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Household Need for Liquidity and the Credit Card Debt Puzzle

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In the 2001 U.S. Survey of Consumer Finances, 27% of households report simultaneously revolving significant credit card debt and holding sizeable amounts of low-return liquid assets; this is known as the “credit card debt puzzle”. In this article, I quantitatively evaluate the role of liquidity demand in accounting for this puzzle: households that accumulate credit card debt may not pay it off using their money in the bank, because they anticipate needing that money in situations where credit cards cannot be used. I characterize the puzzle in survey data, and calibrate a dynamic stochastic heterogeneous-agent model of household portfolio choice, where consumer credit and liquidity coexist as means of consumption and saving, where households consume a cash good and a credit good, and where cash consumption is subject to uncertainty. The model accounts for between 44% and 56% of the households in the data who hold consumer debt and liquidity simultaneously, and for 100% of the liquidity held by a median such household. Under reasonable calibration alternatives, the model can capture the entire puzzle group size as well. One-half of money demand in the model is precautionary.

Key words: Credit card debt, precautionary demand for money

JEL Codes: E21, E41

1. INTRODUCTION

In the 2001 U.S. Survey of Consumer Finances, 27% of households reported revolving an average of \$5,766 in credit card debt, with an APR of 14%, and simultaneously, holding an average of \$7,338 in liquid assets, with a return rate of around 1%. In fact, 84% of households who revolved credit card debt had some liquid assets that could be, but were not, used for credit card debt repayment. This apparent violation of the no-arbitrage condition has been termed the “credit card debt puzzle”.

This article is the first to focus on need for liquidity as an explanation for the puzzle: households that accumulate credit card debt may choose not to pay it off using money in the bank because they anticipate needing that money in situations where credit cards cannot be used. Some household monthly expenditures are not payable with credit cards. These expenses are substantial, and may be predictable (such as mortgage and rent payments, utilities, babysitting, and daycare services), or unpredictable (such as major household repairs, auto repairs, and other types of emergencies). Households face uncertainty regarding which types of expenses will be necessary in a given month, and whether credit will be accepted in payment. For example, large contractors may accept credit cards for home repairs, while smaller outfits may not. The unpredictable nature of cash needs may warrant holding large liquid balances for *precautionary* reasons, in addition to holding money for predictable cash expenses, since inability to pay in emergencies may be very

costly. Thus, even for a household with accumulated credit card debt, drawing down liquid assets below some threshold may not be optimal.

The goal of this article is to evaluate this hypothesis quantitatively, by answering two questions: (1) Can the need for liquidity account for the number of households that revolve debt while having money in the bank?; and (2) *How much* liquidity is optimal for a household, given the risk it is exposed to?

I use data from the Survey of Consumer Finances and the Consumer Expenditure Survey to study in detail the demographic and economic characteristics of households that simultaneously borrow on credit cards and save in liquid accounts. I also present evidence that demonstrates the importance of liquid assets in monthly household expenditures, and the presence of considerable uncertainty in these expenses.

Next, I develop a dynamic stochastic partial-equilibrium model of household portfolio choice. Infinitely lived households face two types of uninsurable idiosyncratic risk, consume two goods, and allocate their portfolios between two assets. There is a two-market structure; in one of the markets, credit cannot be used. The two types of idiosyncratic risk are income shocks and shocks to liquid expenses, with the latter modelled as preference shocks. Essentially, the model is a stochastic incomplete-market partial-equilibrium version of a Lucas–Stokey-style cash-credit good model.

I calibrate the model by matching it to properties of consumption out of liquid assets in household-level data, as well as to distributional characteristics in the data. To do this, I divide consumption in the data into cash-only and cash-or-credit goods, and study their relative properties. The calibration is based on the simulated method of moments. The benchmark calibrated model accounts for between 44% and 56% of households who revolve debt while holding money in the bank; for a median household in this category, the model accounts for 100% or more of its liquidity holdings. The range refers to two alternative calibrations, depending on the specification of the income process that households face. I also show that, with a reasonable alternative specification for the borrowing limit, the model can account for 100% of the size of the puzzle group, without compromising liquidity demand predictions. I then use the model to measure the quantitative contribution of each of the shocks to the puzzle. I find that expense shocks are essential for generating the puzzle group in the data, and that about one-half of the liquidity holdings in the model are precautionary.

There are four key contributions. First, I demonstrate that the liquidity-need hypothesis generates predictions that closely match the facts. Debt puzzles have prompted many researchers to question rationality in household decision making; this article shows that these puzzles can arise naturally within a standard rational-expectations framework. Second, this article is the first, to my knowledge, to separate consumption empirically into cash and credit goods, allowing measurement of a new type of idiosyncratic risk to expenses that leads to predictions of significant precautionary demand for liquidity. Third, I obtain new estimates of the elasticity of substitution between cash and credit goods. Previous attempts to estimate this elasticity, using deterministic representative-agent models, suggest that cash and credit goods are substitutes. My estimate, allowing for uncertainty in liquid consumption, indicates that cash and credit goods are complements instead. Fourth, the mechanism presented here may help account for a broader class of portfolio allocation puzzles related to co-existence of debt and liquidity.

Previous literature on the puzzle began with Gross and Souleles (2002), who document the phenomenon, and note that transaction demand for liquidity may contribute, but dismiss the contribution as likely insignificant. Lehnert and Maki (2002) study whether households may run up credit card debt strategically in preparation for a bankruptcy filing, to be discharged during the filing, while keeping assets in liquid form, in order to convert them to exemptible assets. The authors find that the puzzle is more prevalent in U.S. states where exemption levels are higher. However, my analysis indicates that most puzzle households are unlikely to file for bankruptcy,

as they hold significant positive financial and non-financial wealth. Bertaut and Haliassos (2002), and Haliassos and Reiter (2005) study whether households may hold liquidity and credit card debt simultaneously as a means of self-(or spouse) control. If one spouse in the household is the earner, and the other is the compulsive shopper, it is argued that the earner will choose not to pay off credit card debt in full in order to leave less of the credit line open for the shopper to spend. This motive is unlikely to account for many households in the puzzle category, since it is a costly way of imposing control. A household in the puzzle group loses, on average, \$734 per year from the costs of revolving debt, which amounts to 1.5% of its total annual after-tax income. Lowering the credit limit or holding fewer credit cards are readily available and less costly options for control. In complementary empirical work, Zinman (2007) suggests that “borrowing high and lending low” can arise due to the liquidity premium of checking and savings accounts, which he calculates to be significant in survey data. Laibson *et al.* (2003) examine a related puzzle: the coexistence in household portfolios of credit card debt and retirement assets. A key difference, however, is that retirement assets involve a significant penalty for early withdrawal. The authors explain this behaviour with time-inconsistent decision making by households, which makes them patient in the long run, but impatient in the short run. The explanation cannot apply to the credit card debt puzzle, because the tradeoff is between two short-run decisions, and liquid asset withdrawal does not incur a penalty.

The article is structured as follows. In Section 2, I characterize the credit card debt puzzle in the data. Section 3 lays out the model and briefly analyses its properties. Section 4 presents detailed information on the calibration strategy. Section 5 shows the fit of the model and resulting calibration. Section 6 presents the results from the calibrated model, details the shock decomposition, and discusses the results. Section 7 concludes. Some details of the data are in the Supplementary Appendix.

2. DATA

In this section, I first describe the credit card debt puzzle in the data. I then characterize household use of liquid assets in consumption, and the extent of uncertainty that households may face in liquid consumption.

I use two U.S. household surveys: the 2001 Survey of Consumer Finances (SCF) and the Consumer Expenditure Survey (CEX) from 2000 to 2002. The SCF is a triennial cross-sectional survey that has detailed information on household assets and liabilities. In particular, it distinguishes revolving credit card debt from purchase balances that are immediately paid off, and despite its cross-sectional nature, allows to assert persistence of this revolving debt. The CEX is a rotating panel, where each household is interviewed for five consecutive quarters, four of which (second through fifth) are made public. The advantage of the survey is detailed measurement of all aspects of household monthly consumption: in each interview, the household is asked to recall all of its expenditures in the preceding three months.¹ Although it is less careful about measuring assets and credit card debt, there is sufficient information on credit card debt and liquid asset holdings. I use the CEX to study the properties of household consumption in goods paid by liquid assets versus other methods.

I focus on the post-college working-age population, studying all households with heads of age 25–64 years. I separate the samples in both surveys into three subgroups: those who have

1. A total of 65% of the expenditure data are collected via direct questions about the month and amount of expenditure, while 35% of the expenditures are measured by questions on quarterly spending, and then divided into three average-monthly amounts. The latter procedure applies to food, for example. This procedure will understate volatility of consumption of such goods; see below.

TABLE 1
The credit card debt puzzle in 2001

	Borrow	Borrow and save	Save
<i>Puzzle size:</i>	<i>Percent distribution</i>		
SCF	5%	27%	68%
CEX	7%	29%	64%
<i>Interest rates:</i>			
Credit cards	14.8%	13.7%	9.8%
Checking accounts (avg. across groups)		0.7%	
Savings accounts (avg. across groups)		1.2%	

Notes: Credit cards are bank-type and store cards that allow revolving debt. Liquid assets are checking, savings, and brokerage accounts. Interest rates on checking and savings accounts are from a survey by Bruce (2002), and represent national averages for the entire population. Credit card interest rates are self-reported in the SCF.

more than \$500 in revolving credit card debt and less than \$500 in liquid assets (“borrowers”), those who have more than \$500 of both (“borrowers and savers”, *i.e.* the puzzle group), and those who have liquid assets but less than \$500 of revolving credit card debt (“savers”).² To define the puzzle group, I take only the households that revolve debt *habitually*, that is, report repaying their balance off in full only sometimes or never. As credit card debt, I include only the balance due on the credit card left over after the last statement was paid—thus excluding recent purchases and balances that were paid off. The definition of liquid assets used in this article includes checking accounts, savings accounts, and brokerage accounts (*i.e.* idle money in a brokerage house that is not being invested in stocks). As no data are collected on household cash holdings, I am not able to include currency holdings in the definition of liquidity. Under the premise that those with bank accounts do not hold much currency, the only households that are likely to be affected by this data restriction are those in the borrower category, some of whom may not have bank accounts and are thus forced to hold currency. While there are no survey data on currency holdings in the U.S., according to Prescott and Tatar (1999), between 47% and 67% of those without bank accounts in different surveys report not to have enough money to make it worth opening an account, which could be interpreted as such households spending most of their available money during the month. Since this is a small group in the data (see below), I do not expect exclusion of cash to have a strong bearing on my results. Additional details of the surveys, the sample selection process, and the puzzle measurement methods are described in the Supplementary data appendices A.1 and A.2.

2.1. *Demographics of the puzzle*

Table 1 measures the credit card debt puzzle in the data. I present measurements from both data sets to demonstrate that they are close. (The groups are very similar in both surveys in terms of relevant characteristics; I omit further comparison here.) Around 27% to 29% of the U.S. population were simultaneously borrowing and saving in 2001. Only between 5% and 7% of the population were credit card borrowers with little or no observed liquid assets, and the rest have no significant credit card debt. Notice that these numbers imply that of all habitual credit card debt

2. I choose the \$500 threshold to follow other literature on this subject. Higher thresholds still yield a significant puzzle in the data, and the subgroups’ characteristics are robust to the threshold as well.

TABLE 2
Demographics

	Borrow	Borrow and save	Save	Share in population
<i>Share of subgroup with characteristic</i>				
Race: white	0.70	0.78	0.74	0.75
Marital status: married	0.48	0.62	0.58	0.59
Have dependent children	0.45	0.41	0.39	0.40
Head works full-time	0.76	0.85	0.80	0.81
Head white-collar/prof.	0.48	0.61	0.58	0.58
Education: less than HS	0.13	0.05	0.13	0.11
HS/some college	0.73	0.61	0.51	0.55
College degree or more	0.14	0.33	0.36	0.34

Source: 2001 SCF. Weighted averages within subgroups.

revolvers, 80–84% have some liquid assets that they could in principle use to pay down their debt. The last three rows of the table give average interest rates that households report paying on their credit card debt versus national interest average rates on checking and savings accounts. Very few of the puzzle households report paying zero “teaser” interest rates on credit cards, and the average rate is around 14% for borrower–savers, around 15% for borrowers, and around 10% for savers. It is also clear that there is a significant premium in credit card rates, giving the appearance of a violation of the standard no-arbitrage condition.

Table 2 breaks down some of the demographic characteristics of the subgroups from the SCF. Each cell of the table shows a percentage of the subgroup that has the characteristic. For example, the first line shows that 70% of the borrower group, 74% of the saver group, and 78% of the borrower–saver group are white. Comparing the numbers for different characteristics to the overall sample average shown in the right column, it appears that the borrower–saver group is not demographically distinct relative to the overall population. The group is skewed very slightly towards white households (78% versus 75% overall average), towards married households (62% versus 59%), towards heads employed full-time (84% versus 81%), and in white-collar occupations (61% versus 58%). The share of households in this group with dependent children is on par with the overall average. They also tend to be slightly better educated: the group has the fewest households with education of less than high school (5% versus 11%), while the share of those with a college degree or above is the same as it is in the total sample. The saver group compares similarly to population averages, while the borrower group is the one that is least educated, comprises most unmarried households, and is skewed most toward non-white households.³

In addition, Figure 1 gives the size of the borrower–saver group by age category. While there is a slight hump in this profile between ages 30 and 50 years, the size of the puzzle is significant in all age groups, giving the impression that life-cycle differences are not the first-order issue for this puzzle.

2.2. Asset data

Table 3 presents income and asset information for each subgroup. The borrower–savers are in the middle of the income distribution; their mean after-tax annual income is \$52,114, as compared

3. These conclusions are confirmed in formal probit analysis, not presented here.

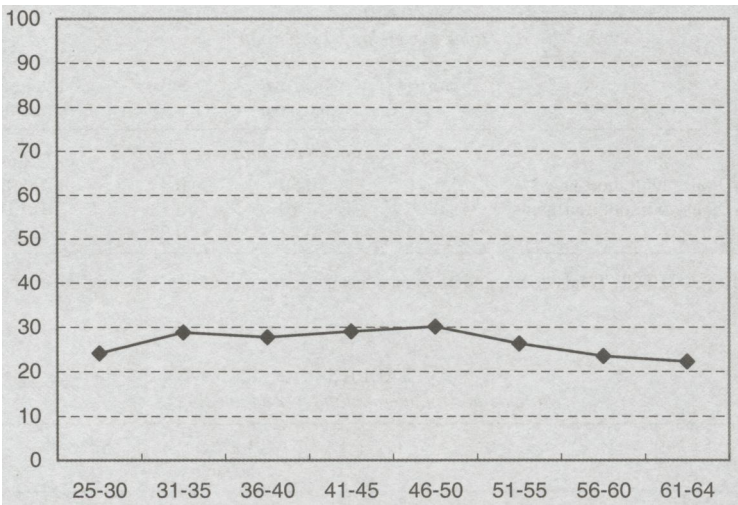


FIGURE 1
Size of the puzzle group by age, percent. *Source:* 2001 SCF

TABLE 3
Income and asset holding, U.S. dollars

		Borrow	Borrow and save	Save	B&S 45–55th debt ptile
Credit card debt:	Mean	5,172	5,766	317	3,622
	Median	3,340	3,800	0	3,800
Liquid assets:	Mean	227	7,237	17,386	7,652
	Median	200	3,000	3,200	4,000
Total after-tax income:	Mean	28,032	52,114	64,331	51,843
	Median	25,350	43,600	39,950	47,250
Other financial assets:	Mean	5,293	45,641	129,357	34,536
	Median	0	5,100	5,500	2,300
Net wealth:	Mean	36,231	187,912	466,462	181,413
	Median	9,450	84,640	104,830	104,450
Liquid assets as share of monthly after-tax income	Mean	0.12	1.71	2.53	2.15
	Median	0.10	0.79	0.88	0.9

Source: 2001 SCF. “Other financial assets” include IRA’s, mutual funds, bond and equity holdings, annuities, life insurance. Net wealth is all financial and non-financial assets, net of liabilities.

to \$64,331 for the saver group, and \$28,032 for the borrowers. They hold, on average, about 1.7 times their monthly income in liquid assets (and 0.8 in the median), as compared to the liquidity holdings of savers of 2.5 times monthly income (and equal to it in the median).⁴ Several further insights are important. First, the median borrower–saver household has \$3,000 in liquid assets. Another way to present this is in the last column of the table: a household with credit

4. A concern may arise that these numbers could be collected at the beginning of the month, say, when the paycheck has just arrived into the account. As per the Federal Reserve Board of Governors, which collects the data, SCF interviews are conducted throughout the month, and these asset numbers, averaged across households, thus represent a monthly average on the account. The Federal Reserve Board declined to release interview dates. Thus, I will treat liquidity measurements as monthly averages, and will carefully treat liquidity in the model to match the same average concept.

TABLE 4
Home ownership by subgroup

	Borrow	Borrow and save	Save	Share in population
% of subgroup with characteristic				
Own house with mortgage	0.41	0.59	0.47	0.50
Own house without mortgage	0.06	0.10	0.13	0.12
Rent	0.40	0.23	0.28	0.28

Source: 2001 SCF. Totals do not add up to one because some categories of homes are excluded.

TABLE 5
More details on financial assets and housing

		Borrow	Borrow and save	Save	B&S 45–55th debt pctlle
Money markets, CD's:	% own	3	16	23	22
	Mean	37	3,558	11,521	3,405
	Median	0	0	0	0
Mut. funds, bonds, stocks:	% own	19	46	44	51
	Mean	1,768	15,794	70,634	11,561
	Median	0	0	0	100
IRA's, annuities, life insurance:	% own	22	54	52	54
	Mean	3,287	24,670	51,735	20,757
	Median	0	1,000	500	400
Housing, net of debt:	% own	42	71	62	73
	Mean	11,016	50,612	82,088	50,475
	Median	0	27,000	28,000	37,000

Source: 2001 SCF.

card debt in the 45th to 55th percentile in the borrower–saver category has median liquid assets of \$4,000. Second, a look at the significant and positive net worth of these households suggests that strategic bankruptcy behaviour, as per Lehnert and Maki (2001), is unlikely for at least the majority of the puzzle households. Finally, note that the median household in the puzzle group, in either presentation, has credit card debt about equal to its liquidity holdings; if it were to use the liquidity to pay off debt, the household would be left with little or no money in the bank in most cases.

Table 4 shows that homeowners, especially those who still have a mortgage on their home, are more likely to be in the puzzle group. Homeowners with a mortgage constitute 59% of the borrower–saver group, compared to only 50% of the overall population, while renters are underrepresented in this group. This is important because home owners are more likely to encounter significant, and potentially unexpected, expenses on homes and their maintenance.

One fact that comes out in the previous two tables is that the households in the puzzle category do have holdings of less-liquid assets—for example, households with the median amount of credit card debt in the borrower–saver category have a median of \$2,300 in other financial assets (the corresponding mean is \$34,536, Table 3). First, these are higher-return assets, which challenges the view that the puzzle could arise from lack of financial sophistication. Second, while the median holdings of these assets are small, such assets could perhaps be liquidated to pay down credit card debt, which might be a less costly option than holding on to the revolving debt. I investigate this possibility in Tables 5 and 6.

TABLE 6
Frequency of transacting in financial and housing assets

	Borrow	Borrow and save	Save
% money mkt. holders who can write checks	0	47	66
% stock/bond holders with trading act.	7	38	48
% trading act. holders who traded ^a	100	67	78
Thus: % of stock/bond holders who did not transact ^a	93	74	63
% of home owners with cashout refinance ^a	4	3	3
% of home owners with HEL's ^a	5	1	2
% of home owners with HELOC's ^b	9	15	15

Source: 2001 SCF. ^a In the last year. ^b A current open line of credit, opened any time.

In Table 5, I break down household asset holdings in order of decreasing liquidity. First, the majority of financial assets held by borrower–saver households are retirement accounts such as IRA’s, which are subject to large penalties for early withdrawal, and thus illiquid—these constitute around 60% of financial assets. Second, a median household in the borrower–saver category has no other financial assets; only 16% of borrower–saver households have CD’s or money market accounts, and 46% of borrower–saver households have stocks, bonds or mutual funds. Third, the majority of borrower–saver households have home equity, at about \$25,000 in the median, and just over \$50,000 in the mean.

Table 6 presents the self-reported frequency of transacting in these assets. Given the number of households that have a money market account, only 4% of borrower–saver households are able to write checks on such an account, while CD’s are subject to early-withdrawal penalties. Next, about 75% of those who hold either stocks or bonds directly report not transacting in them over the previous year. In addition, 43% of stock holders have stock of their own employer, and 20% of stock holders have stock *only* of their employer, further suggesting that liquidating this stock is not an option. Finally, few households report accessing their home equity. Only 4% of the borrower–saver *homeowners* reported having either refinanced their mortgage with a cash-out option, or taken out a home equity loan (HEL). About 15% of the borrower–saver home owners, and hence just 9.3% of all borrower–savers, reported having an open home equity line of credit (HELOC).

Thus, most households in the borrower–saver category either do not have assets that they can liquidate to pay down their credit card debt, or even if they have them, do not exercise this option. This is consistent with these assets having high observed or unobserved transaction costs. For example, transacting in stocks and bonds requires payment of brokerage fees, but capital-gains tax considerations may add even more significant costs. Similarly, tapping home equity is typically quite costly, as appraisal and closing costs are usually at 1–2% of home equity. It may be cheaper even for those households that do have less-liquid financial assets not to exercise these options in order to repay credit card debt.

A related issue is the optimality of the portfolio choice in the first place where a household chooses to tie up assets in less liquid form (housing or stocks and bonds) while revolving credit card debt. From the data on holdings of less-liquid assets, it may appear puzzling that some borrower–saver households would not keep more liquidity in the bank and pay down their credit card debt, instead of allocating their portfolios to less liquid assets. However, this is not necessarily surprising. First, timing is key: these assets may have been locked up long before the household became a credit card debtor, and liquidating is then costly, as shown above. Second, thinking about housing purchase, the choice of how much money to use as downpayment is not just about

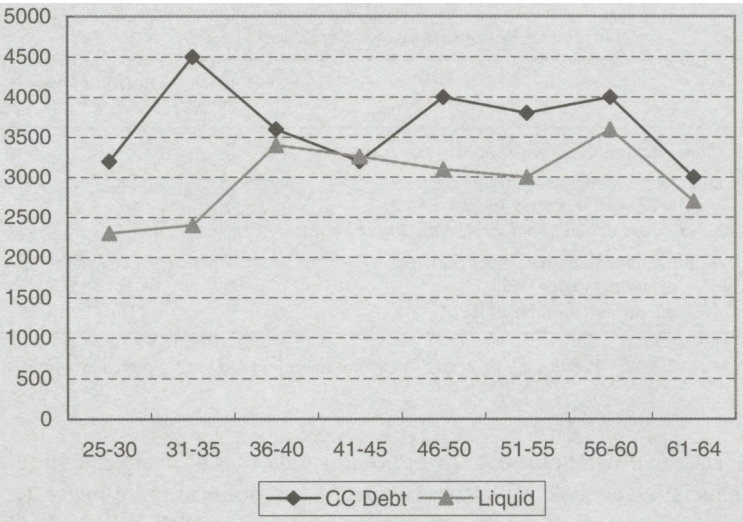


FIGURE 2
Median credit card debt and liquid assets, borrower-saver group by age

the immediate tradeoff between debt and the amount of equity, but also about the terms of the mortgage for the following 30 years. For instance, putting an extra amount into a downpayment on a house may reduce the home owner’s interest rate on the mortgage for the life of the loan; this benefit could easily outweigh the cost of carrying significant credit card debt at 14% for several years. Third, in relation to stocks and bonds, many of these assets are likely acquired passively by lower-income households, for example as compensation or through inheritance.

Finally, to address the life-cycle angle one more time, Figure 2 presents the breakdown of liquid assets and credit card debt for borrower-savers by age. These age profiles are fairly flat, confirming that life-cycle differences are not a key characteristic of the puzzle.

2.3. Liquidity and consumption

Having characterized the borrower-saver group, I now turn to characterizing the role that liquid assets play in the portfolios and consumption of these households. The evidence presented below is consistent with the hypothesis that households have liquid assets to self-insure against expense shocks in goods that cannot be paid using credit cards, which may lead them to hold liquidity simultaneously with the debt.

Table 7 shows that liquid assets play a dominant role in consumer transactions, even though credit card usage grew noticeably between 1990 and 2002. In 2002, liquid payment methods—cash, checks, and debit cards—accounted for 77% of total consumer transactions, or 65% of their total value. Adding in electronic payments that are often backed by a checking account directly, the numbers go up to 79% and 71%, respectively. In contrast, credit cards accounted for only 24% of the value of all consumer purchases in 2002.

I next characterize, using the CEX, household-level expenditures using liquid assets. I am interested in their magnitude, as well as their volatility, as a gauge of uncertainty against which households may have to insure using liquid assets. First, I separate out the group of goods that can be viewed as payable predominantly by liquid assets. Information on how people pay for a given good is not collected in the CEX. I rely on the 2004 American Bankers Association (ABA) survey

TABLE 7
Aggregate consumer transactions, shares by method of payment

	Transaction number			Transaction value			
	1999	2000	2002	1990	1999	2000	2002
Liquid	78.2	77.8	76.7	81.2	70.3	68.8	64.9
Checks	27.9	26.9	24.4	61.3	46.2	43.9	39.0
Cash	44.2	43.5	41.3	19.6	19.4	18.9	19.5
Debit	6.1	7.4	11.0	0.3	4.7	6.0	8.4
Electronic	1.5	1.8	2.4	0.7	3.4	4.2	5.6
Credit Cards	17.4	17.7	17.6	14.5	22.5	23.9	24.0

Source: Statistical Abstract of the U.S. 2003.

of payment methods to extract the relevant goods, making some conservative assumptions along the way to overcome data limitations. In this survey, consumers were asked how they normally pay at different types of stores and for different types of bills. The details of the 2004 wave of this survey are available in the Supplementary Appendix A.3.

The ABA survey confirms the aggregate consumer transaction picture: liquid payment methods dominate household expenditures. Consumers report paying house-related types of bills, such as rents, mortgages, insurance, and utilities, by check or direct debit from the account. They also tend to pay for child care and tuition with liquid instruments, though I do not include intermittent expenses such as tuition in the cash-only group, as they are likely to skew upwards the perception of volatility. Home repairs are not asked about in the survey; however, in the SCF, households name emergencies as their number two reason for saving, preceded only by retirement planning.⁵ Judging by the SCF data, households save for retirement in nonliquid retirement accounts, while emergencies, including home-related ones, by definition are likely to require liquid savings. In terms of payment methods in stores, the evidence suggests that while credit cards are dominant in department stores, gas stations and convenience stores, liquid payment methods dominate in supermarkets, drug stores, restaurants, and transit systems. Backed by this information, I choose the group of cash-only goods that consists of rents, mortgages, utilities, household maintenance, and repairs, household operations, property taxes, public transportation, health insurance, cash contributions, food, alcohol, and tobacco. For most of these goods, a liquid payment method is required. This is not true for food, alcohol and tobacco, where consumers often have the credit option. I include these as cash goods since consumers still predominantly choose to pay for them using liquid methods; this issue is discussed in more detail in the Supplementary Appendix.

The cash good group selection is designed to be conservative. First, no durable goods, such as appliance or auto purchases, are included. Thus, for example, the cash-good category excludes many situations that may be reflections of emergencies that require liquid payment—such as an emergency purchase of (or downpayment on) a durable to replace—rather than repair—a broken one. Similarly, medical payments, which include co-pays or other out-of-pocket expenses, many of which can be unpredictable and may require a liquid payment—are not included either, because some medical expenses may be payable by credit card and I do not have sufficient information to discern the liquid portion of these payments. Instead, many of the categories that are included—such as food, property insurance, etc.,—are paid on monthly basis and are predictable. Thus, in measuring the volatility of cash-good consumption using a lot of the “smooth” good categories, while excluding many that may reflect other types of emergencies, will tend to understate my

5. The question reads “What are your most important reasons for saving?” Respondents choose as many as they want in the order of declining importance.

TABLE 8
Household liquidity holding and consumption patterns

		Borrow	Borrow and save	Save
<i>U.S. Dollars</i>				
Liquid assets:	Mean	227	7,237	17,386
	Median	200	3,000	3,200
Monthly cash-only good cons:	Mean	1,659	2,223	1,763
	Median	1,464	1,979	1,512
Liquid assets/cons:	Mean	0.1	3.4	10.0
	Median	0.1	1.5	2.0

Source: SCF, CEX. Household levels, weighted averages.

measurements of the uncertainty in liquid expenditures that households face. Third, auto insurance payments and auto repairs, education expenses, and pension and insurance payments are not included as cash goods, even though many of these expenses may be liquid. I show below robustness of volatility measures to alternative definitions of the cash-only good group.

Table 8 presents household liquid asset holdings relative to average monthly consumption of cash-only goods. In the borrower–saver group, the median household has 1.5 times its average monthly liquid consumption in liquid assets, while the mean household has 3.4 times the amount. Compare these with the holdings of the savers, who have on average 10 times their mean monthly liquid spending, or twice the monthly spending amount in the median. This evidence is consistent with precautionary demand for money: households have liquid asset amounts that are in excess of what they spend on average per month, and those who are sufficiently well-off are holding much more liquidity than those in the middle. That is, richer households buffer themselves more fully, while borrower–saver households may be constrained from doing so completely, but still choose not to use all of their liquid assets to pay down debt.

To see further whether the notion of precautionary demand for liquidity is supported by the data, I look at volatility of cash-only consumption at household level as a reflection of possible uncertainty in liquid expenses that households face. Measuring raw volatility of consumption may not be fully informative about uncertainty, as it may also reflect seasonal volatility, for example, as well as other factors that may be predictable to the household. In my measurement, I first exclude from the expenditures all purchases made as gifts, to remove some of the seasonality in the consumption series. Second, I filter out the predictable component of expenditures, by estimating the following model:⁶

$$\log\left(c_{it}^{liq}\right)=\beta\mathbf{X}_{it}+u_i+\varepsilon_{it}\tag{1}$$
$$\varepsilon_{it}=\rho\varepsilon_{i,t-1}+\eta_{it}.$$

The vector **X** includes, depending on specification, household observables, such as age (a cubic), education, marital status, race, earnings, family size, home ownership status, as well as seasonal effects (a set of month dummies). Several such specifications all produced nearly identical

6. One important distinction between measuring income versus consumption uncertainty is that the measures of income volatility are often translated directly into measures of income shocks, while consumption volatility reflects only the *endogenous response* of the household to its idiosyncratic shocks, which may be larger than the response. *E.g.* after a breakdown in the home, one may choose to make fewer repairs than is recommended, to conserve the expense. This mapping between volatility and uncertainty will be discussed further in the Calibration section.

TABLE 9
Average variance of household cash-good log-consumption, monthly data

	Borrow	Borrow and save	Save
<i>Liquid consumption (residual), ε_{it}</i>			
Benchmark	0.056	0.058	0.065
Excluding food ^a	0.084	0.082	0.096
Excluding food and property taxes	0.096	0.099	0.113
<i>Unpredictable liquid consumption, η_{it}</i>			
Benchmark	0.053	0.057	0.064
Excluding food ^a	0.079	0.080	0.096
Excluding food and property taxes	0.092	0.098	0.113

Source: CEX. Measures variance over time of the unpredictable component of household log-consumption in cash-only goods, averaged across households. ^a “Food” includes food, alcohol, and tobacco.

results. u_i is the household fixed effect. The residual ε_{it} is the idiosyncratic component of liquid consumption, which I model as an AR(1) process with a normally distributed disturbance η_{it} .

Table 9, rows 1 and 4, show variance over time of log-consumption in the cash-only good category. To construct this measure, I first take the variance of the residuals ε and η over the 12 months of observation for each household, and then average this variance across households. Thus, I get the average measure of household-level consumption volatility, which I take to capture household response to idiosyncratic expense risk. First, variance of liquid consumption is significant in the benchmark measure, ranging between 0.056 and 0.065 for the total residual ε , and between 0.053 and 0.064 for η . Liquid consumption volatility is slightly higher for savers, and lowest for borrowers, which is consistent with differing ability of these groups, given their asset positions, to insure against shocks in consumption. Again, housing-related expenditures constitute the bulk of the cash-only good group and a sizeable portion of them is likely to be unpredictable. Indeed, expenses that pertain to home maintenance are the most volatile in the cash-only category, while expenses such as food are the least volatile.

To show robustness of these measures to the inclusion of food, alcohol, and tobacco, as well as to the inclusion of predictable but more “lumpy” expenditures, like property taxes, I examined many different permutations of cash-good group measurements, taking out from the benchmark measure above food/alcohol/tobacco, insurance payments, property tax payments, and other predictable expenses. I present results for two such permutations: (a) the benchmark minus food/alcohol/tobacco, and (b) group (a) minus property taxes. As is evident, the more I exclude such predictable expenses, the more volatility of the remaining group increases. The benchmark cash-good category gives by far the most dampened measure of consumption volatility. To be conservative, this is the measure I will use to calibrate the model, with the understanding that it gives a lower bound on liquid expenditure volatility.

2.3.1. Consumption volatility and measurement error in the CEX. When measuring idiosyncratic volatility in expenses in the CEX, an important concern is that this volatility, as measured by variance of ϵ above, or at least the transitory component η , is created not by underlying expense shocks, but by measurement error. This issue is worth examining further since the standard deviation of ϵ will be an important calibration target in the model. While there is uncertainty about the nature and magnitude of measurement error that is impossible to address conclusively, in this section, I use information from Attanasio *et al.* (2004, 2011) and the BLS (Garner *et al.*, 2006) to investigate its possible nature and impact on cash-good consumption.

TABLE 10
Quality of CEX data: cash-good categories, 1997 CEX

Good	Best survey component	CEX/PCE ratio	Share directly reported
Food at home*	IS	0.86	0.78
Food away*	DS	0.74	0.69
Alcohol*	DS	≈0.35	0.88
Tobacco*	DS	0.51	0.96
Household operations*	IS	1.09	0.96
Owner-occupied*	IS	1.26	
Rent + utilities*	IS	0.98	0.84
Tenant-occupied	IS	1.05	0.85
Electricity	IS	1.02	
Gas	IS	0.86	
Water	IS	0.69	
Telephone	IS	0.82	0.99
Other household ops ^a	IS	1.03	
Mass transit	IS	0.98	0.59
Taxi	IS	0.67	
Health insurance	IS	1.84	0.90
Auto repairs ^b	IS	0.67	0.91
Medical expenses, ex. insurance premia ^b	IS	0.17	0.91

*Category comparably measured between CEX and PCE (BLS). ^aOther household operations include household insurance, furnishings, repairs. ^bNot part of cash-good definition. DS and IS are diary and interview surveys, respectively. Sources: Attanasio *et al.* (2011), Bee *et al.* (2011), Garner *et al.* (2006).

For each commodity in the cash-good category, Table 10 presents three pieces of information. The first shows whether the BLS considers the good to be better measured in the diary survey (DS) or the interview survey (IS), as cited by Attanasio *et al.* (2011), Garner *et al.* (2006), and Bee *et al.* (2011). According to the table, the only goods in the cash-good group that have been shown to be better measured by the diary than the interview are food away from home, alcohol and tobacco. This suggests that the interview survey, which is the one I use, is best for the majority of the cash-good group; this is encouraging, since the interview covers a household for twelve months, while the diary—only for two weeks, which would make it impossible to measure household-level time variation in expenses.

The second column in the table reports the criterion that the BLS uses to study reliability of CEX measurement. This is the CEX/PCE ratio, which calculates how closely a particular commodity in the CEX, when aggregated using household weights, approximates total consumption of the same commodity in the NIPA Personal Consumption Expenditures measure. Garner *et al.* (2006), point out that many commodities in the CEX are measured differently than in the PCE, so that the aggregated CEX commodities are not always directly comparable and the ratio is often not equal to 1 for that reason. In Table 10, the comparably measured categories are marked by an asterisk.

As is clear, for most comparably measured goods that are in the cash-good category, the ratio of CEX to PCE is high, approaching 1, which suggests relatively accurate measurement. For example, one key category among cash goods is the household operations category, which constitutes 56% of cash-good expenses on average, and which replicates the aggregate NIPA measure very well. The most salient exception for cash goods overall are again alcohol and tobacco, and to a lesser extent, food away from home; their total share in the cash-good category is 11%. The BLS cites alcohol and tobacco as categories that are systematically underreported, due to the sensitive nature of the goods, and the CEX/PCE ratios clearly demonstrate that.

Whether one considers a CEX/PCE ratio close to 1 to be sufficient evidence of lack of measurement error depends on the model of measurement error that one has in mind. In particular, if one believes that error is mean-zero and independent across time and households, then a CEX/PCE ratio of 1 would only mean that the error nets out across households, but that at household level, there is still fluctuation created by measurement error. However, in that case we would expect the CEX/PCE ratio to be 1 for all commodities, while even for the subset of the *comparable* ones presented in the table, it is clear that the ratios are heterogeneous. If we examine comparable goods outside of the cash-good group, such as apparel, for example, we find further heterogeneity (for example, the ratio is 0.8 for shoes, 0.63 for women's apparel, etc.)

In addition, for nearly all comparably measured goods and services, we find the CEX/PCE ratio to be either at or below 1, and very rarely above (see Garner *et al.* (2006), table 2). By introspection, we might expect that measurement error could be the result of survey respondents forgetting some of their expenses. If so, when compared to NIPA data, aggregated CEX expenses should understate consumption, and the CEX/PCE ratios below 1 confirm that. Further, we might expect that households are more likely to forget smaller expenses on the goods that they purchase often, such as groceries or clothing, and remember well expenses that are caused by more major events, such as a repair. Examining the ratios broadly confirms this view; while household operations have CEX/PCE ratios of about 1, food and clothing have ratios of around 0.7–0.8. Under this view of measurement error caused by forgetting incidental expenses in more minor goods, a high CEX/PCE ratio is an indication of relatively less error in reporting.

This evidence suggests that if measurement error is present in the CEX, as is likely, it does not just consist of a classical error, but also has a significant, possibly dominant, memory error component. It is then useful to examine what this memory error would do not only for the mean of consumption, but also for the variance of measured log-consumption, relative to true consumption. To formalize the argument, in Supplementary Appendix B I present a simple example model of measurement error that includes both classical error and memory error of the sort just discussed.⁷ This model demonstrates that if memory error is present, the mean of measured consumption will be smaller than the mean of true consumption, consistent with the CEX/PCE evidence that we observe in the data. In addition, I show that sufficiently large memory error would also understate the *variance*, and coefficient of variation, of measured consumption relative to true consumption. Thus, if both classical and memory error are present, it is possible that measured consumption volatility could be understated by measurement error, rather than exaggerated, if memory error is sufficiently large. Gottschalk and Hyunh (2010) reach a similar conclusion for earnings inequality in the Survey of Income and Program Participation, showing that measurement error reduces it by 20%.

Finally, the third column of the table includes the share of observations on the given good that are directly reported, as opposed to allocated or imputed, which could be an additional source of error. Again, we see that the shares of directly reported expenses are lowest for food and alcohol, while for household operations, for instance, they are directly reported. Incidentally, this is also consistent with the presence of memory error: households may be less prone to directly report expenses that they are more likely to forget.

Table 10 includes two expense categories that are not in my cash-good definition: medical expenses, net of insurance premia, and auto repairs. I do not include them because they may be payable by credit card; however, these categories are also likely to include expenses that result from unexpected, potentially major, events and may require a liquid payment. While these categories are not defined comparably in the CEX and PCE, because in the case of both,

7. I thank Marjorie Flavin for suggesting the idea and a setup of the formal argument.

TABLE 11
Volatilities of individual cash-good categories

Good	Avg share of cash-goods	Avg household coef. of variation
Food at home	0.23	0.33
Food away	0.08	0.87
Alcohol	0.02	1.45
Tobacco	0.02	0.92
Housing expenses	0.56	0.39
Housing excl. mortgage, rent, tax	0.23	0.63
Mortgage	0.17	0.36
Property tax	0.06	0.35
Repairs/maintenance	0.03	2.26
Rent	0.11	0.39
Utilities	0.16	0.39
Other household ops.	0.03	1.52
Public transportation	0.02	2.65
Health insurance	0.05	0.71
Auto repairs ^b	0.02 ^c	2.32
Medical expenses, ex. insurance premia ^b	0.02 ^c	1.97
All cash goods	0.68 ^c	0.32

^aOther household operations include household insurance, furnishings, repairs not elsewhere classified. ^bNot part of cash-good definition. ^cShare given is of total expenses.

PCE, unlike CEX, includes payments from insurance companies and non-profits on behalf of households, they are categories that are measured well by the interview survey and are relatively free of imputation. I include them in the discussion to compare measured volatility of these expenses to that of the goods included in the cash-good group.

To sum up, although measurement error requires speculation, there is evidence that most cash goods are measured fairly reliably, that memory error appears to play a role, and that as a result, overall measurement error need not overstate volatility of consumption. I complete the discussion by measuring variability of reported consumption of each of the cash goods. Table 11 shows the results, together with average share of each good in total cash-good consumption. I report coefficients of variation (CV) of consumption, rather than standard deviation or variance of logs, because for some goods, households report zero expenses in some months. Clearly, most categories are much more volatile than food, and certainly significantly more than the cash-good category overall, in some cases by orders of magnitude. If I were to remove the more stable items from the cash-good definition, the target volatility of consumption would increase, thus increasing the degree of uncertainty that drives precautionary demand for liquidity in the model.

It is also worth pointing out that in the data over time, there is variation in relative prices of cash and credit goods that I do not observe in my short time sample, nor model explicitly. The possibility of such price variation likely affects precautionary motive of households as well, and would act similarly to the idiosyncratic preference shocks in the model. Insofar as my measurements do not capture this source of variation, the measured volatility of cash-good consumption likely understates true volatility for this reason as well.

2.4. *Data summary*

The facts that I documented in this section inform the modelling and calibration choices that I make. First, demographic analysis suggests that households in the borrower–saver category are not distinguishable from other households; in particular, there is not a pronounced life-cycle

component to the puzzle, and no obvious reason to suspect that something inherent in household preferences leads them to accumulate liquid assets but not use them to repay debt. Thus, the model is an infinite-horizon one where all agents are *ex ante* identical and have identical preferences. Second, the majority of such households have only liquid financial assets, non-liquid retirement ones, and a house with a mortgage. Those who do have home equity or other less-liquid financial assets do not frequently transact in those assets, suggesting high transactions costs. Based on this, the model will have two assets: a riskless bond and a liquid asset, which the agents use to buffer against income risk and preference risk. Third, cash-only good consumption is a significant portion of household expenses, so all households in the data appear to require liquid assets for transaction purposes, including to buffer against sizable uncertainty in consumption of such goods. The model will reflect this in the fact that households partly consume in a market where only liquid assets are accepted, and this consumption is subject to idiosyncratic preference shocks.

3. MODEL

Time is discrete. There is a $[0,1]$ continuum of infinitely lived agents. Each period is divided into two subperiods that differ by their market arrangements. There are two consumption goods: one consumed in subperiod 1, the other in subperiod 2. There are also two assets available to agents in each period. One is money, denoted m_{jt} , which represents all liquid assets, including checks and debit cards. The subscript j stands for the subperiod, while t is for the period. The other instrument is a non-contingent bond, b_{jt} , borrowing through which at a rate r_t captures consumer credit, to be interpreted as a credit card in the current context; saving in it is also allowed. In the goods market in the first subperiod, either money or credit can be used in trade. In contrast, during the second subperiod, consumer credit is not allowed in trade.⁸

During each period, households are subject to uninsurable idiosyncratic income and preference uncertainty. There is no aggregate uncertainty. The shocks on income and preferences are independent of each other, and do not realize simultaneously. At the beginning of the first subperiod, the household's income shock s_t realizes. I model $s_t \in S$ as a discrete Markov process, with $S = \{s_1, s_2, \dots, s_n\}$. The transition matrix is given by $\Gamma(s_t, s_{t+1})$, with each entry denoting probability of entering state s_{t+1} given the currently realized state s_t . Agents then supply labour inelastically and earn their income, consume with either credit or money, and allocate their resources between the two instruments in a household portfolio.

At the start of the second subperiod, the consumer's preference shock z_t realizes, also assumed to be a discrete Markov process with $z \in Z = \{z_1, z_2, \dots, z_k\}$, and transition matrix $\Pi(z_t, z_{t+1})$. After the realization of z , the second subperiod's market opens. Here, households choose consumption conditional on their preference shock realization; crucially, they cannot produce or borrow in this market, so they do not have access to additional income when they need to consume. Note that the sequential timing structure is not critical for the results. The model could have the two markets co-existing in time, for example; the important feature is only that a household makes its portfolio decisions for the entire period at its start—which is realistic, given that liquid spending opportunities can arrive continually and randomly throughout the month, while additional income does not.

8. The question of why credit cannot be used is beyond the scope of this article. There are several approaches to it in the macro literature in similar contexts: one is to assume spatial separation between the earner and the shopper, as in Stokey–Lucas-style cash-credit good models; another is to assume that agents are anonymous, as in money search models following Kiyotaki and Wright (1989). See Telyukova and Wright (2008) for a theoretical treatment of a monetary search model of money and credit that addresses the issue in more detail.

In the first subperiod, the household's state variables are its current knowledge of the idiosyncratic shock processes and its current portfolio: $x_{1t} \equiv (s_t, z_{t-1}, m_{1t}, b_{1t})$. The state in the second subperiod also incorporates previous subperiod's consumption: $x_{2t} \equiv (s_t, z_t, m_{2t}, b_{2t}, c_{1t})$. Agents take prices as given. Due to the absence of aggregate uncertainty, the environment is stationary, and hence prices are time-invariant.

Lifetime utility, non-separable in the two consumption goods, is given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_{1t}, z_t c_{2t}),$$

where it is assumed that $\forall j = \{1, 2\}$, where j denotes the subperiod, $u \in C^3$, $u_j(\cdot, \cdot) > 0$, $u_{jj}(\cdot, \cdot) < 0$, and the functions satisfy Inada conditions, $\lim_{c_j \rightarrow 0} u_j(c_j, \cdot) = \infty$ and $\lim_{c_j \rightarrow \infty} u_j(c_j, \cdot) = 0$. I assume that the preference shock is multiplicative on the utility of second-subperiod consumption. I formulate the household problem recursively.⁹ In the first subperiod, a household solves the following problem:

$$\begin{aligned} V_1(s_t, z_{t-1}, m_{1t}, b_{1t}) &= \max_{c_{1t}, m_{2t}, b_{2t}} \mathbb{E}_{z_t | z_{t-1}} V_2(s_t, z_t, m_{2t}, b_{2t}, c_{1t}) \\ \text{s.t. } c_{1t} + m_{2t} &= s_t + m_{1t} + b_{2t} - b_{1t}(1+r) \\ r &= \begin{cases} r^b & \text{if } b_{1t} \geq 0 \\ r^s < r^b & \text{if } b_{1t} < 0 \end{cases} \\ b_{2t} &\leq \bar{B} \\ c_{1t} \geq 0, m_{2t} &\geq 0 \end{aligned} \quad (2)$$

r is the interest rate that is charged on debt (or paid on savings) at the beginning of subperiod 1; there is an interest spread on r , with the saving rate below the borrowing rate. There is an exogenous credit limit \bar{B} on the household, while $b_{2t} < 0$ denotes saving in the bond.

In the second subperiod, households choose cash-only consumption, once the preference shock realizes:

$$\begin{aligned} V_2(s_t, z_t, m_{2t}, b_{2t}, c_{1t}) &= \max_{c_{2t}} u(c_{1t}, z_t c_{2t}) + \beta \mathbb{E}_{s_{t+1} | s_t} V_1(s_{t+1}, z_t, m_{1,t+1}, b_{1,t+1}) \\ \text{s.t. } c_{2t} &\leq m_{2t} \\ m_{1,t+1} &= m_{2t} - c_{2t} \\ b_{1,t+1} &= b_{2t} \end{aligned} \quad (3)$$

Notice from the third constraint that no interest on consumer debt is accumulated in this subperiod—this is the grace period typical of a credit card billing cycle. Note also that in this subperiod, no portfolio rebalancing can take place if a household experiences a low shock and has money left over at the end of the period. This restriction captures the continual nature of unpredictable expenses in the data: since in reality, expense shocks could hit any time throughout the month, a low expense shock at any point would not cause the household to spend the remainder of its precautionary liquid balances to pay off debt before the month is over.

9. The Principle of Optimality applies here as is standard. In addition, existence and uniqueness are guaranteed as long as standard assumptions are made on the utility function and the constraint space to make the problem bounded.

Using the state-variable notation defined above, the stationary decision rules from the first-subperiod problem are $c_1(x_{1t})$, $m_2(x_{1t})$, and $b_2(x_{1t})$; the decision rule of the second-subperiod problem is $c_2(x_{2t})$. In addition, let $\lambda(x_{1t})$ and $\mu(x_{2t})$ be the Lagrange multipliers associated with the credit constraint and the money constraint, respectively. We get the following Euler equations, which, along with the budget constraint and the Kuhn–Tucker conditions on the multipliers characterize the solution to the household decision problem:

$$\mathbb{E}_{z_t|z_{t-1}} u_1(c_{1t}, z_t c_{2t}) = \mathbb{E}_{z_t|z_{t-1}} \{ \beta \mathbb{E}_{s_{t+1}|s_t} \mathbb{E}_{z_{t+1}|z_t} u_1(c_{1,t+1}, z_{t+1} c_{2,t+1}) + \mu_t \} \quad (4)$$

$$\mathbb{E}_{z_t|z_{t-1}} u_1(c_{1t}, z_t c_{2t}) - \lambda(x_{1t}) = \mathbb{E}_{z_t|z_{t-1}} \{ \beta \mathbb{E}_{s_{t+1}|s_t} (1+r) \mathbb{E}_{z_{t+1}|z_t} u_1(c_{1,t+1}, z_{t+1} c_{2,t+1}) \} \quad (5)$$

$$z_t u_2(c_{1t}, z_t c_{2t}) = \beta \mathbb{E}_{s_{t+1}|s_t} \mathbb{E}_{z_{t+1}|z_t} u_1(c_{1,t+1}, z_{t+1} c_{2,t+1}) + \mu_t \quad (6)$$

In this model, households will insure against income shocks by saving in the bond b (or, on the flip side, by taking out consumer loans against this asset for consumption in the first subperiod), and against preference shocks by setting aside a part of their assets in the liquid asset m each period. That is, income uncertainty does not affect precautionary motive for holding liquidity, as the portfolio can be rebalanced every period; similarly, preference uncertainty does not lead to precautionary bond demand. Also, the bond here is modelled as one asset: households can borrow against it or save in it, but never do both. One could model this asset as two separate ones, but as long as the bond remained as liquid as it currently is in the model (*i.e.* no transactions costs for liquidation), and the interest rate on saving is below the interest rate on borrowing, no household would ever not deplete its holdings of the bond to repay all of the consumer debt. Hence, capturing these as one asset delivers the same result.

The population subgroups in the model are generated endogenously by idiosyncratic shock dynamics. Some agents may, after a series of low income shocks, find themselves depleting their savings in the bond and going into debt, but even when they accumulate debt, they will always choose to hold positive amounts of the liquid asset. These will be the “borrower–savers” in the model, and the point of the computational exercise is to evaluate how large this group can be, and how much money they will choose to hold optimally even when it co-exists with consumer credit. The “saver” and “borrower” groups also come naturally out of the model. If a household borrows against b and then is hit by a high preference shock, and as a result spends all of its money holdings at the end of the period, it will be classified as a “borrower” for that period, as we will observe it at one point during the period as having no liquidity. If a household has savings in the asset b , then regardless of its liquidity position, it will be classified as a “saver”. Clearly, households in the model will move in and out of these subgroups depending on their income and preference shock histories, so that no households would be in any subgroup permanently. This feature is mirrored in the data.

In order to compute the model, I merge the assets m_1 and b_1 into cash on hand in the first subperiod. I solve the problem of the household in two stages: the first-subperiod problem (the outer maximization) is solved by value function iteration with piecewise linear interpolation, while the second-subperiod problem (the inner maximization) is solved directly from the first-order condition, by approximating the derivative of the value function.

4. CALIBRATION

I choose model period to be a month, which is a natural frequency for studying household decisions that involve credit card statements and paychecks. The functional form for the household utility function is of the standard CRRA form, which incorporates a CES aggregator between the two

consumption goods:

$$u(c_{1t}, z_t c_{2t}) = \frac{((1-\alpha)c_{1t}^\nu + z_t \alpha c_{2t}^\nu)^{\frac{1-\gamma}{\nu}}}{1-\gamma} \text{ with } \gamma > 1.$$

The utility function gives three parameters to calibrate: α , ν and γ . β , the discount factor, is the fourth. The other parameters have to do with the shock processes on income and preferences, as well as prices (the interest rates). I calibrate the parameters of the income process outside the model and set $\gamma = 2$ to be in lower part of the standard range in the literature. I set the debt limit B to be equal to one-half the largest annual income in the economy for all households; I discuss the sensitivity of the results to this choice below. The monthly interest rate on saving in nonliquid financial assets is set to match the annual rate of 4%, so that $r_s = 0.0033$. I set $r_b = 0.011$, which corresponds to the annual rate of 14%, the average interest rate paid on revolving credit card debt as reported by the debtors I observe in the SCF.

I estimate the remaining parameters within the model by a minimum distance estimator. I select the target moments to be unrelated to the main data observations of interest—the size of the credit card debt puzzle in the data, as well as the magnitude of household liquidity demand; these key quantities are left free to gauge the performance of the hypothesis.

4.1. *Income process*

The calibration of the income process at monthly frequency is a non-trivial task, as the longitudinal income data that are available and normally used for measuring idiosyncratic risk are annual. In order to calibrate the income process for the model, I use estimates of income uncertainty after observables have been controlled for from two different studies: Guvenen and Smith (2010), hereafter GS, and Heathcote *et al.* (2010), hereafter HSV. The two estimates differ by how they control for observables; in GS, the estimation is based on a heterogeneous-income-profile specification, while in HSV, the specification is a homogeneous-profile one. From each, I use the estimates of the residual income process consisting of an AR(1) component with persistence parameter ρ_s and standard deviation of innovation σ_η , and a transitory component with the standard deviation σ_ε . The GS parameters are given at annual frequency by $\rho_s = 0.75$, $\sigma_\eta = 0.19$, $\sigma_\varepsilon = 0.15$. The HSV estimates are $\rho = 0.97$, $\sigma_\eta = 0.10$, $\sigma_\varepsilon = 0.25$. I explore these two alternatives in my model because they have different implications in terms of the nature of risk that households face.

I convert these parameters into a monthly income process by simulating, at monthly frequency, a log-income process that also has the AR(1) + transitory component structure. The simulated monthly observations are then aggregated into annual ones, on which I estimate the annual process as described above. This estimation is done by a minimum-distance estimator on the variance-covariance matrix as described in Guvenen (2009). The monthly parameters ρ_s^m , σ_η^m , and σ_ε^m are estimated by recursion, such that the postulated monthly process aggregates to one with the annual parameters listed above. For the GS process, I get $\rho_s^m = 0.975$, $\sigma_\eta^m = 0.076$, and $\sigma_\varepsilon^m = 0.576$; for the HSV process, I get $\rho_s^m = 0.997$, $\sigma_\eta^m = 0.04$, and $\sigma_\varepsilon^m = 0.75$. I discretize these processes into a six-state Markov chain using the Rouwenhorst (1995) discretization method.

4.2. *Idiosyncratic preference risk*

The remaining parameters—the discount rate β , the parameters of the consumption aggregator α and ν , and the preference process parameters—are calibrated together within the model. In this

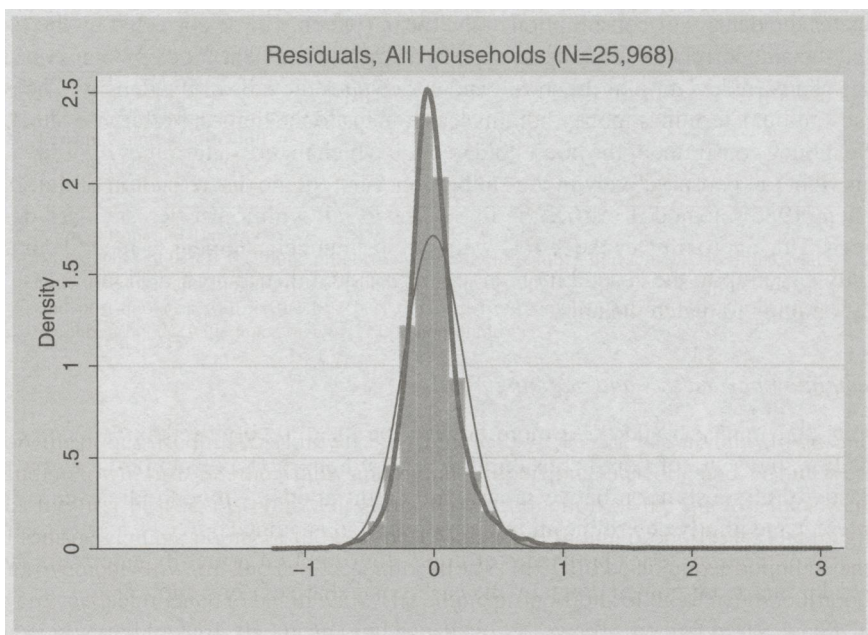


FIGURE 3
Residuals of log-consumption of the cash good, benchmark measure, all households

subsection, I describe in some detail the calibration of preference shocks. In the subsection that follows, the remaining parameters are described.

For the preference shock parameters, I assume that the log of the preference shock, $\log(z_t)$, follows an AR(1) process with a Gaussian disturbance, so the parameters to calibrate are persistence ρ_z and standard deviation σ_z of this process. I then discretize this AR(1) into a five-state Markov chain. The choice of an AR(1) is motivated by the idea that households have both constant pre-committed expenditures, and some additional expenditure shocks (extreme events), both of which have to be captured in the shock process. In terms of data already described, the shock’s AR(1) is meant to mirror the AR(1) in the residual of liquid consumption ε_t , as described in (1).

The preference shock process is clearly not observed in the data, but the way households respond to these shocks is, through their liquid consumption. Thus, the preference shock process has to match properties of log-consumption of cash-only goods in the data, namely its persistence (measured as autocorrelation) and volatility (standard deviation). For the calibration targets, the standard deviation is computed by subgroup of households, so in total, I get four calibration targets for the shock process. As described extensively in the data section (Table 9), the volatility of liquid consumption is sensitive to how the cash-good group is computed. Of all the measures that I have examined, the benchmark measure (the most inclusive) produces the smallest volatility of consumption; in the estimation below, I use this benchmark measure for maximum discipline on the model.

To convince the reader that normal disturbances are a reasonable assumption for the shocks, and that the calibration does not overstate the tail shocks, Figure 3 plots the consumption residual ε_{it} for the benchmark measure of liquid consumption, together with a non-parametric kernel estimator of its density (thick red line) and the corresponding normal approximation (thin green line). According to the graph, normal distribution approximates the actual distribution well. While

it understates the density of consumption at the mean (which will be corrected by the fact that I will match the autocorrelation of consumption as a targeted moment), it overstates consumption within one standard deviation of the mean, and understates the tails of the density. The right tail of the distribution determines money holdings, as it maps to the highest preference shock, which causes the money constraint of the household to bind, which in turn determines liquidity demand. I treat this right tail conservatively in the calibration. First, in the discretization of the shocks by the Tauchen (1986) method, I restrict the five states to fall within just two standard deviations of the mean. This approximates the AR(1) well, but is an understatement of the tails in the data. Also, I only target up to the second moment of the residual distribution of liquid consumption, without attempting to match the tails.

4.3. *Remaining parameters and mapping to targets*

To calibrate β , α and ν , I add three more targets: the mean revolving debt-to-income ratio in the population, the share of liquid consumption in total household consumption, and a measure of the elasticity of substitution between cash and credit goods. Although all seven calibration targets interact and jointly determine all five parameters, β is pinned down primarily by the debt-to-income ratio, the time series properties of liquid consumption primarily determine the shock process, and α and ν are pinned down by the cash-good share of consumption and the elasticity measure.

The estimation of the parameter ν as part of the SMM procedure deserves some attention, as it is non-standard. Previous estimates of this parameter come from deterministic cash-credit good models, in which the cash-in-advance constraint always binds, so that aggregate cash-good consumption equals aggregate money demand. A direct implication of this class of models is that ν can be measured in closed form from the regression coefficient that measures sensitivity of aggregate money demand to the gross nominal interest rate. In contrast, in my model cash-good consumption and money demand are distinct, due to the presence of idiosyncratic risk, so that the cash-in-advance constraint is often not binding. As a result, the model no longer has a closed-form implication for the parameter ν . This is discussed in more detail in the next section.

Instead, I run a similar regression on household-level data, using the interest rate that the household currently faces as the measure of the opportunity cost of holding cash, and thus of the cost of the cash good. The regression is: $\ln(c_{2i}/c_{1i}) = \kappa_0 + \kappa_1 \ln(1 + r_i) + \omega_i$. Those who are debtors face a different opportunity cost of the cash good ($r_i = r^b$) than those who are savers ($r_i = r^s$); I measure the sensitivity of the cash-credit good ratio to the cross-sectional variation in this cost. Since this regression parameter does not directly translate into the parameter ν in closed form, I will run the same regression on simulated model data and estimate ν such that the two regression coefficients match.

The CEX does not provide information on the interest rate that the households are paying on their credit card. To measure r^b in the CEX, I use the fifth-interview question on the finance charges that the household reports paying on the credit card, dividing that amount by the average of the two credit card balances reported by the households in the second and fifth interviews. For households who are not debtors, I assign the current Federal Funds rate (based on month and year) as the bond interest rate.¹⁰ The resulting regression gives the coefficient of about -0.29 on the interest rate (with a standard error of 0.037), suggesting a negative relationship, as would be expected, but little sensitivity of the consumption ratio to the interest rate.

I measure the cash-good share of household consumption directly in the CEX at household level, then average across households. The last target, the debt-to-income ratio, gauges how well

10. The results are robust to using the 3-month Treasury Bill rate instead.

TABLE 12
Calibration targets—data and model

Target	Data	Model (GS inc.)	Model (HSV inc.)
<i>Autocorrelation (annual) of log liquid consumption:</i>	0.226	0.226	0.223
<i>St. dev. of log liquid consumption: Borrowers</i>	0.203	0.158	0.164
<i>Borrowers and savers</i>	0.211	0.212	0.212
<i>Savers</i>	0.217	0.248	0.236
<i>Share of liquid cons in total</i>	0.683	0.628	0.696
<i>Regression coefficient: $\log(c_2/c_1)$ on r</i>	−0.285	−0.257	−0.273
<i>Mean debt/income ratio</i>	0.070	0.071	0.069

the model does in reproducing the most relevant dimension of the aggregate economy, given the article’s focus. As the debt measure, I choose total revolving debt, computed in the SCF. This measure includes all unsecured debt as well as home equity lines of credit, with credit card debt in the vast majority, since the uptake of home equity lines is very low in the 2001 data.

In sum, I estimate the five parameters within the model based on seven moments. For each set of parameters in the minimization process, the procedure solves the model, simulates a 502-month panel of 100,000 households, computes the moments from it, and compares them with the moments in the data. I use the simplex method of Nelder and Mead (1965), parallelized at parameter level as suggested by Lee and Wiswald (2007). The weighting matrix is the identity matrix in the first step, subsequently adjusted to correct for moments computed with highest variance (those moments that concern the borrower group, which is smallest in the data). Data covariances of the moments in question are not possible to compute in this exercise, since the moments come from two different data sets.

5. MODEL FIT AND RESULTING PARAMETERS

I present the results of two calibrations, one with the GS income process, and one with the HSV process. In each case, all the parameters are re-estimated to the same targets. In order to assess the fit of the calibrated model, Table 12 presents the target moments in the data and the model.

The calibrated model fits most targets closely. The model with the GS income calibration understates the share of liquid consumption in total consumption slightly (model’s 0.63 versus the data’s 0.68). It matches nearly perfectly the standard deviation of log-liquid consumption for the borrower–saver group, although it overpredicts somewhat the dispersion of that moment across groups. All other targets are matched very well. Under the HSV calibration, this pattern is repeated, with the share of liquid consumption in total and the dispersion of standard deviation of liquid consumption for savers closer to the data.

Table 13 presents the two resulting calibrations; the parameters are similar in both, with the exception of σ_z . The discount factor in the two calibrations is equivalent to 0.91 in annual terms. The parameters of the CES aggregator are in themselves of interest and a contribution of this article, as discussed above. In order to match the high cash-good share of consumption, α , the weight on cash-only goods in the CES utility function has to be high, at 0.93–0.96. The parameter that measures elasticity of substitution between cash and credit goods is between −2.36 and −3.48, that is, cash and credit goods are complements rather than substitutes, with the elasticity of substitution of 0.22–0.3.

TABLE 13
Calibration

	Parameter	Model (GS)	Model (HSV)
Interest rates	r_s	0.0033	0.0033
		(annual $r_s=0.04$)	
Risk aversion/IES	r_b	0.0107	0.0107
	γ	2.0	2.0
Income process parameters	ρ_s^m	0.975	0.997
	σ_η^m	0.076	0.040
	σ_ε^m	0.576	0.750
Discount rate	β	0.992	0.992
Consumption aggregator parameters	α	0.934	0.954
	ν	-3.482	-2.360
Preference shock process: AR(1) with discretization	ρ_z	0.536	0.494
	σ_z	0.947	0.585

It is worthwhile to compare these estimates to previous ones from the deterministic cash-in-advance literature. For example, Chari *et al.* (1991) and others after them find a lower estimate for α of around 0.62. Their ν tends to be on the order of 0.79–0.84, producing the elasticity of substitution on the order of 4.76 to 6. These results come from the model where, as I discussed above, (aggregate) money demand and liquid consumption are equal to each other. Once idiosyncratic preference uncertainty is introduced into the model, aggregate liquid consumption becomes much less sensitive than money demand to nominal interest rates, because all the households who do not hit their liquidity constraint have liquid consumption that is not sensitive to the movement in interest rates. (See also Telyukova and Visschers (2011)). Insofar as the elasticity of substitution can still be linked to this sensitivity, the elasticity should be expected to be much lower in this model than in the deterministic version, which is confirmed in my results using micro data.

Finally, the estimates of the preference process are of importance, since this study presents a new, and to my knowledge first effort to quantify unobservable idiosyncratic uncertainty specific to liquidity needs. The estimated monthly AR(1) parameter on $\log(z)$ is around 0.49–0.54. The AR(1) specification is flexible, encompassing anything from a very persistent shock process to an i.i.d. one; these estimates suggest that the extreme realizations of the shock are not persistent, which is to be expected given the properties of liquid consumption discussed in Section 2. The standard deviation of the shock process is estimated at 0.95 in the GS calibration, but only 0.59 in the HSV calibration. Under HSV, the agents face more persistent income risk and higher income dispersion, so the preference shocks need not be as disperse to match household-level standard deviation of liquid consumption over time.

Based on the analysis of the calibration targets, the parameterization described above produces a realistic economy in terms of the mapping to the relevant data dimensions. In Table 14, I examine in addition the model’s implications for cross-sectional dispersion of annual income and consumption. Overall cross-sectional dispersion in the data results from many types of heterogeneity across households, from which the model abstracts.¹¹ The income calibration takes this into account by putting in only the residual income dispersion, estimated after observables such as labour experience have been controlled for in panel data. I construct a comparable measure

11. In my sample, overall cross-sectional variance of log-income is 0.45 and of log-nondurable consumption is 0.24, which is in line with the numbers reported, *e.g.* by Krueger and Perri (2005).

TABLE 14
Cross-sectional dispersion of annual income and consumption

Target	Data	Model (GS)	Model (HSV)
<i>Variance of income (GS)</i>	0.11	0.13	
<i>Variance of income (HSV)</i>	0.25		0.31
<i>Variance of cash-only consumption</i>	0.17	0.08	0.31
<i>Variance of cash-or-credit consumption</i>	0.54	0.07	0.24
<i>Variance of total nondurable consumption</i>	0.20	0.07	0.29

Notes: The measures of variance here refer to the residual variance of the log-variable, once observables have been controlled for. See text for details.

of residual variation of consumption in the data, but I do not have information on labour market experience in the CEX annual cross-section. The consumption variance measures used in Table 14 are derived using the HSV methodology, by first regressing log-annual consumption (cash, credit and total nondurable consumption) on a cubic in potential labour market experience (age - years of education - 5) and an education dummy, and extracting the residual.

The variance of income in the model is by construction close to that in the data (the discrepancy comes from the fact that I decompose the annual income process into a monthly one, discretize, and then re-aggregate—with resulting approximation issues). The resulting variance of total (non-durable) consumption varies, not surprisingly, based on the properties of the stochastic process on income. The model with the GS income calibration, which puts more emphasis on transitory variation in income, produces variance of total consumption that is under one-half of that in the data. In contrast, the model with HSV calibration produces variance of total consumption that is only slightly lower than variance of income, and so overstates dispersion by about one-third. This is not surprising, since in the HSV calibration, the income shocks have significantly higher persistence than the GS case. It is well known that in models of this type, agents are unable to self-insure against very persistent shocks well, and do much better with transitory shocks, and this model confirms that result.

In addition, it is worthwhile to look at the components of consumption. In the GS calibration, cash-good consumption variance is nearly equal to credit-good consumption variance, and both are at about half of income variance. In the HSV calibration, cash-good consumption variance is higher than credit-good consumption variance; there is noticeable consumption-smoothing in credit goods, but not in cash goods. The intuition comes from the two sources of idiosyncratic uncertainty that both contribute in different ways to creating fluctuations in consumption. Preference shocks create individual-level volatility in cash-good consumption. The cross-sectional dispersion in both credit-good and cash-good consumption is driven primarily by income shocks, since these create long-run dispersion in wealth, which in turn translates into differing abilities of households to self-insure against the expense shocks. In addition, the dispersion is reinforced by complementarity between the two consumption goods in either calibration. Thus, the logic for smoothing in each component of consumption is still linked primarily to the properties of the income process; the more persistent this process, the harder it is for agents to self-insure against the fluctuations.

Finally, notice that both models produce the counterfactual result that credit-good consumption variance is equal to or below that of cash goods, and under both calibrations, the model underpredicts volatility of credit-good consumption. This is the result of the fact that in the data, many credit goods are semi-durable (*e.g.* clothing, vehicle maintenance expenses, etc.), and are likely also affected by expense shocks that I do not model.

TABLE 15
Results—subgroup size (percent)

	Data	Model (GS)	Model (HSV)
Borrowers	5.2	2.2	7.0
Borrowers and savers	27.1	11.8	15.2
Savers	67.7	86.0	77.8

TABLE 16
Results—liquid-asset-to-income ratio, median, and mean households

	Median household			Mean household		
	Data	Model(GS)	Model(HSV)	Data	Model(GS)	Model(HSV)
Borrowers	0.10	0.73	1.00	0.12	0.72	0.80
Borrowers and savers	0.79	0.82	1.18	1.71	0.79	1.00
Savers	0.88	0.73	0.50	2.53	0.89	1.01

6. RESULTS

6.1. *The credit card debt puzzle*

To measure how much of the puzzle is accounted for by the liquidity need hypothesis, I focus on the size of the three subgroups, as well as liquidity holdings of borrower–savers.

Table 15 gives the size of the three subgroups in the data and the model. In the model, the size of the borrower-and-saver group is between 12% of the population in the GS calibration, and 15% in the HSV calibration, while in the data, it is 27%. Thus, the model, depending on the calibration, accounts for between 44% and 56% of the puzzle group size. Further, the model overstates the size of the saver group. Under the GS calibration, the size of the borrower group is understated. The reason is that the model’s borrower group consists only of those who are constrained at the end of the month, while in the data, there may be some households who have very few liquid assets throughout the month and year; these households are not captured by the model, since it is never optimal to hold zero liquidity. Under the HSV calibration, the size of the borrower group is larger than in the data: more households under this calibration who are constrained at the end of the period are also debtors; this is likely driven by a higher dispersion of the low-income states.

In order to measure liquid assets, I have to map money holdings in the data to those in the model. As I discussed, a cross-sectional average of money holdings in the SCF reflects an average monthly amount of money in a bank account. Since in the model I observe money holdings at two points during the month, I average the two observations for each household to map to the observed amount in the data.

In Table 16, I present average monthly liquid asset holdings relative to income, in the model and data. The left three columns are for a median household. For the median borrower–saver household, the model matches its liquidity holdings very well, overstating them in the HSV calibration. For the median saver household, the model accounts for 83% of the liquidity holdings under the GS calibration, and 57% under the HSV calibration. Under both calibrations, and particularly under the HSV one, the model counterfactually predicts savers’ liquidity-to-income ratio to be below that of borrower–savers. This is because money holdings in the model are not as disperse as in the data (the upper tail is not matched), while income dispersion better matches that in the data and is higher under the HSV calibration. Looking separately at distribution of money

TABLE 17
Shock decomposition—subgroup size (percent)

	Benchmark (GS)	Model (GS, no shocks)	Model (GS, no pref. shock)
Borrowers	2.2	0.0	15.0
Borrowers and savers	11.8	0.0	0.0
Savers	86.0	100.0	85.0

holdings and income in the model by subgroup (not presented) reveals the expected increasing pattern of both from borrowers to savers.

The model is not calibrated to account for the upper tail of the wealth distribution, and thus has a harder time accounting for the *mean* household in each group. Still, for the mean borrower–saver household, the model matches between 46% and 58% of liquidity holdings in the data, depending on the calibration. Clearly, the mean saver household represents the top of the distribution, and the model performs the worst on this dimension, matching between 35% and 40% of liquidity held by these households in the data.

Finally, for the borrowers, the model overpredicts liquidity holdings. This comparison between the model and data is tenuous; it is not likely that *all* borrower households in the data never hold liquid assets during the month, given their average liquid spending documented above. Many of these may instead be households observed at the end of the month, when they have drawn down all of their liquid assets, most likely due to binding resource constraints. Thus, it may be more appropriate, in the borrower case, to compare the data number to the end-of-month liquid holdings in the model, which are 0, in which case the model and data match.

6.2. *Sensitivity to the borrowing limit*

As one sensitivity check, I re-compute the model with the GS calibration and a lower borrowing limit, assuming that all households can borrow only up to one-half of the annual *average* income in the economy. If I do not re-estimate any of the parameters of the model, the central implications of the model are all robust to the re-specification; in particular, the size of the borrower–saver group, as well as the liquidity holdings of each group do not change. However, there is one important and predictable change: the debt-to-income ratio in this economy falls by more than half. If I instead re-estimate this economy to match the debt-to-income ratio in the data, the parameters change; notably, the discount factor β has to be lowered somewhat (to about $\beta=0.987$). In this circumstance, the size of the borrower–saver group in the economy comes up to 28%, thus matching the size of the puzzle in the data, while optimal liquidity demand remains robust.

6.3. *Model decomposition: role of the shocks*

In order to understand the role of the idiosyncratic income and preference shocks in generating the credit card debt puzzle, I re-compute two versions of the model with the GS calibration, first shutting down all shocks, and then shutting down only preference shocks. All the parameters are kept the same as in the baseline calibration. Tables 17 and 18 present the results for the credit card debt puzzle. It is immediately clear that unless both shocks are present, the model cannot account for the puzzle, since it does not generate a borrower–saver group; moreover, the model in that case severely underpredicts liquidity demand.

The model with both the income and preference shocks shut down (referred to as “GS, no shocks” in both tables) reduces to a deterministic representative-agent model. In this model,

TABLE 18
Shock decomposition—liquid-asset-to-income ratio, median household

	Benchmark (GS)	Model (GS, no shocks)	Model (GS, no pref. shock)
Borrowers	0.73	–	0.50
Borrowers and savers	0.82	–	–
Savers	0.73	0.34	0.36

there is no dispersion of consumption, and in steady state, the model would generate constant consumption in both cash and credit goods. The computation of the model, given the benchmark calibration, produces a solution that is just out of the steady state (as the condition $\beta = 1 + r$ is violated), so there is a very slight decline in household consumption over time. However, the solution (as well as the steady state) features positive savings, and thus, the household is a saver. The size of the borrower–saver group is 0. The liquidity holdings of the household are at 34% of its income, which is just under 47% of the benchmark model.

If only the preference shocks are shut off (“GS, no pref. shock”), there is still no borrower–saver group in the model. This model is a heterogeneous-agent model due to idiosyncratic histories of income shocks, but there is no precautionary liquidity demand here, since cash-good consumption is deterministic. The dispersion properties of this model (not in the tables) are nearly identical to those of the GS benchmark model, confirming the intuition that it is the income uncertainty that drives cross-sectional dispersion of consumption in both goods. Because in this model everyone’s liquidity constraint binds at the end of the period, anyone with debt here is a borrower. This group is 15% of the population in the stationary distribution. A saver household’s liquidity holdings are essentially the same as in the no-shock model, confirming the intuition that income shocks alone do not alter the size of liquidity demand. This version of the model accounts for just under 50% of the savers’ liquidity holdings in the full model. In sum, preference shocks are necessary for generating the borrower–saver group in the model, and for matching the magnitude of liquidity holdings of this group in the data; when present, these shocks at least double the liquidity demand relative to the model without such shocks.

6.4. Discussion of the results

The results presented above demonstrate that precautionary demand for liquidity goes a long way towards accounting for the credit card debt puzzle within a standard rational-expectations framework. To be sure, the model does not account for all liquidity holdings of the *mean* household, and there are households in the data who hold such large amounts of liquidity that precautionary demand cannot be the dominant reason. On the other hand, the results presented above may be seen as a lower bound on both liquidity demand and the size of the borrower–saver group, because there are reasons to hold liquidity that the model abstracts from. One example is the minimum balance requirement on checking accounts. Many banks allow their holders to avoid sizable fees by maintaining a minimum balance in the account at all times. Anecdotally, this minimum balance requirement can go as high as \$1,000 or more. I abstract from this requirement in the model due to lack of data on minimum balances. However, if many checking account balances have some minimum positive amount that they need to exceed, then the total amount of liquidity that the model can account for will rise, possibly substantially. The argument would, of course, be more nuanced given that one would have to consider when it may be optimal to dip below the minimum balance for a household that finds itself in the borrowing–saving situation.

But if this situation is temporary, this channel may still increase the puzzle household's liquidity demand in the model, and it will certainly increase the demand of saver households; this may be one way to help account for average liquidity holdings as well.

Another example is fixed participation costs in illiquid asset markets: it may be optimal for low-wealth households to have, *e.g.* only a checking account because saving in other assets requires paying a transaction cost. My model abstracts from such fixed costs. One result is that the model currently captures only one channel that gives rise to precautionary liquidity demand, namely, preference uncertainty. There is, of course, a second source of uncertainty in the model—income uncertainty—but it plays a role only in generating disperse non-liquid asset holdings, as households insure against this shock by saving or borrowing in the asset *b*. The reason is that it is costless in the first subperiod to acquire additional liquidity from a credit card in the event of a low income shock. Yet even predictable expenses may require precautionary money holdings in the face of income risk. For example, if one should lose one's job, one still needs to pay the mortgage each month. The idea, then, is that both preference (expense) and income uncertainty may provide a precautionary motive for holding liquidity for most households, and if this channel is modelled by adding a direct cost of transfers from consumer credit to liquidity, both the size of the borrower–saver group and liquidity holdings in the model would likely increase.¹²

7. CONCLUSION

This article presents the first examination of liquidity demand as an explanation for the credit card debt puzzle. I examine the hypothesis that there is a significant share of household expenditures each month that cannot be paid by credit card, so that households need to keep liquidity in the bank at all times to pay for these expenditures. Thus, if a household accumulates credit card debt, but does not have enough money both for its needed precautionary amount and for debt repayment, it will optimally choose to revolve the debt in favour of keeping a sufficient supply of liquidity.

The central contribution of the article is a detailed measurement of how much of the puzzle this hypothesis can account for. First, I document the puzzle carefully in the data, which requires a split of household consumption into cash-only goods and cash-or-credit goods, based on survey evidence. I then pose a dynamic stochastic model of household portfolio choice with two consumption goods and two types of idiosyncratic uncertainty timed so that portfolio decisions have to be made before spending needs are known. The model is then calibrated by matching of moments in the data to model moments. The parameter estimates are in themselves of interest, providing new or even first measurements of magnitudes of unobservable idiosyncratic expense risk and the elasticity of substitution between cash and credit goods in micro data. For example, whereas in deterministic cash-credit good models, cash and credit goods were estimated to be substitutes, my model implies that they are complements.

In terms of the puzzle, I find that, depending on the calibration, the hypothesis successfully accounts for at least one-half of the households who revolve debt while having money in the bank, and under reasonable calibration alternatives can account for the entire group. For a median such borrower–saver household, the model accounts for their entire liquid asset holdings. I also decompose the model in terms of the role of the two types of idiosyncratic shocks, and find, for example, that one-half of the liquidity demand in the model is precautionary.

12. I confirmed this intuition in two-period examples, since a full extension of the model with fixed costs of adjustment becomes significantly harder computationally. For example, liquidity demand in an extended example increases by 30–50% relative to the benchmark.

I discussed some limitations of the exercise, which are left to future research. First, the model does not perform as well for the mean household as it does for the median. This is because it abstracts from many important reasons for why a household in the data might hold liquidity, such as various participation costs in non-liquid asset markets, and because it is not calibrated to capture the top tail of the wealth distribution. Second, in order to measure idiosyncratic expense shocks in liquid consumption, I had to rely on the residual of consumption measures in the Consumer Expenditure Survey, which likely includes measurement error of uncertain nature and magnitude; this error may or may not overstate uncertainty in consumption as discussed in the empirical section. On balance, it is apparent that transaction and precautionary liquidity demand is a key factor in accounting for the credit card debt puzzle.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

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