Federal Reserve Bank of New York
Staff Reports

Why Use Debit Instead of Credit?
Consumer Choice in a Trillion-Dollar Market

Jonathan Zinman

Staff Report no. 191
July 2004

Why Use Debit Instead of Credit? Consumer Choice in a Trillion-Dollar Market
Jonathan Zinman
Federal Reserve Bank of New York Staff Reports, no. 191
July 2004
JEL classification: D14, D91, E41, G29

Abstract

Debit cards are overtaking credit cards as the most prevalent form of electronic payment at the point of sale, yet the determinants of a ubiquitous consumer choice—"debit or credit?"—have received relatively little scrutiny. Several stylized facts suggest that debit-card use is driven by behavioral factors. The popular view is that debit-card use presents a puzzle for canonical economic models. However, we should not overlook standard cost-based motives for using debit cards. Principally, the 50 percent of debit-card users who revolve credit-card balances would pay interest to charge purchases on the margin and hence might rationally choose to use debit rather than credit to minimize transaction costs. Debit-card use might also be rational for consumers lacking access to a credit card or facing a binding credit limit. I document robust effects of these types of credit-card use on debit use and show that such effects are consistent with a canonical model of consumer choice. This paper also shows, however, that it is difficult to distinguish sharply between canonical and behavioral motives for debit-card use in publicly available data. More generally, I develop analytical frameworks for testing competing canonical and behavioral models and find evidence consistent with important roles for both pecuniary and psychological motives.

Zinman: Research and Market Analysis Group, Federal Reserve Bank of New York (e-mail: jonathan.zinman@ny.frb.org). The author thanks Dan Bennett and Lindsay Dratch for excellent research assistance; Gautam Gowrisankaran, Charlie Kahn, and Jamie McAndrews for conversations that sparked this paper; Aprajit Mahajan for help implementing his measurement error correction; Paul Calem and Kevin B. Moore for advice on and access to the SCF credit score variables; and Bob Avery, Bob Chakravorti, Tom Davidoff, Kathleen Johnson, Dean Karlan, Beth Klee, Dave Skeie, Victor Stango, and lunch/seminar participants from the Federal Reserve Bank of New York, Federal Reserve Bank of Chicago, the Economics of Payments conference at the Federal Reserve Bank of Atlanta, and the Applied Microeconomics Conference at the Federal Reserve Bank of San Francisco for helpful comments.

I. Introduction

Debit cards have surpassed credit cards to become the most common form of Visa point-of-sale ("POS") transaction in the United States (Visa 2002). Overall, debit was used for over 15.5 billion POS transactions totaling \$700 billion in the year 2002 (CPSS 2003).[1] This represented about 35% of electronic payment transaction volume and 12% of POS noncash payments (Gerdes and Walton 2002).[2] Debit's ascension has been sudden, with 47% of households using it by 2001, up from 18% in 1995 (Table 1). Industry observers predict continued strong growth for debit, while forecasting relatively weak growth in credit card charge volume.[3]

Despite debit's growth and prominence, the determinants of debit use have largely escaped academic scrutiny.[4] The introductory quotes belie that fact that there *are* actually potentially important, pecuniary cost-based reasons for using debit. Principally, the 53% of credit card users who revolve balances incur interest costs to charge purchases on the margin (i.e., they don't get the float), and hence might rationally choose to use debit rather than credit in order to minimize transaction costs.[5] This motive holds even for the "small" (Laibson et al. 2003) fraction of consumers who simultaneously hold nontrivial stocks of low-yielding liquid assets and expensive credit card debt. Debit use might also be rational for consumers lacking access to a credit card or facing a binding credit limit.

But perhaps 29% of debit users lack any price-based reason for doing so (Table 2). Accordingly we should take seriously the popular notion that debit use serves as a form of commitment device against the type of "overspending" with credit cards posited by Ausubel (1991), Prelec and Simester (2001), and Bertaut and Haliassos (2002).[6] Such hypotheses seem plausible in part because it would be relatively

---

[1] Virtually all debit volume is attributable to consumers— businesses rarely use debit at the point-of-sale.
[2] Credit card transaction volume totaled \$1.6 trillion in 2002 (CPSS 2003).
[3] See, e.g., McDonald and Wasserstrom (2003), Lyons (2004).
[4] Hancock and Humphrey (1998) note a lack of studies on the determinants of payment choice generally. But see footnote 7 for some more recent studies.
[5] Some might question whether revolving credit card balances at "high" rates can be squared with traditional rationality in the first place. Indeed, computational consumption function models underpredict credit card borrowing, whether they posit exponential (Carroll 2001) or quasi-hyperbolic time discounting (Angeletos et al. 2001). But the models do predict *some* credit card borrowing (e.g., by 30% of households at a real rate of 15% in Carroll's model). Gross and Souleles (2002) show that credit card borrowing does respond strongly to price.
[6] See also, e.g., Mann (2002). The time-inconsistency implied by concerns about "overspending" or "undersaving" has been formalized via quasi-hyperbolic preferences; see, e.g., Laibson (1997).

cheap to use debit in this fashion— I show below that the pecuniary cost of "incorrectly" choosing debit rather than credit is perhaps $12 per month. This cost is comparable, in present value terms, to the estimated $2,000 that consumers with sophisticated quasi-hyperbolic preferences should pay to commit themselves not to borrow on credit cards (Laibson et al. 2004). Other stylized facts also fuel the intuition that one or more "behavioral" explanations drive debit use. Most provocative is that debit tends to be used for smaller transactions involving instantaneous consumption, with credit cards used to purchase larger, more durable items (Reda 2003)— a pattern consistent with the mental accounting model in Prelec and Loewenstein (1998). Yet neither behavioral nor more traditional explanations for debit use have been put to the test.[7]

Identifying the correct model(s) of debit use has implications for high-frequency intertemporal consumer choice more generally. Validation of the puzzle outlined in Table 2 would add to the growing list of consumer behaviors in financial markets that that have proven difficult to explain with straightforward applications of canonical models.[8] More specifically, validation of a spending control motive for debit use that operates via mental accounting would bear on the existence and welfare implications of time-inconsistent preferences.[9] On the other hand, evidence that consumers respond strongly to the pecuniary marginal cost of payments, in the face of small stakes, would be compelling support for traditional rationality (Miravete 2003).

The primitives of the debit vs. credit choice also have implications for modeling and regulating the industrial organization of payments networks. Specifically, a growing theoretical literature finds that the relative efficiency of alternative pricing practices, merchant acceptance rules, and governance

[7] Rysman (2004) uses transaction-level data to estimate network effects in payment card networks. Hayashi and Klee (2003) examine complementarities between electronic payment use and other types of technology adoption. Kennickell and Kwast (1997), Carow and Staten (1999), Mantel (2000), and Stavins (2001) find effects of consumer demographic characteristics on payment choice. Boeschoten (1998) examines demographic and transaction size effects on payment choice in the Netherlands. Frame and White (2004) discuss the difficulty of identifying demographic effects on debit use, and find a relative dearth of empirical work on financial innovation generally. Humphrey, Kim, and Vale (2001) find that retail payment choice is responsive to price in aggregate data from Norway.

[8] See, e.g., Canner, et al. (1997) and Moskowitz and Vissing-Jorgensen (2002) on asset allocation, and Gross and Souleles (2002) and Laibson, et al. (2003) on the simultaneous holding of expensive credit card debt and low-yielding liquid assets.

[9] The possibility that debit serves as a "virtual" commitment device (via mental accounting rules) seems particularly important, since this mechanism would be a cheap way for time-inconsistent agents to help implement their time-zero consumption plans relative to devices that actually render assets illiquid.

arrangements depends critically on the elasticity of consumer demand for payments services (Chakravorti 2003).[10]

Accordingly this paper puts competing consumer choice models of debit use to the test. It starts by developing a standard ("canonical") consumer choice model that focuses on consumer sensitivity to the (implicit) relative price of electronic payments at the POS. The lack of consumer-level data on explicit transaction fees is not much of a constraint, as I show that the first-order theoretical determinant of relative payments price is often whether the consumer has been revolving balances on her credit card--and hence must "borrow-to-charge". One thus can use widely available household data to test whether consumer behavior is consistent with joint optimization over payment options. Specifically, a canonical model of consumer choice generates the following testable predictions: 1. consumers who revolve credit card balances ("revolvers") should be more likely to use debit than those who don't ("convenience users"); 2. revolvers facing binding credit constraints should be more likely to use debit than revolvers who don't; 3. convenience users should be less likely to use debit than those without credit cards (since they should exploit the float and minimize low-yielding transaction balances). I find statistically and economically significant support for these predictions, and show that the observed empirical relationships are likely driven by causal effects of the credit card variables of interest on debit use.

The results are thus *consistent* with a large canonical motive for debit use. The question then remains whether such results rule out alternative, behavioral models. I use a specific behavioral model to show that they do not, and that privately held data on individual transaction characteristics are needed to sharply distinguish the canonical model from the leading behavioral alternative. Publicly available data does permit some relatively coarse tests that pit the two models against each other, and these yield some new stylized facts that seem consistent with the behavioral model.

Overall then this paper makes two types of contributions. First, it develops analytical frameworks for testing consumer choice models using publicly and privately available data. These empirical approaches build on the fresh insights that: a) contrary to popular belief, there are nontrivial canonical

[10] See Rochet and Tirole (2002) for a specific and seminal example.

(pecuniary cost-based) motives for using debit; and b) behavioral motives can be formalized in a model and generate distinct predictions that are testable with varying precision in public and private data. Second, the paper develops new stylized facts from publicly available data, some of which lend credence to the canonical model, and others, which point to the behavioral model. On balance the empirical findings are consistent with important roles for both canonical and behavioral motives in driving debit use.

The paper proceeds as follows. Section II details the consumer's problem at the POS and develops a canonical model where relative pecuniary marginal cost drives payment choice. This model generates sharp predictions on specific relationships between credit use and debit use. Section III describes the data and empirical model used to test these predictions. The Survey of Consumer Finances' information on credit and debit use, combined with its rich detail on household characteristics, financial attitudes, and elements of credit and transactions demand, make it well-suited to identify the causal effect of credit card use on debit use. Section IV presents the core results on the impact of credit card use on debit use. The findings support the canonical model's key predictions. Section V refines the point estimates on these core results. It shows that several types of data limitations imply that the estimated correlation between revolving and debit use in the SCF is probably a conservative lower bound on the true causal effect. Section VI examines whether results that are consistent with the canonical model can rule out competing explanations. It develops a specific behavioral model of payment choice, drawing heavily on Prelec and Loewenstein (1998). This model does generate predictions that are distinct from the canonical model, and these predictions are empirically testable—in principle. Unfortunately, identifying the sharpest distinctions between the two models requires information on the nature, timing, and method of specific purchases that is not publicly available. The SCF does permit some relatively coarse tests of the behavioral model. The results of these tests are mixed, with some delivering new stylized facts that are consistent with a unique behavioral motive, and others suggesting nothing that would lead to the rejection of a null hypothesis of canonical consumer optimization. Section VII concludes with some brief speculation on the paper's implications for electronic payment adoption, and for modeling consumer choice more generally.

II. Consumer Choice at the Point-of-Sale

This section details the consumer's payment choice problem at the POS, and models it using a canonical framework where pecuniary cost minimization drives the decision. I describe how debit and credit offer essentially identical advantages relative to alternative payments media, and how they enjoy virtually identical acceptance. Therefore it proves straightforward to boil down the POS payment choice to one between debit and credit. Turning to the choice between debit and credit, it is shown that while credit offers float to convenience users, and superior fraud protection and reward incentives during the sample period, debit is a relatively cheap alternative for certain consumers. Specifically, a canonical model generates clear predictions on which consumers should be more likely to use debit— those who revolve credit card balances, those who face binding credit card credit limits, and those who lack a credit card.

Traditionally, the literature on media of exchange have focused on acceptance, security, portability, time costs, and pecuniary costs as the key elements of payment choice (Jevons 1918). I begin by briefly comparing debit, credit, and alternative payments media along each of the first four dimensions, and then develop a simple model of consumer choice between debit and credit based on pecuniary costs.

Acceptance: Debit and credit enjoy similarly widespread acceptance as payments devices; indeed, Shy and Tarkka (2002) treat them as equivalent. Rough equivalence has come about due to the rise of "offline" debit, whereby an ATM card with a Visa or Mastercard mark can be used, as a debit card, anywhere the credit card brand is accepted.[11] In essence then, one can use debit wherever one can use

[11] Hayashi, et al. (2003) provides a thorough guide to the debit card industry's institutions and operations.

credit (with a few exceptions, including online purchases, car rentals, etc.)[12] Consequently debit and credit are essentially equivalent along this margin when compared to cash or check.[13]

Security: Debit and credit now offer essentially identical fraud protection, and hence offer similar protection against theft compared to cash or check.

Portability: Obviously, debit and credit are plastic card-based media, offering identical advantages over bulkier cash and checkbooks.

Time costs: From the consumer's vantage point, debit and credit transactions are typically processed exactly the same way, using either a POS terminal or signature-based transactions. These methods may be more or less time-consuming than cash or check, depending on the situation. Debit does offer the additional advantage of "cash back" in some cases, but empirically this is not a dominant feature of debit use.[14]

Clearly, debit and credit offer very similar attributes along the acceptance, security, portability, and time cost margins. Presume then for a moment that transaction demand is exogenous, and that an optimizing consumer holding one bank credit card, when confronted with a POS transaction, chooses her payment medium in two steps by:

1. Deciding whether to use "paper" (cash, check) or "plastic" (debit, credit), based on the four margins discussed above.
2. Minimizing pecuniary costs, conditional on the choice in step 1.

Then in the case where the consumer is using plastic, she faces the following problem:

[12] Imperfect substitutability between debit and credit on the acceptance margin will generate bias in favor of the null hypotheses developed below. See Section VI for discussion.
[13] For simplicity, I ignore "smart" or prepaid cards (only 3% of US households used them widely in 2001), and Automatic Clearing House payments ("autodebits", which tend to be used for recurring bill payments and not at the POS).
[14] About 17% of debit transactions involve cash back (Breitkopf 2003), and only about 29% of debit users ever get cash back (December 1996 Survey of Consumer Attitudes and Behavior). Note also that cash back is only available in the 25% of merchant locations where there are the POS terminals required for "online" (PIN-based) debit (Breitkopf 2003).

(1) $\text{Min}\ [C_d(p), C_c(H, f, r(R, r_{purch}, B, L))]$

C_d and C_c and represent the marginal (implicit) pecuniary cost of using debit and credit, respectively. The direct cost of C_d debit depends on p, the amount of the transaction fee that is sometimes levied.[15] During the sample period under consideration in this paper only about 15% of debit cardholders faced transaction fees (Marlin 2003), and the modal nonzero fee was 25 cents (Dove 2001). Most fees are charged on online debit transactions only; charges per offline or credit card transaction have been very rare in the United States.

The cost C_c of using credit depends first on H, whether the household has a credit card. Assume for simplicity that households lacking a credit card (H=0) do so only for supply reasons. (This seems plausible in a standard consumer choice framework, since holding a credit card is essentially costless in the pecuniary sense, given the prevalence of no-fee cards and strong fraud protection.) Then C_c is infinite for these households.

C_c also depends on f, the "rewards" benefits available per unit charged. These typically have been more prevalent and generous for credit than debit, and can be valued at approximately one cent per dollar charged for the 50% or so of cardholders earning rewards.

C_c depends finally on r, the effective interest rate at which the consumer must borrow (or float) to charge a purchase at the point of sale. r in turn is determined by R, a discrete variable capturing whether the consumer revolved a balance at her last credit card payment due date (assume for the moment that the consumer holds only one credit card; I consider the complication of multiple cards below). In cases where R =1, i.e., where the consumer did not pay her balance in full, then she must borrow-to-charge—each dollar charged on the margin begins accruing interest immediately at the consumer's "purchases"

[15] For the purposes of discussion I assume that debit transactions clear with an effective interest rate of zero, ignoring settlement lags (which can provide a day or two of float) and costly checking account overdrafts (Fusaro 2003).

rate, r_{purch}.[16] In contrast, when R = 0 the consumer typically enjoys the float of a zero-interest loan for up to 60 days,[17] so r<0.[18]

Overall the stakes of making the "correct" payment choice at the POS, conditional on R, can be substantial: a revolver with nonzero but nonincreasing demand for credit card debt, who used her credit card to borrow-to-charge rather than using debit and made credit card payments only once per month, would spend about $12 more per month to charge an amount equal to one-half of one month's median income ($2,000) at the median rate revolvers face (14.5% APR).

r also depends discretely on whether B, the amount outstanding on the credit line L, exceeds L. When B>L typically three adverse things happen to the consumer: i) the rate on the outstanding balance increases substantially, i.e., $r_{over} >> r_{purch}$; ii) an overlimit fee ranging from $20-$30 is incurred, and iii) her credit rating worsens.[19] r may also vary smoothly with B and L, depending on the option value of borrowing (more on this in Section IV).

The key insights from framing the choice problem in this way are straightforward: we find that debit is relatively attractive to households lacking a credit card, revolving a credit card balance, or facing a binding credit card limit constraint, because each of these conditions raises the marginal cost of using credit relative to debit. This suggests the following empirical test:

(2) $Y_i = \alpha + \beta_H H_i + \beta_R R_i + \beta_F F_i + \delta X_i + \varepsilon_I$

---

[16] The Federal Reserve Board of Governors' biannual publication "Shop: The Card You Pick Can Save You Money" states: "Under nearly all credit card plans, the grace period applies only if you pay your balance in full each month. It does not apply if you carry a balance forward." See, e.g., the January 1998 or August 2001 versions. Nationally representative surveys have found evidence suggesting that most credit card holders are cognizant of the interest rates charged on their plans; e.g., Durkin (2000) reports that at least 85% are aware of their APRs, and Durkin (2002) reports that 54% of holders consider rate information the "most important" disclosure, with 78% of holders responding that the APR is a "very important" credit term (compared to only 25% for rewards).

[17] For example, say I paid a bank credit card balance in full on January 10th (a payment due date, typically one month after a statement closing date). Then my balance netting charges and credits during the period from January 11st to February 10th must be paid in full on or before *March* 10th in order for me obtain free float on purchases made between March 11th and April 10th.

[18] For analytical simplicity, we can incorporate the opportunity cost of transaction balances, incurred by using debit, into the effective interest rates. This simply increases the reward to floating, and reduces the effective r_{purch} by the amount of the opportunity cost.

[19] Furletti (2003) is an excellent source of information on credit card pricing and related developments.

Where i indexes consumers, Y is a measure of debit use, H and R are defined above, F is a 1/0 measure of whether the household faces a binding credit card limit constraint, and X includes several variables that can be used to help identify the model by capturing other payments costs, payments and credit demand, and tastes. The canonical consumer choice model predicts that β_R and β_F will be positive, and that β_H will be negative. In each case the null hypotheses is that $\beta = 0$.

Thus far we have considered an optimizing consumer facing a marginal decision. This begs the question, however, of why, if the revolving consumer does not wish to borrow more on the margin and is capable (in a cash flow sense) of using money from her checking account (via a debit transaction) to settle marginal transactions over time, she does not: a) simply pay down any credit card balance *in advance* (say immediately after getting paid), and then b) use her credit card to transact until the next pay date. A likely explanation is that the value of the apparent foregone arbitrage is actually less than the transaction cost of making more frequent credit card payments. Consider a worker who is paid every two weeks and carries the median credit card balance ($1,800) at the median interest rate (14.5% APR) for SCF revolving households. Even under the extreme assumptions that the household has sufficient cash flow to pay off the entire balance upon salary receipt, and that the credit card is a perfect substitute for checking account balances as a payments device, the marginal finance charge incurred for the two-week period is only around $3.50 (assuming that the payment takes a few days to settle, and that charges are incurred smoothly over the two week period). This seems comparable to the time and hassle costs of making an extra credit card payment per month.[20]

More generally the above model takes transaction and revolving balances as given, and considers the marginal decision of whether to pay using debit or credit. Of course this leaves unexplained the relatively small number of households who make the seemingly puzzling, inframarginal decision to

---

[20] In a similar vein, Brito and Hartley (1995) show that transaction costs can induce consumers to use credit cards instead lower-cost personal loans.

simultaneously buy debt low (hold transaction balances) and sell it high (revolve credit card balances). One can show, however, that these households do not drive the key results in this paper.[21]

For the moment the model also ignores (or subsumes in X) debit transaction fees, cash back motives, rewards incentives, and differences in acceptance. This approach is motivated by data limitations discussed below. Note however that in each case the unobserved information will bias the estimates towards acceptance of the null, if at all, since any effect is to produce revolvers who rationally do not use debit (due, e.g., to rewards incentives), or convenience users who rationally do use debit (due, e.g., to cash back transactions). The nature and magnitude of these potential biases are discussed in greater detail in Section V. For now I focus on the empirical implementation of equation (2) subject to data constraints.

III. Data and Identification

This section details the data and identifying assumptions employed to implement equation (2), and thereby test whether consumers behavior is consistent with the canonical model. It focuses only on identifying the reduced-form causal effects of credit card use on debit card use, and postpones consideration of whether the resulting estimates actually can be used to distinguish between canonical and behavioral motives until Section VI.

I use data from the 2001 Survey of Consumer Finances (SCF), a nationally representative cross-section of approximately 4,000 U.S. households. The SCF contains some information on debit use and detailed data on credit card use, financial status, and household characteristics.[22] It does not contain any information on debit transaction fees, rewards incentives, or cash back usage.

---

[21] Only 16% of households in the base regression sample simultaneously revolve and hold transaction balances exceeding one month's income. Ongoing work explores whether this apparent "short-term debt puzzle" is actually a rational response to checking account pricing, credit card teaser rates and balance transfer pricing, downpayment constraints, and/or strategic bankruptcy.

[22] For more information on the SCF see, e.g., Aizcorbe, et al. (2003).

Let us begin by limiting the sample to households with credit cards (H=1), and ignoring the credit constraint variable (F), for simplicity. Equation (2) then becomes:

(3) $Y_i = \alpha + \beta_R R_i + \delta X_i + \varepsilon_i$

Now Y = 1 if the household reports using a debit card and zero otherwise,[23] and R =1 if the household did not pay its most recent balance in full on *any* bank credit card. (I maintain the linear functional form for notational simplicity, despite the binary dependent variable.) Recall from the previous section that the canonical model predicts $\beta_R>0$. Unfortunately, the SCF does not report balances for individual credit cards, but rather total balances outstanding over *all* of the household's credit cards. This creates a downward bias on the effect of R if some households use separate credit cards for borrowing and transacting, and motivates close consideration of samples that are restricted to the 25% of households with only a single credit card.

As in equation (2), X contains household characteristics and other marginal cost variables designed to remove any unobserved correlation between debit use and revolving behavior. These covariates are detailed below.[24]

In some cases it will be useful to pool SCF cross-sections. The survey has been conducted every three years since 1989, and asked questions on debit use since 1992 (Table 1 shows the rapid growth of debit use among SCF households from 1992 to 2001). As the SCF lacks any panel component in the years under consideration, the pooled specifications simply add year effects T to produce:

---

[23] See Appendix 1 for the debit use survey question. The SCF yields proportions of debit users comparable to other surveys; e.g., the Standard Register's *National Consumer Survey of Plastic Card Usage*, a random phone survey of 1,202 households, found that 37% were debit users in March 1999. The 1998 SCF (collected January-August) found that 34% of households were debit users.

[24] One issue not captured in the notation is that the SCF produces 5 implicate observations per household in the interest of maximizing precision in the presence of substantial imputation of certain financial variables; see, e.g., Kennickell (1998) or Little (1992). Although I use the full dataset of 5 observations per household (and correct standard errors accordingly, using the routine provided by the 2001 SCF codebook at http://www.federalreserve.gov/pubs/oss/oss2/2001/codebk2001.txt), reported sample sizes will be based on the number of *households*.

(4) $Y_i = \alpha + \beta_R R_i + \delta X_i + \tau T_t + \varepsilon_i$

Estimating (3) or (4) using OLS (linear probability), probit, or logit will, under the usual distributional assumptions about the error term, produce the true causal effect of revolving credit card debt on debit use if there are no unobserved characteristics that are correlated with both revolving status and debit use. I therefore use the richness of SCF data to condition on several characteristics and behaviors that potentially confound interpretation of β_R. Specifically:

- β_R will be biased downward if R is positively correlated with latent credit demand, given that the SCF only captures a single snapshot of behavior; e.g., if a household is ramping up their credit card balances (as opposed to having reached a steady-state debt level), it will be less inclined to use debit since it is using the credit card to *borrow* as well as charge at the POS (i.e., not simply using the credit card as a payment device). Accordingly, I include financial, life cycle, and attitudinal proxies for credit demand among the X (control) variables. These are detailed in Section IV. Table 1 shows two examples of how debit use does appear to vary systematically by demographics (age and education).
- conversely, β_R will be biased upward if consumers are indifferent (and hence randomly choose debit or credit at the POS), or if both revolving behavior and debit use are driven by some unobserved "taste for plastic". The former source of bias can be addressed by using additional information on wealth, income, and spending (as proxies for transaction demand and price sensitivity), along with data on credit card interest rates and line utilization that affect the marginal cost of charging and are of independent interest. The latter problem should be ameliorated by adding data on the use of other electronic payments instruments to the set of covariates.

Adding measures of F, the binding credit constraint variable, to this model is then straightforward. The natural measure is based on credit card credit line utilization, producing:

$$(5)\ Y_i = \alpha + \beta_R R_i + \beta_F F_i + \delta X_i + \tau T_t + \varepsilon_i$$

in the case where we restrict the analysis to credit card holders, and:

$$(6)\ Y_i = \alpha + \beta_R R_i + \beta_F F_i + \beta_H H_i + \delta X_i + \tau T_t + \varepsilon_i$$

when we estimate the distinct credit card access (holding) effect as well.

IV. Core Results

This section presents results obtained from estimating equations (3)-(6), which are designed to identify the effects of credit card use on debit card use. The findings are consistent with the canonical model, as they suggest that both revolving a card balance and facing a binding credit limit significantly increase debit usage. The effect of holding a credit card is less robust, but not inconsistent with the canonical model. In all, the results are consistent with consumers responding strongly to the relative marginal cost of payment instruments at the POS.

I first estimate β_R, the effect of revolving credit balances on debit use, by implementing models (3) and (4) on several samples from the SCF.[25] The key results, presented in Table 4, suggest that revolvers are significantly more likely to use debit, to the tune of perhaps 6 percentage points (which is 17% of the baseline probability). The "base" specification contains several covariates in the X vector that are designed to identify β_R. These variables include controls for debit card supply (census region,[26] housing type, and ATM cardholding status); and for life-cycle and transient proxies for transaction demand and secular tastes which might effect payment choice (income last year, last year's income

[25] Throughout the paper I report probit marginal effects with SCF sample weights; using linear probability or logit produces virtually identical results. The results are also robust to using unweighted estimation on samples that exclude wealthy households *a la* Hayashi and Klee (2003).
[26] Census region is not available in the 2001 SCF public release; results estimated on the 1995 and 1998 do not change if region is omitted.

relative to average, number of household members, homeownership status, marital status, attitudes toward borrowing for luxury items, occupation, age, gender, educational attainment, military experience, race, and 1-digit industry).[27] Table 3 presents some related summary statistics, and detailed variable definitions are available in Appendix 2. The (psuedo) R-squareds are high by cross-sectional standards (e.g., 0.23 when using probit on the pooled sample).

The first two columns of results in Table 4 show the effects of omitting some or all of these control variables. Column 1 omits all of the X's, and simply produces a univariate correlation between debit usage and revolving behavior. Column 2 includes only those X's that plausibly are determined independently of R, namely housing type, household size, age, marital status, homeownership, race, gender, education, and income. Column 3 includes all the variables in the base specification.[28] Overall these results suggest, not surprisingly, that the covariates are critical to identification, with the base specification producing point estimates that are generally one-half the size of the raw correlation between debit use and revolving status. Importantly, the base specification appears robust to adding additional information designed to control for the particularly worrisome types of heterogeneity discussed in Section III. Adding covariates that plausibly capture additional information on transactions demand (including functions of wealth, and of the level of spending relative to income) tends to reduce the point estimates slightly but not significantly (results not shown). Adding covariates that might be correlated with a taste for plastic, including usage of other electronic payments and/or computer banking, does not change the results either (not shown).

Table 4 also exhibits the effects of limiting the sample based on cardholding (Column 4) and charging behavior (Column 5). These cuts are motivated by the measurement issues discussed in Section III, but in fact leave the results unchanged in most cases. The results are also robust to other alternative measures of revolving behavior (not shown). These include: using total credit card balances or self-

[27] Results do not change if one-digit occupation code is used instead of, or in addition to, industry.
[28] Appendix 3 displays the correlations between debit usage and the control variables from a regression using this specification on the 1995-2001 pooled sample.

reported habitual revolving behavior to define R (instead of the most recent credit card revolving balance), discarding the 14% of revolvers who hold charge cards (and can thereby float) from the sample, and conditioning on the number of bank credit cards held by the household (as well as on the interaction of this count with revolving status).

Reading across rows in Table 4, the estimation samples include the individual SCF cross-sections from 1995, 1998, and 2001, as well as the three samples pooled together.[29] This strategy is motivated by two trends: 1) the rapid growth in debit usage over time (Table 1), which implies that both the average and marginal debit users might vary across the cross-sections; 2) rapidly changing supply conditions; specifically, the dramatic increase in debit's acceptance and fraud protection over the sample period. Comparing results across the three sample years suggests stability in the relationship between revolving and debit use from 1998 to 2001, but not between 1995 and the other two survey years. Estimates using the base specification on the 1995 cross-section are substantially smaller, and insignificant. Simulations in Section V show that the 1995 results could indeed be explained by inferior debit supply conditions.

Table 5a presents estimates of the effect of credit card holding on debit use. Note first that this presents a power problem, particularly in 1995, since there are few households that use debit but lack a credit card (Table 5b, column 5).[30] It is not surprising then that β_H is often imprecisely estimated, although the 1998 and 2001 data do deliver the sign predicted by the canonical model (Table 5a, columns 3 and 4). Column 2 of Table 5a shows that adding credit card holding, H, to the base specification including R does not change the effect of revolving status (compare this to Column 1, which replicates the base covariate specification estimated on the cardholding sample in Table 4). This regression is estimated on the "full" SCF, which excludes only those households without a checking account or nonpositive income. Column 3 presents the estimates of β_H from the same regression. Adding additional controls for

[29] I omit the 1992 data because the question on debit lacks the later emphasis on usage (see Appendix 1). Adding 1992 data to the pooled sample tends to reduce the point estimates slightly. I omit households lacking a checking account (14% of households) or with nonpositive income (0.7% of households). Including these households does not change the results.

[30] β_H might be attenuated as well, since cardholding mechanically effects revolving. This type of econometric problem is discussed in Angrist and Krueger (1999).

bank credit card supply— including housing tenure, employment tenure, debt burden, and loan deliquencies— does not change the results significantly (not shown). Column 4 includes only H as the regressor of interest, and considers only convenience users in order to maximize sample homogeneity. The results are similar to those obtained with the full sample. Overall the effect of H is often large-- with reductions in debit use of up to 7.5 percentage points— but significant only in the 1998 sample. The data thus preclude drawing firm conclusions as to whether credit card *holding* actually reduces debit use.

Table 6 presents estimates of the effect of binding credit constraints on debit use using equation (5). The first panel presents results from a regression where revolvers are divided into three utilization categories based on the ratio of their most recent bank card balances to their credit limit, with convenience users as the omitted category.[31] As predicted by the canonical model, the most intense credit card borrowers-- the 7% of the sample with utilization rates of 75% or greater-- appear discretely and significantly more likely to use debit than the least intense revolvers.[32] The result holds in every sample but the 1995 cross-section.

Additional results suggest that future credit constraints may be as important as current ones in driving debit use. If only current credit constraints matter, than we would expect discrete jumps in debit use only at the bottom and top of the utilization distribution. Such jumps would capture the revolving and credit limit effects, respectively. But if the anticipation of future credit constraints matters, we might find that the credit limit begins to bind at utilization levels substantially below 100%, if consumers hold buffer stocks of available credit. The latter case appears to hold. Whether one demarcates line usage as in panel one, or by conditional terciles (producing much lower cutoffs for medium and high intensity, shown in panel two), it appears that debit usage jumps discretely and significantly for medium, but not again for

[31] I use total bank credit card balances and the credit limit variable (x414) in constructing the utilization measures; using total credit card balances instead has little impact on the results.
[32] Gross and Souleles (2002) use utilization categories of 0-50%, 50-90%, and >90% in their analysis of the impact of credit constraints on interest rate elasticities and propensities to consume out of available credit. This demarcation is impractical in my sample since only 3% of households have utilization >90%. Presumably this low proportion is due to: a) underreporting of credit card borrowing, and b) the fact that the SCF credit line variable may include lines from multiple cards.

high, intensity users.[33] Panel three explores this further by dividing revolvers based on conditional quartiles of line utilization, and finds again that the second discrete jump in debit use occurs somewhere in the middle of the utilization distribution. Finally, it also appears that households reporting no emergency access to capital from family or friends are much more likely to use debit at lower utilization levels, although none of the differences by this proxy for buffer liquidity are statistically significant. These findings raise the question of whether credit constraints might actually bind at R=0, and thereby bias β_R and β_F downward, but conditioning on the size of the credit limit itself does not change the results.

Table 7 displays evidence suggesting that the utilization and revolving effects on debit use operate through reductions in bank credit card charges, as one would expect. Mechanically, that is, one expects to find revolvers charging less on their credit card if they are in fact minimizing the marginal cost of POS payments by not borrowing-to-charge. This appears to be true, resoundingly, regardless of how one measures revolving behavior.[34] The table presents results only from the 2001 and pooled samples for brevity's sake, and in both samples one finds large reductions in the level of credit card charges for revolvers relative to convenience users. The $428 and $344 reductions in the 2001 and pooled samples (column 1), respectively, each amount to 60% of the sample mean; estimating mean charges using tobit instead of OLS, or estimating median charges using least-absolute-deviations, produces equal or greater proportional reductions (not shown). Debit users do not exhibit significantly greater reductions than non-users, however, suggesting that some revolvers may switch to cash or check rather debit to manage their payments costs. This makes sense if, as hinted earlier, credit may actually dominate debit as a medium of exchange along certain dimensions (e.g., fraud protection, acceptance), a possibility explored in Section V.

---

[33] The finding here seems analogous to the discrete jump in the propensity to consume out of available credit among medium intensity users found in Gross and Souleles (2002).

[34] A data limitation in the SCF motivates experimentation with the alternative measures of R presented in the second and third columns of results in table 7. The problem is that the SCF only captures *the previous month's* charges, and presumably some fraction of households started revolving only *after* choosing not to pay the previous month's balance in full. For this fraction one would not necessarily expect to observe lower charges in the previous month. Accordingly, the regressions presented in column 2 define revolvers as those who are currently revolving a balance and report habitually revolving a balance; column 3 regressions take the more extreme step of excluding current-but-not-habitual revolvers from the sample.

Overall, the evidence on the effect of revolving, utilization, and (to a lesser extent) credit card holding is consistent with consumers responding strongly to *discrete* differences in the marginal cost of payments alternatives at the POS. Evidence on the impacts of *smaller* cost differences is inconclusive, however. Specifically, a higher interest rate on credit card balances makes it more expensive to borrow-to-charge, all else equal; accordingly, we might then expect to find debit use increasing in this rate, for revolvers. The data produce point estimates (not shown) that are generally "right-signed", but small and imprecisely estimated; e.g., in the pooled sample, the probability of debit usage appears to increase by .09 percentage points (0.2%) for every 100 basis point increase in the interest rate for revolvers (but not for convenience users), with a t-statistic of only 0.43. Some of the imprecision may be due to the fact that we observe only the household's current rate on the card with the largest balance. Given the prevalence of teaser rates, for example, we might underestimate the effect of credit card interest rates on debit use if the observed interest rate understates the typical rate. As such I replicate the analysis on the 78% of households reporting interest rates greater than 9.99%, and find that the estimated point estimate in the pooled sample does increase twofold (but with a t-statistic of only 0.53).

In all, the standard errors and measurement limitations do not rule out large effects on the intensive rate margin. The confidence intervals allow for debit usage increases of up to 0.9 percentage points per 100 basis point increase in the credit card interest rate. This would imply a substantial price response, given the base probability of debit use (40%) and the observed spread of interest rates (1st percentile = 1.99%, 99th percentile = 23.9%). Issuer data could be used to estimate this effect more precisely (see Section VI).

Summarizing the key results presented in this section, it appears that households do behave in a manner that is *consistent* with a canonical model of consumer choice. This is evidenced by the economically and statistically significant effects of revolving status and credit limit constraints on debit use. The point estimates suggest that canonical motives could account for a perhaps 25% of cross-sectional debit use (if we simply sum the absolute values of β_R and β_H in the base pooled sample, and scale by proportion of debit-using households). The next section finds that these point estimates are likely to be conservative lower bounds on the true casual effects of interest.

V. Measurement Error and Interpretation

This section explores how measurement error might impact the key estimates presented in Section IV. In particular, seven different measurement issues could bias β_R downward and thereby understate the causal effect of revolving on debit use. The discussion below draws on regression results presented in Table 8. Appendix 4 contains more detail on related variable construction and estimation procedures.

1. Mismeasurement of R, revolving behavior

Section IV considered alternative definitions of R based on different *reported* measures of credit card borrowing. A deeper problem is that the reports themselves may systematically understate revolving prevalence. *Total* credit card borrowing in the SCF falls far short of aggregate figures compiled from issuers, and while comparison on the *extensive* margin is less definitive, Gross and Souleles (2002) find revolving prevalence in issuer data that is consistent with substantial underreporting in the SCF. I address this "misclassification" problem in two ways. The first approach exploits SCF interviewer observations on the quality of a household's responses. Limiting the sample to those most likely to respond truthfully (Table 8, column A) and accurately (column B) increases the estimated effect of revolving on debit use by up to 4 percentage points, but not significantly so. The second method implements the Mahajan (2004) corrections for misclassification error in binary regressors, using the most recent measure of bank credit card revolving as the true R of interest, and the habitual measure of revolving as the instrument. If we assume that misclassification of R is independent of the covariates, then β_R is essentially unchanged at 0.064 in the base specification; more realistically, allowing the misclassification to vary with race, income, education, age, gender, and industry increases β_R very slightly to 0.066. Overall then it appears that misclassification of R does not significantly attenuate estimates of β_R.

2. Omitted strategic default motives

β_R might also understate the true causal effect of revolving if the model fails to capture strategic default. In particular, a revolver who is contemplating bankruptcy, or simply not making interest payments, might rationally elect to continue borrowing-to-charge rather than using debit.[35] Accordingly, I use imputed SCF credit scores (Barakova et al. 2004) to re-estimate the base specification on a sample of high-risk borrowers. Column A shows that the point estimate in the high-risk pooled sample increases slightly; this result is driven by stability in the 1995 and 1998 estimates, as the 2001 point estimate (column B) increases sharply. Alternately, conditioning on functions of the credit score in the pooled base sample *reduces* the point estimate by about 2 to 2.5 percentage points but also leaves the qualitative results unchanged. Overall there is little suggestion that omitted strategic default motives dramatically impact the results.

3. Cash back motives for debit use

The ability to get cash back at the POS via an online debit transaction makes debit use attractive by eliminating a separate trip to the ATM (which consumes time, and may require a transaction fee). Practically, the absence of data on cash back usage in the SCF might attenuate β_R because some proportion C of convenience users should use debit regularly (and exclusively) to obtain cash back. (Of course no bias will result if the other regressors capture cash back demand.) I explore the magnitude of this potential bias via a simulation that randomly assigns an "exclusive cash back" motive to non-revolving debit users in the SCF. Raw data suggests that C is low-- calculating it directly in the December 1996 Survey of Consumers (SOC) yields 7%. This is not surprising in light of other data showing that cash back transactions are relatively infrequent, and that relatively few debit users initiate them (only 18% in the April/May 1999 PSI Global Survey, 29% in the SOC). As such I conduct simulations allowing for weak and strong exclusive cash back motives, where C = 7% and C = 40%,

[35] About half of bad credit card debts are written off without the debtor filing for bankruptcy (Dawsey and Ausubel 2002).

respectively. β_R rises to 0.079 in the former case (column A), and to 0.158 in the latter case (column B). Thus it appears that unobserved cash back motives could produce substantial downward bias on β_R.

4. Fraud costs/security precaution

Credit cards offered superior fraud protection during the sample period studied in the paper (Thomson 2002). As such, some revolvers might rationally borrow-to-charge rather than using debit, if the expected fraud loss on a marginal transaction exceeds the expected marginal finance charge. But adding the SCF's categorical measures of appetite for financial risk as additional covariates leaves β_R unchanged. This SCF variable is probably an imperfect proxy for expected fraud loss, however, so I tap market research on preferences for online debit to help develop a rough idea of the extent to which unobserved security concerns might influence estimates of β_R. The *STAR 2000 Consumer Awareness, Trial and Usage Study* found that 51% of debit users preferred online debit, among whom 54% cited better security (due to the PIN requirement) as the primary reason for their preference. Accordingly, let us assume that (.51*.54) = 27.5% of debit users will use *only* online debit; given the relative scarcity of PIN terminals (compared to offline facilities), this implies that debit is an unobservably poor substitute for credit for these consumers. I simulate the effect this might have on β_R by randomly assigning a "security precaution" motive to a proportion S of revolvers who do not use debit, taking 27.5% as the strong case, and an arbitrary 5% as the weak case.[36] β_R rises to 0.085 in the weak case (column A) and to 0.134 in the strong case (column B). Overall, it seems that unobserved security precautions might lead to some attenuation of β_R. Note again, however, that the simulations overstate the true β_R to the extent the unobserved security precautions were effectively observed in the first place, via the X's.

[36] Note that this strong case is almost certainly too extreme, since presumably many consumers who refuse to use offline debit still use online debit and the outcome of interest is a binary measure of debit use.

5. Rewards incentives favoring credit use

Credit cards typically offer more generous rewards (e.g., frequent flier points, cash back, etc.) than debit.[37] The marginal benefit of these rewards might exceed the marginal cost of borrowing-to-charge for many consumers, implying that any unobserved net benefit could bias β_R downward. Assume then that some fraction Z of revolvers prefers to borrow-to-charge, rather than use debit, in order to obtain rewards. I simulate a "strong" version of the rewards motive by setting Z to 60%, in light of recent survey evidence that rewards are "very important" or "somewhat important" to nearly 60% of bank credit card holders (Durkin 2002). The "weak" version is motivated by the roughly 20% of SCF households who report credit card interest rates of less than 10%. The latter case produces a β_R of 0.115, with the former yielding a huge increase to 0.274. In all it seems likely that omitted information on rewards usage leads to substantial downward bias on the estimated revolving effect.

6. Multiple bank credit cards

As discussed earlier, the SCF captures total bank credit card balances across *all* cards. R therefore must be derived from this aggregate measure, whereas the precise test of interest requires information on whether the consumer has the ability to float on any *single* bank credit card. The most direct test of the degree to which this biases β_R is to limit the sample to households holding a single credit card (Table 4); however, this approach invites sample composition effects. Alternatively, one could make assumptions on the degree to which those *appearing* to borrow-to-charge in the data are in fact rationally floating. The rewards and security simulations, which also treat revolvers who do not use debit, give a sense as to how large the bias could be.

7. Debit card supply and merchant acceptance

Although debit is available and accepted widely today-- as 80% of ATM cards sport the offline Visa logo alone (Dove 2002), and as PIN terminals steadily increase in prevalence— this was much less

[37] Despite widely publicized new programs on the debit side, the *STAR 2002 Annual Consumer Survey* found that only about 6% of consumers get ATM or debit rewards (c.f. Marlin 2003). In contrast, credit card incentives have been prevalent for years. The December 1996 SOC found that 56% of credit card holders had a card with rewards.

true in 1995. Practically, this implies that during the early part of the sample period under consideration in this paper, there were nonusers who would have used debit given the right supply conditions. If some of these consumers instead borrowed-to-charge, β_R would again be biased downwards. This effect probably helps explain why the revolving effect is so much lower in 1995 than in later years.

Overall then, it seems plausible that data limitations significantly dampen β_R, the estimated effect of revolving on debit use.[38] Better data on cash back, rewards, and individual card balances would be particularly useful for generating more accurate estimates of the true casual effect. I now turn to this issue of interpreting such estimates as tests of competing models of consumer choice.

VI. A Behavioral Alternative to the Canonical Model: Theory & Evidence

Thus far the model and empirical tests have yielded evidence that is *consistent* with a canonical model of consumer payment choice at the POS. But these results have not *distinguished* between a canonical model and any alternative models.

As such this section develops a specific behavioral model of payment choice at the POS, drawing heavily on Prelec and Loewenstein (1998). It shows that this model does generate predictions that are distinct from the canonical model, and these predictions are empirically testable—in principle. Unfortunately, identifying the sharpest distinctions between the 2 models requires information on the nature, timing, and method of specific purchases that is not available in any public dataset. The SCF does permit some relatively coarse tests of the behavioral model, however. The results of these tests are mixed, with some delivering new stylized facts that are consistent with a unique behavioral motive, and others suggesting nothing that would lead to the rejection of a null hypothesis of canonical consumer optimization.

[38] Note that missing information on the prevalence of debit transaction fees is *not* likely to bias estimates on β_R, since fees are: 1. not very prevalent (see Section II); and 2. typically charged only on *online* debit transactions. As such fees are unlikely to influence the *extensive* margin of debit use, all else constant, since in most cases consumers will have the option of a fee-free offline transaction.

Mental accounting and payment choice

The informal argument that debit helps "control spending" can be formalized via a model that incorporates mental accounting and impatience.[39] The Prelec and Loewenstein (1998) model of mental accounting with a "pain of paying" seems especially apt, since it produces distinct, intuitive motives for using debit relative to credit besides canonical cost minimization. In Prelec and Loewenstein, the act of paying produces cognitive transaction costs that act as both a tax on consumption and a distinct source of disutility. But these negative effects can be buffered by consumption or anticipation thereof. These substantive interactions between consumption and payments produce incentives to *decouple* payments from consumption, and may help explain the prevalence of flat-rate pricing and prepayment even in markets where pay-per-usage would seem to minimize costs for the consumer.[40] The optimal decoupling strategy depends on the *type* of consumption— e.g., it tends to favor delayed payment for durable goods, but prepayment for instantaneous consumption. This stands in stark contrast to the canonical model, where the type of consumption is immaterial to payment choice.

A credit card is an effective decoupling device because it delays payment, thereby attenuating the payment pain ascribed to any particular consumption event. Credit cards also lump payments together and thereby capitalize on any convexity over distinct "losses" produced by payments (Thaler 1985). Credit cards may thus promote *hedonic efficiency*, defined essentially as minimizing the payment costs (including experienced pain) associated with consumption. The tension is that credit cards (and decoupling schemes in general) may reduce *decision efficiency* (and hence *outcome efficiency*) if the adaptive role of payment pain is to counteract present-biases that produce overspending when left unchecked (Prelec 1991).[41] Debit, which a relatively instantaneous form of payment, offers less

[39] Impatience alone, even with time-inconsistent preferences, is insufficient to induce debit use, since the debit card does not actually provide a commitment device that renders assets illiquid (and thereby protected from future impatient selves).
[40] But see, e.g., DellaVigna and Malmendier (2004) and Miravete (2003) for alternative explanations of prepaid and flat rate contracts.
[41] Prelec and Loewenstein (1998) distill the tension between decision and hedonic efficiency as follows: "consumers wish to know how much consumption costs, but do not wish to unduly think about how much it costs" (p. 26).

decoupling than credit— and consequently more decision benefits and fewer hedonic benefits, all else equal.[42]

One can capture the tension between hedonic and decision motives with a reduced-form parameter m_t, defined as the net mental accounting cost m for transaction t, for credit relative to debit. The consumer's problem is now:

(7) Min [$C_d(p)$, $C_c(H, f, r(R, r_{purch}, B, L), m_t)$]

The problem faced by our behavioral consumer therefore is identical to the one faced by the canonical consumer in (1), except that if the additional risk of overspending with credit is sufficiently great (or small) compared to the marginal pain of paying with debit, then debit use becomes more (or less) attractive.[43] m_t need not be large to swamp pecuniary cost considerations in this case, as the financing cost of using credit to borrow-to-charge averages perhaps 0.6% (60 basis points) of the purchase price.

Testing the Model

Unfortunately, we do not observe individual transactions in the SCF data (or in publicly available retail payments data generally). Therefore one can not test the starkest prediction of this behavioral model in the SCF— namely, that *hedonic* benefits, and hence payment choice, will vary with type of good being purchased, all else equal.[44] Accordingly I must drop the transaction subscript and explore

[42] All else is frequently not equal— as suggested by the revealed preference for prepayment in some contexts—and one could allow debit and credit to each have distinct hedonic and decision costs and benefits. Instead, for expositional purposes, I focus on the tension between the hedonic benefits provided by credit and the decision benefits provided by debit.
[43] The decision cost of credit can be thought of as the consumer's expected underestimate of the shadow utility cost of foregone future consumption if she fails to commit herself, *ex-ante*, to using debit for transaction t.
[44] Specifically, conditional on marginal cost as defined in the canonical sense, debit should be used for instantaneous consumption and credit for durable consumption. In contrast, the canonical model predicts that only marginal cost should matter. It follows, in stark contrast to the behavioral model, that under the canonical model one should never observe the contemporaneous use of debit and credit by a given consumer (if we make the appropriate allowances for cash back transactions and the odd case where debit offers superior acceptance or rewards). These predictions are testable, in principle, using data that combines consumer-level information on credit card terms and revolving behavior with data on individual purchases made by that consumer (specifically, what was bought when, using which payment method). Such data exists (see Rysman 2004) but is privately held.

regrettably coarse ways in which the *decision* benefits of debit relative to credit might manifest in the SCF data.

We should expect consumers with high m's to use debit relatively often. This can be illustrated via a thought experiment where revolving consumers are given the option of using debit cards for the first time. Under a behavioral model, debit cards help consumers with high m's implement their optimal consumption plan by avoiding overspending; i.e., credit card balances fall. Under a canonical model, the option to use debit only impacts the decision of how to pay, not how much to consume (holding constant a small income effect). So credit card borrowing is essentially unchanged. It follows that if m is large enough on average (across consumers), then we might find a negative correlation between credit card balances and debit use. Accordingly I estimate the following equation on 1995-2001 pooled SCF data:

(8) $B_i = \alpha + \beta_R Y_i + \delta X_i + \tau T_t + \varepsilon_i$

Where B is a measure of spending or credit card balances and, as before, Y is debit use, X includes the covariates in the base specification, and T includes survey year dummies. As a concession to the previously observed robust positive correlation between discrete revolving behavior and debit use, I restrict the sample to revolvers. This permits a test of whether debit use is negatively correlated with credit card balances (on the intensive margin), as the behavioral model predicts. I estimate (8) using several different measures of credit card borrowing, estimators, and sets of included covariates, and find no evidence of a significant negative correlation.[45]

The mental accounting benefits of debit could manifest in other ways, so next I explore whether households who have fallen behind on loan payments appear more likely to use debit. Again, the imagined mechanism is that a household overspends and then begins using debit to help control spending.

[45] In fact, the debit coefficient is typically positive but insignificant. Outcome measures included bank credit card balances— in levels, logs, and scaled by income— and a binary variable for whether spending exceeded income in the previous year (it did for 22% of the sample). Estimators included tobit, median regression, and probit. Control specifications added the credit card interest rate to the base specification, and deleted credit attitude variables from the base specification.

I test for this channel by adding a variable for late payments to equation (4). Some specifications also include an interaction between this variable and R, the revolving variable. The main effect of late payment is always large and significant (in the 6 to 11 percentage point range, depending on specification), but its interaction with R (and with H, credit card holding) is always negative, relatively small, and insignificant. These findings are consistent with a mental accounting role for debit that operates globally, but not specifically through controlling credit card spending.

A final test of whether debit might be used to control credit card spending on the intensive margin attempts to exploit the (in)congruence between stated beliefs and actions. The notion is that consumers who aver debt aversion[46] but find themselves revolving might be more likely to begin using debit to control their spending. The data certainly seem consistent with this story, as interactions between favorable attitudes toward borrowing and revolving behavior produce robust negative correlations with debit use, while leaving the revolving coefficient unchanged or larger than before (Table 9).[47]

The tests reported thus far have produced some suggestive evidence that appears consistent with the popular notion that debit is used to manage spending. There is less support for a mental accounting channel that works via the intensive margin of credit card borrowing specifically, although the interactions between credit attitude variables and revolving behavior seem to point in this direction. The impact on the intensive margin of credit card borrowing is particularly important for identifying canonical marginal cost effects, since mental accounting effects that operate on this margin could *independently* produce the observed correlation between revolving and debit use. Put another way, the revolving effect on debit use could be produced *either* by a spending control motive that reduces but does not eliminate revolving behavior, or by traditional cost minimization.

---

[46] The SCF asks several questions on whether the respondent thinks it is "all right to borrow" for specific types of purchases. See Appendix 2 for wording and variable construction.

[47] The table focuses on attitudes towards buying a vacation, jewelry, or a car on credit. (Other attitude variables are included in some specifications but the results on these variables are not reported to conserve space.) The first two seem most directly related to the type of discretionary or impulse goods that might be prone to overspending, and they also have the lowest incidence of favorable attitudes (7% and 16% for jewelry and vacations, respectively). The car variable is featured because: 1. it is the lone

On the other hand, a behavioral motive for debit use that *eliminates* revolving creates a different problem for interpreting β_R, since this channel works *against* finding a positive correlation between revolving and debit use.[48] Mechanically, if consumers with a high mental accounting cost to using credit (a high m, in the notation of equation 7) use debit to help self-impose a blanket prohibition on credit card borrowing, then equation (4)'s β_R is actually a reduced-form combination of parameters with opposite signs. On one hand, a behavioral effect operating on the *extensive* margin produces $\beta^{me}{}_R < 0$; on the other hand, the *intensive* behavioral effect described above and the canonical effect (call these $\beta^{mi}{}_R$ and $\beta^{c}{}_R$, respectively) produce positive correlations between revolving and debit use. Accordingly β_R will obscure the true magnitudes of $\beta^{me}{}_R < 0$, $\beta^{c}{}_R > 0$, and $\beta^{mi}{}_R > 0$.

As noted at the outset, the descriptive statistics suggest that we need to take seriously the possibility that $\beta^{me}{}_R < 0$ via a mental accounting channel that eliminates revolving (but not necessarily card *holding*). Table 2 suggests that as many as 29% of debit users are driven by this motive; i.e., they forego free float (and miles, etc.) by using debit despite the lack of any apparent pecuniary incentive to do so. One therefore needs either substantial underreporting of revolving behavior in the SCF, and/or substantial understatement of the cash back/time cost motive, to rule out a mental accounting channel that works by eliminating revolving among credit card holders.

What Table 2 does not capture is that its puzzle will be even larger if debit enables some users to choose not to *hold* a credit card in order to avoid the temptation to overspend. Note that the upper bound on this effect is relatively small, since only 17% of debit users in 2001 do not hold a credit card. (These 17% of debit users comprise only 9% of *all* households.) And presumably many of these 17% lack a credit card by constraint, not by choice; regressions of cardholding on standard demand and supply variables (e.g., age, education, income, employment history, credit history) yield high R-squareds (in the 0.20 range), and most of the variables are statistically and economically significant. Moreover, 42% of

---

attitude variable that is ever significant in regressions with a main attitude effect but without interactions between attitude(s) and revolving, and 2. it is the attitude variable with the highest favorable incidence (85%).

these households report being credit constrained. Nevertheless cardholding is also positively correlated with positive credit attitudes, which seems at odds with the canonical model (where consumers should float and collect miles, even if they don't intend to revolve) and leaves the door open for a small temptation avoidance effect.[49] This effect would reinforce the hypothesized canonical effect of credit card access on debit use; i.e., both $\beta_H^c < 0$ and $\beta_H^m < 0$.

In sum, this section has developed several analytical and empirical points regarding attempts to distinguish competing models of consumer choice over payments media:

1. There is a specific, plausible behavioral alternative to the canonical model: mental accounting with impatience and a pain of paying, a la Prelec and Loewenstein (1998).
2. This behavioral model is empirically distinguishable from the canonical model, in principle. Unfortunately the sharpest distinctions between the models' predictions concern transaction characteristics that are not observable in publicly available data.
3. The impact of any unobserved behavioral motive on estimates of canonical effects using equation (4) or (5) is ambiguous:
   a) A spending control mechanism where consumers use debit to reduce the *intensity* of credit card revolving, but not eliminate it, will lead to overestimates (upward bias).
   b) A temptation avoidance mechanism where debit enables consumers to forgo holding a credit card altogether will lead to slight overestimates (in absolute value terms) of the canonical effect of credit card access.
   c) On the other hand, a spending control mechanism that eliminates revolving, conditional on card holding, will downward bias the canonical price effect.

[48] Note that any behavioral channel that eliminates *revolving* via debit use does not generally do so by eliminating *charging* altogether, as only 16% of nonrevolving debit users have *higher* charges throughout the distribution than both revolving debit users specifically and credit card holders generally.

[49] Note, however, that there is little evidence of a negative *interaction* between debit use and credit attitudes on credit card holding, as one might expect if debit use were critical to temptation avoidance. The main credit attitude effects are jointly significant in all specifications, and the coefficients on vacation and jewelry are, e.g., 0.04 each (on a cardholding base of 0.77) in the specification where they are the only two attitude variables included.

4. Empirically, there is some evidence that appears consistent with each of the confounds 3a)-c), although the results are suggestive at best, given SCF data limitations. New stylized facts show that:

- There is no significant correlation between (credit card) spending and debit use. This is inconsistent with spending control explanations for debit use.
- There is a strong correlation between falling behind on loan payments and debit use, although this effect is not particularly strong for revolvers. This is consistent with a spending control explanation that operates globally, but not necessarily via credit card borrowing.
- Revolvers who profess to be debt averse are much more likely to use debit. This is consistent with a spending control explanation that operates on the intensive margin of credit card borrowing (confound 3a).
- A potentially sizeable proportion of debit users report holding a credit card but not revolving balances, and hence lack an obvious canonical motive for using debit regularly. This is consistent with a spending control motive that operates through the elimination of revolving credit card balances (confound 3b). If this mechanism exists, it does not appear to work by eliminating credit card *charges* altogether.
- Any temptation avoidance effect must be small in the limit, since only 17% of debit users lack a credit card and evidence points to credit card rationing as a leading explanation. Nevertheless credit attitudes do help predict credit card holding, conditional on traditional supply and demand variables, which admits the possibility that a small number of debit users do indeed control spending by declining to hold credit cards (confound 3c).

VII. Conclusion

This paper has developed analytical frameworks for testing models of consumer payment choice, and has found evidence consistent with important roles for both canonical and behavioral motives. The results have at least two implications for the evolution of the retail payments industry and related policy issues. First, they suggest that debit and credit are partial substitutes. This casts doubt on the widespread assumption, shared by bankers and theorists alike, that debit's growth has come largely at the expense of cash and checks (Reosti 2000; Chakravorti and Shah 2003). Second, the results imply that the adoption of general purpose stored-value cards will likely depend not only on network effects and safety/convenience advantages relative to paper-based media, but also on the marginal cost (broadly defined) faced by the consumer relative to credit and debit.[50] For example, if, in equilibrium, the pecuniary transaction cost for stored-value proves less than for debit (due, e.g., to lower verification costs), then stored-value will become a viable way for revolvers to avoid borrowing-to-charge.

The results also point in a specific direction for further research, using data that combines transaction characteristics with account-level information on credit card pricing and revolving behavior. Such data would permit sharp tests of competing models of high-frequency intertemporal consumer choice.

[50] Santomero and Seater (1996), motivated in large part by prepaid cards, model a consumer choosing among several media of exchange.

References Cited

Aizcorbe, Ana M., Arthur B. Kennickell and Kevin B. Moore (2003). "Recent Changes in U.S. Family Finances: Evidence from the 1998 and 2001 Survey of Consumer Finances." *Federal Reserve Bulletin* 89(January): 1-32.

Angeletos, George-Marios, David Laibson, Andrea Repetto, Jeremy Tobacman and Stephen Weinberg (2001). "The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical Evaluation." *Journal of Economic Perspectives* 15(3): 47-68.

Angrist, Joshua D. and Alan B. Krueger (1999). "Empirical Strategies in Labor Economics." *Handbook of Labor Economics, Volume 3*. O. Ashenfelter and D. Card, Elsevier Science B. V. 3**:** 1277-1366.

Ausubel, Lawrence M. (1991). "The Failure of Competition in the Credit Card Market." *American Economic Review* 81(1): 50-81.

Barakova, Irina, Ralph Bostic, Paul Calem and Susan Watcher (2004). "Does Credit Quality Matter for Homeownership?" Institute for Law and Economics, University of Pennsylvania Law School. Research Paper No. 03-40.

Bertaut, Carol C. and Michael Haliassos (2002). "Debt Revolvers for Self-Control." Mimeo.

Boeschoten, Willem C. (1998). "Cash Management, Payment Patterns, and the Demand for Money." *De Economist* 146(1): 117-142.

Breitkopf, David (2003). "Customers Get Savvier in Debit Debate." *The American Banker*. Special Report: Retail Delivery, May 6**:** 4A.

Brito, Dagobert L. and Peter R. Hartley (1995). "Consumer Rationality and Credit Cards." *The Journal of Political Economy* 103(2): 400-433.

Canner, Niko, Gregory N. Mankiw and David N. Weil (1997). "An Asset Allocation Puzzle." *American Economic Review* 87(1): 181-91.

Carow, Kenneth A. and Michael E. Staten (1999). "Debit, Credit, or Cash: Survey Evidence on Gasoline Prices." *Journal of Economics and Business* 51: 409-421.

Carroll, Christopher D. (2001). "A Theory of the Consumption Function, with and without Liquidity Constraints." *Journal of Economic Perspectives* 15(3): 23-45.

Chakravorti, Sujit (2003). "Theory of Credit Card Networks: A Survey of the Literature." *Review of Network Economics* 2(2): 50-68.

Chakravorti, Sujit and Alpa Shah (2003). "Underlying Incentives in Credit Card Networks." *The Antitrust Bulletin* 48(1): 53-75.

CPSS (2003). "Statistics on Payment and Settlement Systems in Selected Countries - Figures for 2002." *CPSS Publication no. 60*. November.

Dawsey, Amanda E. and Lawrence M. Ausubel (2002). "Informal Bankruptcy." Mimeo.

DellaVigna, Stefano and Ulrike Malmendier (2004). "Contract Design and Self-Control: Theory and Evidence." *Quarterly Journal of Economics* 119(2): 353-402.

Dove, Consulting (2001). *Electronic Payments Instruments Study: Summary Report Prepared for the Federal Reserve System's Retail Payments Office*. December 5.

Dove, Consulting (2002). *Debit Issuer Survey: Cardholder Fees & Industry Outlook*. August 2.

Durkin, Thomas A. (2000). "Credit Cards: Use and Consumer Attitudes." *Federal Reserve Bulletin*(September): 623-634.

Durkin, Thomas A. (2002). "Consumers and Credit Disclosures: Credit Cards and Credit Insurance." *Federal Reserve Bulletin*(April): 201-213.

Frame, W. Scott and Lawerence J. White (2004). "Empirical Studies of Financial Innovation: Lots of Talk, Little Action?" *Journal of Economic Literature* XLII(1): 116-144.

Furletti, Mark (2003). "Credit Card Pricing Developments and Their Disclosure." Discussion Paper, Payments Cards Center, Federal Reserve Bank of Philadelphia.

Fusaro, Marc (2003). "Check Bouncing Goes Mainstream: An Empirical Study of Bounce Protection Programs." Mimeo, Northwestern University.

Gerdes, Geoffrey R. and Jack K. Walton, II (2002). "The Use of Checks and Other Noncash Payments Instruments in the United States." *Federal Reserve Bulletin* 88(8): 360-74.
Gross, David B. and Nicholas S. Souleles (2002). "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data." *The Quarterly Journal of Economics* 117(1): 149-85.
Hancock, Diana and David B. Humphrey (1998). "Payment Transactions, Instruments, and Systems: A Survey." *Journal of Banking & Finance* 21: 1573-1624.
Hayashi, Fumiko and Elizabeth Klee (2003). "Technology Adoption and Consumer Payments: Evidence from Survey Data." *Review of Network Economics* 2(2): 175-190.
Hayashi, Fumiko, Richard Sullivan and Stuart E. Weiner (2003). *A Guide to the ATM and Debit Card Industry*, Federal Reserve Bank of Kansas City.
Humphrey, David B., Moshe Kim and Bent Vale (2001). "Realizing the Gains from Electronic Payments: Costs, Pricing, and Payment Choice." *Journal of Money, Credit, and Banking* 33(2): 216-234.
Jevons, W. Stanley (1918). "Money and the Mechanism of Exchange." *The Bankers Practical Library*. New York, Appleton. Vol. 3.
Kennickell, Arthur (1998). "Multiple Imputations in the Survey of Consumer Finances." Federal Reserve Board of Governors Working Paper.
Kennickell, Arthur and Myron Kwast (1997). "Who Uses Electronic Banking? Results from the 1995 Survey of Consumer Finances." *Proceedings from the Federal Reserve Bank of Chicago's Annual Conference on Bank Structure and Competition*.
Laibson, David (1997). "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics* 112(2): 443-477.
Laibson, David, Andrea Repetto and Jeremy Tobacman (2003). "A Debt Puzzle." *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*. P. Aghion, R. Frydman, J. Stiglitz and M. Woodford. Princeton, NJ, Princeton University Press. Chapter 11**:** 228-266.
Laibson, David, Andrea Repetto and Jeremy Tobacman (2003). "Wealth Accumulation, Credit Card Borrowing, and Consumption-Income Comovement." *Mimeo*.
Laibson, David, Andrea Repetto and Jeremy Tobacman (2004). "Estimating Discount Functions from Lifecycle Consumption Choices." *Mimeo*.
Little, Roderick (1992). "Regression with Missing X's: A Review." *Journal of the American Statistical Association* 87(420): 1227-37.
Lyons, Richard G. Jr. (2004). "So You Think Debit Card Growth Is Impressive Now? Just Wait." *American Banker* 169(39).
Mahajan, Aprajit (2004). "Misclassified Regressors in Binary Choice Models." Mimeo, Stanford University.
Mann, Ronald J. (2002). "Credit Cards and Debit Cards in the United States and Japan." *Monetary and Economic Studies* 20(1): 123-59.
Mantel, Brian (2000). "Why Don't Consumers Use Electronic Banking Products? Towards a Theory of Obstacles, Incentives, and Opportunities." Emerging Payments Occasional Paper Series, Federal Reserve Bank of Chicago. EPS-2000-1.
Marlin, Steven (2003). "Debit Card Usage Is Rising." *Bank Systems and Technology Online*.
McDonald, John and Eric Wasserstrom (2003). *Q-Series: UBS Electronic Payments Summit-Takeaways for Banks and Card Issuers*. UBS Investment Research, Global Equity Research, New York, June 26.
Miravete, Eugenio J. (2003). "Choosing the Wrong Calling Plan? Ignorance and Learning." *The American Economic Review* 93(1): 297-310.
Moskowitz, Tobias J. and Annette Vissing-Jorgensen (2002). "The Returns to Entrepreneurial Investment: A Private Equity Premium Puzzle." *American Economic Review* 92(4): 745-78.

Prelec, Drazen (1991). "Values and Principles: Some Limitations on Traditional Economic Analysis." *Socioeconomics: Toward a New Synthesis*. A. Etzioni and P. Lawerence. New York, M.E. Sharpe.
Prelec, Drazen and George Loewenstein (1998). "The Red and the Black: Mental Accounting of Savings and Debt." *Marketing Science* 17(1): 4-28.
Prelec, Drazen and Duncan Simester (2001). "Always Leave Home without It: A Further Investigation of the Credit-Card Effect on Willingness to Pay." *Marketing Letters* 12(1): 5-12.
Reda, Susan (2003). "2003 Consumer Credit Survey." *STORES Magazine*. November.
Reosti, John (2000). "Debit Cards Seen as No Threat to Credit Card Revenues." *American Banker*. June 29.
Rochet, Jean-Charles and Jean Tirole (2002). "Cooperation among Competitors: Some Economics of Payment Card Associations." *RAND Journal of Economics* 33(4): 549-570.
Rysman, Marc (2004). "An Empirical Analysis of Payment Card Usage." Mimeo, Boston University.
Santomero, Anthony M. and John J. Seater (1996). "Alternative Monies and the Demand for Media of Exchange." *Journal of Money, Credit, and Banking* 28(4): 942-960.
Shy, Oz and Juha Tarkka (2002). "The Market for Electronic Cash Cards." *Journal of Money, Credit, and Banking* 34(2): 299-314.
Stavins, Joanna (2001). "Effect of Consumer Characteristics on the Use of Payment Instruments." *New England Economic Review*(3): 19-31.
Thaler, Richard (1985). "Mental Accounting and Consumer Choice." *Marketing Science* 4(3): 199-214.
Thomson, Financial (2002). "Bank of America Launches Campaign to Ease Customers' Security Concerns." *ATM & Debit News* 3(2): 1.
Visa (2002). "Consumers Choosing Debit Cards More Often, Visa U.S.A. Announces Debit Outpaces Credit." San Francisco, CA. Press Release, September 16.

Table 1. Debit Use in the Raw, Over Time

		Has Checking Account and Positive Income (The "Screened Sample")										
Year(s)	*Full Sample*	*Screened Sample*	*No High School*	*College Degree*	*Age 18-34*	*Age 65+*	*No Credit card*	*Has Credit card*	*One Credit card*	*Convenience Users*	*Revolving*	*High Utilization*
1992	0.09 3906	0.11 3429	0.01 226	0.16 1917	0.14 620	0.04 829	0.06 682	0.13 2747	0.10 9645	0.13 1724	0.13 1023	0.14 134
1995	0.18 4299	0.20 3795	0.09 188	0.25 2072	0.30 701	0.10 881	0.14 643	0.23 3152	0.19 914	0.19 1876	0.25 1275	0.20 156
1998	0.34 4305	0.39 3821	0.14 183	0.44 2156	0.57 642	0.17 832	0.33 674	0.40 3147	0.36 952	0.32 1880	0.48 1267	0.54 176
2001	0.47 4442	0.51 3989	0.31 199	0.58 2301	0.72 656	0.22 847	0.43 608	0.53 3380	0.45 996	0.44 2027	0.61 1353	0.72 183
1995-2001	0.34 13046	0.37 11605	0.18 570	0.43 6529	0.53 1999	0.16 2560	0.30 1925	0.40 9679	0.34 2862	0.33 5783	0.45 3895	0.51 515

Each cell presents the proportion of U.S. households in a given SCF (sub-)sample that report using debit, and the number of households in the sample under consideration. Proportions obtained by weighting SCF means by variable x42001. The "screened sample" includes only households with a checking account and positive income. The "convenience users" sample includes bank credit card holders only. High utilization is defined as revolving bank credit card balances greater than 75% of available credit limit.

Table 2. Debit Use in the Raw
A Puzzle for Standard Consumer Choice Theory?

Household Type	Debit-Using Households		
	1995	1998	2001
No credit card	17%	21%	17%
Revolves credit card balances	52%	51%	50%
Exclusive cash back user	4%	4%	4%
No obvious cost advantage to debit use	**27%**	**24%**	**29%**

"Revolves credit card balances" is defined as currently revolving on a bank credit card. "Exclusive cash back user" is based on the December 1996 Survey of Consumers, and captures households that report using debit only for transactions involving cash back (total debit transactions per month equal to cash back debit transactions per month), have a credit card, but don't typically revolve balances.

Table 3. Means for Selected Regressors and Covariates

Bank Credit Card Holders Sample

SCF Year(s)	*Has Bankcard*	*Revolves*	*Vacation borrow*	*Jewelry borrow*	*ATM card*	*Income > normal*	*Income < normal*	*Spend > income*	*E-Payments*	*Computer Banking*
1995	1.0	0.56	0.17	0.07	0.74	0.08	0.14	0.18	0.66	0.04
1998	1.0	0.55	0.15	0.06	0.77	0.10	0.13	0.17	0.80	0.08
2001	1.0	0.53	0.16	0.07	0.79	0.13	0.13	0.15	0.84	0.25
Pooled	1.0	0.54	0.16	0.07	0.77	0.11	0.13	0.16	0.77	0.13

Full Sample

SCF Year(s)	*Has Bankcard*	*Revolves*	*Vacation borrow*	*Jewelry borrow*	*ATM card*	*Income > normal*	*Income < normal*	*Spend > income*	*E-Payments*	*Computer Banking*
1995	0.76	0.42	0.16	0.07	0.70	0.08	0.15	0.18	0.63	0.04
1998	0.76	0.41	0.14	0.06	0.73	0.10	0.14	0.17	0.76	0.07
2001	0.80	0.42	0.15	0.07	0.76	0.12	0.13	0.16	0.81	0.21
Pooled	0.77	0.41	0.15	0.06	0.73	0.10	0.14	0.17	0.74	0.11

Each cell presents a weighted SCF sample mean for the variable listed in the column heading. The first panel considers the "base" sample, containing only bank credit card holders with checking accounts and positive annual income. The second panel includes households without a bank credit card as well. Please refer to Appendix 2 for variable definitions.

Table 4. The Effect of Revolving Credit Card Balances on Debit Use

SCF Survey(s)	1	2	3	4	5
1995	.059*** (.019) 3152	.034 (.021) 3152	.014 (.020) 3152	.018 (.031) 914	.011 (.029) 2139
1998	.159*** (.022) 3147	.101*** (.025) 3147	.087*** (.025) 3147	.122*** (.041) 952	.098** (.039) 2170
2001	.167*** (.021) 3380	.098*** (.024) 3380	.083*** (.026) 3380	.053 (.047) 996	.089** (.043) 2319
Pooled	.137*** (.013) 9679	.082*** (.014) 9679	.063*** (.014) 9679	.064*** (.024) 2862	.068*** (.022) 6628
Covariates	none	exogenous only	base	base	base
Sample	base	base	base	one card only	R=1 if no charges last month only

*** Significant at the 99% level. ** Significant at the 95% level.

Each cell shows the probit marginal effects coefficient and standard error on R (the revolving variable), as well as the regression sample size, from estimating a version of equation (3) or (4) on SCF data. Debit use is the dependent variable, and point estimates can be multiplied by 100 to translate the magnitudes into percentage point terms. All standard errors are calculated using the imputation correction provided in the SCF codebook. Covariate specifications are described in Section IV of the text. All samples exclude households without a checking account or with nonpositive income. The "base" sample includes only bank credit card holders; regressions featured in Column 5 assign R=1 only to those households that compiled no bank credit card charges on their most recent statement and exclude other revolvers from the sample.

Table 5a. The Effect of Credit Card Holding on Debit Use

Results On:	1 *Revolving (R=1)*	2 *Revolving (R=1)*	3 *Cardholding (H=1)*	4 *Cardholding (H=1)*
SCF Survey(s)				
1995	.014 (.020) 3152	.007 (.017) 3795	.029 (.021) 3795	.032 (.020) 2519
1998	.087*** (.025) 3147	.097*** (.025) 3821	-.075** (.035) 3821	-.060* (.032) 2554
2001	.083*** (.026) 3380	.091*** (.026) 3989	-.057 (.036) 3989	-.046 (.037) 2636
Pooled	.063*** (.014) 9679	.064*** (.014) 11605	-.031 (.019) 11605	-.019 (.018) 7709
Regressors Included	R only	R and H	R and H	H only
Sample	base	full	full	convenience users only

*** Significant at the 99% level. ** Significant at the 95% level. * Significant at the 90% level.

Each cell shows the probit marginal effects coefficient and standard error for the variable listed in the column heading, as well as the regression sample size, from estimating a version of equation (3), (4), or (6) on SCF data. Debit use is the dependent variable, and point estimates can be multiplied by 100 to translate the magnitudes into percentage point terms. All standard errors are calculated using the imputation correction provided in the SCF codebook. All regressions here include the "base" covariate specification described in Section IV of the text. The "base" sample includes only bank credit card holders (and Column 1 therefore replicates the base covariate specification results in Table 4, column 3 for reference). The two "full" sample columns present results on R (the revolving dummy) and H (the credit card holding dummy) from the same regression (reading across any row), on a sample that includes both cardholders and nonholders and excludes only those without a checking account or nonpositive income. Column 4 includes only convenience users in the sample and hence omits the variable R from the regression.

Table 5b. Debit Use x Credit Use

SCF survey(s)	1 *Debit, revolving (R=1)*	2 *No debit, revolves*	3 *Debit, R=0, has credit card (H=1)*	4 *No debit, R=0, H=1*	5 *Debit, H=0*	6 *No debit, H=0*
1995	0.11	0.31	0.06	0.27	0.03	0.21
1998	0.20	0.21	0.11	0.24	0.08	0.16
2001	0.26	0.16	0.17	0.21	0.09	0.11
Pooled	0.15	0.19	0.14	0.36	0.05	0.11

Each cell reports the weighted proportion of households in the base regression sample. Proportions should sum to 1 across rows, but may not exactly due to rounding.

Table 6. Credit Limit Utilization and Debit Use

SCF Sample	N	*0<utilization<0.25*	*0.25-0.75*	*>0.75*	*0<utilization<0.13*	*0.13-0.42*	*>0.42*	*0<utilization<0.10*	*0.10-0.25*	*0.25-0.50*	*>0.50*
1995	3152	.028 (.023)	.009 (.026)	-.040 (.033)	.032 (.027)	.023 (.026)	-.020 (.026)	.038 (.030)	.020 (.030)	.016 (.031)	-.027 (.028)
1998	3147	.061* (.031)	.121*** (.035)	.115** (.051)	.054 (.036)	.111*** (.036)	.111*** (.035)	.048 (.039)	.086** (.041)	.123*** (.042)	.114*** (.039)
2001	3380	.053* (.031)	.100*** (.034)	.183*** (.047)	.046 (.036)	.104*** (.036)	.111*** (.036)	.057 (.037)	.054 (.042)	.128*** (.040)	.111*** (.039)
Pooled	9679	.050*** (.017)	.081*** (.020)	.089*** (.028)	.046** (.020)	.082*** (.020)	.071*** (.021)	.053** (.022)	.052** (.023)	.094*** (.023)	.069*** (.022)
Emergency Funds	2782	.044 (.035)	.093** (.040)	.186*** (.059)	.037 (.040)	.086** (.042)	.116*** (.042)	.048 (.042)	.043 (.049)	.107** (.048)	.120*** (.045)
No Emergency Funds	599	.098 (.076)	.189*** (.072)	.175* (.098)	.092 (.088)	.191** (.078)	.134* (.077)	.114 (.100)	.097 (.089)	.246*** (.080)	.117 (.083)

*** Significant at the 99% level. ** Significant at the 95% level. * Significant at the 90% level.

Each cell presents the probit marginal effects coefficient and standard error on the bank credit card credit limit utilization variable listed in the column heading, from estimation of equation (5), on a sample of bank credit card holders with checking accounts and positive income from the SCF survey year listed in the row heading. Debit use is the dependent variable, and point estimates can be multiplied by 100 to translate the magnitudes into percentage point terms. Households with zero utilization (convenience users) comprise the omitted category. Each regression contains the base specification covariates described earlier. Each panel presents results for a different demarcation of utilization categories, as motivated in the text. Emergency funds variable is taken from SCF variable x6443, "In an emergency could you or your (spouse/partner) get financial assistance of $3,000 or more from any friends or relatives who do not live with you?", which first appeared in the 2001 SCF.

Table 7. Revolvers Have Lower Credit Card Charges

R defined as:	1 *Currently revolving*	2 *Habitual too*	3 *Non-habitual revolvers excluded*	4 *Low intensity utilization*	5 *Medium intensity utilization*	6 *High intensity utilization*
Sample						
2001 Sample	-428*** (58)	-364*** (51)	-454*** (61)	-418*** (66)	-429*** (77)	-441*** (71)
Pooled sample	-344*** (33)	-355*** (29)	-395*** (32)	-345*** (35)	-305*** (46)	-387*** (41)
2001 debit users	-430*** (79)	-398*** (62)	-480*** (78)	-405*** (83)	-423*** (92)	-464*** (89)
2001 nonusers	-393*** (89)	-276*** (89)	-374*** (99)	-430*** (105)	-386*** (133)	-332** (124)
Pooled debit users	-328*** (53)	-390*** (44)	-412*** (48)	-305*** (59)	-269*** (77)	-417*** (56)
Pooled nonusers	-343*** (40)	-314*** (39)	-364*** (43)	-370*** (43)	-317*** (55)	-334*** (60)

*** Significant at the 99% level. ** Significant at the 95% level.

Each cell presents the coefficient and standard error on a measure of revolving behavior R, from a weighted OLS regression of level bank credit card charges in the previous month on R and the usual ("base") set of covariates. Bank credit card charges are measured in 2001 dollars and censored at the 99^{th} percentile to reduce the influence of outliers. All definitions of R start with the standard 1/0 variable for whether the household revolved bank credit card balances after their most recent statement (Column 1). Column 2 modifies this definition by only counting those who are both currently revolving *and* report habitually revolving as R==1; column 3 modifies it by excluding current revolvers who do not report habitual revolving from the sample. The final three columns present results from a single regression (reading across any row), with utilization measured by conditional terciles and convenience users (standard definition) serving as the omitted category.

Table 8. Measurement Issues and the Effect of Revolving on Debit Card Use

Baseline Results

Pooled:	2001:
0.063	0.083
(0.014)	(0.026)

Alternate Methods	**Alternate Results** A	B
Misclassified R: Use Interviewer Observations	0.088 (0.020)	0.104 (0.036)
Misclassified R: Mahajan Correction	0.064 (0.014)	0.066 (0.014)
Strategic Bankruptcy: Incorporate SCF Credit Scores	0.079 (0.072)	0.186 (0.139)
Cash Back Motive: Simulate	0.079 (0.015)	0.158 (0.015)
Security Precaution: Simulate	0.085 (0.015)	0.134 (0.015)
Rewards Motive: Simulate	0.115 (0.015)	0.274 (0.018)

Each cell presents the probit marginal effects coefficient and standard error on R, the revolving variable, for a specification described in the row title, using the base set of covariates described earlier. As in tables 3-5, debit use is the dependent variable and one can multiple the point estimates by 100 to translate the magnitudes into percentage point terms. Please see Appendix 4 for additional details on sample restrictions, variable construction, and estimation procedures. Estimates are based on the pooled sample of credit card holders unless noted otherwise.

Interviewer observation regressions limit the sample to those who report "truthfully" (column A), and both "truthfully" and "accurately" (column B).

The Mahajan correction regressions are done two ways: first, assuming misclassification of R to be independent of covariates (column A); second, allowing the misclassification to vary with race, education, income, age, gender, and industry (column B).

Strategic bankruptcy regressions are estimated on a sample of "high-risk" borrowers only, using the pooled sample (column A) and 2001 sample (column B).

Cash back motive regressions simulate the impact of an "exclusive cash back" motive assigned to 7% (column A) and 40% (column B) of non-revolving debit users.

Security precaution regressions simulate the impact of a fraud risk motive that leads consumers to prefer online debit and credit card transactions over offline debit, and hence to borrow-to-charge due to the relative scarcity of PIN terminals. Columns A and B explore cases where 10% and 27.5% of revolvers who do not use debit are assumed to have this preference, respectively.

Rewards motive regressions simulate the impact of a borrow-to-charge motive arising from rewards that produce marginal benefits exceeding the marginal financing cost. Columns A and B explore cases where 20% and 60% of revolvers who do not use debit are assumed to have this motive.

Table 9. Debt Aversion: Beliefs, Actions, and Debit Use

revolving ("R")	.063*** (.014)	.063*** (.014)	.063*** (.014)	.067*** (.014)	.068*** (.014)	.081*** (.016)	.072*** (.015)	.123*** (.036)	.084*** (.016)	.135*** (.036)	.119*** (.043)
vacation	.006 (.018)	.011 (.018)			.013 (.019)	.089*** (.032)			.070** (.033)	.071** (.034)	.078** (.034)
jewelry	.026 (.026)		.028 (.025)		.038 (.026)		.112** (.043)		.086** (.044)	.088** (.045)	.097** (.045)
car				-.048** (.021)	-.045* * (.022)			-.017 (.028)		-.026 (.028)	-.011 (.029)
vacation*R						-.106*** (.032)			-.089** (.034)	-.091** (.034)	-.091** (.035)
jewelry*R							-.118*** (.041)		-.085* (.045)	-.082* (.046)	-.084* (.046)
car*R								-.066* (.039)		-.056 (.039)	-.076* (.041)
other "ok" variables?	N	N	N	N	Y	N	N	N	N	N	Y
other interactions?	N	N	N	N	N	N	N	N	N	N	Y

*** Significant at the 99% level. ** Significant at the 95% level. * Significant at the 90% level.

Each column presents results for the variables of interest from a single specification of equation (4) estimated on the base pooled SCF sample. The first column displays results for the base specification. Succeeding columns present results from other specifications of interest featuring different combinations of credit attitude variables and their interactions with the revolving variables. Blank cells indicate that the variable of interest is not included in the regression specification reported in that column. The bottom two rows indicate whether the three additional SCF variables on borrowing attitudes, and their interactions with the revolving variable, are included in the reported specification. Results for these additional variables and their interactions are not reported in the table.

Appendix 1. Debit Use Variable Survey Question

Question wording and interviewer instruction is identical across the 1995, 1998, and 2001 surveys, and goes as follows:

```
X7582       A debit card is a card that you can present when you buy
            things that automatically deducts the amount of the
            purchase from the money in an account that you have.

            Do you use any debit cards?

            Does your family use any debit cards?

            INTERVIEWER: WE CARE ABOUT USE, NOT WHETHER R HAS A DEBIT
            CARD

             1.  *YES
             5.  *NO
```

Source:
Codebook for 2001 Survey of Consumer Finances, Board of Governors of the Federal Reserve System

Question wording and interviewer instructions differ in 1992, producing less emphasis on debit *use*:

```
7582         B4.      Do you (or anyone in your family living here) have
                      any debit cards?
                      (A debit card is a card that you can present when
                      you buy things that automatically deducts the
                      amount of the purchase from the money in an account
                      that you have).

                      1.  YES
                      5.  NO
```

Source:
Codebook for 1992 Survey of Consumer Finances, Board of Governors of the Federal Reserve System

Appendix 2. Data Definitions

Variable	Definition and SCF variable number(s)
Uses a debit card	x7582=1
Revolves a credit card balance ("most recent" or "current" measure)	Total bank credit card balances after last payments made were greater than zero (from x413)
Has a credit card	x7973 = 1 (question asks about bank credit cards; i.e., Visa, Mastercard, Discover, Optima)
Reports carrying a credit card balance regularly ("habitual" measure)	Doesn't always pay off balances each month on bankcards and store cards; (x432=3 or x432=5)
Credit card credit limit utilization*	(Bank credit card balances)/(total credit card limit), where latter variable is x414; censored at 1
Has one credit card	x411= 1; x411 asks about bank credit cards
Credit card interest rate	x7132 (interest rate on new balances); censored at 99th percentile, missing for those without bankcards
Credit card charges	x412 (bankcards); censored at 99th percentile
Age categories	18-34, 35-54, 55-64, 65+; from x14 (household head's age)
Married	Married and living together; x8023=1
White	Household head is white; x6809=1
Male	Household head is male; x8021=1
Education (highest attainment categories)	Maximum of spouses' attainment where relevant (from x5901 and x6101); Categories are: no high school, high school, some college, college degree+
Number of persons in household categories	Censored at 5 in base specification; from x101
Housing type categories	Ranch/farm, mobile home/RV, and other; from x501.
Owns home	(x508=1 or x601=1 or x701=1)
Industry, occupation	x7402, x7401 (public use data provides only seven industry and six occupation categories). Omitted category is "not doing any work for pay".
Self-employed	x4106 = 2
Ever in Military	x5906 = 1
Region (9-level Census Division)	x30074 (not available in 2001 public use data)
Income: total last year	x5729 censored at 99th percentile, then divided into

	four categories (approximately quartiles) based on pooled sample distribution in 2001 dollars.
Income last year relative to normal	High/Low/Normal categories, from x7650
Has an ATM card	x306 = 1
O.K. to borrow for vacation	“whether you feel it is all right for someone like yourself to borrow money... to cover the expenses of a vacation trip”; x402 = 1
O.K. to borrow for fur coat/jewelry	see above for question scripting; x404 = 1
Net worth	Calculated per routine provided in SCF codebook; censored at 99th percentile; then divided into four quartiles (approximately) based on pooled sample distribution in 2001 dollars.
Spending relative to income in past year	x7510 (exceeded/equaled/less)
Uses electronic payments (direct deposit, auto billpay, and/or smart card)	(x7122 = 1 or x7126 = 1 or x7130 = 1)
Uses computer banking	x6600 = 12, or any other “institution” variable = 12; see Stata code below**
Emergency Funds Available	x6443 = 1
Reported truthfully (interviewer observation)	please see Appendix 4
Reported accurately (interviewer observation)	please see Appendix 4
Appetite for financial risk	x3014
Late payments	Behind schedule paying back any loan, sometimes got behind in past year, turned down due to bad credit, or committed bankruptcy in past 10 years.***
Self-reported credit constrained	Turned down, rationed, or discouraged during past 5 years... if did not reapply and get full amount.****
Sample weight	x42001

* I use bankcard balances rather than total credit card balances in the numerator of the utilization variable in part for conceptual reasons, and in part because a) the credit limit variable (x414) is always >0 for those with bankcards (but sometimes zero for those with other credit cards but no bankcard), and b) total credit card balances exceed the credit limit variable far more frequently than bankcard balances do.

** gen computerbank=0; for var x6600 x6601 x6602 x6603 x6604 x6605 x6606 x6607 x6870 x6871 x6872 x6873 x6608 x6609 x6610 x6611 x6612 x6613 x6614 x6615 x6874 x6875 x6876 x6877 x6616 x6617 x6618 x6619 x6620 x6621 x6622 x6623 x6878 x6879 x6880 x6881 x6624 x6625 x6626 x6627 x6628 x6629 x6630 x6631 x6882 x6883 x6884 x6885 x6632 x6633 x6634 x6635 x6636 x6637 x6638 x6639 x6886 x6887 x6888 x6889 x6640 x6641 x6642 x6643 x6644 x6645 x6646 x6647 x6890 x6891 x6892 x6893: replace computerbank=1 if X==12

*** Code available upon request. No bankruptcy questions in 1995.

**** gen srconstr= (x407==1 | x407==3 | x409==1); replace srconstr=0 if x408==1

Appendix 3. Correlations Between Debit Use and Base Specification Covariates

Regressor of Interest	Result	
revolving	.063***	(.014)
Covariate	**Result**	
age 35-54	-.099***	(.018)
age 55-64	-.128***	(.022)
age 65+	-.162***	(.025)
2 household members	.016	(.023)
3 household members	.022	(.027)
4 household members	.039	(.029)
5+ household members	.036	(.032)
mobile home/RV	.060	(.039)
ranch/farm	-.032	(.045)
industry: not working	.007	(.029)
industry: ag/forestry	.006	(.066)
industry: mining/construct.	.058*	(.032)
industry: wholesale/retail	.030	(.027)
industry: FIRE, etc.	.083***	(.027)
industry: transport/services	.020	(.022)
industry: gov't/military	-.034	(.032)
high school	-.002	(.044)
some college	.046	(.046)
college+	.039	(.044)
has ATM card	.434***	(.010)
owns home	-.042**	(.017)
income: 2nd quartile	.050	(.033)
income: 3rd quartile	.049	(.034)
income: 4th quartile	.086**	(.033)
income > normal year	.016	(.022)
income < normal year	.029	(.021)
male	.003	(.023)
married	-.002	(.022)
Ever served in military	-.015	(.017)
o.k. finance jewelry	.026	(.026)
o.k. finance vacation	.006	(.018)
self-employed	-.067***	(.019)
white	.002	(.019)
2001	.344***	(.017)
1998	.210***	(.018)

This table shows the probit marginal effects on each covariate included in the base covariate specification estimated on the base SCF pooled sample. Please see Appendix 2 for detailed variable definitions. The omitted industry category is manufacturing. The "FIRE" industry category includes "business & repair services" in addition to the standard finance, insurance, and real estate. The "transport" industry category also includes communications, utilities, personal services, entertainment and recreational services, and professional & related services. Industry dummies are jointly significant, household size dummies are not jointly significant.

Appendix 4.
Sample Construction and Estimation for Selected Regressions in Table 8

Exploiting interviewer observations: I label a household "truthful" if the interviewer judges that the respondent had at least good understanding of the questions (variable x6525), was not suspicious about the study before the interview (x6527), and exhibited average or better interest in the interview (x6529). I label a household "accurate" if the household referred to documents at least "sometimes" when answering questions (x6536). 55% of households are labeled truthful in the pooled sample, 22% are labeled accurate, and 15% qualify as both.

Strategic Bankruptcy: Estimates are calculated on a sample including only "high-risk" borrowers, where "high-risk" is defined by applying a standard industry cutoff to an imputed credit rating in the SCF. See Barakova, et. al. (2004) for more details on this variable. Specifically, SCF credit scores were transformed to match the distribution of FICO scores, and only households with scores below 660 (approximately the 15^{th} percentile) were included in the estimation. In regressions where the score was included as a control variable, linear and quadratic functions produced virtually identical results.

Cash back motive: This is simulated by randomly assigning an "exclusive cash back" motive to a proportion C of non-revolving debit users in the SCF. I do this by generating a binary variable E that takes the value of one for those assigned the exclusive cash back motive, and including E as an additional covariate in the base specification. I conduct simulations with two alternative values of C, a weak version (7%) drawn from the 1996 SOC, and a strong version (40%) chosen with reference to other survey findings (see text).

Security precaution: This is simulated using the same procedure described above for the cash back motive; in the security case, however, the simulated motive is assigned to a different sub-sample, namely revolvers who do not use debit. The hypothetical weak and strong versions of this motive are discussed in the text and Table 8.

Rewards motive: This is simulated using the same procedure described above for the security case.