological changes.[31]

[31]The distribution of simulated withdrawal costs from the estimated model without withdrawals from

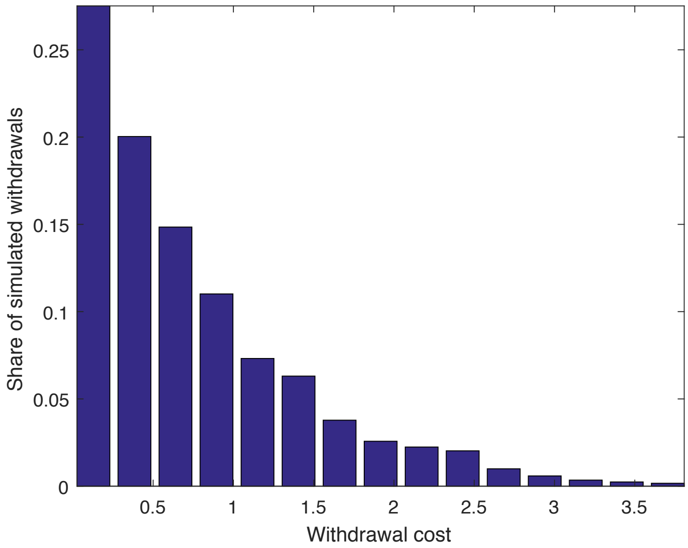

Figure 8: Distribution of simulated withdrawal costs

7.3.3 Value of payment instruments

The emergence of electronic means of payment, including credit and debit cards, has coincided with growing anti-cash sentiment. A leading opponent is Rogoff (2016), who describes cash as a "curse" because it aids crime and tax evasion, and constrains monetary policy by inhibiting negative interest rates. Evidence on the consumer welfare of cash relative to other payment instruments is limited and varied, however. Alvarez and Lippi (2017) estimated that eliminating cash altogether and forcing consumers to pay with credit would cost a mere $2 per year, but Alvarez and Argente (2019) find that Uber customers who prefer cash (disproportionately lower income) suffer an average loss of 50 percent of the ride value when they have to use payment cards. Fulford and Schuh (2017) estimated the value of credit card payments is 0.3 percent of annual consumption for convenience users (no high-interest debt). Koulayev et al. (2016) estimated that consumer welfare declines 1-3 percent in response either to a per-transaction fee of 3.6 cents for debit cards or to surcharging credit card payments that offset the merchant discount fee. And consumers lose utility when they prefer cash but it is not accepted for payment, of course.[32]

cash at home (beginning-of-day adjustment to cash on hand) is qualitatively similar but shifted to the right with a range of $[2, 5.2]$.

[32]None of these studies provides a comprehensive general equilibrium analysis of social welfare, which requires incorporating a market for revolving credit, details of bank and non-bank payment services, and

Model	Cash holdings before transaction	withdrawal	Withdrawal amount	probability	Cash use share	Cash costs	Payment utility
Full	25.49	10.68	31.9	.056	.32	16.6	459.0
No cash	0	0	0	0	0	0	336.1
No debit	36.52	15.42	45.3	.072	.47	52.0	357.8
No credit	29.60	12.66	36.8	.063	.37	40.8	401.3
No cards	123.95	55.42	162.1	.177	1.00	219.4	-76.7

Table 8: Cash management with counterfactual payment instruments

To measure consumer welfare associated with payment instruments, we simulated the estimated model under different counter-factual scenarios with exclusion of instruments (equivalently, non-acceptance). Table 8 reports simulation results for cash management decisions and consumer utility in each scenario. For reference, the first row repeats the estimation results of the full model with all instruments. See Appendix C for details of modifications made to the model for the counterfactual simulations.

Eliminating any single payment instrument would entail much larger welfare declines than previous welfare simulations. Elimination of debit cards is the most welfare-reducing, as payment utility would be 22 percent lower and cash management costs would more than triple. Eliminating cash would entail an even larger reduction in payment utility (27 percent), but cash management and related costs would disappear so consumer welfare would be slightly higher than without debit cards. Eliminating credit cards is the least welfare-reducing counterfactual, as payment utility falls less than eliminating cash or debit cards, but cash costs increase less than eliminating debit cards. In every case, welfare declines by about an order of magnitude more than in the counterfactual simulations of changes in cash management costs. Note that eliminating just one of the payment cards would not alter dramatically the cash landscape, however. Withdrawal probabilities and cash holdings would be modestly higher, and the cash share would be 5 to 15 percentage points higher; these effects are slightly greater for debit cards.[33]

Eliminating *both* payment cards would make consumers markedly worse off and entail much larger increases in cash activity. Payment utility would decline 117 percent and

the fee structure of the two-sided credit card markets.

[33]Recall these welfare comparisons are for POS transactions only, so including online transactions and bill payments would increase the utility of payment cards relative to cash and worsen the welfare loss from eliminating either payment card.

the cost of cash managment would rise more than 1,300 percent. The probability of cash withdrawals would more than triple to nearly one in five payments being preceded by a withdrawal instead of one in 26. Cash holdings before a transaction would increase roughly five-fold to $124. For perspective on the last outcome, note that Briglevics and Schuh (2013) reports consumers holding $110 (inflation-adjusted to 2010 dollars) in the mid-1980s.[34] At that time, debit cards had not fully diffused yet and credit cards were not used as widely for smaller value payments, so the counterfactual simulation provides a reasonable comparison with actual cash holdings between the two periods.

8 Conclusions

This paper reports the successful estimation of a dynamic optimizing model that blends modern theories of cash inventory managment and payment choices with daily, transactions-level data from diary surveys. The estimated model reveals that cash demand and payment use are jointly determined, influencing each other in economically meaningful ways. A key new insight is that utility from optimal consumer payment choices turns out to be larger than utility lost from cash management costs. The monetary literature's focus on minimizing cash management costs through low inflation and technological change, though important, has obscured the greater net benefit accruing from using cash to finance certain consumption expenditures and manage liquidity portfolios.

Novel discovery of greater value of cash for consumer welfare raises important questions about the future of cash and related policy implications. If eliminating currency would reduce consumer welfare about as much as eliminating debit or credit cards, would anticipated benefits to monetary policy (taxing deposits) and crime fighting be sufficient to increase overall social welfare? If debit cards linked to commercial bank deposits have not replaced currency, would the introduction of a digital currency linked to a Central Bank's balance sheet fare any better in reducing the demand for cash? Likewise, why haven't cryptocurrencies such as Bitcoin eliminated the demand for currency by now, and

[34]See their Table 1 based on the Survey of Currency and Transactions Account Usage conducted by the Federal Reserve Board in 1984 and 1986.

will they ever?

Although the estimated model in this paper is not sufficient to answer these questions conclusively, its success and results motivate future research to extend the blended model in several important dimensions. From the consumer's perspective, it is important to: 1) go beyond POS transactions by including online transactions, bill payments, and other payments that account for a large portion of total consumer expenditure value; 2) go beyond cash and debit or credit cards by incorporating all payments instruments in consumers' wallets; and 3) allowing for heterogeneous cash withdrawals. relax model restrictions on the consumers' payment planning horizon. Expanding consumers' decision by endogenizing the number of payments and value of consumer expenditures, and introducing the concept of costly shopping trips would enable us to analyze the usefulness of payment instruments in reducing transactions costs.

To obtain a full assessment of social welfare and evaluation of public policies, however, it will be necessary to add the supply side of the payment system. Introducing merchant acceptance of payments (as in Hunyh, Nicholls, and Shcherbakov 2019, for example) is essential for capturing the full demand and supply of payment services in general equilibrium. More generally, integration of the process of search, exchange, and settlement of transactions that is central to New Monetarist models (as in Chiu and Molico 2010, for example) is a natural direction to extend our framework. Finally, a complete general equilibrium model requires the introduction of payment networks for all type of instruments. Without this complete general equilibrium specification, public policies pertaining to regulation of payment card interchange fees, such as Federal Reserve Regulation II, or provision of payment services with faster settlement, such as the Federal Reserve's FedNow^{SM} Service, can not be evaluated properly for social welfare implications.[35]

Finally, although the new payments diary data are impressive and valuable they require further development to estimate an extended model. Perhaps most importantly, balances of non-cash assets and liabilities—especially checking and revolving credit card

[35] For more details, see `https://www.federalreserve.gov/paymentsystems/regii-about.htm` for Reg II and `https://www.frbservices.org/financial-services/fednow/index.html` for FedNow^{SM}.

accounts—are essential for completely characterizing CIA and liquidity constraints, and for tracking the cash-flow relationships that link portfolio management and settlement of payment for consumer expenditures envisioned by Samphantharak, Schuh, and Townsend (2018). More details about the nature of asset and liability accounts, such as the costs and benefits of specific credit cards, and tracking of the exact payment card or instrument used (instead of a simple category like "credit card") would allow useful enhancements of the theoretical specification of payment utility. Accurately measuring merchant acceptance for each payment opportunity also is essential to relaxing the current model's implicit assumption that sellers accept every payment instrument.

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Appendix A Data appendix

This appendix provides additional details about the Survey (SCPC) and Diary (DCPC) of Consumer Payment Choice and their data. Originally, the SCPC and DCPC were produced by the Federal Reserve Bank of Boston but these data programs are now managed by the Federal Reserve Bank of Atlanta. Data, questionnaires, and associated data reports for each year and survey can be obtained from the Atlanta Fed's consumer payment website.[36] For specific details about the 2012 SCPC and DCPC, see Schuh and Stavins (2014), Angrisani, Foster, and Hitczenko (2014), Hitczenko (2015), and Greene, Schuh, and Stavins (2018).

A.1 Survey Instruments

The SCPC is a 30-minute online questionnaire based on respondent recall that is administered annually each fall beginning in 2008. In most cases, respondents completed the 2012 SCPC at least one day before the DCPC, although the lag may be up to several weeks. SCPC respondents received $20 incentive compensation for completing the survey. The SCPC is taken first and responses are used to tailor the design of the DCPC for each respondent's adoption patterns.

The DCPC is a 20-minute mixed-mode diary survey that was administered for the first time in October 2012. For three consecutive days, respondents were asked to record all payment and cash management transactions in a physical memory aid. Each night, respondents also completed an online survey to report their cash holdings (including denominations) and the transactions recorded in their memory aid, and to answer follow-up questions about the transactions. If they completed the SCPC, DCPC respondents also received additional incentive compensation of $60 for completing all three diary days.

The survey instruments primarily are designed to track payment and cash management activity for nine common instruments: cash, checks (personal, certified, or cashier's), money orders, traveler's checks, debit cards (also ATM cards), credit cards, prepaid

[36] `https://www.frbatlanta.org/banking-and-payments/consumer-payments/`.

cards, online banking bill payment and bank account number payment.[37] The SCPC also measures consumer adoption of bank accounts that are associated with the payment instruments: checking, saving, credit card, and prepaid card (some of which may be managed by non-banks).

Performance of the survey instruments was relatively good in all dimensions. Item response rates for most survey questions were well above 90 percent. Both survey instruments included real-time error checking methods, and respondents had access to RAND staff for technical and conceptual assistance. The vast majority of respondents rated their interest in both surveys as 4 or 5 on a five-point Likert scale (5 being most interesting).

A.2 Sampling methodology

Respondents in the 2012 SCPC and DCPC were selected from the RAND Corporation's *American Life Panel* (ALP).[38] Currently, the ALP "is a nationally representative, probability-based panel of more than 6,000 participants who are regularly interviewed over the internet." In 2012, however, the ALP was in the process of transitioning from a convenience sample to nationally representative over multiple years. Consequently, the 2012 SCPC and DCPC subsamples of the ALP were randomly re-selected using standard methods to match the U.S. population characterized by the Current Population Survey. The matched 2012 SCPC-DCPC sample included 2,468 respondents who completed all three days of the DCPC. The participation rate of respondents selected for the survey and diary participation was nearly 100 percent. Hitczenko (2015) and Angrisani, Foster, and Hitczenko (2014) provide details of the joint sampling methodology for the 2012 survey instruments.

The primary reporting unit in the ALP is a consumer rather than household. Sampling consumers is easier and less expensive than surveying all members of a household. Consumer-based sampling also is likely to produce better estimates of individual payment

[37] Newer payment instruments such as text/SMS (Venmo and Zelle) and cryptocurrencies (bitcoin) are not included. Applications like PayPal or ApplePay are not payment instruments *per se* but use them to process payments in ways that compete with traditional banking services.

[38] See `https://www.rand.org/research/data/alp.html`.

choices, especially for currency where the head of household may not track all activity. Sampling consumers could lead to mismeasurement of other aspects of payments, like joint bank accounts and shared household bills like utilities. However, proper random selection of consumers should yield a sample that is representative of U.S. households and produces unbiased aggregate U.S. estimates.[39] A separate quarterly survey provides a wide array of time series demographic characteristics for each ALP consumer that can be merged with the SCPC and DCPC.

A.3 Survey design

The SCPC and DCPC were jointly implemented with a common sample of respondents. Starting in September, the SCPC was implemented first and completed prior to the DCPC. In most cases, respondents completed their SCPC at least one day prior to their DCPC. In some cases, the delay may have been a month or so, which could have had minor effects on the synchronization of responses between survey instruments related to adoption of accounts or payment instruments.

Respondents who completed their SCPC were randomly assigned to start their consectutive three-day diaries from September 29 through October 31, with the last diaries being completed on November 2. Each wave of more than 200 DCPC respondents also was randomly selected to be representative of U.S. consumers and staggered across the month so that each day had (in expectation) an equal share of respondents who were completing days one, two, and three of the diary. This procedure is designed to smooth any possible effects of diary fatigue that might lead to incomplete diaries or reduced response quality during a diary period and requires "burn in" (September 29-30) and "cool down" (November 1-2) periods from which the data are not used.

The resulting DCPC data form a balanced longitudinal panel for October 1-31 with fixed entry and exit predetermined by the sampling design and diary methodology. Together, the sampling methodology and survey design make the DCPC sample represen-

[39] In 2012, the convenience sample nature of the ALP produced around 100 households with two cohabitating adults. This household subsample does not exhibit any large differences from the single-adult sample.

tative of U.S. consumers for each day of the month and for the entire month. However, the data for individual consumers only extend three days and may not be representative of the individual consumer's monthly payment and cash management behavior. Thus, individual consumer data cannot be projected to the full month.

A.4 Data measurement

The primary input for this paper is the DCPC transactions-level data on payments and cash management. For payments, the DCPC measures the following seven items: 1) exact time of day (hour, minute, and a.m. or p.m.); 2) the payment value (dollars and cents); 3) the payment instrument; 4) the location (in-person or not); 5) the device used (computer, mobile phone, etc. or none); 6) payment type (retail, person-to-person, or bill); and 7) the merchant type (payee). The SCPC measures payment use as the number of payments per month made (volume), which is measured implicitly in the DCPC as the recorded number of payments per day. However, we do not use the SCPC payment volume data because they rely on respondent recall, hence more susceptible to potential measurement error, and do not include dollar values.[40]

For cash management, the DCPC measures cash holdings (stock) and other cash-related activities (flows). Every night, respondents record the total dollar values of currency held in their "pocket, purse, or wallet" by denomination (the number and value of $1 bills, $5 bills, etc.) but excluding coins. Every day, respondents record the number and dollar values of cash withdrawals by location, cash deposits, and other aspects of cash-related transactions such as conversion of coins to notes.

The 2012 DCPC did not collect stock and flow data on other assets or liabilities, such as bank checking and credit card accounts. The 2012 DCPC collected data on reloadings of prepaid cards, which are quite similar to cash, but did not collect the balances and withdrawals of specific prepaid cards. Subsequent DCPC's have collected data on balances in *primary* checking accounts only. However, these data are insufficient to track the cash flow of demand deposits if there are multiple accounts, joint account holders, or

[40]Despite relying on recall, the SCPC data on payment use are surprisingly close to the DCPC estimates except for cash, where the DCPC estimates are significantly higher perhaps due to better tracking.

other complexities in household management of checking account stocks and flows.

A.5 Data cleaning

For every consumer and every day, the DCPC data should measure exactly the following cash-flow identity:

$$\text{cash tonight} = \text{cash last night} + \text{withdrawals} - (\text{deposits} + \text{cash payments}).$$

In practice, however, there is potential error in this measurement. To minimize the potential measurement error, the online diary survey uses this exact accounting cash-flow identity and other techniques for real-time error checking and data correction to ensure that the daily cash-flow identity holds. More than 70 percent of daily consumer-level cash-flow identities held within a rounding error ($1 per transaction allowing for coins).

When individual consumer-day cash-flow identities did not hold, we cleaned the micro data following methods used in other consumer or household surveys that collect dynamic cash data, such as the Townsend-Thai Monthly Survey (see Samphantharak and Townsend 2009). When cash-flow errors were negative, suggesting that respondents spent more cash (or made more deposits) during the day than they recorded, we increased their end-of-day cash holdings sufficiently to eliminate negative cash-flow entries. One explanation for these negative errors is that respondents used cash stored in their home or elsewhere, which was not collected in the 2012 DCPC but is estimated in the SCPC to be much larger than cash in wallet. Measurement errors also may have occurred in reporting of the cash stocks or withdrawals but positive cash-flow errors are smaller and less common. In any case, we trusted respondent reporting of cash management and adjusted end-of-day cash holdings whenever the cash-flow identity was violated.

In the few cases where cash was used to pay bills (which were excluded from the sample), we adjusted the respondent's cash holdings by subtracting the amount of the bill so our measure of cash holdings reflects only cash balances held for making POS transactions. This procedure is not entirely innocuous. For example, consumers who make a large bill payment with cash may make a withdrawal beforehand, in which case they might withdraw cash to cover POS expenses as well. However, our estimation sample has only five instances where a cash bill payment is preceded by a withdrawal that is larger than the amount of the bill payment, so this restriction is unlikely to influence our results. In any case, bill payments often involve different means of payment (online banking, bank account number payment) that are unavailable at the point of sale and likely entail different decision making than POS payments such as planning and budgeting at monthly or annual frequencies. Sexton (2015) also argues that bill payments involve aspects of behavioral economics.

Appendix B Estimation details

B.1 Overview

The goal of the estimation is to find the structural parameters, $\theta = \left\{b_L, b_U, R, \gamma_0^h, \gamma_{p\leq 10}^h, \gamma_p^h, \gamma_0^d, \gamma_{p\leq 10}^d, \gamma_p^d\right\}$, for which the model's predictions are closest to the data. In principle this could be done using maximum likelihood estimation. That is, for any θ, we could (i) solve the model described by equations (1) and (2) using value function iteration, (ii) use the resulting policy functions to compute the probability of observing the withdrawals and payment instrument choices found in our data, (iii) evaluate the likelihood of observing the DCPC data conditional on θ, (iv) use numerical optimization to find θ that maximizes this likelihood function.

The problem with this approach, called nested fixed-point algorithm (NFXP) in Rust (1987), is that it is too slow to be operational. The outer-loop of the NFXP algorithm, the maximization of the likelihood function, requires a large number of iterations and each of these requires a value function iteration (the inner-loop) that takes a long time, especially for the high values of β that are plausible for our application.

This problem has been well understood in the literature and creative solutions have been proposed to get around it. We resort to a conditional choice probability (CCP) estimator originally proposed by Hotz and Miller (1993); Hotz et al. (1994) for dynamic discrete choice problems and later extended by Bajari, Benkard, and Levin (2007) (BBL) to problems that include continuous choice variables. The basic idea is the following: in the NFXP algorithm, the value function is used to find the optimal policies. The CCP estimator inverts this mapping and tries to find the value function using the policy functions. The advantage of this is that if the data was indeed generated by the model (our null hypothesis), then we can infer the optimal policies from the data. These policies can then be used to recover the value functions using forward simulations, since the value functions are just the discounted sums of utilities derived from these optimal policies. Hence, given a sequence of optimal choices, and a guess for θ it is easy to calculate the value functions. Most importantly, there is no need for value function iteration to get the value functions. Having constructed the value functions this way for any particular θ, the only thing that is left is to find the optimal choices implied by θ, compare them to the data, and find the vector of θ that gives the best fit. Compared with the NFXP algorithm, the fixed-point problem of the inner loop is replaced by simulation.

BBL offers a variation of this method by noting that for many problems the value function is a linear combination of the structural parameters, θ, and some basis function:

$$V(m; p, \epsilon, b) = \sum \theta \cdot \mathcal{B}(m; p, \epsilon, b).$$

To illustrate this, compute the value of a short sequence of payments. First, let us compute the value of making a \$15 and a \$20 dollar debit card transaction for somebody who has \$50 in cash and makes no withdrawal. This is simply the discounted sum of the payment utilities minus the cost of carrying the cash for two trnsactions:

$$\begin{aligned}
&\sum_{t=1}^{2}\beta^{t-1}\left[-R\cdot m_t + u^d(p_t) + \epsilon_t(d)\right] \\
&\quad = -R\cdot 50 + \gamma_0^d + \gamma_p^d\cdot 15 + \epsilon_1(d) + \beta[-R\cdot 50 + \gamma_0^d + \gamma_p^d\cdot 20\epsilon_2(d)] \\
&\quad = [R\ \gamma_0^d\ \gamma_p^d\ 1]\begin{bmatrix} -(50+\beta\cdot 50) \\ 1+\beta \\ 15+\beta\cdot 20 \\ \epsilon_1(d)+\beta\epsilon_2(d) \end{bmatrix}.
\end{aligned}$$

As can be seen the basis functions corresponding to each element in θ, are just a discounted sum of the variables that the structural parameters multiply. This means that if we estimate the policy functions from the data, draw sequences of the shocks, and simulate individual choices, we can recover these basis functions. Having recovered the basis functions, the value function for any θ can be computed quickly, and hence the implied withdrawal and payment choices for a particular vector of θ can be computed easily. These choices can then be compared to the choices observed in the data, and the structural parameters will be chosen to maximize the fit of the model to the data.

The linear decomposition of the value function is only possible it the withdrawal cost shocks are uniformly or normally distributed. In these cases, the value function scales simply with the (unknown) parameters of the shocks. Therefore, the basis functions can be recovered from a single simulation. For other distributions, the linear structure would no longer apply and the basis functions would have to be simulated over and over again for each new vector θ.

B.2 First-stage - Simulation

In the simulations we will recover the basis function for $E[W(m;p,b)]$ by implementing the method outlined above. To do that we will have to discretize the space of possible cash in wallet values. For each node of this space, we will approximate the expected value by the average of 10,000 simulations. (Each simulation is for a sequence of 7,200 transactions, the length dictated by our choice of β, see footnote 28.)

First, we fit a Pareto-distribution to our data on transaction values, see Figure 1. Then we estimate a non-parametric model for payment choices. We divide the data into bins by transaction values and cash in wallet, and compute the probability of choosing each each payment instrument in every bin. For withdrawals, we use the observed distributions in the data, conditional on the cash-in-advance constraint.

In each simulation we draw, transaction values, withdrawal cost shocks (uniformly distributed between 0 and 1), and payment instrument shocks (uniformly distributed between 0 and 1) for 7,200 transactions. For each draw of the withdrawal shock, we check whether the CIA constraint is binding or not and then match the quantile of the shock to the quantile of observed withdrawal amounts for the respective CIA state (no withdrawal being \$0). For each POS transactions we need to simulate (i) the payment instrument choice and (ii) the expected value of the random utility component. For the payment instrument choice we use the payment instrument choice probabilities computed from the data for the respective bin and the uniformly distributed payment instrument shock to simulate which instrument is used. The expected value for the random payment instrument is given by $E[\epsilon(i)|\text{i is chosen}] = \gamma - \log[\Pr(i)]$ in our model. (Note that $\log[\Pr(i)]$ is negative if the choice probabilities are less than one. The lower the choice probability for instrument i is in the data, the larger the random component $\epsilon(i)$ has to be for it to be chosen.)

B.3 Second-stage - Method of moments

We use a method of moments estimator to recover the structural parameters. For any θ, we compute the value both for making and not making a withdrawal, using the simulated value function for every transaction in our estimation data set. This tells us if a withdrawal is made. Similarly, given the amount of cash in the wallet at the point of sale, we can compute the probability for choosing each of the payment instruments for every transaction in our estimation data set

First we use 7,500 initial guesses to evaluate the objective function (using an identity matrix for weighting). From the 11 most successful initial guesses we start a simplex algorithm to find the best estimate, θ_1. (The choice is dictated by the number of cpus we can use in parallel computing in MATLAB.) We use this to calculate the optimal weighting matrix. Then we take another 7,500 initial guesses to evaluate the objective function, this time with the optimal weighting matrix. From the 11 most successful initial guesses we start a simplex algorithm to find the reported structural estimate, θ^*.

B.4 Standard errors

The standard errors are derived by reestimating the model on 200 bootstrapped samples. Since the transactions in the DCPC form an unbalanced panel, we bootstrap individuals in the process and keep the distribution of the number of transactions by respondent the same as in the original sample.

Appendix C Counterfactual models

For clarity, we briefly spell out the models used in the counterfactual simulations. The simplest cases are the models with cash and one type of payment card. These models retain the structure of the benchmark model (described by equations (1) and (2)), but the payment instrument choice equation (1) only includes either debit or credit cards. Formally, either $i \in \{h, c\}$ or $i \in \{h, d\}$.

C.1 No cash

In these simulations consumers choose between credit and debit cards at the point of sale. The model collapses to a sequence of logit models, with a value function of

$$V(p) = \max_{i \in \{d,h\}} u^i(p) + \epsilon(i) + \beta E\left[V(p')\right]. \tag{3}$$

Since the only endogenous state variable in the benchmark model was cash holdings, decisions made in the current choice situation have no effect on subsequent transactions.

C.2 No cards

The counterfactual model is an extension of the Baumol–Tobin model with stochastic transaction values and withdrawal costs. Consumers choose withdrawal policies to solve

$$\begin{aligned} W(m; p, b) = \max & -b \cdot \mathcal{I}(m^* \neq m) - R \cdot m^* + \beta E\left[W(m^* - p; p', b')\right] \\ & m^* \geq m, \quad m^* \geq p. \end{aligned}$$

After observing the value of their next transaction, p, and the withdrawal cost, b, consumers decide whether to adjust their cash holdings. Then they make a cash payment (only choice) and move on to another withdrawal decision before their next transaction. Without payment cards, consumers must always have enough cash to pay for the current transaction, p.

The counter-factual model uses the same withdrawal and holding costs as in Table 5, but no utility from card payments. Timing in the counter-factual model also is the same. Thus, consumers know with certainty the amount of their next transaction and are not forced to hold precautionary balances to accommodate the low-probability occurrence of very large-value transactions as in Alvarez and Lippi (2013), which are much less likely for retail payments.