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

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Abstract

Data from the 2012 Diary of Consumer Payment Choice (DCPC) is used to estimate payment instrument choice for U.S. consumers. The data shows substantial changes compared to a similar study by Klee (2008) (which used data from 2001): Checks have virtually disappeared from purchase transactions, while still play a role in bill payments. Cash, on the other hand, still plays a large role for low-value transactions. As opposed to analyzing payment instrument choices in isolation the data allows to look at sequences of payment instrument choices and how they relate to cash withdrawals. Preliminary results indicate that such forward-looking behavior of consumers might be important.

Keywords: payment instrument choice, money demand, cash, cash withdrawals, payment cards, Diary of Consumer Payment Choice, DCPC

Extremely preliminary! Please do not cite or distribute!

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1 Introduction

A popular commercial campaign by the U.S. bank Capital One asks listeners, "What's in your wallet?" This paper attempts to answer this question using a panel of micro data from the new 2012 Diary of Consumer Payment Choice (DCPC). Aside from prurient interests in other peoples' wallets, the question and answer offers fresh insights into the transformation of the money and payment system from paper to electronics in the United States, where consumers choose to adopt, carry, and use one of nearly a dozen means of payment to buy goods and services.

There have been a number of recent contributions on this topic in various countries that have micro-level transactions data (see, for example, Fung, Huynh, and Sabetti (2012) for Canada, Bounie and Bouhdaoui (2012) for France and von Kalckreuth, Schmidt, and Stix (2009) for Germany). For the U.S., Klee (2008) looked at grocery store checkout data from 2001 to analyze payment instrument choice. First, we replicate her approach on the DCPC data. The striking result is that over the last decade payment instrument choice has undergone a remarkable transformation. Next, we use the DCPC to analyze the links between payment instrument choice and money demand to see how the benefits associated with the use of new payment technologies changes the demand for transactions balances.

We extend the current models of payment instrument choice to allow consumers to look forward to future transactions. This fits very naturally into the random utility maximizing framework of, for example, Klee (2008) or Michael and Rysman (2012). In those models consumers choose a payment instrument to maximize the (partly random) utility derived from payment services. Since the DCPC provides observations on successive transactions, it is natural to assume that a rational consumer maximizes the expected utility from all future transactions. Given that the expected utility of a transaction depends on the set of available payment instruments, and this set can change as the consumer depletes her cash holdings, an intertemporal link appears between current and future transactions and the demand for cash balances. Take, for example, a consumer who has \$20 in her purse (along with a credit card) to pay for the next two transactions worth \$18 and \$3, respectively. Clearly, a choice to use cash know will make her use the credit card[1] to settle the following small value transaction, which would usually paid for with cash. Conveniently, the logit choice model extends nicely to a dynamic framework, as shown first by Rust (1987), resulting in a closed form solution for the expectation of the value function, making the solution and estimation of such models feasable.

The paper is organized as follows: Section 2 draws a quick comparison between the DCPC data and Klee (2008) and estimates simple multinomial logit models for several types of transactions. Section 3 describes the dynamic extension of the payment instrument choice model and discusses how it can be solved. Section 4 extends that model to allow for withdrawals, linking payment instrument choice and cash demand. Section 5 describes the results of the estimation, while Section 6 concludes the paper.

[1] Assuming, for now, that withdrawals are not feasable.

2 Payment instrument choice

2.1 Payments transformation 2001-2012

This subsection replicates the econometric analysis in Klee (2008) on the DCPC data. First, we need to restrict our data to make sure that the results are comparable. The transactions used in her estimation all came from a grocery store chain that accepted cash, check, debit and credit cards (signature debit was recorded as credit card payment), moreover she restricted her sample to transaction values between \$5 and \$150 (2001 dollar prices)[2]. The DCPC has a much broader scope, it tries to cover all consumer transactions, not just purchases at grocery stores. In fact, it also has information on not in person payments (such as on-line purchases), bill payments and automatic bill payments. For the results in this subsection we only used transactions carried out at "grocery, pharmacy, liquor stores, convenience stores (without gas stations)", where cash, check, debit or credit card was used[3], and kept the range of transaction values unchanged in 2001 dollars.

As in Klee (2008) we estimate a multinomial logit model to model the payment instrument choice. The indirect utility of respondent n from using payment instrument p in transaction t is modeled as:

$$u_{ntp} = x_t \beta_{1p} + z_n \beta_{2p} + \epsilon_{ntp},$$

where x collects transaction specific explanatory variables (value of sale, indicator variable for weekend) while z denotes respondent specific variables (household income, age, education, gender, marital status) and ϵ_{ntp} is assumed to be an i.i.d. Type 1 Extreme Value distributed error term. Note that since the variables on the right hand side do not vary by payment instrument, the coefficients β are assumed to be different for each payment instrument. The assumption about the error terms guarantees a closed form solution for both the expected utility of each choice situation and the choice probabilities.

The expected utility of a bundle b of payment instruments takes the "log-sum" form:

$$E[v_t(b)] = \left[\ln \left(\sum_{i \in b} \exp(\delta_t^i) \right) + \gamma \right],$$

where the utility depends on the bundle b of payment instruments that the consumer has: having an additional payment instrument i in the bundle, means that the summation in the argument of the ln function is taken over more payment instruments. (γ is Euler's constant.)

The variables were chosen so as to match the specification in Klee (2008) as close as we could[4].

[2]Note that her data is not meant to be representative of the U.S. payment system.

[3]The DCPC also has data on prepaid card, bank account number payment, money order, travelers' checks, text message and other payments. For grocery stores, their share is negligible.

[4]We have no information on the number of items bought and if the respondent used a manufacturer coupon to get some discount, nor do we have information on whether she resides in urban or rural area an if she is a home-owner or not.

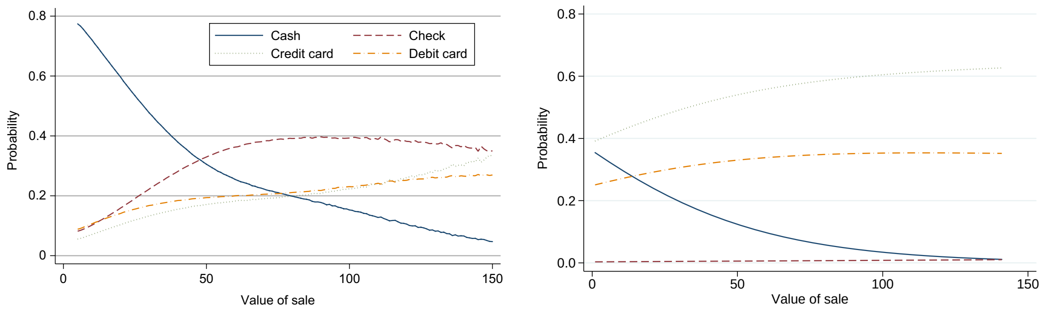

Figure 1: Payment instrument choice at grocery stores in 2001 (left, from Klee (2008)) and 2012 (right)

Given the indirect utilities the probability of respondent n choosing payment instrument p for transaction t is:

$$\Pr(p|x_t, z_n) = \frac{\exp(u_{ntp})}{\sum_p \exp(u_{ntp})}.$$

Figure 1 compares the estimated payment choice probabilities at different transaction values in 2001 and 2012. The left panel is taken from Klee (2008), while the right panel is obtained from carrying out the estimation described above. First note, that checks have essentially disappeared from grocery stores over the past decade. Second, the probability of choosing cash has roughly halved at all transaction values and the graph still maintains its negative slope, showing that cash is used overwhelmingly for low-value transactions. Credit and debit cards have stepped into the void left by the decline of cash at low transaction values and checks at larger values of sale. In particular, while the choice probability for PIN debit (orange dash-dotted line) exhibits a hump-shaped pattern, credit (including signature debit) increases monotonically over this range of purchase values.

2.2 Payment instrument use in different contexts

As already mentioned above, the DCPC has data on a broad range of payment contexts. In this subsection we drop the data restrictions imposed by the need for comparability in the previous subsection and re-do the same estimations.

2.2.1 In-person vs. not in-person purchases

Figure 2 shows payment instrument use probabilities by transaction values. For in-person (or point-of-sale (POS)) transaction (left panel) the graph tells a similar story to the one for grocery stores only (note that the scale of both axes has changed). Checks are rather unimportant, the change in cash use probability between low and high transaction values is by far the biggest among all payment instruments, though credit card use increases fairly quickly and does not level off even at transaction values as high as \$1000. An

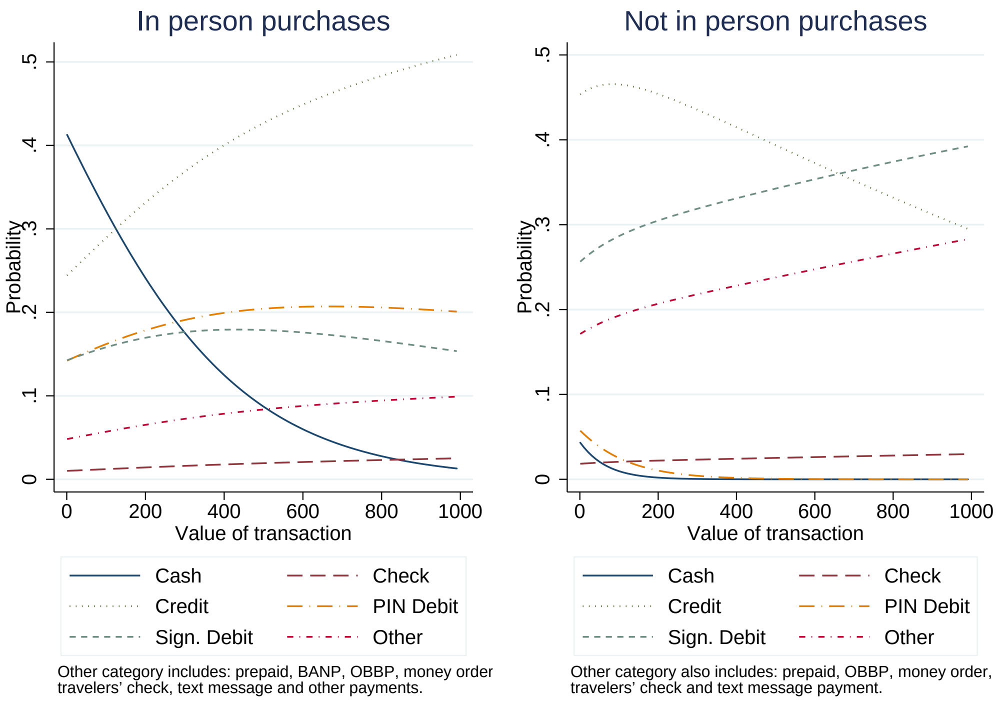

Figure 2: Payment instrument choice at the point-of-sale (left) and not in-person (right)

important change is that we are able to separate out signature debit transactions from credit cards. There is not much of a difference between the two types of debit cards, though PIN debit use seems to level off at somewhat higher transaction values. The increase in the "Other" category with the transaction value is largely the result of a few purchases made with money order, which are of fairly high value. Since there aren't many large value transactions (the 99th percentile is at $341), these are a non-trivial portion of all large transactions.

Not-in-person purchases are dominated by credit and signature debit card payments, and bank account number payments also represent about 10 percent of all not-in-person transactions. Interestingly check use is not common in these types of payments, either.

2.3 Bill payments

Lastly, we look at bill payments. Not surprisingly online banking bill payments and bank account number payments are both popular for both types of bills. More interestingly, checks are just as frequently used for bill payments as its electronic counterparts. For automatic bill payments, checks, obviously, disappear and their role is largely taken over by online banking bill payments. There is still a non-trivial share of cash payments, predominantly for lower value bills. Interestingly, credit and debit cards are not often used to make bill payments (automatic or not).

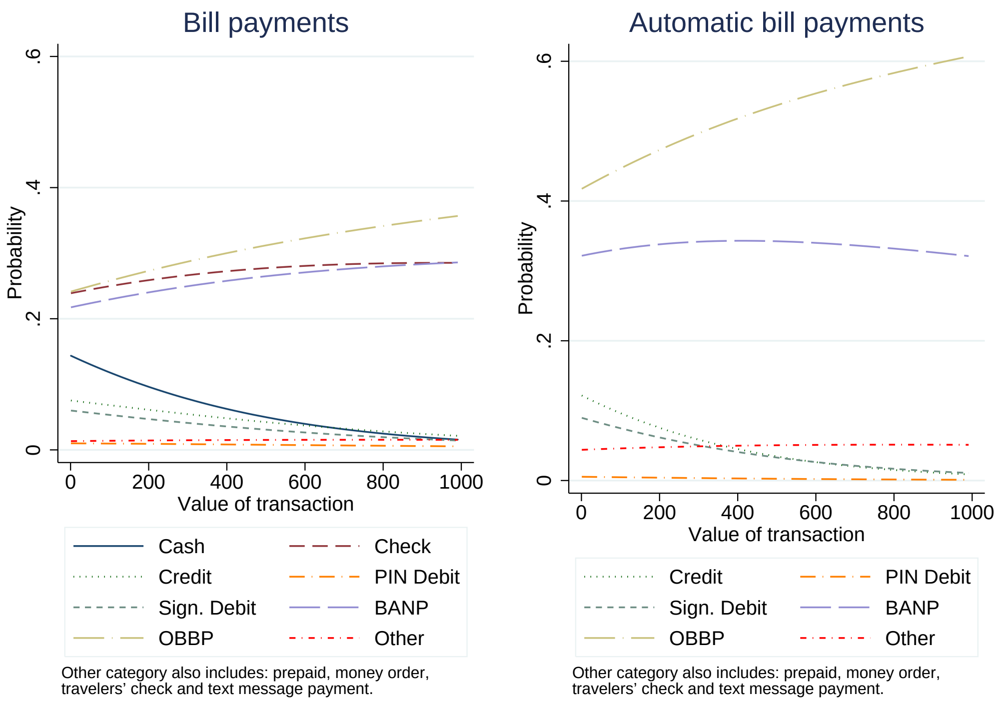

Figure 3: Payment instrument choice for bill payments (left) and automatic bill payments (right)

3 Dynamic model of consumer payment choice

The goal is to move beyond the static optimization used in earlier studies (e.g. Klee (2008)) and described briefly in Section 2.1. In particular, we want consumers to take not only the current utility from choosing a payment instrument into account but also the effect of this choice on the utilitiy derived from subsequent transactions. As an example, take a consumer who has \$20 in her purse to pay for the next two transactions worth \$18 and \$3, respectively. Assume that withdrawing cash is not possible, for now. Since these are both low value transactions, her utility from using cash is fairly high (compared to credit or debit) in both cases, but in relative terms she may be much better off using cash for the \$3 payment. If consumers are able to predict the full sequence of transactions that they are about to make over a time period, it is reasonable to assume that they also recognize the intertemporal nature of their choices.

The next subsection spells out the dynamic program, drawing on Rust (1987) as described in Train (2009). The basic idea is that under certain assumptions about the structure of the problem, the desirable property of the closed-form solution of the static multinomial logit models extend to dynamic models in a rather natural way.

3.1 The dynamic problem

Given that the availability of one of the payment instruments, cash, changes if it is used in a transaction, a link exists between current and future transactions: Deciding to use cash now, may reduce the number of available instruments in future transactions, leading to a drop in the expected utility derived from that transaction. If cash balances are insufficient to settle a transaction, the consumer will no longer be able to take advantage of a high realization of ϵ^{cash} or of a high value of δ. A forward-looking consumer will take this potential loss of utility into account, when making the payment instrument choice in the current transaction. That is, she would maximize

$$\begin{aligned} V(m_t, t) &= \max_{i_t \in \{h,c,d\}} u^i_{ndt} + E\left[V(m_{t+1}, t+1)\right] \\ u^i_{ndt} &= \beta_j x_{ndt} + \gamma x_{ni} + \epsilon_{ndti} = \delta_{ndti} + \epsilon_{ndti}, \end{aligned}$$

where $V(m_t, t)$ denotes the value of having m_t amount of cash before making the tth transaction, and $E[.]$ is the mathematical expectation operator taken over the realizations of the shocks for future transactions. The instanteneous utiltiy from using a payment instrument has three parts. Some variables x_{ndt} only differ across individuals (n) or days (d) or transactions (t), but not across payment instruments (i). Demographic variables are the obvious example, but the transaction value is also like that. For these variables separate coefficients (β_i) will have to be estimated. Other explanatory variables are specific to a payment instrument (for example, whether a credit card gives rewards) and are only included in the indirect utility function for that instrument. For these variables only a single paramter is estimated and these are collected in γ. Finally, there is a random component of the utility distributed independently and identically Type I generalized extreme value. The n and d subscripts will be dropped in what follows. The consumer chooses between cas**h**, **c**redit and **d**ebit (assuming, for simplicity, that she has enough cash to pay for the tth transaction, $m_t \geq p_t$, if not the current utility would be modified in a trivial way). The evolution of m is given by

$$m_{t+1} = m_t - p_t \cdot \mathcal{I}(i_t = h),$$

where $\mathcal{I}$ is an indicator variable taking the value of 1 if cash is choosen ($i = h$) and 0 otherwise. The program has a finite number of "periods" (transactions) T, which is known to the consumer, and can be solved by evaluating the expectation on the right-hand side from the last period backwards. For simplicity, for now, assume that there is no value to carrying cash over from one day to the next, resulting in

$$V(m_T, T) = \begin{cases} \max_{i \in \{h,c,d\}} u_T^i & \text{if} \quad m_T \geq p_T \\ \max_{i \in \{c,d\}} u_T^i & \text{if} \quad m_T < p_T \end{cases},$$

i.e. the continuation value after transaction T is 0, regardless of the amount of cash on hand after the final transaction of the day.

3.2 Period $T-1$

Note that, given the simplifying assumption about end-of-day withdrawals, the last period collapses to the multinomial logit choice problem, with expected utilities given by

$$E[V(m_T, T)] = \begin{cases} \ln\left(\sum_{i \in \{h,c,d\}} \exp(\delta_{Ti})\right) + \gamma & \text{if} \quad m_T \geq p_T \\ \ln\left(\sum_{i \in \{c,d\}} \exp(\delta_{Ti})\right) + \gamma & \text{if} \quad m_T < p_T \end{cases}, \tag{1}$$

just like in the static case of the previous section. This means that, iterating backwards, the choice problem for $T-1$ is

$$V(m_{T-1}, T-1)] = \\ \begin{cases} \max_{i \in \{h,c,d\}} u_{T-1}^i + E\left[V(m_{T-1} - p_{T-1} \cdot \mathcal{I}(i_{T-1} = h), T)\right] & \text{if} \quad m_{T-1} \geq p_{T-1} \\ \max_{i \in \{c,d\}} u_{T-1}^i + E\left[V(m_{T-1}, T)\right] & \text{if} \quad m_{T-1} < p_{T-1} \end{cases}. \tag{2}$$

While this function looks complicated, it is not hard to evaluate it. Given m_{T-1} we know which one of the two branches in equation (2) is relevant.

3.2.1 Insuffiecient cash for the current transaction, $m_{T-1} < p_{T-1}$

Starting with the simpler case, assume that $m_{T-1} < p_{T-1}$, meaning that: (i) in the current period only debit or credit can be choosen and (ii) $m_T = m_{T-1}$. From (ii) we know which branch of $E\left[V(m_T, T)\right]$ in equation (1)) is the relevant one, so all the terms in equation (2) are known and the choice probability for, for example, credit will given by

$$\Pr(i_{T-1} = c | m_{T-1} < p_{T-1}) = \\ \frac{\exp(\delta_{T-1}^c + E\left[V(m_{T-1}, T)\right])}{\exp(\delta_{T-1}^c + E\left[V(m_{T-1}, T)\right]) + \exp(\delta_{T-1}^d + E\left[V(m_{T-1}, T)\right])},$$

which collapses to the logit choice probability, since the expected utility terms for period T added to δ^i_{T-1} are the same and they all appear additively in the argument of the exp(.) operator, that is

$$\Pr(i_{T-1} = c|m_{T-1} < p_{T-1}) =$$
$$\frac{\exp(\delta^c_{T-1}) \cdot \cancel{\exp(E[V(m_{T-1}, T)])}}{\exp(\delta^c_{T-1}) \cdot \cancel{\exp(E[V(m_{T-1}, T)])} + \exp(\delta^d_{T-1}) \cdot \cancel{\exp(E[V(m_{T-1}, T)])}} =$$
$$\frac{\exp(\delta^c_{T-1})}{\exp(\delta^c_{T-1}) + \exp(\delta^d_{T-1})}.$$

It is worth to keep this simple and intuitive principle in mind: *Dynamic considerations only affect payment instrument choice if the current choice reduces the expected utility when entering into the next transaction.* In this model, card use cannot do that[5]. (The probability for debit card use will be analogous.)

3.2.2 Cash is an option in $T-1$, $m_{T-1} \geq p_{T-1}$

If $m_{T-1} \geq p_{T-1}$, then we have to be a bit more careful in computing next period's expected utility. Writing down the choice probability for credit cards for this case will highlight the difference:

$$\Pr(i_{T-1} = c|m_{T-1} \geq p_{T-1}) =$$
$$\frac{\exp(\delta^c_{T-1} + E[V(m_{T-1}, T)])}{\exp(\delta^h_{T-1} + E[V(m_{T-1} - p_{T-1}, T)]) + \sum_{j=c,d} \exp(\delta^j_{T-1} + E[V(m_{T-1}, T)])}.$$

Note the new first term in the denominator (the terms referring to credit and debit have been collapsed into a summation). Since cash is now available in period $T-1$ debit and credit probabilities will decrease somewhat, hence the appearance of the new term.

Importantly, however, the formula reveals that the continuation utility after choosing cash may be different than the continuation utility after choosing cards. In particular, the first argument of $E[V(., T)]$ is now $m_{T-1} - p_{T-1}$ if cash is chosen in $T-1$, whereas it is m_{T-1} if cards are used in period $T-1$. This is the way consumers account for the fact that cash use now may limit their choices in the following transaction. Note, however, that the principle stated above still applies: If (i) $m_{T-1} - p_{T-1} \geq p_T$ or (ii) $m_{T-1} < p_T$ then there is no "real" effect of the payment instrument choice in $T-1$ on the value function in T; since in (i) the consumer has enough cash to make both the $(T-1)$th and the Tth transaction with cash and in (ii) she would not have enough cash to pay for the Tth transaction even if she did not pay cash for transaction $T-1$. This argument extends to more transactions: If (i) $m_t - p_t \geq \sum_{s=t+1}^{T} p_s$ or (ii) $m_t < min_s\{p_s\}_{s=t+1}^{T}$ then the expect utilites in the formulas will be the same and the choice probabilities

[5] In reality, it is very much the case that checking account balances may drop to levels where they cannot be used, or that consumers max out their credit card(s). Unfortunately we do not have data on that.

will collapse to the logit probabilities. Checking whether either of these special cases do infact hold speeds up the evaluation of the expected utility tremendously for consumers who make many transactions a day.

The choice probability for cash will be, conditional on $m_{T-1} \geq p_{T-1}$, simply,

$$\Pr(i_{T-1} = h | m_{T-1} \geq p_{T-1}) = \frac{\exp(\delta^h_{T-1} + E\left[V(m_{T-1} - p_{T-1}, T)\right])}{\exp(\delta^h_{T-1} + E\left[V(m_{T-1} - p_{T-1}, T)\right]) + \sum_{j=c,d} \exp(\delta^j_{T-1} + E\left[V(m_{T-1}, T)\right])}. \tag{3}$$

3.3 Period $T - 2$

With these probabilities in mind we can move back one more period in the iteration to complete the description of the solution. The value function still looks similar to equation (2),

$$V(m_{T-2}, T-2)] = \begin{cases} \max_{i \in \{h,c,d\}} u^i_{T-2} + E\left[V(m_{T-2} - p_{T-2} \cdot \mathcal{I}(i_{T-2} = h), T-1)\right] & \text{if} \quad m_{T-2} \geq p_{T-2} \\ \max_{i \in \{c,d\}} u^i_{T-2} + E\left[V(m_{T-2}, T-1)\right] & \text{if} \quad m_{T-2} < p_{T-2} \end{cases}.$$

but the expected utility calculations are a bit more involved (see Rust (1987)):

$$E[V(m_{T-1}, T-1)] = \begin{cases} \ln\left(\sum_{i \in \{h,c,d\}} \exp\left(\delta^i_{T-1} + E\left[V(m_{T-1} - p_{T-1} \cdot \mathcal{I}(i_{T-1} = h), T)\right]\right)\right) + \gamma & \text{if} \quad m_{T-1} \geq p_{T-1} \\ \ln\left(\sum_{i \in \{c,d\}} \exp\left(\delta^i_{T-1} + E\left[V(m_{T-1}, T)\right]\right)\right) + \gamma & \text{if} \quad m_{T-1} < p_{T-1} \end{cases}.$$

The only remaining piece of the puzzle is to spell out $E\left[V(m_{T-1} - p_{T-1} \cdot \mathcal{I}(i_{T-1} = h), T)\right]$, and $E\left[V(m_{T-1}, T)\right]$, given m_{T-2}.

3.3.1 Case of $m_{T-2} < p_{T-2}$

Again, starting with the simpler case of $m_{T-2} < p_{T-2}$, where only cards can be used in $T-2$ and $m_{T-1} = m_{T-2}$. If $m_{T-2} < p_{T-1}$ (i.e. not enough cash to pay for transaction $T-1$, either), then $m_T = m_{T-2}$ and checking if $m_{T-2} \geq p_T$ or $m_{T-2} < p_T$ determines which branch of equation (1) is relevant, but in any case $E\left[V(m_{T-2}, T)\right]$ can easily be evaluated and given that now, by assumption, $m_T = m_{T-2}$ this is all that is needed.

For $m_{T-2} \geq p_{T-1}$, there are two possibilities: cash may or may not be used in transaction $T-1$. The probability of cash being used was derived in equation (3) so simple substitution gives

$$\begin{aligned} E\left[V(m_{T-1} - p_{T-1} \right. & \left. \cdot \mathcal{I}(i_{T-1} = h), T)\right] = \\ & \Pr(i_{T-1} = h | m_{T-2} >= p_{T-1}) \cdot E\left[V(m_{T-2} - p_{T-1}, T)\right] \\ & + (1 - \Pr(i_{T-1} = h | m_{T-2} >= p_{T-1})) \cdot E\left[V(m_{T-2}, T)\right], \end{aligned} \tag{4}$$

where the expectations on the RHS are given by equation (1).

3.3.2 Case of $m_{T-2} \geq p_{T-2}$

These cases are dealt with similarly, the point is again to go back all the way to evaluating the known $E\left[V(.,T)\right]$ function and figuring out the probabilities of all possible branches. There are two possibilities in period $T-2$: (i) cash is used or (ii) cash is not used. (ii) implies $m_{T-1} = m_{T-2}$ and leads to similar calculations to the ones in the previous subsection.

(i) Implies $m_{T-1} = m_{T-2} - p_{T-2}$ and now this value of cash-on-hand will have to be checked against p_{T-1} and p_T to figure out the expected values, but these calculations are again paralell to the ones in the previous section.

Thus we have demonstrated, that the terms $E\left[V(m_{T-2} - p_{T-2} \cdot \mathcal{I}(i_{T-2} = h), T-1)\right]$ and $E\left[V(m_{T-2}, T-1)\right]$ can be computed from functions that are readily known, hence we are again left with the task of computing the choice probabilities in transaction $T-2$ given m_{T-2} using the equation (3), and can continue the recursion all the way up to the first transaction.

4 Incorporating withdrawals

The dynamic model of Section 3 can be used to calculate the benefits of having cash on hand. The goal of this section is to use that information and data on withdrawals to estimate the costs associated with obtaining cash to characterize cash demand. Theoretical models of cash demand show that the assumptions made about the cash spending behavior of consumers affects parameters of the cash demand function in an important way. For example, the $-\frac{1}{2}$ interest elasticity of the Baumol-Tobin model drops to $-\frac{1}{3}$ in the slightly different setting of Miller and Orr (1968), whereas the interest elasticity is not constant in Alvarez and Lippi (2009). The DCPC data gives observations on cash spending behavior so the econometrician does not have to rely on assumptions about consumers' cash use, when estimating cash demand.

4.1 Simple model of withdrawals

Since, solving the dynamic model of Section 3 is already computationally involved we propose a simple model for withdrawals: Consumers can choose before every transaction they make to withdraw cash first. If they choose to do so, we assume that they withdraw enough cash to possibly settle all of their remaining transactions with cash. That is, we assume, for now, that there is no limit on how much cash they can withdraw (cleary, a simplifying assumption for cashbacks) and that there is no variable cost of carrying cash within the day. The main reason for this assumption is to keep the model as simple and easy to solve as possible. The fixed cost of making a withdrawal and the lack of carrying/holding cost implies that consumers will make at most one withdrawal during the day, moreover, there is no reason to make a withdrawal after the last point of sale transaction.

Formally, if a consumer decides to make a withdrawal before transaction t, her new cash balances will be $m_t = \bar{m}_t \equiv \sum_{s=t}^{T} p_s$. The costs to making a withdrawal will be modeled as

$$c_t = \alpha z_n d + \epsilon_t,$$

where $z_n d$ is a vector of consumer and day specific explanatory variables and ϵ_t follows a logistic distribution.

The choice of the consumer before each transaction is now:

$$E[\mathsf{W}(m_t, t)] = \begin{cases} E\left[V(\bar{m}_t, t, W = 1)\right] - c_t & \text{if} \quad \mathcal{I}_t^w = 1 \\ E\left[V(m_t, t, W = 0)\right] & \text{if} \quad \mathcal{I}_t^w = 0 \end{cases}, \tag{5}$$

where $\mathcal{I}_t^w$ is an indicator variable for withdrawals (1 if there is a withdrawal, 0 otherwise). Note that due to the one withdrawal a day limit, W is a state variable: If a withdrawal was made before on the day consumers will not have the option (nor the need) to make additional ones since they will be able to make all payments using cash. On the other hand, if they have not used up their withdrawal opportunity, than in the current or in any one of the future transactions they may do so.

Formally,

$$E\left[V(\bar{m}_t, t, W = 1)\right] = \max_{i \in \{h,c,d\}} u_t^i + E\left[V(m_t - p_t \cdot \mathcal{I}(i_t = h), t + 1, W = 1)\right],$$

with $m_t - p_t = \sum_{s=t+1}^{T} p_s$, meaning that the choice probabilities will not be affected by the cash-in-advance constraint, since it will not bind in the remaining transactions.

The more computationally involved part will be the evaluation of $E\left[V(m_t, t, W = 0)\right]$, where the possibility of a future withdrawal will have to be included at each future transaction. However, the backward iteration described in Section 3 will still work in principle, with the appropriate modifications. In particular, the random component of the withdrawal cost was chosen to still yield closed form solutions, as the withdrawal choice is now essentially a simple logit choice model, with the latent utilities described by equation (5).

5 Results

The model is estimated by choosing parameters (α, β, γ) to maximize the likelihood of observing the sequence of payment instrument and withdrawal choices.

5.1 Marginal effects

The marginal effects are computed for the final transaction in Table 1, so they coincide with what a multinomial model (with the same estimated parameters) would give. The main difference compared to Klee (2008) is that the effect of transaction values on cash use drop to about a quarter of what see found. Part of the explanation is obviously the inclusion of a dummy variable for small value transactions, which was motivated by the fact that some merchants only take cash for small transactions. The other reason is that our dynamic framework controls for explicitly for one of the main reasons transaction values might matter: the cash in advance constraint.

	Marginal effects*		
	Cash	Debit	Credit
TransVal	-0.0013	0.0009	0.0004
Under $10r	0.2012	-0.1205	-0.0807
HHIncome	-0.0000	-0.0000	0.0000
Age	0.0017	-0.0017	-0.0000
Female	0.0122	0.0085	-0.0207
RewardDC	0.0152	-0.0168	0.0016
Revolver	0.0871	0.0309	-0.1180
RewardCC	-0.0367	-0.0131	0.0498

*For dummy variables, marginal effect is a change from 0 to 1. TransVal=$12.53, income, age at sample average.

Table 1: Marginal effects for the final transaction on a day

Daily	Choice probabilities*		
transactions	Cash	Debit	Credit
1	0.4070	0.2397	0.3533
2	0.2947	0.2851	0.4202
3	0.2289	0.3117	0.4595
4	0.1827	0.3303	0.4870
5	0.1484	0.3442	0.5074

*Dummy variables set to 1, except for "Under$10". TransVal=$12.53, income, age at sample average.

Table 2: Choice probabilities of the first daily transaction for different total number of transactions

5.2 Are consumers forward-looking?

Our model and the rest of the literature on payment choice can be thought of as two extremes: We endow consumers with a lot of information about their future transactions while the rest of the literature thinks about them as completely myopic. Does this difference make a difference empirically? The simplest answer to this question is to compare the choice probabilities from the two models. As noted before, the choice probabilities coincide with what a multinomial logit model would give for the final transaction, but may differ if consumer have some transactions left.

In what follows we will compare the choice probabilities for the first transaction of the day and vary the total number of daily transactions. She is assumed to start the day with $20, has average household income, average age and all daily transactions are assumed to be $12.53 (median transaction value).

Table 2 shows that the model predicts widely different choice probabilities in the five scenarios. In particular, the probability of using cash drops from 40 percent in the case of a single transaction, to just below 30 percent even if she makes one more transaction. The drop in the probability of using cash is monotonic, in the case of a third transaction it is only roughly half of what it would otherwise be. Since our choice model (like other multinomial logit model) posses the independence of irrelevant alternatives property the relative probabilities of debit and credit do not change.

5.3 Withdrawal costs

Given the estimates of α, β, γ the model can be used to conduct a cost-benefit analysis of cash withdrawals. In particular, given $\hat{\alpha}$, we compute the average withdrawal cost for our sample:

$$\bar{c} = \frac{\sum_n \sum_d \hat{\alpha} z_{nd}}{N * D}$$

and relate it to the expected benefit of having cash defined as:

$$\Delta EV = E\left[V(p_T^{md}, 0, T)\right] - E\left[V(0, 0, T)\right],$$

that is the difference in the expected utilities from making a payment of \$12.53 for the average consumer (see previous subsection). In fact we compute this difference for debit and credit card holder, debit card holders who do not have a credit card and credit card holders who do not own a debit card.

$$\begin{aligned} \frac{\bar{c}}{\Delta EV^{DC}} &\sim 6.15 \\ \frac{\bar{c}}{\Delta EV^{D}} &\sim 3.24 \\ \frac{\bar{c}}{\Delta EV^{C}} &\sim 4.19 \end{aligned}$$

The calculations show that withdrawal costs are not recouped until the seventh transaction for debit and credit card holders. For consumers, with a smaller set of available payment instruments, having cash is more valuable and the four (debit) or five (credit) transactions can tip the balance in favor of a withdrawal.

5.4 Shadow value of cash

There is another way to measure the usefulness of cash, in line with the monetary economics literature, by computing the shadow value of cash, denoted by λ. Originally, that measures the change in the utility from relaxing the cash-in-advance constraint by an infinitesimal amount. We measure it by adding $\Delta_\$ = \$1, \$5, \$12.53$ to the beginning of day cash holdings of each individual on each day and compute the average of the resulting changes in expected utilties

$$\lambda = E\left[V(m_n d + \Delta_\$, t = 1)\right] - E\left[V(m_n d, t = 1)\right].$$

Again, the same concept of ΔEV is used to normalize λ:

$$\begin{aligned} \frac{\lambda_1}{\Delta EV^{DC}} &\sim 0.0164 \\ \frac{\lambda_5}{\Delta EV^{DC}} &\sim 0.1117 \\ \frac{\lambda_{12.53}}{\Delta EV^{DC}} &\sim 0.2892 \end{aligned}$$

The costless relaxation of everybodies budget constraint yields on average about a quarter of the expected utility of increaing the payment instrument choice set from debit and credit to cash, debit and credit of the hypothetical consumer of the previous subsection. This suggests a number of people in our sample are already able to use cash for all or their transactions; for them the shadow value is zero. Of course, doing away with the restriction of zero continuation value at the end of the day would likely change this result.

6 Conclusion

Payment instrument choice is ultimately a dynamic decision: using an instrument for a transaction may limit its availability in future transactions. The Diary of Consumer Payment Choice allows us to study this decision for the case of cash. The (preliminary) result of the simple model in this paper show that these effects may be substantial and can help to better understand how consumers make payments.

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