U.S. Consumer Demand for Cash in the Era of Low Interest Rates and Electronic Payments*

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Abstract

U.S. consumers' demand for cash is estimated using the 2008 and 2009 waves of a new, public data set, the Survey of Consumer Payment Choice (SCPC). The methodology follows similar recent studies (for example by Attanasio, Guiso, and Jappelli (2002) and Lippi and Secchi (2009)), but extends their models by allowing for credit card use in the spirit of Sastry (1970). In the low-interest rate environment of the Great Recession we find significant interest elasticity of cash demand for credit card borrowers, while the interest elasticity for non-borrowers is closer to zero, in fact, insignificant in most specifications. The results also show that different locations for obtaining cash (bank teller, check cashing stores) are important determinants of cash holdings.

Keywords: Cash demand, Baumol-Tobin model, Survey of Consumer Payment Choice, SCPC

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1 Introduction

A key challenge for studies of money demand is to precisely estimate the interest elasticity at very low levels of interest, since it is a crucial input into estimations of the welfare cost of inflation. A vast amount of literature has estimated quantity equations using time-series data to infer the relationship between monetary aggregates (mostly M1) and other aggregate macro variables (see for example Robert E. Lucas (2000), Ireland (2009) and references in Walsh (2003)). These estimations all have difficulties at capturing the interest elasticity at low interest rates, since there are few observations in aggregate data when interest rates were close to zero. A related point comes up in Ireland (2009) when he suggests that the functional form in Robert E. Lucas (2000) is the geared towards matching a few uncharacteristic observations after the second World War but doesn't do a good job in more recent samples. Furthermore, time-series estimations attempt to identify a stable relationship between macro variables and monetary aggregates, when the economic content of the monetary aggregates are constantly changing.[1] Figure 1 highlights how the share of the domestic component of M1 to GDP has changed over the last half a century. Interestingly, the share of (domestic) currency to GDP is fairly stable.

Mulligan and Sala-i-Martin (2000) restrict the scope of their analysis to a subset of M1, consumers' demand for demand deposits, which enables them to use household level data to study this part of money demand. They emphasize that in their sample many households do in fact earn zero interest rate on their bank accounts, so for them the relevant decision in the management of transactions balances is the adoption of an interest–bearing account (extensive margin).

Historically the Baumol (1952)–Tobin (1956) (BT) model has been used to describe individuals' behavior on the intensive margin, the decision of how to split money balances between interest–bearing and non-interest–bearing instruments. While that model gives very specific predictions about the interest and spending elasticities of cash demand, the emergence of a number of new payment instruments (for example credit cards, debit cards and prepaid cards) means that these predictions are unlikely to hold today. For example the adoption and use of payment cards affects the demand for cash, so special account of these technologies has to be taken. While the canonical BT model has been extended by a number of authors, few have actually tested these extensions in micro data. An example of such an estimation is Lippi and Secchi (2009), where the effects of free withdrawal opportunities is tested on household level data from Italy.

Our paper follows the methodology of Mulligan and Sala-i-Martin (2000) and uses a new, public, micro data set, the Survey of Consumer Payment Choice (SCPC), to estimate a different subset of the U.S. money demand, households'

[1] For example, checking accounts were not allowed to pay interest before 1980, while they did after Regulation Q was phased out. Also, while it was reasonable to think of M1 as the stock of all payment instruments before credit cards became widespread, it is less reasonable now. Note that credit cards are bank assets, while components of M1 are bank liabilities.

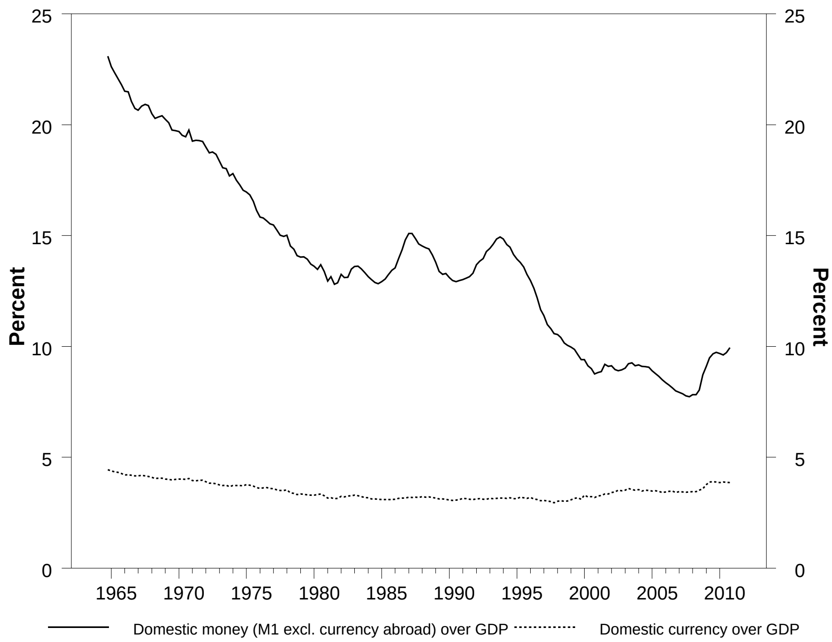

Figure 1: Selected components of M1 relative to GDP

demand for *cash*. Figure 2 depicts the average dollar value of cash withdrawals from the 2008 and 2009 waves of the SCPC along with checking and money market account interest rates.

During this period, interest rates were generally low, between 0.05 and 0.6 percent in the sample and they drop by about 50 percent from 2008 to 2009. At the same time average cash withdrawals increase from \$ 101 to \$ 119, in line with the prediction of BT-model that lower alternative costs of holding cash increase withdrawal amounts and cash holdings. To see if this aggregate relationship also holds at the micro level the adoption of interest–bearing accounts and payment instruments is estimated first for the respondents in the survey and conditional on these decisions an extension of the Baumol-Tobin model is estimated. To our knowledge, the last study on U.S. households' cash management is Daniels and Murphy (1994) which used data from the mid-1980s. Given the spread of ATM networks since then and the emergence of a number of new payment instruments (stored-value cards, on-line payments)[2] we find it interesting to revisit the question.

A number of interesting results emerge. First, since Mulligan and Sala-i-Martin (2000) the adoption rate of interest–bearing accounts has doubled, so we do not find the account adoption decision as crucial as they do. The interest elasticity of cash demand is found to be significantly different for individuals

[2]For a longer description of these new instruments see Foster et al. (2011).

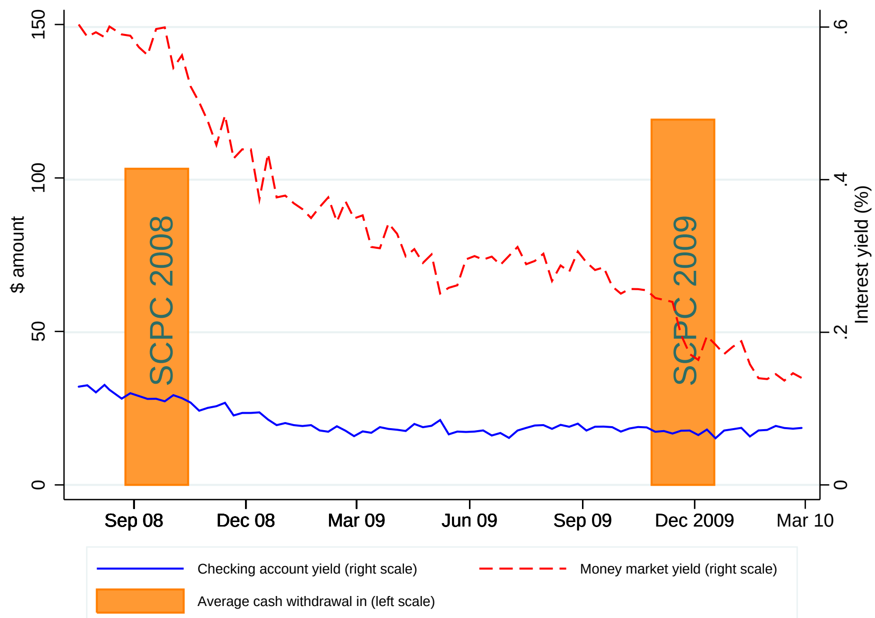

Figure 2: Interest rates and average cash withdrawals during SCPC waves

who revolve a credit card balance (revolvers) than for those who pay off their credit card debt at the end of the grace period (convenience users). Moreover, the SCPC contains data on a number of variables that are directly related to cash management, such as the respondent preferred location of cash withdrawal (ATM, bankteller, check cashing store, etc) and their assessment of various characteristics of payment instrument (security, acceptance, cost). These factors affect cash use decisions significantly in all specifications.

The rest of the paper is organized as follows: Section 3 reviews the theory behind microeconometric studies of currency demand. Section 2 contains a lengthy description of the new data set used in the paper, Section 4 explains the econometric approach used to derive the results described in Section 5. Section 6 discusses the key results, Section 7 compares these findings to those in similar studies while Section 8 concludes.

2 Data

The main data sources are the 2008 and 2009 waves of the Survey of Consumer Payment Choice (SCPC), which contains (i) comprehensive information on the adoption and use of all payment instruments by U.S. households, (ii) including detailed information on their cash management practices for the first time since the mid-1980's, (iii) their subjective assessment on various characteristics of these payment instruments, (iv) and is representative of the U.S. non-institutionalized adult population. For more details on the SCPC see Foster et al. (2009) and Foster et al. (2011).

The main advantage of the cross-sectional data for cash demand estimation is that it contains more than 3000 observations, all at near-zero interest rates. Even after the necessary data transformation this leaves us enough observations to investigate the interest elasticity of cash demand both on the intensive and extensive margins. Moreover, the detailed information on bank accounts enables us to match this sample with the rich data on bank account yields provided by Bank Rate Monitor (BRM), which yields more precise data on the opportunity cost of holding cash, than Mulligan and Sala-i-Martin (2000) had access to, who used marginal tax rates to proxy for the alternative cost. The SCPC also provides unique information on payment instrument use, including the preferred location for cash withdrawal, which is an important determinant of the cost of obtaining cash.

To keep the exposition in the paper focused, we present the main descriptive statistics along with a brief description of the main features of the data in this section and relegate the details of all the data manipulation performed to the Appendix A.

2.1 Descriptive statistics

Table 1 shows the descriptive statistics for the key variables in our analysis, both for the whole sample and for the subsample on which the estimation is carried out. For the estimation the sample had to be restricted due to missing observations and the need to have a group that is homogeneous with respect to their payment instrument portfolio.

The cash variables in the survey are: the amount of cash usually withdrawn from the primary withdrawal location, the number of withdrawals, cash in respondent's wallet and cash in her property and additionally from the last two series a total cash holdings variable was constructed by adding them up. On average across all locations, people withdraw about a hundred dollars per transaction. As already shown in Figure 2 the average amount of withdrawal increased from 2008 to 2009 as interest rates decreased. The increase in total cash holdings over time, which results from an increase in cash holdings on the respondents' property, is rather striking: in 2009 respondents reported one-fifth more total cash than in the year before.

These measures of cash management are slightly different from the ones used by Attanasio, Guiso, and Jappelli (2002) and Lippi and Secchi (2009). In their data, the Survey of Household Income and Wealth (SHIW) of the Bank of Italy, the amount of cash holdings that the household usually keeps for everyday expenses is measured, which corresponds to BT theory but may be imprecise, influenced by the ability of respondents to accurately recall such numbers. The SCPC, on the other hand, asks for cash holdings on the property and for cash in the wallet at the time of the survey. While recalling is not needed to answer

Variable	Full sample 2008	Full sample 2009	Estimation sample 2008	Estimation sample 2009
Cash management ($)				
Amount usually withdrawn	102	119	90	130
	(140)	(167)	(115)	(182)
Cash in wallet	79	69	58	75
	(310)	(113)	(94)	(124)
Cash on property	157	229	178	260
	(577)	(933)	(745)	(1132)
Total cash holdings	230	291	231	327
	(659)	(943)	(754)	(1138)
Number of withdrawals (per month)	4.3	5.1	4.6	4.8
	(6.4)	(7.4)	(6.6)	(8.0)
Interest rates (%)				
Checking account rate at commercial banks	0.120	0.064	0.118	0.063
	(0.052)	(0.025)	(0.048)	(0.025)
Checking account rate at thrifts	0.332	0.150	0.332	0.151
	(0.153)	(0.083)	(0.159)	(0.084)
Money market account rate at commercial banks	0.632	0.228	0.645	0.212
	(0.200)	(0.117)	(0.166)	(0.097)
Money market account rate at thrifts	0.733	0.419	0.725	0.421
	(0.454)	(0.185)	(0.463)	(0.194)
Highest interest rate	0.427	0.188	0.450	0.179
	(0.354)	(0.163)	(0.356)	(0.165)
Account adoption (%)				
Checking account adopter	91.3	91.8	99.5	99.3
	(28.3)	(27.4)	(7.0)	(8.1)
Savings account adopter	78.0	71.3	92.9	92.0
	(41.4)	(45.3)	(25.7)	(27.2)
Money market account adopter	.	28.8	.	42.2
	(.)	(45.3)	(.)	(49.4)
Any interest bearing account adopter	84.6	80.8	100.0	100.0
	(36.1)	(39.4)	(0.0)	(0.0)
Branches (per 1000 residents)	0.4	0.3	0.3	0.3
	(0.3)	(0.2)	(0.1)	(0.2)
Payment methods (%)				
Debit or ATM card adopter	84.9	83.9	100.0	100.0
	(35.8)	(36.7)	(0.0)	(0.0)
Credit card adopter	78.3	72.2	100.0	100.0
	(41.3)	(44.8)	(0.0)	(0.0)
Revolver	35.9	29.1	47.2	43.3
	(48.0)	(45.4)	(50.0)	(49.6)

Table 1: Descriptive statistics

Table entries are means and standard deviations (in parenthesis).

these questions accurately, neither of the SCPC variables correspond directly to cash holdings for transactions purposes. Cash on the property might include cash holdings for non-transaction purposes, while cash in the wallet may understate the cash held for transactions purposes. For this reason we will present regression results for all variables, though we believe that the amount usually withdrawn and the cash in wallet measures are the most relevant measures for estimating the BT model.

Interest rates have roughly halved over our sample period. Perhaps more interestingly, like Attanasio, Guiso, and Jappelli (2002) we find substantial cross-sectional variation in interest rates.[3] The standard deviation of the interest variables is around 50 percent, and always above one-third of the mean.

Account adoption is very high for both checking accounts and any interest–bearing account, however there is a substantial decrease of about 7 percentage points in the adoption of savings accounts from 2008 to 2009. More importantly, only 15 and 20 percent of the respondents do not have interest–bearing accounts in 2008 and 2009, respectively. This result is notable, because Mulligan and Sala-i-Martin (2000) reported that 59 percent of U.S. households did not have interest–bearing financial assets in 1989. This significant increase in the share of interest–bearing account adopters is an additional motivation for revisiting the issue of money demand.

As highlighted in a spate of recent research, the methods by which households can get access to funds are important determinants of cash use. This implies that the identification of partial effects of, say, interest rates on cash holdings has to take the heterogeneity in account access technologies into consideration. This is why the comprehensive information on payment instrument adoption and use in the SCPC is so advantageous. There are interesting changes in the use of payment technologies, as respondents tend to drop payment cards. Accordingly, the incidence of revolving also decreases over the sample period.

Moreover, the SCPC enables us to dig deeper into cash management practices, as it contains data on where people most often get cash (e.g. ATM, bank teller, check cashing store, retail stores, employer). These variables help us to better control for the convenience and cost of withdrawing cash. Figure 3 highlights that, as expected, withdrawal amounts vary substantially across locations, so accounting for the location can be important in the regressions. The chart also shows that the majority of the respondents either use ATMs or bank tellers to obtain cash.

3 Cash inventory management

This section reviews the Baumol-Tobin model that was used to inform cash demand estimation in the literature and extensions of it that give further insights

[3]Part of this variation might come from different composition of accounts across states. For example, in richer states more people may hold checking accounts with high minimum balance requirements and correspondingly higher interest rates.

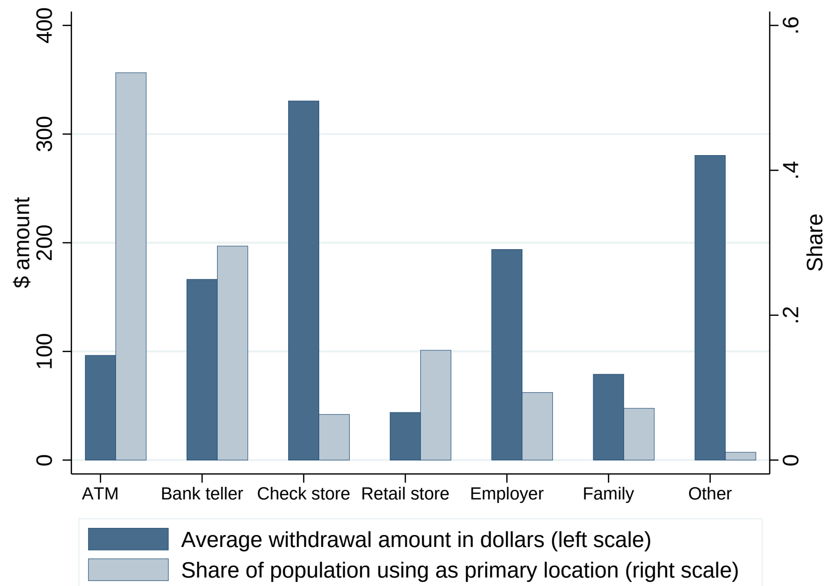

Figure 3: Cash withdrawals by location

into how certain payment technologies, such as credit cards, may affect cash demand.

The model, illustrated in its simplest form in Figure 4, assumes that individuals withdraw cash from their interest–bearing bank account to finance a predetermined stream of cash spending, so the sum of all withdrawals ($\sum W$) will equal total cash spending (C) in a period. Given this constraint, agents choose their withdrawal amount (W) to minimize the sum of withdrawal costs ($b \cdot \frac{C}{W}$) and the foregone interest earnings on money holdings ($R \cdot M$). Since cash spending, C, is assumed to be uniformly distributed over time, the average cash holdings equal 0.5 times the amount withdrawn.[4] Formally, the problem

[4]Note that since the basic model is deterministic it will always be optimal for the decision-maker to deplete her cash holdings before withdrawing money again. As Alvarez and Lippi (2009) shows, with a stochastic consumption flow individuals would get cash sooner, that is they would withdraw currency even when they still have some in their wallet as a precaution against running out of cash and thereby foregoing a consumption opportunity.
The unconditional mean of the "cash in wallet" variable in Table 1 seems to be supportive of the Alvarez and Lippi (2009) as the simple relationship in the original BT model, which predicts $M = \frac{W}{2}$, does not hold, respondents tend to have more cash on them.

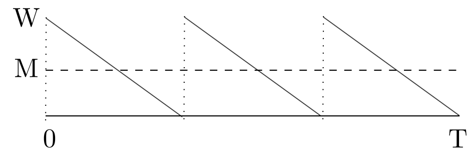

Figure 4: Baumol-Tobin model
The figure shows the prediction of the basic BT model for cash balances over time, assuming a deterministic and evenly distributed consumption stream over a period T. W denotes the amount of withdrawals while M stands for the average amount of cash holdings.

can be stated as

$$\begin{aligned} min_{M,W} \qquad & R \cdot M + b \cdot \frac{C}{W} \\ s.t. \qquad & M = \frac{W}{2} \\ \Rightarrow \qquad & M = \sqrt{\frac{bC}{2R}}. \end{aligned}$$

Taking logs yields

$$\log(M) = 0.5 \cdot \log(C) - 0.5 \cdot \log(R) + 0.5 \cdot \log\left(\frac{b}{2}\right),$$

which is the formula that has lead to microeconometric money demand estimations of the form:

$$\log(M_i) = \beta_1 \cdot \log(C_i) + \beta_2 \cdot \log(R_i) + \mathbf{X_i}'\gamma + \epsilon_i,$$

where $\mathbf{X_i}$ is a vector of proxies for the cost of withdrawing cash, a direct measure of which is rarely available to the econometrician. The withdrawal location variables should be good proxies, for example, check cashing stores charge fees explicitly for their services, while going to a bank teller involves higher time costs than using ATMs. Previous research has found that demographic characteristics are also useful proxies. The error term, ϵ_i, is usually interpreted as classical measurement error in the dependent variable. The simple model predicts an interest rate elasticity of -0.5 and a cash spending elasticity of 0.5 for both cash withdrawals and cash holdings. Section 7 provides a brief review of these estimations.

3.1 Extensions

This basic BT framework has been updated by a number of authors to incorporate the improvements in transactions technologies since the 1950's. Since the cash demand equation estimated in this study is informed by the predictions of these models, a brief review of three relevant extensions follows.

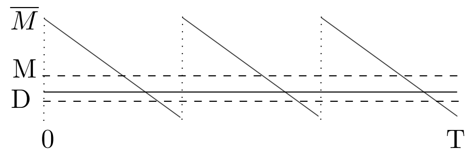

Figure 5: Baumol-Tobin model with borrowing
The main difference compared to the BT model is that consumers can now go into debt. Withdrawals will occur after cash holdings have been depleted. This means that consumers accumulate some debt (D) during the process. At the moment of the withdrawal this debt is repaid, hence the cash balance after withdrawing W will be less than $\overline{M} < W$.

3.1.1 Credit cards

A staple of the U.S. payments markets, more so than in the rest of the world, is the presence of credit cards. Sastry (1970) introduced credit card use into the BT framework, by allowing agents to continue consumption even in the event of zero cash holdings by borrowing at a "penalty rate" of interest, higher than what she earns on deposit accounts, as depicted in Figure 5. Lewis (1974) pointed out that this modification can lead to very small (in absolute value) or even positive interest rate elasticities. While the model is not a realistic description of credit card use, and White (1976) has found that it is not consistent with observed movements in checking account balances, we believe that it's simplicity makes it useful to gain some intuition on how credit cards affect cash demand.

In this model the opportunity cost of holding cash and the penalty for running out of cash are connected through the interest rates. The rational consumer takes this relationship into account when choosing a cash management policy. Depending on the correlation between the two interest rates their effects can reinforce or dampen each other. A positive correlation means that when the alternative cost of holding cash increases the penalty of a "cash-out" also increases, which provides some incentives for agents to hold more cash despite the higher foregone interest. A negative co-movement, on the other hand, suggests that these effects reinforce each other: for example, a drop in the foregone interest would already lead to increased cash holdings, which is amplified by a parallel rise in the cost of a "cash-out".

Adding credit card borrowing to the BT-model complicates the solution a bit. In the basic BT model the decision maker had only one choice variable: how much cash to withdraw, everything else followed from that. In particular, as noted above, the assumptions guaranteed that the optimal policy will be such that cash balances will be depleted before a withdrawal (see footnote 4). With borrowing, however, the lower bound of the no-action region also becomes a decision variable. Now, the decision maker will have to choose W and at what level of credit card debt to make that withdrawal, $(\overline{M} - W)$, where $\overline{M}$ denotes the amount of cash that she has in her purse right after paying off the accumulated debt from the cash just withdrawn. The optimization now becomes[5]:

$$min_{\overline{M},W} \quad R\frac{\overline{M}^2}{2W} + b \cdot \frac{C}{W} + R^{cc}\frac{(W-\overline{M})^2}{2W},$$

where the last term measures the average amount of debt over the period for a given cash holding policy. The solution for M and W is

$$\begin{aligned} W &= \left(\frac{2 \cdot C \cdot b}{R}\right)^{\frac{1}{2}} \left(\frac{R^{cc}}{R+R^{cc}}\right)^{\frac{1}{2}}, \\ M &= \frac{W}{2} = \left(\frac{C \cdot b}{2R}\right)^{\frac{1}{2}} \left(\frac{R^{cc}}{R+R^{cc}}\right)^{\frac{1}{2}}. \end{aligned}$$

These equations collapse to the BT model as $R^{cc} \to \infty$. Taking logs on both sides results in

$$\begin{aligned} \log(M) = 0.5 \cdot \log(C) - 0.5 \cdot \log(R) + 0.5 \cdot \log(R^{cc}) - 0.5 \cdot \log(R + R^{cc}) \\ + 0.5 \cdot \log\left(\frac{b}{2}\right). \end{aligned} \tag{1}$$

Compared to the BT model there are two additional terms, both involving the interest paid on credit cards. To compute the interest elasticity one can differentiate through by $\log(R)$, which, under the assumption that $\frac{\partial R^{cc}}{\partial R} = 0$, yields $-0.5\left[1 + \frac{1}{R+R^{cc}}\right]$, that is, the interest elasticity is higher (in absolute value) than in the original model.

However, it is more plausible to assume that R and R^{cc} are related by the term structure of interest rates adjusted for risk premia. In this case the above formula for the interest elasticity is altered by the cross-derivative term $\frac{\partial R^{cc}}{\partial R}$,

$$\frac{\partial \log(M)}{\partial \log(R)} = -0.5\left[1 + \frac{1}{R+R^{cc}}\right] + 0.5 \cdot \frac{\partial R^{cc}}{\partial R}\left[\frac{R}{R^{cc}} - \frac{R}{R+R^{cc}}\right], \tag{2}$$

noting that the sign of the right hand side depends on the sign of $\frac{\partial R^{cc}}{\partial R}$: for any $\frac{\partial R^{cc}}{\partial R} > 0$ $\left(\frac{dR^{cc}}{dR} < 0\right)$ the interest elasticity of cash demand will decrease (increase) in absolute value compared to the $\frac{\partial R^{cc}}{\partial R} = 0$ case.

The main takeaway from equation (1), for the purposes of this paper, is that credit card interest rate is an important variable to control for in a regression. Moreover, the correlation between interest rates on credit cards and checking accounts will alter the interest elasticities predicted by the original BT model. Unfortunately, however, we do not have data on credit card interest rates paid by individuals so it is impossible to test above specification directly. In the estimation below we will use information on credit card debt to proxy for the potential effect of credit card interest rates.

[5]For details about the model setup and solution see Sastry (1970)

Convenience users of credit cards (those who pay off their debt before the end of the grace period) face zero interest rate on credit cards, which does not vary with other interest rates (as long as they keep paying off their debt it remains zero). Consumers who revolve credit card debt (revolvers), however, face positive interest rates and these rates may vary with other interest rates in the economy. Exploiting this variation in R^{cc} that is observable in the SCPC, a model that allows for different interest elasticities for convenience users and revolvers looks like:

$$\log(M_i) = \beta_1 \cdot \log(C_i) + \beta_2 \cdot \log(R_i) + \beta_3 \cdot \log(R_i) \times revolver_i + \mathbf{X_i}'\gamma + \epsilon_i. \quad (3)$$

The important thing to remember when interpreting the coefficients in this specification is that β_3 is the product $\frac{\partial \log(M)}{\partial \log(R^{cc})} \frac{\partial \log(R^{cc})}{\partial \log(R)}$, rather than the elasticity of cash demand with respect to the credit card interest rate.

3.1.2 Free withdrawal opportunities

Recently, Lippi and Secchi (2009) introduced the possibility of free withdrawals into the BT framework, in an attempt to model the effects of ATM networks. They argue that this modification should decrease the interest elasticity and the level of cash demand. In their model, the simple relationship between average cash holdings and the number of costly withdrawals of the original BT-model, $\frac{C}{2M}$, is replaced by a decreasing and strictly convex function of the average amount of cash held, denoted by $F(M)$. One should think of a more advanced account access technology as one in which an additional dollar withdrawn lowers the number of costly withdrawals by more ($F''(M)$ is a bigger positive number). The optimization problem then becomes:

$$min_M \quad R \cdot M + b \cdot F(M),$$

with the first-order optimality condition:

$$F'(M) = -\frac{R}{b},$$

where F' denotes the first derivative of F. Totally differentiating this condition yields the key insight in Lippi and Secchi (2009):

$$\frac{dM}{dR}\frac{R}{M} = \frac{1}{\frac{F''(M)\cdot M}{F'(M)}},$$

which says that the interest elasticity of cash demand depends inversely on the elasticity of the number of costly withdrawals (F(M)) to M.[6] The interpretation is that with better account access technologies a dollar withdrawn saves more in withdrawal costs, so when consumers balance lost interest and costly withdrawals, they will be willing to forego more interest income for a given amount withdrawn hence the lower interest elasticity of cash demand.

[6]It is easily verified that in the BT model, where $F(M) = \frac{C}{2M}$, $\frac{F''(M)\cdot M}{F'(M)} = -2$.

	Baumol-Tobin	Credit cards	ATMs
		Withdrawals	
Level of cash withdrawals	$\sqrt{\frac{2bC}{R}}$	$\sqrt{\frac{2 \cdot C \cdot b}{R} \frac{R^{cc}}{R+R^{cc}}}$	$\leq \sqrt{\frac{2bC}{R}}$
Interest elasticity	$-\frac{1}{2}$	?	$[-\frac{1}{2}, 0]$
Spending elasticity	$\frac{1}{2}$	$\frac{1}{2}$	$[\frac{1}{2}, 1)$
		Average cash holdings	
Level of cash holdings	$\sqrt{\frac{bC}{2R}}$	$\sqrt{\frac{C \cdot b}{2R} \frac{R^{cc}}{R+R^{cc}}}$	$\leq \sqrt{\frac{bC}{2R}}$
Interest elasticity	$-\frac{1}{2}$	?	$[-\frac{1}{2}, 0]$
Spending elasticity	$\frac{1}{2}$	$\frac{1}{2}$	$[\frac{1}{2}, 1)$
		Number of withdrawals	
Number of cash withdrawals	$\sqrt{\frac{CR}{2b}}$	$\sqrt{\frac{CR}{2b} \frac{R+R^{cc}}{R^{cc}}}$	$F(M)$
Interest elasticity	$\frac{1}{2}$	?	$[0, \frac{1}{2}]$
Spending elasticity	$\frac{1}{2}$	$\frac{1}{2}$	$[\frac{1}{2}, 1)$

Table 2: Predicted elasticities of various models

This insight can be incorporated into the estimated cash demand equation by adding an interaction term of a measure of account access technology with interest rates. Following Lippi and Secchi (2009) we will use the number of bank branches per population in a state as a proxy for easier access to bank accounts. The cash demand equation becomes:

$$\begin{aligned} \log(M_i) = \beta_1 \cdot \log(C_i) + \beta_2 \cdot \log(R_i) + \beta_3 \cdot \log(R_i) \times revolver_i \\ + \beta_4 \cdot \log(R_i) \times branches_i + \mathbf{X_i}'\gamma + \epsilon_i. \end{aligned} \tag{4}$$

We summarize the three versions of the BT model in Table 2. All of these models have testable predictions for the interest and spending elasticities of cash holdings, the amount of cash withdrawn and the number of withdrawals.

3.1.3 Adoption of interest-bearing accounts and payment instruments

An implicit assumption behind all of the above models is that the decision-maker has access to an interest-bearing bank account and certain payment instruments. However, as Table 1 shows this is not true for all U.S. households. More importantly, the decision to open such an account is likely to be endogenous with respect to cash management practices. This means that the errors in the cash demand equations are likely to be correlated with the adoption of payment instruments. For these reasons all microeconometric studies of money demand have to model the decision to adopt bank accounts and payment instruments for the Baumol-Tobin model to be estimated consistently.

This paper assumes, following Attanasio, Guiso, and Jappelli (2002) and Lippi and Secchi (2009), that the adoption decisions for the interest-bearing checking account, debit card and credit card are three separate choices.[7] While this is clearly a simplification, note that we model *interest-bearing* account adoption, so it is feasible for someone to adopt a non-interest-bearing checking account but have a debit card.

The adoption decision in all cases is assumed to take the form of a cost-benefit analysis (see Mulligan and Sala-i-Martin (2000), Attanasio, Guiso, and Jappelli (2002)). The benefits can be thought of as interest income, or less time spent with completing transactions while the costs usually include one time setup costs and usage or maintenance costs (e.g. monthly account or card fees, minimum balance requirements). On some of these factors (such as financial wealth and interest rates) data is available, while other inputs into the adoption decision, for example, the time it takes to understand the workings of a new payment instrument, are harder to measure. If the net benefits, benefits minus costs, are positive the individual will choose to adopt an instrument:

$$\begin{aligned} z_i^* = \theta_0 + \theta_1 \cdot Y_i + \theta_2 \cdot wealth_i + \boldsymbol{\theta_3}'\mathbf{R_i} + \boldsymbol{\theta_4}'\mathbf{X_i} \\ + \boldsymbol{\theta_5}'\mathbf{importance_i} + \boldsymbol{\theta_6}'\mathbf{assessment_i} + \varepsilon_i \end{aligned} \tag{5}$$

$$z_i = \begin{cases} 1 & z_i^* > 0 \\ 0 & z_i^* \leq 0 \end{cases},$$

where z_i is a binary variable indicating adoption of an interest-bearing bank account or a payment instrument, z_i^* is a continuous latent variable, Y_i denotes family income, $\mathbf{R_i}$ is a vector of the interest rates available to the consumer, $\mathbf{importance_i}$ is a self-reported measure of the importance of payment instrument characteristics (acceptance, security and cost), $\mathbf{assessment_i}$ is a vector with respondent's assessment of these characteristics for the instrument in question. We interpret the error term as the sum of all other factors that are known to the decision-maker, but not to the econometrician (see Chapter 2 in Train (2009)) and assume that it is independent from all other explanatory variables and follows a standard normal distribution.

The variables that are included into the selection equations, equation (5), but not into the cash demand regressions are: dummies for whether respondent thinks acceptance, costs or security are the most important payment characteristics, the checking and money market interest rates for commercial banks and thrifts at the state level (in logs) and the number of bill payments per month.

Using the inverse Mills-ratios from the probit equations for payment instrument and interest-bearing account adoption in the second stage regressions will eliminate the bias due to the endogeneity of the adoption decision. The second stage equation becomes

$$\begin{aligned} \log(M_i) = & \beta_0 + \tau \cdot t + \beta_1 \cdot \log(Y_i) + \beta_2 \cdot \log(R_i) + \beta_3 \cdot \log(R_i) \times revolver_i \\ & + \beta_4 \cdot \log(R_i) \times branches_i + \gamma \cdot X_i + \rho' \boldsymbol{\lambda_i} + \epsilon_i, \end{aligned} \tag{6}$$

[7] The analysis was extended to more payment instruments, prepaid cards in particular, but the results were unchanged. For a model with more payment instruments, where individuals adopt a portfolio of payment instrument, taking the substitutability and complementarity of the instruments into account see Koulayev et al..

where M_i denotes a cash variable of interest, "usual amount of cash withdrawal at primary location", cash on person, cash on property or total cash holdings (which is just the sum of the previous two), R_i denotes the alternative cost of holding cash, Y_i denotes income (a proxy for cash spending), X_i denotes individual characteristics[8] that serve as proxies for the parameters in the BT model, $\lambda_{\mathbf{i}}$ is a vector of the inverse Mills-ratios computed from equation (5) and we allow for a time-varying intercept τ. The error term in equation (6), ϵ_i, is interpreted as measurement error in the dependent variable, which leaves the estimated coefficients unbiased.

The potential sources of the measurement error all stem from the fact that the variables in our data do not correspond perfectly to their counterparts in the Baumol-Tobin model. For example, withdrawals measure the amount withdrawn at the most frequently visited withdrawal location, not the total amount withdrawn.[9] Although cash holdings are measured more accurately, they may not correspond exactly to cash holdings used to finance everyday expenditures. These measurement problems all result in measurement errors with nonzero mean, which the constant term in the regression should absorb.

4 Estimation method

The sample and the system of equations to be estimated (three adoption equations and the cash demand equation, equations (5) and (6)) require two modifications to the Heckman (1979) procedure. Other than these adjustments, the methods used in this paper are similar to those in a number of recent cash demand estimation (see for example Attanasio, Guiso, and Jappelli (2002)).

The first adjustment to the Heckman (1979) procedure is necessitated by a "mini-panel" in our sample. The 2008 SCPC respondents were asked to participate in the 2009 wave and many of them did (for details see Appendix A)[10]. Adoption decisions in the first stage equations are likely to be highly correlated over time, for example, a respondent with a debit card in 2008 is likely to have a debit card in 2009 as well. To take this autocorrelation over time (for the panel observations) into account, random effect probit models were estimated in the first stage. In all three cases, the estimated autocorrelation in the errors were highly significant.

The second adjustment is that instead of estimating one selection equation, we have to estimate three: for interest-bearing account, credit card adoption and debit card adoption. For this reason we used the two-step version of the Heck-

[8]For the full list please refer to Table 9 in Appendix B.1.

[9]Withdrawals also have a nonstandard distribution, in that, it is a mixture of continuous distributions (resulting from, say, withdrawals at the bank) and discrete distributions (ATM withdrawal). This means that the errors in this regression are clearly not normally distributed, but the central limit theorem still applies, hence our estimates are asymptotically normally distributed.

[10]Similar econometric issues emerge in the studies that use the Bank of Italy's SHIW data set (Attanasio, Guiso, and Jappelli (2002), Lippi and Secchi (2009)), which also has a subset of respondents who are surveyed in multiple waves.

man (1979) estimator: estimating the three probit selection equations in the first step, then using the resulting inverse Mills-ratios as explanatory variables in the cash demand equation (second step) estimated with ordinary least-squares (OLS).[11] The consistency of OLS is not affected by the presence of generated regressors (the inverse Mills-ratios), however, these generated regressors cause the OLS standard errors to be biased downwards.

Following Lippi and Secchi (2009) we correct this bias by bootstrapping the standard errors, using 1000 repetitions. Given the "mini-panel" in the sample, the bootstrapping procedure itself is not entirely straightforward. Instead of bootstrapping the *observations* for the cash demand equations we bootstrapped *individuals*, thus making sure that in every bootstrap sample the composition of the sample remains the same. In other words, the number of panel observations, the number of 2008 only observations and 2009 only observations is the same in every bootstrapped sample as it is in the original sample.

Given that our sample is relatively small and shrinks further due to missing observations, we estimated the second stage equations on a pooled cross-section of all households from the 2008 and 2009 waves of the survey[12].

5 Results

5.1 Adoption equation

The adoption equations for interest–bearing accounts, credit and debit cards are presented in Table 3. The reported numbers are the marginal effects computed at the sample means.

Some common patterns across the three adoption equations emerge from Table 3. Income is highly significant both statistically and economically, a doubling of the income (from the average) would increase the chances of interest–bearing account and debit card adoption by 72 and 114 percentage points respectively and that of credit card adoption by 64 percentage points. The high correlation of income and credit card adoption is a well established fact in the literature (see, for example, Schuh and Stavins (2010) and references therein). Schuh, Shy, and Stavins (2010) describe how this can lead to transfers from low-income to high-income households. Wealth affects credit and debit card adoption, but to a lesser degree. Also the marginal effect of wealth on debit card is negative, suggesting that wealthier people are more likely to have credit cards than debit

[11]In principle this could be done using full-information maximum likelihood. Koulayev et al. estimates a bundled choice model of the adoption and use of payment instruments using the SCPC.

[12]To check the robustness of the findings we dropped the 306 panel observations from 2009, re-run the estimations and got similar results. In another robustness check, we only kept the panelists and re-run the estimations using OLS in the second-stage and again found similar results. With a fixed-effect estimator on the panel sample the results changed markedly, the point estimates became mostly insignificant. Since we only have two observations per respondent to estimate individual fixed effects we do not take this result as conclusive evidence against our specification and plan to revisit the issue of panel estimation once more data, the 2010 wave of the survey, becomes available.

Table 3: Adoption equations

	(1) Interest bearing account		(2) Credit card		(3) Debit card	
log(income)	0.721***	(0.172)	1.141***	(0.257)	0.642***	(0.186)
log(wealth)	0.0823	(0.0692)	0.291***	(0.0839)	-0.268***	(0.0782)
Age	0.00656	(0.0109)	0.0417***	(0.0140)	-0.0417***	(0.0137)
Latino	-0.251	(0.530)	-0.327	(0.511)	-0.528	(0.625)
Black	-0.142	(0.454)	-1.429***	(0.474)	-0.267	(0.505)
Male	0.136	(0.236)	-0.186	(0.254)	0.199	(0.257)
Less than high-school educated	-1.629*	(0.864)	-2.225***	(0.863)	-2.212**	(0.876)
High-school educated	-0.204	(0.310)	-1.139***	(0.350)	-0.457	(0.324)
Single	-0.486	(0.395)	-0.0404	(0.424)	-0.642	(0.441)
Married	-0.201	(0.321)	-0.0653	(0.343)	-0.454	(0.341)
Number of household members	-0.147	(0.111)	-0.359***	(0.117)	-0.162	(0.129)
Has children	0.467	(0.332)	0.306	(0.332)	0.782*	(0.404)
Employed	0.380	(0.303)	0.00421	(0.339)	0.268	(0.312)
Unemployed	-0.117	(0.979)	-1.193	(0.934)	0.0753	(1.036)
Disabled	-0.252	(0.627)	-1.372**	(0.650)	-0.110	(0.646)
Self-employed	-0.314	(0.361)	0.219	(0.459)	-0.838**	(0.362)
Income rank: 1st	0.629	(0.410)	0.436	(0.434)	0.0146	(0.488)
Income rank: 2nd	0.367	(0.474)	0.243	(0.519)	0.350	(0.559)
Income rank: 3rd	0.770*	(0.419)	-0.0998	(0.441)	-0.0182	(0.484)
Time dummy	0.334	(0.348)	-0.120	(0.418)	-0.0551	(0.372)
Branches (per 1000 residents)	0.897	(0.948)	1.343	(1.100)	-1.072*	(0.649)
Acceptance	-0.235	(0.255)	-0.358	(0.281)	-0.390	(0.274)
Cost	-0.200	(0.253)	0.0263	(0.276)	0.0287	(0.281)
Security	0.243	(0.209)	0.103	(0.229)	-0.179	(0.215)
log(commercial bank checking rate)	0.200	(0.292)	-0.240	(0.331)	0.0873	(0.300)
log(thrift checking rate)	-0.113	(0.153)	-0.124	(0.171)	0.104	(0.153)
log(commercial bank checking rate)	0.0902	(0.227)	0.301	(0.261)	-0.0398	(0.247)
log(thrift checking rate)	0.164	(0.144)	-0.0795	(0.163)	0.0780	(0.153)
Cost rating of cash	-0.869**	(0.349)				
Security rating of cash	0.391***	(0.142)				
Acceptance rating of cash	-0.124	(0.331)				
Cost rating of credit cards			0.462**	(0.214)		
Security rating of credit cards			0.326	(0.217)		
Acceptance rating of credit cards			1.840***	(0.624)		
Cost rating of debit cards					-0.0372	(0.195)
Security rating of debit cards					0.348**	(0.158)
Acceptance rating of debit cards					0.474**	(0.189)
Pseudo R^2	0.0776		0.2118		0.3789	
Observations	2055		2060		2059	

Marginal effects; Standard errors in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cards. Neither the importance of certain payment instrument characteristics nor the interest rates have significant effects on adoption. The latter contrasts with the result in Mulligan and Sala-i-Martin (2000) that a change in interest rates leads to important changes in interest–bearing account adoption. A possible explanation for this difference is that there are far more interest–bearing account adopters now than in the Mulligan and Sala-i-Martin (2000) study. Relative ratings of payment instrument characteristics, on the other hand, are highly significant.

Interest–bearing account adoption is unaffected by wealth unlike credit and debit card adoption. Individuals who rated cash as more secure than other payment instruments were more likely to open an interest–bearing account, while those who said that cash is less costly compared to other payment instruments were less likely to adopt an interest–bearing account. The latter is somewhat contrary to our intuition, those who like cash are probably using it more hence an interest–bearing account to help manage their cash inventory would be useful.

Credit cards are less prevalent among less educated or larger families, individuals with disabilities, unemployed and blacks. Those who think that credit cards are relatively cheap, widely accepted and secure are more likely to own one. The acceptance rating in particular has a very high coefficient, suggesting that any policy that affects the acceptance of credit cards relative to other instruments is likely to result in substantial substitution across payment instruments.

Debit card adoption is negatively affected by age, less than high-school education and self-employment, moreover singles and married respondents also have lower probability of adoption, while having children is positively related to debit card adoption. As for the relative characteristics, those who think that debit cards are relatively more secure or more widely accepted are more likely to adopt it.

5.2 Cash demand equations

The next two subsections discuss the results of the cash-demand estimation using withdrawals and total cash holdings as the dependent variable. The regressions for cash in wallet and cash on property will be discussed more briefly, since these latter regressions resemble the former two in many ways. As noted above, the reported regressions were only estimated on a subsample of 999 to 1,402 with interest–bearing account, debit cards and credit cards.

Tables 4 and 5 contain five different specifications for the withdrawal and the total cash holdings equations, respectively. We view the last column as the benchmark model, but as the tables show most of the point estimates are robust to the various specifications. The full estimation output, with all control variables (except for seasonal and "sampling" dummies), is in Table 9 in Appendix B.1. The first column in Tables 4 and 5 can be interpreted as a "naive" test of the model in Section 3.1 without any regard to the adoption decision outlined in the previous section or the demographic or other variables controlling for payment technologies. The following columns are the results from models with increasingly richer set of explanatory variables, adding the inverse Mills-ratios in the second column, a year and the monthly dummies in the third column, demographic variables in the fourth before estimating the complete model which also controls for payment technologies.

5.2.1 Cash withdrawals

The main finding is that while the interaction of interest rates with bank branches does not seem to be important in explaining the amount withdrawn, all of the other control variables are significant with the coefficients displaying the expected signs The magnitudes are also sensible although both the income and the interest-rate elasticities are smaller (in absolute value) than the ones predicted by the model. Most notably, the interaction of the log interest rate with the dummy for revolvers is significant both statistically and economically.

Adding the Mills-ratios to the list of regressors (column (2)) raises the spending (income) elasticity markedly. Not all of the Mills-ratios are significant, only credit card and debit card adoption has significant effect: people who are more likely to adopt these cards are also withdrawing more cash on average. Controlling for year and seasonal effects in column (3) reduces the interest elasticity somewhat, but leaves the parameters mostly unchanged.

When demographic variables are added in column (4) the income elasticity doubles and the wealth elasticity decreases, as does the interest elasticity, while the role of the Mills-ratios remaining unchanged.

Finally, the last column (5) also controls for the payment characteristic ratings, withdrawal location and the existence of rewards credit cards. In the last, benchmark regression the magnitude of the interest elasticity declines further, it remains significant at the 5 percent significance level, while the location of cash withdrawal turns out to have a big influence on the usual amount withdrawn. Controlling for withdrawal location and payment characteristics increases the adjusted R^2 substantially, from 0.164 to 0.252. Check cashing store has high positive coefficients while ATM, retail stores and family have negative ones. These results corroborate the evidence from recent cash demand estimations (for example Lippi and Secchi (2009), Stix (2004)), which found significant negative effects of ATM networks on cash holdings. In fact, given the detailed data in the SCPC we can further breakdown the non-ATM-users and find sensible results: whenever the cost of withdrawal is high, as in the case of check cashing stores, the amount withdrawn increases, while the withdrawal amount is small when withdrawal costs are low, the case of ATMs and cash back at retail stores. The more conventional explanatory variables, listed in Table 9, also have sensible coefficients: age, self-employment, unemployment and male are positively correlated with cash withdrawals, while household size is negatively related. The significance of debit card adoption disappears.

Table 4: Specifications for usual amount of cash withdrawals

	(1)	(2)	(3)	(4)	(5)	(6)
log(interest rate)	-0.125***	-0.132***	-0.111***	-0.095***	-0.085**	-0.033
	(0.033)	(0.033)	(0.035)	(0.035)	(0.033)	(0.031)
log(interest rate) × branches	0.002	0.045	0.047	0.031	0.052	0.058
	(0.056)	(0.060)	(0.060)	(0.062)	(0.053)	(0.052)
log(interest rate) × revolver	0.129***	0.131***	0.130***	0.131***	0.124***	
	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	
log(income)	0.066	0.136***	0.127***	0.246***	0.257***	0.259***
	(0.043)	(0.047)	(0.047)	(0.054)	(0.052)	(0.052)
log(wealth)	0.131***	0.122***	0.127***	0.092***	0.084***	0.099***
	(0.020)	(0.020)	(0.021)	(0.022)	(0.021)	(0.020)
Rewards credit card					0.168***	0.114**
					(0.054)	(0.053)
Cost rating of cash					-0.059	-0.118
					(0.081)	(0.082)
Security rating of cash					0.050	0.049
					(0.032)	(0.032)
Acceptance rating of cash					0.071	0.098
					(0.090)	(0.093)
Location: ATM					-0.115	-0.121
					(0.123)	(0.125)
Location: Bankteller					0.194	0.204
					(0.123)	(0.124)
Location: Check cashing store					0.699**	0.763**
					(0.342)	(0.340)
Location: Retail store					-0.781***	-0.797***
					(0.128)	(0.130)
Location: Employer					0.019	-0.002
					(0.224)	(0.217)
Location: Family					-0.583***	-0.587***
					(0.184)	(0.189)
Mills(interest bearing account)		-0.638	-0.717	-0.518	-0.378	-0.250
		(0.472)	(0.468)	(0.501)	(0.516)	(0.519)
Mills(credit card)		0.346*	0.362**	0.436**	0.412**	0.407**
		(0.178)	(0.176)	(0.182)	(0.173)	(0.173)
Mills(debit card)		1.540***	1.502***	1.105***	0.714**	0.636*
		(0.264)	(0.262)	(0.367)	(0.363)	(0.333)
Time dummy			-0.051	-0.110	0.014	-0.036
			(0.240)	(0.227)	(0.226)	(0.224)
Constant	2.831***	2.079***	2.095***	0.538	0.491	0.536
	(0.452)	(0.504)	(0.538)	(0.637)	(0.621)	(0.627)
Adjusted R^2	0.104	0.117	0.120	0.164	0.253	0.236
Observations	1402	1402	1402	1402	1402	1402

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Cash holdings—total

Table 5 presents the estimates for total cash holdings. Table 4 and Table 5 shows many similarities between the two measures on cash management, there are some differences however. The wealth elasticity is about twice as high for total cash holdings than for cash withdrawals. While the point estimate for the interest elasticity is similar to the cash withdrawal estimations, it becomes insignificant for convenience users. For the interaction term with revolvers, however, the point estimates and the significance levels are very similar to the previous estimation. The other interaction term is still highly insignificant.

The first column of Table 5 looks quite different from the last one, with the significant interest elasticity and insignificant income elasticity. Moreover the point estimate for the spending elasticity is very small, while the log of wealth matters a lot.

Controlling for the adoption decisions (column (2)) increases the income (spending) elasticity, while two of the Mills-ratios themselves are again insignificant. Adding a time dummy in column (3) changes little, but the coefficient on log(interest rate) again becomes smaller (in absolute value).

Demographic variables in column (4) have two main effects: they render the Mills-ratio from the debit card adoption equation insignificant and also raise the coefficient on log(income) and make them significant.

Finally, the last column of Table 5 containing our preferred specification, shows that payment instrument related variables do matter for total cash holdings, although increase in the adjusted R^2 is not nearly as big as in the case of the cash withdrawal equations. To sum up, for total cash holdings only revolvers have an interest elasticity that is significantly different from zero, wealth has a more pronounced effect. As for the other control variables, older, disabled, self-employed, men seem to hold more cash, and credit card rewards are still significant. People who use ATMs or retail stores most often to get cash hold significantly less currency.

5.2.3 Cash holdings—in wallet and on property

In this subsection total cash holdings are split into cash in wallet and cash on property, the results for these estimations are in columns three and four in Table 9, respectively. The results for cash in wallet resemble those in from the previous estimations, but the cash on property regressions show markedly different results. Only the specifications analogous to column (5) in Tables 4 and 5 are discussed.

For cash holdings in respondents' wallet, the narrowest measure of cash holdings in the SCPC, the interest elasticity is indistinguishable from zero in this regression just like in the previous estimation, but the significant interest rate elasticity of revolvers remains. The income elasticity in this specification is significant and of sensible magnitude, while the wealth elasticity is higher than in the "withdrawals equation", the point estimate is very close to the one estimated for total cash holdings. The relative characteristics are insignificant

Table 5: Specifications for total cash holdings

	(1)	(2)	(3)	(4)	(5)	(6)
log(interest rate)	-0.130**	-0.135**	-0.118*	-0.109*	-0.092	-0.033
	(0.059)	(0.059)	(0.061)	(0.061)	(0.059)	(0.031)
log(interest rate) × branches	-0.118	-0.084	-0.093	-0.087	-0.081	0.058
	(0.132)	(0.131)	(0.132)	(0.129)	(0.122)	(0.052)
log(interest rate) × revolver	0.104**	0.106**	0.105**	0.110***	0.110***	
	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)	
log(income)	0.086	0.134*	0.120	0.222**	0.256***	0.259***
	(0.071)	(0.079)	(0.079)	(0.088)	(0.087)	(0.052)
log(wealth)	0.241***	0.233***	0.237***	0.183***	0.180***	0.099***
	(0.031)	(0.031)	(0.032)	(0.034)	(0.033)	(0.020)
Rewards credit card					0.203**	0.114**
					(0.094)	(0.053)
Cost rating of cash					-0.038	-0.118
					(0.136)	(0.082)
Security rating of cash					-0.066	0.049
					(0.057)	(0.032)
Acceptance rating of cash					0.204	0.098
					(0.156)	(0.093)
Location: ATM					-0.600***	-0.121
					(0.160)	(0.125)
Location: Bankteller					-0.073	0.204
					(0.159)	(0.124)
Location: Check cashing store					0.113	0.763**
					(0.387)	(0.340)
Location: Retail store					-0.838***	-0.797***
					(0.182)	(0.130)
Location: Employer					0.474	-0.002
					(0.329)	(0.217)
Location: Family					-0.328	-0.587***
					(0.281)	(0.189)
Mills(interest bearing account)		-0.314	-0.284	-0.117	-0.359	-0.250
		(0.882)	(0.883)	(0.908)	(1.013)	(0.519)
Mills(credit card)		0.176	0.158	0.195	0.314	0.407**
		(0.249)	(0.247)	(0.251)	(0.274)	(0.173)
Mills(debit card)		1.161**	1.047**	0.232	-0.032	0.636*
		(0.463)	(0.457)	(0.772)	(0.718)	(0.333)
Time dummy			0.060	-0.046	0.092	-0.036
			(0.476)	(0.476)	(0.482)	(0.224)
Constant	2.310***	1.806**	2.028**	0.492	0.524	0.536
	(0.750)	(0.847)	(0.940)	(1.054)	(1.054)	(0.627)
Adjusted R^2	0.097	0.098	0.099	0.128	0.160	0.236
Observations	1355	1355	1355	1355	1355	1402

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and the importance of the withdrawal location remains. The inverse Mills-ratios are insignificant, except for credit card adoption which is significant at the 10 percent level. As for the demographic variables, they show up similarly to the total cash equation, with the exception of the employment status variables, which are not significant anymore.

For cash holdings on property, reported in the last column of Table 9 in Appendix B.1, the interest elasticity is insignificant and so is the income elasticity. The significant interest elasticity for revolvers remains but only at a 10 percent significance level. Some of the demographic variables (sex, disability and self-employment) show up as highly significant and the importance of the withdrawal location variables also remains. The adoption of different cash management technologies has no effect on this measure of cash holdings. A brief conclusion from the on property cash holdings estimations is that our control variables do not do a good job in capturing the precautionary motives for holding cash, which is probably why this broader definitions of cash holding does not behave according to the inventory theoretical model.

5.2.4 Summary

It seems to be common across all four regressions that while the adoption equations appeared to make sense on their own, they add very little to explaining cash management once we control for demographic characteristics in the cash demand (second stage) equations. This result is clearly at odds with the earlier reduced form studies and even more with Mulligan and Sala-i-Martin (2000), who emphasize interest–bearing account adoption (the extensive margin) as a key factor in money demand. There are a few ways to reconcile this difference. First, it is likely that the store of value function of money is a more important determinant of the demand for demand deposits than of the demand for cash, which would make interest–bearing account adoption a more important decision in their study. Second, their study used data from twenty years ago and in the meantime interest–bearing account adoption has increased markedly. Third, the BRM data set allows us to control for the alternative cost of holding cash more directly, which helps to disentangle the effects of financial wealth and interest rates on cash demand.

Finally, our way of controlling for credit card use identifies a potentially interesting result: it seems that the relevant interest rate for cash management for revolvers is not the one earned on checking or savings accounts but the borrowing rate on credit cards.

6 Discussion

While the estimation results already highlight a number of interesting points, due to the limitations of the data the raw coefficients are less informative about the underlying structural parameters of the theoretical cash demand models. This section bridges that gap, in particular, the cash spending and interest elas-

Table 6: Estimated interest elasticities from different specifications

	Withdrawals	Cash holdings		
		Total cash	In wallet	In property
Convenience users	-0.085	0	0	0
Revolvers	0.04	0.111	0.102	0.109

Coefficients insignificant at the 10 percent level are assumed to be zero.

ticities (the latter for convenience users and revolvers separately) is calculated from the estimated parameters.

6.1 Interest elasticity

As noted in the introduction this variable is of primary importance in monetary economics. As described in section 3.1, the interest elasticity in the presence of credit cards and debit cards can be different from the estimated coefficient on $\log(R_i)$. Since the coefficient on the interaction of the interest rate with the *branches* variable is insignificant in all specifications, we assume that is equal to zero.

For convenience users R^{cc} and $\frac{\partial \log(R^{cc})}{\partial \log(R)}$ are both zero, hence the coefficient on log(interest rate) will be the estimate of the interest elasticity. For revolvers, however, the estimated interest elasticity is the sum of the coefficients on log(interest rate) and log(interest rate) $\times$ revolver. Table 6 shows that the interest elasticity of cash demand for revolvers is positive. This finding is similar to Duca and Whitesell (1995), who found a small positive elasticity for all households. While the models reviewed in Section 3.1 can rationalize this phenomenon under certain conditions, there is little evidence that those conditions did in fact hold. A positive interest elasticity means that as interest rates fell cash holdings of revolvers had to drop as well. In the Sastry (1970) model this could happen if credit card interest rates also dropped, thereby imposing a less severe penalty on cash-outs. However, Figure 6 shows that over the sample period interest rates on credit cards went up, although there are only few available data points. In this case, the simple model would predict an increase in cash holdings to avoid running out of cash.

Given some information on the co-movement of the interest rates we could try to recover the elasticity of the cash demand with respect to the credit card interest rate. As discussed in Section 3.1 this elasticity is a function of β_3, $\frac{\partial \log(R^{cc})}{\partial \log(R)}$. While we do not have data on the credit card interest rates by individuals, we can use the aggregate series underlying Figure 6 to infer the correlation necessary to compute the credit card interest rate elasticity of cash

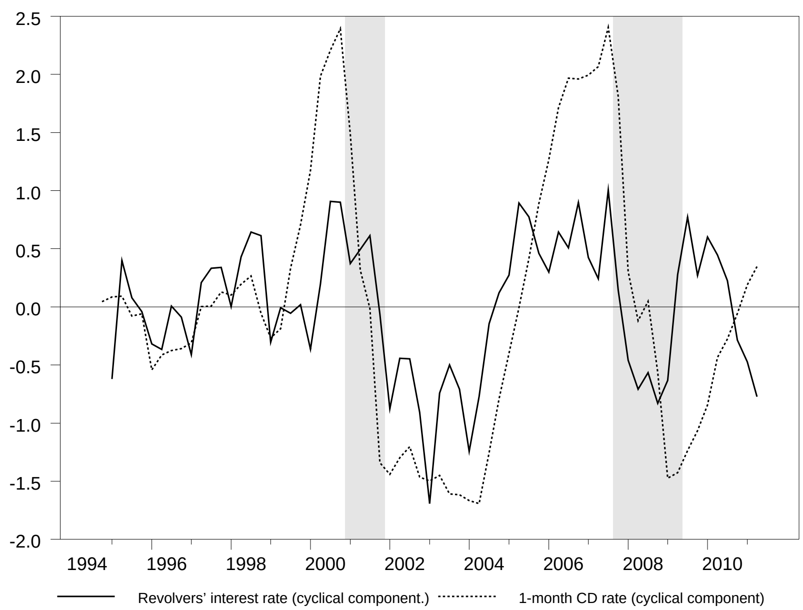

Figure 6: Interest rates on credit card debt and 1-month CDs (both series are detrended with the HP-filter)

demand (β_3) using

$$\beta_3 = \frac{\partial \log(M)}{\partial(\log(R) \times \text{revolver})} / \frac{\partial \log(R^{cc})}{\partial(\log(R) \times \text{revolver})},$$

where the numerator on the right hand side is the estimated coefficient on the interaction term from the cash demand equation. The results from these calculations using the four different cash demand specifications are in Table 7. For the SCPC sample period, 2008:Q3–2009:Q4, a correlation coefficient of -0.79 from the aggregate data depicted on Figure 6. Using this correlation to plug in for $\frac{\partial \log(R^{cc})}{\partial \log(R)}$ we get the estimates of the elasticity of the cash demand with respect to the credit card interest rate shown in the second row of Table 7. Figure 6, however, reveals that this correlation changes considerably over time, so we could get very different estimates of this elasticity. The six-quarter rolling correlation of the log of the interest rates varies between -0.8 and 0.98. The last row of the Table 7 shows the estimated credit card interest rate elasticity in the latter case[13].

Another, more plausible, explanation for the decreasing cash holdings could be the presence of precautionary cash holdings. As explained in Telyukova

[13]As the correlation approaches zero the elasticity with respect to the credit card interest rate can increase beyond any bound

Table 7: Estimates of the credit card interest elasticities from different specifications

	Withdrawals	Cash holdings		
		Total cash	In wallet	In property
$\frac{\partial \log(M)}{\partial \log(R^{cc})}$	-0.159	-0.141	-0.129	-0.138
$\frac{\partial \log(M)}{\partial \log(R^{cc})}$	0.127	0.113	0.104	0.111

Coefficients insignificant at the 10 percent level are assumed to be zero.

(2009), rational agents may hold liquid assets and credit card debt simultaneously. In that case an increase in the credit card interest rate would make this precautionary liquidity more costly and would lead agents to reduce cash holdings.

6.2 Cash spending elasticity

Since the SCPC does not have data on (cash) consumption expenditure, we use the household income variable in our regressions as a proxy for cash expenditures. This means that the estimates of the income elasticity will have to be converted back into the BT framework through,

$$\begin{aligned}\underbrace{\frac{dZ_i}{dC_i}\frac{C_i}{Z_i}}_{\text{Baumol – Tobin model}} &= \frac{dZ_i}{dY_i}\frac{Y_i}{Z_i} \cdot \frac{dY_i}{dC_i}\frac{C_i}{Y_i} \\ &= \beta_1 \cdot \underbrace{\left(\frac{dC_i}{dY_i}\frac{Y_i}{C_i}\right)^{-1}}_{\text{Inverse of the income elasticity of cash spending}},\end{aligned}$$

so the elasticity that we estimate (β_1) should be multiplied by the inverse of the income elasticity of cash spending $(dc/dy \cdot y/c)^{-1}$ to translate our estimate back into the BT model.

6.3 Revisiting the welfare cost of inflation

The estimation results showed that people with credit card debt have significantly interest elasticity of cash demand. Given the important role of the interest elasticity in measuring the welfare cost of inflation our results imply that models that do not predict this pattern are missing a salient feature of households' payment instrument use and hence a potentially important element of the welfare costs.

More generally our results direct attention to models with richer payment instrument portfolios to measure the welfare costs of inflation. Gillman (1993) and Lacker and Schreft (1996) for example build models of costly credit. In such models, shifting payments from cash to credit will involve a trade-off of foregone consumption opportunities (due to lower cash holding) and resource costs of providing payments.

7 Related literature

Much attention in the macroeconomic literature focused on trying to understand the effect of technological changes on the relationship between monetary aggregates and the real economy (see Goldfeld, Fand, and Brainard (1976), Anderson and Rasche (2001) and the references therein). The effect of new cash management practices on money demand was analyzed in Dotsey (1984), who found that controlling for such practices (most importantly, electronic fund transfers) could restore the stability of aggregate money demand functions. A comprehensive survey of the literature on money demand is beyond the scope of this paper. We refer the reader to Chapter 1 of Walsh (2003) and focus on micro level studies on cash or demand deposits that we closely follow in the rest of the paper and briefly mention how they can enhance the estimates from aggregate money demand estimations.

To our knowledge, however, there is only one paper (Daniels and Murphy (1994)) that has analyzed U.S. households' demand for *cash* using micro data. They found that ATM use, credit card use and transactions account adoption all have negative and significant effect on cash holdings. Interestingly, they also report a positive interest elasticity of cash holdings and cite Lewis (1974) as a possible explanation, but did not formally test whether credit card use could explain this.

While we are not aware of any empirical study that analyzes the effect of credit cards on interest elasticities, the effect of credit cards on money demand has also been analyzed before. White (1976) used data from a financial institution on checking account balances and credit card usage to show that credit card spending had a substantial level effect on checking account balances. His estimates show that credit card users essentially decreased their checking account balances by the amount of credit card spending.

A few studies have investigated the demand for portions of M1 using household data from the U.S.: Mulligan and Sala-i-Martin (2000) and Duca and Whitesell (1995) both estimated the demand for demand deposits. Both of these studies waves of Survey of Consumer Finances from the 1980's, which has the drawback that no checking account interest rate data is collected. For this reason, Duca and Whitesell (1995) does not report interest elasticity of their estimated money demand equations, but find, like White (1976), that credit card ownership reduces checking account deposits. As for Mulligan and Sala-i-Martin (2000), they use marginal income tax rates to proxy for interest rates, which enables them to estimate interest elasticities. As Attanasio, Guiso, and Jappelli

(2002) pointed out, the issue with this is that marginal tax rates are highly correlated with financial wealth, which makes is hard to disentangle the effect of interest rates and financial wealth on money demand. The most important contribution of their study is that they draw attention to the effect of changing interest rates on the adoption decision. As a result, the interest elasticity of money demand depends on the level of the interest rate, but remains close to zero at near-zero nominal interest rates.

While cash demand has not been analyzed much in the U.S. lately, there are a number of studies using data from Western European countries that have mostly focused on the effect of debit cards and ATM networks on cash demand. Using data from Italy Attanasio, Guiso, and Jappelli (2002) found that th interest elasticity of cash demand for ATM card holders is higher than for households without ATM cards. Using a model that allows for a more refined way to control for withdrawal technologies Lippi and Secchi (2009) find that ATM card holders have a lower interest elasticity (while both of these studies use the SHIW the latter uses more recent waves of the survey). Alvarez and Lippi (2009), using the same data as the previous study, estimates a structural model of cash use taking into effect that the consumption stream may be random. Their model implies that the interest elasticity of cash demand varies with the level of the interest rate and approaches zero as the nominal interest rate falls to zero.

In studies on the effect of ATMs on cash demand Amromin and Chakravorti (2009) founds that in OECD countries small denomination currency circulation and ATMs are negatively correlated. Stix (2004) found that ATM users hold less cash in their wallet for Austria, similar effects were found by Carbó-Valverde and Rodrìguez-Fernandéz (2009) for Spain. Bounie and Francois (2008) reports that ATM users increase their cash holdings by less following an increase in cash spending than people who withdraw money at the bank counter in France.

8 Conclusion

This paper has estimated cash demand for U.S. customers using recent data from a new, public survey, the SCPC. The data bears out some of the predictions of inventory management models both qualitatively and quantitatively, but there are also important differences. Most notably little effect of interest rates on cash holdings or withdrawals is found (intensive margin), except for credit card borrowers. Moreover, interest rates do not affect the decision to adopt interest–bearing checking accounts (extensive margin). These findings are surprising in the lights of Mulligan and Sala-i-Martin (2000) who found both the extensive and interesting margins important in earlier data.

It is worth stressing that 29 percent of SCPC respondents were revolving credit card debt in 2009, so their estimated interest elasticity could play an important role in welfare cost of inflation calculations. At the same time, the presence of nominal debt highlights the need for a general equilibrium approach to the welfare analysis as opposed to the calculations done in the Bailey (1956) tradition.

Observations	2008	2009	Total
Total	1010	2173	3183
Panel	876	876	
Pooled X-sec sample	529	873	1402
Panel	306	306	
Non-panel X-sec sample	529	567	1096
Balanced panel sample	306	306	612

Table 8: SCPC sample overview

Another key finding is that beyond the control variables commonly used in the cash demand literature the SCPC also offers some new explanatory variables that are highly significant: the primary withdrawal location influences cash management markedly. This finding shows the importance to understand *why* people use certain cash withdrawal locations, which would help to predict how quickly the transformation from cash to electronic instruments may occur, an interesting topic for future research.

Appendix A Data

Pooling the 2008 and 2009 waves of the survey produces an unbalanced two-year panel. The 2008 wave of the survey had 1,010 respondents, while in 2009 the sample size increased to 2,173. Importantly, 876 of the 2008 respondents were also in the 2009 sample. We will discuss ways to deal with this non-randomness in Section 4. The 2008 survey was designed to be representative for the U.S. non-institutionalized, adult population. In 2009 the new respondents were also drawn to be representative of this population. The estimation sample, however, is considerably smaller, since we only report estimates for a subsample who have interest–bearing checking account, credit card and debit card (see Table 1 for adoption rates). Non-response and zero response to variables that enter the estimation in logarithms further decrease the sample size. Table 8 reports the exact details for the composition of our sample.[14] In the end we are left with 1,402 observations, 529 from 2008 and 873 from 2009. Of the 529 respondents in 2008 306 took the 2009 wave of the survey, as well.

A.1 Variable definitions

Unless otherwise noted, the variables come from the SCPC.

Interest rates. Checking and money market interest rates by commercial banks and thrifts were obtained from the Bank Rate Monitor (BRM) data.

[14]The number of observations included in the second-stage regression differs somewhat across the left hand side variables, due to zero response. The largest number of zero responses occurred for cash on property, only 999 observations were left for the second-stage estimation. Table 8 shows the sample composition for the specification when the amount of cash usually withdrawn at the primary location is the dependent variable.

This was merged with the SCPC on the date (week) of the survey completion and the state of residency for every respondent in the SCPC. These four interest rates appear in the adoption equations.

In the cash use equation we looked at the subset of these interest rates for which the respondent indicated the adoption of the corresponding account. If she had access to more than one interest bearing account then we took the lowest of her interest rates as her alternative cost of holding cash. Checking account holders who did not indicate whether they had an interest–bearing checking account were assumed to earn zero interest on that account.

Family income. The SCPC has data on (annual) household income which will proxy for cash spending. Household income in the survey, however, is recorded as a categorical variable (with 17 categories). In the estimation below, we assigned to each household the average of its category's bounds as household income, to convert the variable into a continuous regressor.[15]

Income rank. Binary variables indicating whether respondents' income ranks first, second, third or forth in their household.

Branches. Another variable added to the SCPC from a different data source is the number of bank branches (per 1,000 residents) by states. The Summary of Deposits has data on the number of bank branches by states (as of June 30 of a given year), while the population estimates (by states) come from the Census Bureau. This variable is analogous to the one used by Lippi and Secchi (2009) and is used to control for the availability of modern payment technologies: a higher number corresponds to superior account access technology. While it is the case in the U.S. that bank branches have ATMs there are many ATMs outside of branches, so the number of branches per population should be interpreted as a proxy for account access technologies. Since the SCPC has information about the account access technology that respondents most often use, the number of bank branches is likely to be less important for the estimations in this paper.

Importance of characteristics. Variables "Acceptance", "Cost" and "Security" are binary variables that equal 1 if the corresponding characteristic was rated as the most important by the respondent. The survey also asks about the importance of various characteristics of the payment instruments to the respondents.[16]

[15]For the top income category we assigned the median income of households with over $200,000 in annual income from the 2007 wave of the SCF.
While this data transformation introduces a measurement error on an explanatory variable that is clearly correlated with the error term in the regression, it makes the interpretation of the estimated coefficient on income straightforward. As a robustness check, we re-ran all the estimations using dummy variables for the income categories and the results remained unchanged.

[16]These questions changed over time. In 2008, the SCPC asked for the amount of cash most often withdrawn at any withdrawal location and for the number of withdrawals at any location, while in 2009 it asked for the amount most often withdrawn from the primary withdrawal location, the number of withdrawals from the primary location and the amount usually withdrawn from all other locations and the frequency of withdrawals at these locations. In the regressions we only focus on the primary location in both years. The systematic effects of asking the questions in a slightly different way should be absorbed by the time-dummy in the regressions.

Assessment of payment instrument characteristics. The questionnaire asks respondents to rate the payment instruments on a scale of 1 to 5 based on cost, acceptance and security (5 corresponds to the best outcome, that is very low cost, very secure, very widely accepted). Following Schuh and Stavins (2010), we transformed the absolute ratings of payment instrument $i \in \{$cash, debit card, credit card, stored-value card, check$\}$ into relative ones by for example:

$$\texttt{Cost of i} = \sum_{j \neq i} \left[\log(\texttt{Cost rating of i}) - \log(\texttt{Cost rating of j})\right].$$

Hence, for this set of variables a higher value means that i is more favorable than the other payment instruments based on a particular characteristic.

For the credit and debit card selection equations we measured the relative payment characteristics ($\mathbf{assessment_i}$) relative to the respective payment instrument (credit card and debit card), whereas in the selection equation for interest–bearing account and in the second stage equations these characteristics are measured relative to cash.

Month indicators. The 2008 survey was conducted in September and October, while the 2009 wave was administered between November 2009 and January 2010. Since household spending is seasonal the benchmark regressions include monthly dummies to account for this source of the variation in the data.

Sample indicators. The American Life Panel (ALP), from which the SCPC sample is drawn, changed its source in 2009. The 2009 ALP sample is derived from the Michigan Survey of Consumers and the Stanford Face-to-Face Recruited Internet Survey Platform. To make sure that the "origin" of respondents does not affect the results, dummy variables control for this sampling effect in the regressions. For more details on the SCPC see Foster et al. (2009) and Foster et al. (2011).

A.2 Further data issues and manipulation

The following assumptions are required to convert the raw data into a format suitable for econometric estimation.

- Given that 15-20 percent of the sample reports no interest–bearing account we cannot use these observations in the money demand estimations, since the log-log model is incompatible with exactly zero interest rates. As mentioned in Section 3.1.3, however, measuring the alternative cost of holding money solely by the foregone interest earnings may be too restrictive. For example, checking account holders may enjoy other flow benefits from having an account such as the ability to pay bills conveniently on-line or keeping their money at safe, FDIC-insured institutions. Accounting for these benefits would be an interesting extension of the model.[17]

- ATM card adopters were pooled together with debit card adopters even though the two instruments are not the same, since ATM cards do not

[17] We thank Peter Ireland for this suggestion and plan to follow up on it in future work.

allow households to make purchases directly by swiping their cards. Since all households in our estimation sample will have credit cards, this will not limit their choice of payment method significantly.

Appendix B Detailed regression results

B.1 Cash demand equations

Table 9: Cash demand specifications

	Withdrawals		Cash holdings: Total cash		Cash holdings: In wallet		Cash holdings: In property	
log(interest rate)	−0.085**	(0.040)	−0.092	(0.068)	−0.066	(0.062)	−0.073	(0.092)
log(interest rate) × branches	0.050	(0.084)	−0.083	(0.167)	−0.078	(0.155)	−0.057	(0.213)
log(interest rate) × revolver	0.125***	(0.024)	0.111***	(0.043)	0.102***	(0.033)	0.109*	(0.061)
log(income)	0.253***	(0.046)	0.254***	(0.077)	0.262***	(0.064)	0.153	(0.112)
log(wealth)	0.084***	(0.020)	0.180***	(0.031)	0.150***	(0.026)	0.213***	(0.045)
Age	0.008***	(0.002)	0.011***	(0.004)	0.016***	(0.003)	0.011*	(0.006)
Latino	0.261***	(0.107)	0.107	(0.191)	0.075	(0.195)	−0.054	(0.312)
Black	0.037	(0.106)	0.058	(0.200)	−0.145	(0.155)	0.166	(0.262)
Male	0.131***	(0.049)	0.335***	(0.091)	0.237***	(0.072)	0.268**	(0.115)
Less than high-school educated	0.006	(0.464)	0.539	(0.728)	−0.088	(0.563)	1.348	(1.476)
High-school educated	0.078	(0.078)	0.022	(0.123)	0.126	(0.105)	−0.039	(0.176)
Single	0.124	(0.086)	0.013	(0.161)	−0.080	(0.130)	0.092	(0.225)
Married	−0.034	(0.061)	−0.094	(0.117)	−0.178*	(0.093)	0.000	(0.175)
Number of household members	−0.076***	(0.026)	−0.039	(0.041)	−0.071**	(0.036)	0.028	(0.058)
Has children	0.035	(0.069)	−0.090	(0.114)	−0.074	(0.108)	−0.165	(0.159)
Employed	−0.093	(0.063)	−0.053	(0.109)	0.096	(0.081)	−0.219	(0.152)
Unemployed	0.692***	(0.174)	0.208	(0.588)	0.319	(0.540)	0.547	(0.657)
Disabled	0.297	(0.203)	0.737**	(0.320)	−0.018	(0.252)	0.915***	(0.384)
Self-employed	0.216***	(0.079)	0.267*	(0.144)	0.075	(0.121)	0.474***	(0.185)
Income rank: 1st	0.162	(0.111)	0.155	(0.206)	−0.098	(0.164)	0.372	(0.300)
Income rank: 2nd	0.115	(0.122)	0.298	(0.227)	−0.242	(0.170)	0.623**	(0.314)
Income rank: 3rd	0.106	(0.107)	0.147	(0.203)	−0.238	(0.164)	0.349	(0.297)
Time dummy	0.029	(0.377)	0.102	(1.190)	−0.395	(1.092)	0.291	(1.553)
Rewards credit card	0.168***	(0.052)	0.208***	(0.081)	0.083	(0.073)	0.172	(0.122)
Cost rating of cash	−0.048	(0.087)	−0.039	(0.130)	−0.000	(0.127)	−0.133	(0.196)
Security rating of cash	0.050	(0.032)	−0.064	(0.057)	−0.014	(0.046)	−0.017	(0.076)
Acceptance rating of cash	0.069	(0.084)	0.201	(0.160)	0.159	(0.114)	−0.022	(0.217)
Location: ATM	−0.172***	(0.069)	−0.681***	(0.108)	−0.276***	(0.081)	−0.768***	(0.153)
Location: Bankteller	0.145*	(0.080)	−0.216*	(0.124)	−0.008	(0.100)	−0.118	(0.178)
Location: Check cashing store	0.752***	(0.303)	0.128	(0.357)	0.669**	(0.340)	−0.424	(0.486)
Location: Retail store	−0.830***	(0.088)	−0.907***	(0.141)	−0.654***	(0.112)	−0.873***	(0.189)
Location: Employer	0.008	(0.211)	0.435	(0.307)	0.220	(0.201)	0.805**	(0.406)
Location: Family	−0.629***	(0.138)	−0.402	(0.326)	−0.290	(0.210)	−0.107	(0.392)
Mills(interest bearing account)	−0.385	(0.959)	−0.356	(1.436)	−1.134	(1.285)	−0.345	(3.759)
Mills(credit card)	0.410**	(0.208)	0.310	(0.333)	0.579*	(0.333)	0.009	(0.449)
Mills(debit card)	0.715	(0.489)	−0.042	(0.757)	−0.070	(0.648)	−0.047	(1.354)
Seasonal dummies	Yes		Yes		Yes		Yes	
Demographic variables	Yes		Yes		Yes		Yes	
Sampling dummies	Yes		Yes		Yes		Yes	

Bootstrapped standard errors in parenthesis (1000 replications).

References

Alvarez, Fernando, and Francesco Lippi. 2009. "Financial Innovation and the Transactions Demand for Cash." *Econometrica* 77(2): 363–402.

Amromin, Gene, and Sujit Chakravorti. 2009. "Whither Loose Change? The Diminishing Demand for Small-Denomination Currency." *Journal of Money, Credit and Banking* 41(2-3): 315–335.

Anderson, Richard G., and Robert H. Rasche. 2001. "The remarkable stability of monetary base velocity in the United States, 1919-1999." Working Papers 2001-008. Federal Reserve Bank of St. Louis.
Available at `http://ideas.repec.org/p/fip/fedlwp/2001-008.html`.

Attanasio, Orazio P., Luigi Guiso, and Tullio Jappelli. 2002. "The Demand for Money, Financial Innovation, and the Welfare Cost of Inflation: An Analysis with Household Data." *Journal of Political Economy* 110(2): 317–351.

Bailey, Martin J. 1956. "The Welfare Cost of Inflationary Finance." *Journal of Political Economy* 64(2): pp. 93–110.

Baumol, William J. 1952. "The Transactions Demand for Cash: An Inventory Theoretic Approach." *The Quarterly Journal of Economics* 66(4): pp. 545–556.

Bounie, David, and Abel Francois. 2008. "Is Baumol's "Square Root Law" Still Relevant? Evidence from Micro-Level Data." *Applied Financial Economics* 18(13): 1091–1098.

Carbó-Valverde, Santiago, and Francisco Rodrìguez-Fernandéz. 2009. "Competing Technologies for Payments." Tech. Rep. 12. Fundacion BBVA.
Available at `http://www.fbbva.es/TLFU/dat/DT_12_09_competing_technologies_web.pdf`.

Daniels, Kenneth N, and Neil B Murphy. 1994. "The Impact of Technological Change on the Currency Behavior of Households: An Empirical Cross-Section Study." *Journal of Money, Credit and Banking* 26(4): 867–74.

Dotsey, Michael. 1984. "An Investigation of Cash Management Practices and Their Effects on the Demand for Money." 70: 3–12.

Duca, John V, and William C Whitesell. 1995. "Credit Cards and Money Demand: A Cross-sectional Study." *Journal of Money, Credit and Banking* 27(2): 604–23.

Foster, Kevin, Erik Meijer, Scott Schuh, and Michael A. Zabek. 2009. "The 2008 Survey of Consumer Payment Choice." Tech. Rep. 10.
Available at `http://www.bostonfed.org/economic/ppdp/2009/ppdp0910.htm`.

Foster, Kevin, Erik Meijer, Scott Schuh, and Michael A. Zabek. 2011. "The 2009 Survey of Consumer Payment Choice." Tech. Rep. 1. Available at `http://www.bostonfed.org/economic/ppdp/2011/ppdp1101.htm`.

Gillman, Max. 1993. "The welfare cost of inflation in a cash-in-advance economy with costly credit." *Journal of Monetary Economics* 31(1): 97–115.

Goldfeld, Stephen M., David I. Fand, and William C. Brainard. 1976. "The Case of the Missing Money." *Brookings Papers on Economic Activity* 1976(3): pp. 683–739. ISSN 00072303.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1): 153–61.

Ireland, Peter N. 2009. "On the Welfare Cost of Inflation and the Recent Behavior of Money Demand." *American Economic Review* 99(3): 1040–52.

Koulayev, Sergei, Marc Rysman, Scott Schuh, and Joanna Stavins. "Explaining adoption and use of payment instruments by U.S. consumers."

Lacker, Jeffrey M., and Stacey L. Schreft. 1996. "Money and credit as means of payment." *Journal of Monetary Economics* 38(1): 3–23.

Lewis, Kenneth A. 1974. "A Note on the Interest Elasticity of the Transactions Demand for Cash." *The Journal of Finance* 29(4): pp. 1149–1152.

Lippi, Francesco, and Alessandro Secchi. 2009. "Technological change and the households' demand for currency." *Journal of Monetary Economics* 56(2): 222–230.

Mulligan, Casey B., and Xavier Sala-i-Martin. 2000. "Extensive Margins and the Demand for Money at Low Interest Rates." *Journal of Political Economy* 108(5): 961–991.

Robert E. Lucas, Jr. 2000. "Inflation and Welfare." *Econometrica* 68(2): 247–274.

Sastry, A. S. Rama. 1970. "The Effect of Credit on Trasactions Demand for Cash." *The Journal of Finance* 25(4): pp. 777–781. ISSN 00221082.

Schuh, Scott, Oz Shy, and Joanna Stavins. 2010. "Who Gains and Who Loses from Credit Card Payments? Theory and Calibrations." Public Policy Discussion Paper 10-3. Federal Reserve Bank of Boston.

Schuh, Scott, and Joanna Stavins. 2010. "Why are (some) consumers (finally) writing fewer checks? The role of payment characteristics." *Journal of Banking & Finance* 34(8): 1745 – 1758.

Stix, Helmut. 2004. "How Do Debit Cards Affect Cash Demand? Survey Data Evidence." *Empirica* 31(2): 93–115.

Telyukova, Irina A. 2009. "Household Need for Liquidity and the Credit Card Debt Puzzle." MPRA Paper 6674. University Library of Munich, Germany. Available at `http://ideas.repec.org/p/pra/mprapa/6674.html`.

Tobin, James. 1956. "The Interest-Elasticity of Transactions Demand For Cash." *The Review of Economics and Statistics* 38(3): pp. 241–247. ISSN 00346535.

Train, Kenneth E. 2009. *Discrete Choice Methods with Simulation*, vol. 1. Cambridge University Press, 2nd ed.

Walsh, Carl E. 2003. *Monetary Theory and Policy, 2nd Edition*, vol. 1 of *MIT Press Books*. The MIT Press.

White, Kenneth J. 1976. "The Effect of Bank Credit Cards On the Household Transactions Demand for Money." *Journal of Money, Credit and Banking* 8(1): 51–61. ISSN 00222879.