Switching Costs and Adverse Selection in the Market for Credit Cards: New Evidence

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Abstract

To explain persistence of credit card interest rates at relatively high levels, Calem and Mester (AER, 1995) argued that informational barriers create switching costs for high-balance customers. As evidence, using data from the 1989 Survey of Consumer Finances, they showed that these households were more likely to be rejected when applying for new credit. In this paper, we revisit the question using the 1998 and 2001 SCF. Further, we use new information on card interest rates to test for pricing effects consistent with information-based switching costs. We find that informational barriers to competition persist, although their role may have declined.

JEL Codes: D82, G2
Key Words: Credit cards, consumer switching costs, search, adverse selection

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1. Introduction

Persistence of credit card interest rates at relatively high levels has been the subject of lively debate. Simple explanations based on consumer search have not generally been supported by the data. Berlin and Mester (2004) find that consumer search costs were likely not adequate to explain imperfect competition in the credit card market. They found that the distributions of credit card rates in the 1980s, a time when search costs were thought to be significant, were inconsistent with those derived from many models of search. Ausubel (1991) documented rate stickiness and the persistence of high issuer profits during the 1980s. He proposed an adverse selection model in which low-risk consumers underestimate their likelihood of borrowing and thus are less sensitive to interest rates than high-risk consumers. In this case, card issuers would be discouraged from competing on interest rate, because a rate cut would disproportionately attract high-risk borrowers.

Calem and Mester (1995) proposed an alternative explanation of persistence in credit card rates. They argued that such persistence is consistent with imperfect competition for high-balance customers that is tied to information-based barriers to switching between issuers. In particular, switching costs may arise because card issuers cannot readily distinguish between applicants intending to switch and those intending to accumulate more debt, implying that high-balance customers may have difficulty qualifying for new credit. Adverse-selection effects may compound these switching costs because those seeking to accumulate more debt are likely to have the stronger incentive to respond to a solicitation. For example, they may have been denied higher credit limits by their current issuer on the basis of private information.

Calem and Mester (1995) found general support for these theories using data from the 1989 Survey of Consumer Finances (SCF). They found that households with larger balances were more likely to be rejected or to be granted a lower-than-desired credit limit when applying for new credit and thus might have found it difficult to switch from one card issuer to another. In addition, they found that credit card borrowing was inversely correlated with a household's willingness to comparison shop for loans and deposits.

Much has changed in the credit card industry since 1989. In particular, advances in credit scoring technology and data quality have led to widespread use of automated systems for the prescreening and solicitation of card applicants. Proponents claim that these advances improve issuers' ability to judge creditworthiness and lower evaluation costs. Moreover, marketing innovations, such as the development of affinity card programs, may have improved issuers' ability to target solicitation activity to higher credit-quality borrowers. If so, then the economic significance of information-based barriers to switching should be reduced, enabling the market to become more competitive.

Existing evidence on whether the market has evolved in this direction is mixed and somewhat difficult to interpret. On the one hand, anecdotal evidence concerning the introduction of balance transfer checks coupled with offers of teaser rates suggests that the cost of switching among cards may be lower now. Crook (2002) and Kerr and Dunn (2002) used data from the 1998 SCF to revisit Calem and Mester's (1995) analysis. Using the later data, they find no relation between search behavior and credit card balance, consistent with reduced barriers to searching and switching and, hence, a more competitive market structure. On the other hand, the rapid expansion of solicitation activity and new card issuance in the mid-1990s was accompanied by unexpectedly large increases in delinquency rates (Ausubel 1999, Gross and Souleles 2002), consistent with information-based switching costs or adverse selection problems associated with solicitation activity. Moreover, while spreads between credit card and money market rates trended down some during the 1990s, they continued to exhibit a degree of "stickiness" relative to general market rates.

This paper provides further evidence on possible changes in the informational structure of the credit card market. First, we compare the results using the 1998 and 2001 SCF data with the results using the 1989 SCF data to explore the consistency of the empirical evidence. If information-based barriers to switching have become less important, then pre-existing levels of household credit card debt should be less associated with credit denial in 1998 and 2001 than in 1989. Second, we construct an entirely new test, one that investigates pricing effects attributable to informational barriers to competition, using information on credit card interest rates, which was newly available in the 1998 and 2001 SCF. For this analysis, we also rely on a pseudo credit score that we construct for each respondent to the SCF. We analyze the relationship between credit card balances and interest rates, controlling for other observable risk characteristics via the pseudo credit score.

As in 1989, we find that in 1998 and 2001, high-balance households remain more likely to be rejected or to be granted a lower-than-desired credit limit when applying for new credit. Important in making this conclusion is controlling for reverse causality, i.e., the possibility that households that are temporarily liquidity constrained resort to borrowing on their credit cards and running up balances, rather than high credit card balances resulting in reduced access to credit. We control for this possibility by segmenting the sample of households into groups that are less likely to be subject to liquidity shocks. In addition, we find that a large credit card balance represents an impediment to obtaining a better interest rate, particularly for consumers with lower scores. This holds true for the full sample and also for the subsamples of liquidity unconstrained households. Taken together, our findings suggest that information-based barriers to switching have remained relevant in the credit card market despite the many changes seen in the market over the past decade.

The paper is organized as follows. The following section surveys recent developments in the credit card market. Section 3 reviews the Calem and Mester (1995) hypothesis of informational barriers to competition. This section describes our empirical strategy for evaluating the continuing validity of this theory, including our strategy for handling possible endogeneity problems. Section 4 presents an update of the Calem and Mester (1995) analysis of the relationship between credit card balances and likelihood of being rejected for new credit. Section 5 presents the new empirical analysis of pricing effects, and section 6 concludes.

2. Recent Developments in the Credit Card Market

The credit card market has undergone a number of important changes since the 1980s. These include rapid growth in direct mail solicitations and related marketing innovations; expansion in the use of card credit and in consumer debt burdens; and increased delinquency rates on cards.

Credit card marketing. Some of the most striking changes pertain to activities designed to market cards. The volume of direct mail solicitations grew dramatically from about 990 million in 1991 to about 2.7 billion in 1995, to 3.4 billion in 1998, to 5.0 billion in 2001.[1] Typically, these solicitations offered introductory teaser rates, which are very low relative to average card rates, and also offered balance transfer checks, making it easy for customers to switch their balances outstanding on other cards to the new card being issued.[2] During this period, affinity card or co-branding programs often were used as marketing channels.[3] Co-branding, in particular, increased substantially in popularity during the 1990s; by 1996, the majority of large issuers offered co-branded card products (American Bankers Association, 1995, 1996).

Credit card usage. Another prominent feature of the market during this period was a significant expansion of the use of card credit, both in terms of number of cards used and the amount of outstanding balances. As reported by Durkin (2000) and updated here, the amount of revolving credit outstanding, as a percentage of disposable personal income, increased significantly, from about 5 percent in 1990 to over 9 percent in 2004 (Figure 1). Revolving credit also has become a larger share of consumer credit

[1] See Furletti (2003). His source for these data was BAI Global Mail Monitor.

[2] As cited in a 1998 *Wall Street Journal* article, the market research firm Behavioral Analysis Inc. estimated that almost three-quarters of standard Visa and MasterCard solicitations contained balance-transfer applications and more than 60 percent included teaser rates (Bailey and Kilman, 1998).

[3] Affinity card plans, which gained popularity in the late 1980s, are joint marketing arrangements between a credit card issuer and a group (club, religious group, labor union, professional organization, or business) that markets the card to its members or customers and receives a share of interest or fee income earned on the card (American Bankers Association, 1988). Co-branding refers to the case where the affinity group is a business that markets the card to its customers. In the case of an affinity group that is a non-profit organization, a major appeal to the cardholder is the opportunity to support the organization. In the case of co-branding, consumers typically accumulate "points" good for rebates on purchases of the co-branded product(s). One popular type of co-branding is with airline companies; in this case, accumulated points are exchangeable for flight tickets.

outstanding – in 1990, revolving credit's share was 28 percent; in 2003, its share was 37 percent (Figure 2). The Survey of Consumer Finance data indicate an increase in card balances as well as in cards per household, and in credit limits offered to customers. According to the SCF in 1989, 67 percent of respondent households reported having at least one bank credit card, with an average of two cards per household (among those reporting at least one card). By 1998, 75 percent of households had at least one card, with an average of 2.5 cards per household. By 2001, 79 percent of households had at least one card, with an average of 2.5 cards per household.[4] The average revolving balance among those respondents having at least one card rose from $761 in 1989 to $1577 in 1998; it fell back slightly to $1431 in 2001 (measured in constant 1989 dollars.)

Credit card portfolio performance. At the same time that the use of credit cards expanded, there was deterioration in the performance of credit card portfolios. Delinquency and charge-off rates on credit cards rose between 1995 and 1997, despite a strong economy, to levels nearly as high as the previous peak in 1991, which was tied to the 1990 recession (Figure 3). After peaking in 1997, they remained at historically high levels, rising again during the 2001 recession before subsiding somewhat during the recovery.

The significance of all of these developments was reflected in major realignments of market shares during the 1990s. For instance, MBNA and First USA rapidly grew market share during this period – an achievement widely attributed to their creative uses of affinity and co-branding programs.[5] AT&T and GE entered the market early in the decade via co-branded cards issued by credit card bank subsidiaries and quickly achieved large market shares.[6] Some major issuers were particularly hard hit by

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[4] The SCF uses multiple imputation techniques to fill in missing values, creating five "implicates" of each data record. These figures are based on the first implicate in the SCF data. See Kennickell (1998) for a discussion of the imputation procedure used in the SCF.

[5] MBNA and First USA ranked 15th and lower than 20th, respectively, in 1989. But by 1997 they were among the five largest issuers with respect to owned and managed receivables (American Bankers Association, 1990, 1997). On June 30, 2005, Bank of America announced it will acquire MBNA, with the action expected to be completed by the end of 2005.

[6] As of January 1, 1997, AT&T ranked 8th and GE ranked 17th (American Bankers Association, 1997).

deterioration in credit quality after 1995. For instance, by 1999, Advanta and AT&T had exited the consumer card industry in the wake of deteriorating portfolios.[7]

Credit card competition. It is reasonable to conjecture that these developments indicate an increasingly competitive environment for card issuers. The adoption of automated systems for the prescreening and solicitation of card applications may have reduced consumer switching costs and mitigated adverse selection associated with consumer switching. At the same time, marketing innovations and expanded solicitation activity by card issuers may have increased the willingness of consumers to comparison shop for lower rates, as suggested by Crook (2002) and Kerr and Dunn (2002).

Indeed, growth in card marketing activity and borrowing is consistent with improved credit screening processes and increased competition, both of which may lead to lower prices and an expanded supply of credit. Moreover, deterioration in credit quality is consistent with increased competition prompting issuers to expand usage among less creditworthy customers. In fact, Black and Morgan (1999) demonstrate that between 1989 and 1995, there were increases in the proportions of credit cards held by younger persons, lower-income persons, and those working in blue-collar occupations, and an increase in the overall debt burden (debt payment-to-income ratios) of cardholders. They argue that these factors may help explain the subsequent rise in credit card delinquency.

These observed outcomes also are consistent, however, with information-based switching costs or with adverse selection problems associated with solicitation activity. To the extent that the solicitation draws in less creditworthy customers than expected, or customers who unexpectedly increase their overall borrowing (i.e., retain, rather than transfer, their old balances), then realized charge-off rates would be higher than issuers expected. The evidence presented by Ausubel (1999) and Gross and Souleles (2002) suggest that some of the rise in delinquencies after 1995 was, in fact, unanticipated by issuers.

Rates and spreads. Interest rates on credit cards declined substantially over the past decade, consistent with a general decline in market rates. The average credit card yield declined steadily from

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[7] Major bank mergers and acquisitions during this period, such as Chase Manhattan with Chemical Bank and Bank of America with NationsBank, also caused realignments of market share.

about 18 percent in the first quarter of 1992 to just 12.5 percent in the last quarter of 2004 (Figure 4). It is tempting to conclude that this decline in credit card rates is due to competition taking hold in the credit card market. However, the behavior of *spreads* between credit card rates and other market rates does not necessarily indicate that pricing has become more competitive. Credit card spreads reached historically high levels in 1991 through 1993, following the steep decline in general market rates after 1989, and then returned to levels more comparable with historical spreads as credit card rates fell and general market rates increased (Figure 5). The pattern of rate movements since 1991 also suggests that credit card interest rates have remained sticky and that spreads continue to vary countercyclically. Moreover, it is difficult to draw conclusions based on the behavior of credit card spreads due to two complicating factors. First, these spreads are affected by variation in expected credit losses, which are difficult to measure. Second, as documented by Stango (2002), in recent years issuers have increasingly provided adjustable-rate plans, which likely would have altered the dynamic behavior of measured spreads.[8]

In sum, developments in the credit card market over the past decade suggest that the extent to which switching costs and adverse selection problems may affect the credit card market may have changed, but existing evidence is mixed and difficult to interpret. Our empirical work seeks to shed new light on whether these factors continue to be substantial impediments to competition.

3. Empirical Strategy

Calem and Mester (1995) attributed persistence of credit card interest rates at relatively high levels to an imperfectly competitive market structure tied to information-based barriers to switching between issuers for customers with large balances. They argue that issuers may interpret large card balances as a signal of credit risk because they are unable to distinguish card borrowers who are intending

[8] Stango (2002) reports that the percentage of credit card accounts with a variable rate increased from 3 percent to 57 percent between 1989 and 1994 based on a panel data set of the 250 largest credit card issuers. He argues that offering the choice between fixed and adjustable rate plans represents a way for issuers to price discriminate among customers with different switching costs.

to use a new card to increase their total debt outstanding (thus becoming overextended) and those who are planning just to switch their current balance to the new card. This creates a switching cost because such borrowers are relatively likely to face rejection when they apply for another card; i.e., customers tend to be "locked-in" to their current issuer once they accumulate a sizable balance.[9] Adverse selection effects may compound these switching costs due to important information asymmetries between current and prospective issuers.[10] For instance, as noted, applicants seeking to accumulate more debt may include those who had been denied higher credit limits by their current issuer on the basis of private information.[11]

A simple, stylized example can serve to illustrate the information-based switching cost and adverse selection hypotheses. Suppose that among the population of borrowers many will have the ability to repay one unit of principal, plus interest, but not two units, but that this would not deter these borrowers from borrowing two units and then defaulting. Then issuers will impose a credit limit of one unit and those borrowing the unit will have difficulty switching to another issuer, because that would require seeking additional credit by applying for a new card. Over time, issuers may be able to distinguish which of their own borrowers are less likely to borrow more than they can repay and may grant them higher credit limits, making these borrowers even less likely to switch to another issuer.

Calem and Mester (1995) tested the information-based switching cost hypothesis using data from the 1989 Survey of Consumer Finances (SCF).[12] They found that households with larger balances were

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[9] One could argue that individuals simply might reapply until they find an issuer willing to grant them a card. However, such a process would not be costless. There is the potential for a reduced credit rating resulting from multiple inquiries into the consumer's credit record, and the time and effort expended on the application process. There may also be a psychological cost associated with rejection for credit. Issuers must also bear costs associated with evaluating applications.

[10] Mester (1994) presents and analyzes a theoretical model of adverse selection in credit card markets.

[11] Consumer credit histories available from credit reporting agencies do not indicate changes in credit limits, and even current limits are sometimes not reported (Avery, Calem, and Canner, 2003).

[12] The SCF is a triennial survey of U.S. households sponsored by the Board of Governors of the Federal Reserve System in cooperation with the U.S. Department of the Treasury and conducted by the Survey Research Center at the University of Michigan. The survey provides detailed information on U.S. families' assets and liabilities and their use of financial services, income, and housing and demographic characteristics, as of the date of the interview.

more likely to be rejected or to be granted a lower-than-desired credit limit when applying for new credit, and were more likely to have experienced payment problems, consistent with information-based switching costs and adverse selection problems in the credit card market.

Our empirical strategy for investigating the degree to which this argument may still apply has two parts. First, we revisit the Calem and Mester (1995) analysis of the probability of being denied access to credit and compare the results obtained using 1998 and 2001 Survey of Consumer Finance data with those based on 1989 SCF data.[13] If information-based barriers to switching have become less important, then pre-existing levels of household credit card debt should be less associated with credit denial in 1998 and 2001 than in 1989. Further, we explore the robustness of the results to using information that was available in the 1998 and 2001 SCF but that was unavailable in the 1989 SCF used by Calem and Mester (1995). Specifically, rather than asking simply whether the respondent had been denied credit, the 1998 and 2001 surveys first determined whether credit had been applied for and then whether credit had been denied. Thus, the denial regression can be better specified with the 1998 and 2001 data. We also perform tests that are better able to control for potential endogeneity problems and reverse causality, namely, we repeat our analysis for subgroups of households that are less likely to be subject to temporary negative liquidity shocks and therefore be credit constrained.

Our second test is entirely new and focuses on pricing effects attributable to switching costs among high-balance customers, using new data in the 1998 and 2001 SCF on card interest rates. This test also relies on "pseudo credit scores" that we calculate for each SCF respondent using an imputation equation based on data from a major national credit bureau. Credit scores are summary measures of an individual's credit risk based on records maintained in credit bureau files. Such information includes number and types of credit accounts of the individual; dates opened and closed; outstanding balances on open accounts; payment histories, including occurrences of delinquency; current balances; credit line

[13] We also investigated the probability of experiencing debt repayment difficulties, but for the sake of brevity focus on the more direct test involving probability of being credit constrained. (The results pertaining to repayment difficulties are available from the authors.)

utilization rates; and incidences of "major derogatory" such as bankruptcy filing, legal judgment, or debt collection. It is standard practice for credit card issuers to use credit scores to determine which applications to accept and the terms to assign.

The intuition behind this test is that the relationship between credit card interest rates and account balances would be affected, in a predictable manner, by the informational structure of the market. In the absence of informational impediments to switching, competitive rates should be available to those households expending sufficient search effort, so-called shoppers, with a lower competitive rate for lower-risk households, as measured by the pseudo credit score. Under these circumstances, the credit card interest rate will decline with card balance, since larger balances imply greater benefit from search. It will decline quickly for shoppers to the most competitive available rate (presuming search costs are low), and less quickly for non-shoppers to a rate above the competitive level. However, if there are information-based switching costs and adverse selection effects, they would impede the decline toward a competitive rate as credit card balance increases. Instead, the interest rate may decline only gradually, or it might not decline at all and/or may rise as balance increases.

Importantly, these effects of informational impediments to competition – in particular, the potential for the interest rate to rise with the card balance – may be greater for non-shoppers and those with higher credit risk (i.e., lower credit scores). Aggressive shopping by consumers perceived as low credit risks may overcome switching costs to some degree, since issuers may remain relatively confident that such customers can manage larger card balances or are likely to transfer their balances rather than add to them.

An important potential problem in both of our tests is the possibility of reverse causality and the potential endogeneity of credit card balances, which is included as a regressor. The theory of information-based barriers to switching says that high credit card balance is a signal of elevated credit risk and, therefore, leads to denial of applications and higher interest rates. But there is a possibility that when households are denied credit and are then faced with liquidity shocks, they resort to borrowing on their credit cards. In this case, a positive relationship between credit card balance and the probability of credit denial would not indicate information-based barriers to switching. Alternatively, if the borrower's credit constraints apply to credit card borrowing as well, then the probability of credit denial might be associated (ceteris paribus) with lower credit card balances.

While this is a potential issue, it may not be a significant problem. First, households with large revolving balances tend to maintain their level of card borrowing over long periods of time. A regression of credit card balance on credit card balance lagged five years (and a constant term) using the Panel Study of Income Dynamics data from 1984, 1989, 1994, and 1999 yields a coefficient of 0.59 on lagged balances, which implies a coefficient of 0.90 (= $0.59^{1/5}$) based on annual intervals.[14] This high persistence suggests that, by and large, credit card debt is more associated with medium- or long-term financing (e.g., life-cycle smoothing) than with short-term and unanticipated liquidity shocks. Second, the ability of consumers to substitute card borrowing for other types of credit is limited; for instance, card borrowing typically cannot take the place of an auto loan or home purchase loan.[15] The ubiquity of credit card debt, despite the relatively high interest rates charged, is itself evidence that cheaper alternatives are imperfect substitutes. Finally, it by no means contradicts our proposed information-driven switching cost to observe that causality may sometimes run from credit denial to increased credit card borrowing. Consider, for example, a household that is rejected for a debt consolidation loan because the lender is unsure whether the borrower will end up simply adding to existing balances. Were the household then to increase its credit card borrowing following rejection, the lender would see evidence to justify its reluctance to lend.

Nonetheless, it is important that we try to address this potential issue in our empirical work. To this end, we identify subsamples of households that may be expected to be less subject to temporary

[14] Including time dummies in the regression to control for trend yields a coefficient of 0.61, which implies a coefficient of 0.91 at annual levels. The authors thank Wenli Li for providing these results.

[15] To the contrary, households might reduce their credit card balances after having applications denied because of excessive card debt and they might increase card borrowing after successfully being approved for credit. Therefore, our regression equation might underestimate the impact of informational barriers to switching.

liquidity shocks given their financial condition and, thus less subject to the problem of reverse causality. We find that our results for the entire sample hold qualitatively on these subsamples as well.

With respect to our second test, which investigates the relationship between credit card interest rate and credit card balance, the possibility of reverse causality is less of an issue. To the extent that liquidity constrained households are higher risk and therefore pay higher rates, this would be controlled for in our credit card interest rate regressions by the pseudo credit score, which includes credit card balances as a factor. Also, to the extent that higher rates induce households to borrow less, the bias in the interest rate regression induced by the potential endogeneity of credit card balances would be against finding evidence of information-based barriers to switching. Nonetheless, we investigate whether our interest-rate results are robust across the subgroups of households that are less likely to be subject to temporary liquidity problems.

4. Credit Card Balance and Likelihood of Being Credit Constrained

Specification and variables. We first address whether there has been a change in the informational structure of the credit card market by revisiting the original Calem and Mester (1995) analysis using the 1998 and 2001 Surveys of Consumer Finance and comparing the results to those obtained by Calem and Mester (1995), who used the 1989 SCF. Within this context, we expand and refine Calem and Mester's (1995) specification of control variables for the analysis and sample construction, as described below. Specifically, we estimate the probit model:

$$\text{TURNDOWN} = g(\text{CCBAL}, \text{DELINQUENT}, \mathbf{X1}). \tag{1}$$

TURNDOWN indicates whether a household is credit-constrained and equals 1 if at least once during the five-year period preceding the particular SCF survey, the household submitted an application for credit and had the application denied, in whole or in part, and equals 0 otherwise.[16] CCBAL denotes

[16] The SCF asked: "In the past five years, has a particular lender or creditor turned down any request you (or your husband/wife) made for credit, or not given you as much credit as you applied for?" In 1998 and 2001, the SCF additionally inquired whether the respondent household had made any applications for credit.

total revolving balance on bank credit cards.[17] A positive relationship between CCBAL and TURNDOWN suggests that applicants with large amounts of card debt have difficulty transferring the debt because the debt is viewed as a signal of credit risk, consistent with informational barriers to switching. We believe that this interpretation is valid even though TURNDOWN applies to any application for credit, not just card credit. For a variety of types of credit in addition to card credit, such as unsecured personal loans and lines of credit, cash-out refinance loans, and home equity loans and lines of credit, the potential lender must consider whether a loan applicant intends to add to or transfer existing card balances. Moreover, we have no other reason to expect a positive relationship between CCBAL and TURNDOWN after controlling for the other household financial variables described below.

DELINQUENT is included in equation (1) to control for the influence of applicant credit history on the disposition of loan applications; it equals 1 if within the past year the household fell behind in a payment, and 0 otherwise.

The vector **X1** controls for a variety of economic, demographic, and attitudinal factors that may correlate with a household's demand for credit or with a lender's perception of default risk. Table 1 presents the definitions of all variables used in (1) and in the analysis discussed in the following section, along with the sample means and standard deviations of these variables. Many of the variables in **X1** are identical to variables used in Calem and Mester (1995) and require little elaboration. These include the ratio of monthly home and auto expenses, including mortgage payments, home equity loan payments, and auto loan payments to income (MEXP_INC); the number of years that the head of the household has been at his/her current job (CUREMP); the number of years at the current address (CURADD); a dummy variable identifying homeowners (HOMEOWN); a dummy variable identifying non-white respondents (RACE); and years of schooling of the head of the household (EDU). Also following Calem and Mester (1995), we include the household's total available credit line on bank credit cards; i.e., total credit limit

[17] The SCF asked respondents to report the "balance still owed" on their bank-type credit card accounts "after the last payment was made on these accounts." Throughout the paper, we equate credit card debt with the dollar amount reported in response to this question.

net of outstanding debt (AVAILBAL); and three indicators of the respondent's attitude toward credit (ATT_INST, ATT_VACA, and ATT_JEWE). The latter represent, respectively, attitude toward installment credit generally, toward borrowing to finance a vacation, and toward borrowing to finance the purchase of jewelry or furs, and equal 1 if the respondent believes it is a bad idea to borrow and 0 otherwise.

We have expanded and refined the set of control variables (**X1)** somewhat relative to Calem and Mester (1995). Here, we use a more comprehensive measure of non-liquid financial assets and in contrast to the original specification, we measure liquid assets (LIQ), non-liquid financial assets (NONLIQ), and income (INC) in logs, i.e., our specification includes *ln*(LIQ), *ln*(NONLIQ), and *ln*(INC). We define DEBT_INC as the ratio of household debt to income. Here, household debt excludes home mortgage, home equity loans, and automobile loans, since the monthly payments on these are included in MEXP_INC. Note that households with higher levels of non-auto consumer debt relative to their income may be viewed as greater credit risks when applying for new loans, due to the debt burdens they already carry. In addition, we include a new variable that identifies households with zero non-auto consumer debt (ZERO_DEBT). The relationship between the debt ratio and TURNDOWN may be discontinuous at zero debt, because applications for credit may be especially rare for households with zero debt. We also include a new variable (NO_HEALTH_INS) indicating whether anyone in the household is without health insurance, which could be related to delinquency risk, and we include a new variable (SELFEMP) indicating whether the head of household is self-employed, which could affect either credit demand or perceived risk.

We have included an expanded set of demographic variables relative to Calem and Mester (1995) that allow for interactions of household size, marital status, and age of the household head. Other factors held constant, larger households may have greater demand for credit, or they may be viewed as greater credit risks. Demand for credit and indicators used by lenders to measure credit risk may vary systematically with marital status. Therefore, we include the interaction of household size with the marital status of the head of household. Thus, HSIZE_M is household size if the head of household is married; HSIZE_D is household size if the head of household is divorced or separated; and HSIZE_S is household size if the head of household is widowed or has never married. We include eight dummy variables to control for marital status of the head of household (whether the head of household is married, divorced or separated, widowed, or had never been married) interacted with age. For example, MAR_0034 equals 1 if the head of household is married and 34 years old or younger.[18] These variables control for life-cycle effects on the demand for credit or on financial sophistication, which in turn may affect credit risk.[19]

Addressing potential endogeneity problems. As discussed above, we recognize that this test suffers from potential endogeneity between CCBAL and TURNDOWN. We therefore re-estimate equation (1) for three groups of households who are less likely to be subject to temporary liquidity problems. These groups are homeowners; households with total yearly income of at least $30,000; and households with stock and bond holdings of at least $2,000. If we find a positive relationship between TURNDOWN and CCBAL for these subgroups, this would be confirming evidence of information-based barriers to switching, as these subgroups are less likely to exhibit the potential reverse causality problem.

Our regressions may also be subject to a classic errors-in-variables form of endogeneity due to a mismatch in the time windows used in defining CCBAL and TURNDOWN. Ideally, one would want to observe the value of CCBAL at the time of the credit application to which TURNDOWN corresponds. Instead, TURNDOWN indicates whether the household experienced a rejection for credit any time in the

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[18] The base regression refers to the head of household who is married and over 64 years old. We include MAR_0034, MAR_3554, and MARI_5564 to distinguish heads of household who are married and are 34 years old or younger, between 35 and 54, and between 55 and 64, respectively. We include DIV_0034 and DIV_3454 to distinguish heads of household who are divorced and 34 years old or younger, or between 34 and 54, respectively. We include SNG_0034 and SNG_3554 to distinguish heads of household who are widowed or never married and are 34 years old or younger or between 34 and 54. We include NMAR_5564 and NMAR_65 to distinguish heads of household who are not married and are between 55 and 64 or at least 65 years old. Note that these people may be divorced, widowed, or never married.

[19] Calem and Mester (1995) control for household size, marital status, and age, but do not allow for interactions. In addition, Calem and Mester (1995) control for whether the head of the household is male or female. This variable is highly correlated with marital status and appears to have little additional explanatory power, so we have excluded it.

past five years, while CCBAL measures *current* credit card balances, which may differ from the balances held the time of application for credit.

To a considerable degree, the impact of this timing mismatch is alleviated by the high persistence of a household's credit card debt, as discussed above. More important, the timing mismatch would, if anything, bias the coefficient on credit card balance in our credit denial regressions downward, not upward, and therefore would tend to work against finding evidence in favor of information-based barriers to switching. To see this, consider three cases. First, suppose the household had been hit by a temporary liquidity shock in the past and applied for credit. The bank would have observed a high credit card balance and possibly rejected the application. By the time of the SCF survey, however, the household might have paid down the temporarily high credit card balance, and so we would observe in the data a low CCBAL associated with a credit denial. Next, suppose the household applied for credit and was approved, and then faced a temporary liquidity shock that raised its credit card balance at the time of the survey. This again would bias the coefficient on credit card balance toward zero. Last, consider a household that faced a long-term liquidity shock in the past and raised its credit card borrowing in response. In this case, the information in the SCF regarding the household's credit quality would be valid and the mis-timing would not create a bias in the regression.

As is the case with CCBAL, the relationship between TURNDOWN and DELINQUENT is subject to measurement error and potential endogeneity. Again, there are some mitigating considerations; for instance, for many households, payment problems persist over long periods. Moreover, even if the borrower was not delinquent on any credit at the time of application for credit, current payment problems might be related to other financial circumstances (such as over-indebtedness) that were responsible for rejection of the application.

There is also a potential endogeneity issue with respect to the debt-to-income ratio DEBT_INC. A household's current ratio of consumer debt-to-income depends on whether it was credit constrained in the past. So, the estimated coefficient on DEBT_INC may understate the degree to which indebtedness reduces a household's current access to credits. Similarly, there may be a causality problem with HOMEOWN, since a household might have been rejected for mortgage credit at some point within the past five years, which would lead to HOMEOWN = 0 and simultaneously, TURNDOWN = 1. Thus, equation (1) may exaggerate the extent to which homeownership reduces credit constraints.

The SCF design and estimation. The SCF uses a dual-frame sample design that overlays a standard geographically based random sample with a special sample of relatively wealthy households.[20] Weights are provided for combining observations from the two samples to allow for inferences pertaining to the full U.S population. Calem and Mester (1995) do not make use of these weights, but simply exclude households with incomes over \$250,000 or with more than \$1 million in stocks, bonds, and liquid assets. To improve efficiency and better align our sample with the credit card portfolios of U.S. banks, we include in the sample all households with at least one bank credit card, and apply the population weights in our regressions.[21]

Beginning with the 1989 survey, missing data in the SCF have been imputed using a multiple imputation model.[22] Each missing value in the survey is imputed five times, resulting in five replicate data sets, referred to as "implicates." Calem and Mester (1995) focused on the first implicate, and verified consistency of the results across individual implicates. Here, we pool the five implicates and adjust the estimates of the standard errors of the regression coefficients for multiple imputation, following the procedure described in Kennickell (2000). Essentially, the standard error of the regression coefficient is the average over the five implicates of the standard error of the regression coefficient, i.e., the sigma, for each implicate, plus an adjustment for the sample variance of the sigmas across the implicates.

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[20] See Kennickell (2000) for details.

[21] For completeness, we also estimated the original specifications, applying the original sample restrictions and without weighting, using the 1989, 1998, and 2001 SCF data. Qualitatively the results match those discussed in the paper. We also estimated the regressions using the 1995 survey data. These results are similar to those obtained using the 1998 data.

[22] See Kennickell (1991, 1998) for details.

Results for the full sample. Table 2 presents our estimates of equation (1) for the full sample of households with at least one bank credit card. The main finding is that, as was true in 1989, there remains a significant positive relationship between credit card balances (CCBAL) and being credit constrained (TURNDOWN) in both 1998 and in 2001. This finding is consistent with a continuing role of informational barriers to switching between issuers for borrowers with existing large credit card balances. The estimated coefficient on CCBAL declines in magnitude over time, but the decline is not statistically significant.[23, 24]

Many of the control variables, including income, homeownership status, and incidence of recent delinquency, exhibit relationships to TURNDOWN that are consistent across survey years with respect to the sign and the magnitude or statistical significance of the estimated coefficient.[25] We find relatively little consistency over time, however, in relationships between household demographic variables and likelihood of being denied for credit.

Results for the subsamples. Table 3 presents our estimates of the coefficient on credit card balances (CCBAL) in equation (1) for the subsamples of homeowners; households with income of $30,000 or more per year; and households with stock and bond holdings of $2,000 or more. We also show the coefficient on CCBAL for the full sample as reported in Table 2 to aid in comparisons.[26] As can be seen, there is a consistent positive relationship between credit card balances (CCBAL) and the likelihood of being denied for credit (TURNDOWN) over time, both for the full sample and in each

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[23] Such a decline might reflect some erosion of informational barriers, or it simply might reflect instability due to colinerarity of CCBAL with *ln*(LIQ) (the estimated coefficient on *ln*(LIQ) increases in absolute value over time).

[24] We find that the coefficient on CCBAL in 1989 is statistically different from zero but at a lower level than in Calem and Mester (1995). Apparently with our changes to the specification, more of the relationship between credit card balances and the likelihood of being denied for credit is being captured by the DEBT_INC variable.

[25] One notable difference is that the ratio of non-auto consumer debt to income (DEBT_INC) is positively related to TURNDOWN only in 1989. A possible explanation is that with the expansion of lending to low-credit-quality borrowers during the second half of the 1990s, this variable became more closely tied to demand for credit as opposed to lack of access to credit.

[26] For space considerations we report only the coefficient on CCBAL in Table 3. The complete estimation results are available from the authors.

subgroup. The magnitude of the estimated coefficient on CCBAL is similar across all years and subsamples, and it is statistically significant except in the case of households with higher stock and bond holdings in 1998.

Restricting the sample to applicants for credit. The 1998 and 2001 SCF data include additional information that we can use to refine the sample for which we estimate equation (1), at the cost of not being able to look at changes from 1989, since the information was not included in the 1989 survey. In particular, we estimate equation (1) including only those families that applied for credit in the past five years. This sample restriction mitigates the possibility that households with large credit balances appear to have a high likelihood of being denied credit because they more frequently apply for credit.

Results from estimating equation (1) using this refined sample for these two survey years are very similar to those for the full sample shown in Table 2. In particular, as shown in the last row of Table 3, the estimated coefficient on CCBAL is very close to that reported for the full sample, and remains statistically significant.[27] The observed similarity suggests that unobserved variation across households in credit demand does not have any material effect on our estimation of the specification in equation (1).

Credit card balance and likelihood of credit problems. Calem and Mester (1995) also tested the relationship between CCBAL and DELINQUENT and found that households with larger card debt outstanding remain more likely to experience debt repayment difficulties, other factors held constant. We revisited this analysis as well for 1998 and 2001 and found a significant weakening of the relationship between credit card balance and delinquency. The estimated coefficient of CCBAL was much smaller in 1998 and 2001 compared to 1989, and in 2001 the estimated coefficient was not statistically significantly different from zero. The coefficient and standard error (in parentheses) for CCBAL was 0.0851 (0.0159) in 1989; 0.0181 (0.0065) in 1998; and 0.0071 (0.0075) in 2001[28] Moreover, likelihood ratio tests reject the hypothesis of equality of coefficients between either 1998 or 2001 and 1989. These findings suggest

[27] The complete regression results are omitted for brevity but are available from the authors upon request.

[28] Again, the complete regression results are omitted for brevity but are available from the authors upon request.

that the ability of lenders to screen applicants for credit risk has improved over time, enabling them to fine tune the credit limit in accordance with a household's ability to repay. These results do not conflict with the evidence from equation (1), since they do not imply the absence of informational impediments to switching by high-balance customers, but only that lenders are better able to identify the level of credit card balance at which the informational issues become important. In other words, the informational barriers hypothesis suggests that households with large credit card balances will be subject to tighter credit standards by lenders in order to compensate for their perceived risk, which would unambiguously increase the likelihood of rejection for credit but would have a more ambiguous implication regarding the relationship between credit card balances and likelihood of delinquency.

5. A Test for Informational Barriers to Competition Using Credit Card Interest Rates

The 1998 and 2001 SCF contain information on cardholders' credit card interest rates. Specifically, the survey asked: "What interest rate do you pay on the card where you have the largest balances?" or, for households with zero revolving balances, "What is the interest rate on the card you got most recently?" The SCF also asked: "When making major decisions about credit or borrowing, some people shop around for the very best terms while others don't. What number would your family be on the [1 to 5] scale [almost no shopping to a great deal of shopping]?" Based on the response to this question, we identify households as either non-shoppers (ranking themselves 1, 2, or 3) or shoppers (4 or 5).[29]

This information allows us to implement a new test of information-based switching costs and adverse selection in credit card markets that was not possible at the time of the Calem and Mester (1995) study. As discussed above, the test is based on the premise that the ability of higher-balance customers to obtain the lowest available interest rate through search would be impeded to the extent that informational barriers to switching pertain. A positive or weak relationship between balance and interest rate (more

[29] Note that potential endogeneity of the shopping measure in a credit card interest rate regression is mitigated greatly by the fact that the question pertains to shopping for *any* type of credit, not just card credit.

likely to be observed for non-shopper and higher risk cohorts) would be evidence consistent with such impediments.

Calculating the pseudo credit score. The first step in implementing this test was to derive a pseudo credit score for SCF respondents, since a credit score variable is not part of the SCF data. To do this we used data in a nationally representative sample of individual credit records obtained by the Board of Governors of the Federal Reserve System from a major, national consumer credit reporting agency. This database contains credit scores on about 200,000 individuals along with their full credit records as of June 1999. The credit score provided is roughly comparable to a FICO score, with a lower score indicating greater credit risk (lower probability of repayment).[30]

We developed an empirical model of the score by regressing credit score on various characteristics of the individuals that were included in the credit record database, where we restricted the sample to individuals with at least one credit card. The characteristics that we chose to include were also those that would be available for respondents to the SCF. Some of the key predictive variables were indicators for 30-day delinquency and 60-day or longer delinquency within the past year; past bankruptcy; combined balance and utilization rate on bank card accounts; presence of a mortgage account in the credit file; and age of the individual. The R^2 for the imputation regression equation was 0.70. In the estimation sample, scores ranged from 486 at the 1st percentile to 818 at the 99th percentile, with a median of 722 and mean of 702; predicted scores ranged from 561 at the 1st percentile to 818 at the 99th percentile, with a median of 738 and a mean of 724. Proprietary data considerations constrain our ability to report further details of the specification or estimation results.

The estimated regression model was then applied to the individuals in our 1998 and 2001 SCF data sets. That is, we calculated the pseudo credit score for each individual as the predicted credit score

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[30] FICO scores are commercially available credit scores developed by Fair, Isaac and Company and have become the credit industry standard for evaluating consumer credit risk. FICO scores range from 200 to 900 with higher values representing better credit-quality or lower risk. The national median score for all households (with or without mortgages) is 725. A decline of 20 points in the score doubles the odds of default.

Xb, where **X** consists of data on the variables included in the regression model and **b** is the vector of estimated coefficients.[31]

The relationship between credit card interest rate, balances, and credit score for the full sample. We examine the relationship between credit card interest rate and credit card balances, holding constant credit score and other characteristics. We expect that households who use bank credit cards for transaction purposes only would choose a card primarily on the basis of the annual fee and non-price amenities, and would have comparatively little reason to consider the interest rate. Therefore, we estimate separate models for households with and without a revolving balance. Those with zero revolving balance will be referred to henceforth as "non-revolvers," and those with positive balances will be referred to as "revolvers."[32]

For non-revolvers, we use OLS to estimate the model:

$$\text{RATE} = \gamma_0 + \gamma_1\text{SHOP} + \text{SCORE} \times \boldsymbol{\beta_1}\mathbf{Y} + \gamma_2\text{SCORE}^2 + \boldsymbol{\delta}\mathbf{Z} + \varepsilon. \qquad (2)$$

RATE denotes the respondent's reported credit card interest rate, and SHOP is a dummy variable that equals 1 for shoppers (as defined above), and zero otherwise. The vector **Y** consists of SHOP and 1−SHOP, and the vector **Z** incorporates several control variables: log of household income (*ln*(INC)), years-of-education of the household head (EDU), and three age categorical variables (AGE_3554, which equals 1 if the individual is 35 to 54 years old and 0 otherwise; AGE_5564, which equals 1 if the individual is 55 to 64 years old and 0 otherwise; and AGE_65, which equals 1 if the individual is 65 or older and 0 otherwise).[33] We do not a priori expect a relationship between general credit-shopping behavior and the credit card rate for non-revolvers, since, as noted, the card interest rate will not be their primary focus. Similarly, it is difficult to predict the relationship between interest rates and credit scores

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[31] The main limitation in attempting to predict scores and the main source of unexplained variation in scores in the imputation equation are lack of information in the SCF on episodes of delinquency more than one year old, accounts in collection, and derogatory public records (other than bankruptcy). Moreover, even delinquencies within the past year may be under-reported in the SCF.

[32] We continue to pool all five implicates and adjust standard errors for multiple imputation.

[33] Table 1 includes definitions of these variables, along with their sample means and standard deviations.

for non-revolvers. For instance, those with high credit scores may hold high-rate cards that offer substantial non-price benefits. We allow for a non-monotonic relationship via inclusion of the credit score (SCORE) interacted with shopping characteristics, and the square of SCORE.

For revolvers, we use OLS to estimate the following model:

$$\begin{aligned} \text{RATE} = {} & \gamma_0 + \gamma_1\text{SHOP} + \text{SCORE}\times\boldsymbol{\beta_1}\mathbf{Y} + \text{CCBAL}\times\boldsymbol{\beta_2}\mathbf{Y} + \gamma_2\text{SCORE}^2 + \gamma_3\text{SCORE}\times\text{CCBAL} \\ & + \text{CCBAL}^2\times\boldsymbol{\beta_3}\mathbf{Y} + \gamma_4\text{SCORE}\times\text{CCBAL}^2 + \boldsymbol{\delta}\mathbf{Z} + \varepsilon. \end{aligned} \tag{3}$$

Here CCBAL again denotes revolving balance and **Y** and **Z** are the same as in (2). This model permits the relationship between credit card balances and interest rates to vary with the household's credit risk and shopping propensity.

Table 4 presents the estimation results. As indicated by the large difference in R^2 statistics, substantially more of the variation in interest rates is explained for revolvers compared to non-revolvers, consistent with the hypothesis that non-revolvers are relatively indifferent to the card interest rate.

To investigate the relationship between credit card interest rate and credit card balance, we compute estimated derivatives and also plot the predicted interest rates. Table 5 presents the mean value (and the standard error of the mean) of the derivative of RATE with respect to SHOP, SCORE, and CCBAL for various subgroups of the households. Also shown is the cross-derivative of RATE with respect to CCBAL and SCORE.[34]

Some informative patterns emerge. First, predicted interest rates show little relationship with score or shopping intensity for non-revolvers. As shown in Panel A of Table 5, the derivative of RATE with respect to SCORE is significant at the 10 percent level for shoppers in 1998, but is of a very small magnitude. It is insignificant for nonshoppers in 1998 and 2001 and for shoppers in 2001.[35] As shown

[34] The derivatives will vary for each observation because the values of the independent variables vary over observations. We calculate the derivative for each observation in subgroup of households being considered (e.g., for shoppers), and then compute the mean of the derivative over all the observations in the subgroup. We also compute the standard error of this mean. Table 5 reports these means and standard errors.

[35] Further analysis shows that the significantly positive relationship between RATE and SCORE for the nonrevolvers occurs only for the higher credit-quality households. Evaluating the derivative across three subgroups defined by SCORE, we find that the derivative is insignificantly negative for households with SCORE less than 600;

in Panel B of Table 5, we find no significant difference in rate for non-revolving shoppers and non-revolving non-shoppers – the derivative of RATE with respect to SHOP is insignificantly different from zero in both years. That there is little relationship between credit card interest rate and either score or shopping intensity for non-revolvers is consistent with what one would expect given that non-revolvers have little incentive to choose a card on the basis of the interest rate – they are more likely to be concerned with the annual fee or amenities such as cash-back on purchases.

Second, in contrast to non-revolvers, higher scores for revolvers consistently are associated with lower interest rates, providing evidence of risk-based pricing. RATE and SCORE are significantly negatively related for revolvers, both shoppers and non-shoppers, in 1998 and 2001. Thus, higher credit-quality borrowers tend to get lower interest rates, and the magnitude of the effect is substantial – a ten-point rise in SCORE yields a 20 to 40 basis point decline in RATE. Moreover, the derivative of RATE with respect to SHOP indicates that revolvers who shop get a significantly lower rate than non-shopping revolvers – about 1 to 1.5 percentage points lower. This is consistent with what one would expect given that search is beneficial.

Third, as explained earlier, if there were no informational barriers to switching among card issuers, one would expect to see a negative relationship between a respondent's credit card balance and credit card interest rate, especially for revolvers who shop, since a higher balance should induce more search. However, if informational barriers to switching exist, then we might find a reversal of the relationship between credit card balance and rate, in which the relationship turns positive at higher credit card balances as the informational barriers begin to impede the ability to switch to a lower rate. Moreover, if such barriers exist, we might expect them to be more severe for respondents who have less propensity to shop for rates in the first place (i.e., for non-shoppers) and for those with higher credit risk (i.e., lower scores). To investigate, we estimated the derivative of rate with respect to credit card balance (CCBAL), and looked at how that rate varied for different subgroups of borrowers based on credit score.

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insignificantly positive for households with SCORE between 660 and 700; and significantly positive (at the 10 percent level) for households with SCORE greater than 700.

The low-score group comprised revolvers with credit scores less than 660. The mid-score group comprised revolvers with credit scores between 660 and 700. The high-score group comprised borrowers with scores of 700 or more. In addition, we estimated the cross-derivative of RATE with respect to CCBAL and SCORE. This allows us to test whether the derivative of RATE with respect to CCBAL differs significantly by the level of score.

Our results are presented in Panel C of Table 5. For higher risk cohorts (i.e., those with low scores), we find that the relationship between credit card interest rate and credit card balance is either insignificantly negative (for the shoppers) or insignificantly positive (for the non-shoppers), consistent with the existence of informational barriers to switching. For the most creditworthy borrowers (those with high scores), rate significantly declines with credit card balance for shoppers in both years, but for non-shoppers only in 1998. This is consistent with our a priori expectation that a positive or weak relationship between balance and interest rate is more likely to be observed for non-shoppers and low score (i.e., higher risk) cohorts. A statistical test is provided by the cross-derivative of RATE with respect to CCBAL and SCORE, shown in Panel D of Table 5. The cross derivative is significantly negative indicating that the difference we found in the relationship between RATE and CCBAL at low scores and at high scores is a statistically significant one.

Figures 6 and 7 plot these estimated relationships for the 1998 and 2001 samples. The predicted interest rate for revolvers is plotted, respectively for shoppers and non-shoppers with specified credit scores, in relation to revolving balance amounts (for this graphical analysis, the control variables **Z** are held constant near their sample mean values: $50,000 income, 14 years of schooling, and age between 35 and 54.) The selected credit scores roughly correspond to sub-prime (600 and 640), A− (680), prime (720), and super-prime (760) credits. Predictions from equation (3) are plotted for revolving balance amounts ranging from $500 to $10,000, in increments of $500 (and for the starting value of $1). Overall, the depicted relationships between rate and credit card balance support the view that informational barriers to switching impede the ability of credit card customers to obtain a competitive interest rate through search.

The relationship between credit card interest rate, balances, and credit score for the subsamples. We also calculated the derivatives reported in Table 5 for the full sample for the three subgroups of households expected to be less subject to temporary liquidity shocks: homeowners; households with yearly income of $30,000 or more; and households with stock and bond holdings of $2,000 or more. The results for the subgroups (which are available from the authors) are generally similar to those for the full sample, suggesting that reverse causality is not a significant problem.

6. Conclusions

Previous studies have argued that the informational structure of credit card the market gives rise to consumer switching costs and to adverse selection effects that, in turn, create barriers to competition. In particular, Calem and Mester (1995) argue that the informational structure implies that high balance customers face a lower probability of approval on new credit applications.

The credit card market has evolved over the last decade. In particular, advances in credit scoring technology and data quality have led to widespread use of automated systems for the prescreening and solicitation of card applicants. Such advances may have improved issuers' ability to judge creditworthiness and lowered evaluation costs. Marketing innovations, such as the development of affinity card programs, also may have improved issuers' ability to attract higher credit-quality borrowers, which would also mitigate the adverse selection inherent in mass solicitation programs.

If so, then the economic significance of information-based barriers to switching should be reduced, enabling the market to become more competitive. In particular, if information-based barriers to switching have become less important, then pre-existing levels of household credit card debt should be less associated with credit denial in recent years in comparison to earlier years. To the contrary, we find the relationship between card balance and credit denial to be little changed since 1989. High-balance households remain more likely to be rejected or to be granted a lower-than-desired credit limit when applying for new credit.

We further test for the continuing importance of informational barriers to switching by investigating pricing effects, using new information in the 1998 and 2001 SCF on credit card interest rates. For this analysis, we also rely on a pseudo credit score that we construct for each respondent to the SCF. We analyze the relationship between credit card balances and interest rates, controlling for other observable risk characteristics via the pseudo credit score. Particularly for consumers with lower scores, we find that a large credit card balance represents an impediment to obtaining a better interest rate.

Taken together, our findings suggest that information-based barriers to switching have remained relevant in the credit card market despite the many changes seen in the market over the past decade. These findings, viewed within the context of the substantial growth in credit card borrowing since 1989, suggest that informational barriers to competition persist, but the level of credit card balances at which they become effective may have increased, possibly in part due to technological improvements. While technological innovation may have greatly reduced search costs and improved credit screening capabilities, the persistence of adverse selection may continue to afford market power to lenders with well-established customer relationships.

References

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

Ausubel, Lawrence M., "Adverse Selection in the Credit Card Market," Working Paper, University of Maryland, 1999.

Avery, Robert B., Paul S. Calem, and Glenn B. Canner, "An Overview of Consumer Data and Credit Reporting," *Federal Reserve Bulletin*, 89, February 2003, pp. 47-73.

Bailey, Jeff and Scott Kilman, "Here's What's Driving Some Lenders Crazy: Borrowers Who Think," *The Wall Street Journal*, February 20, 1998, p. A1.

Black, Sandra E. and Donald P. Morgan, "Meet the New Borrowers," *Current Issues in Economics and Finance* 5(3), Federal Reserve Bank of New York, February 1999.

Berlin, Mitchell and Loretta J. Mester, "Credit Card Rates and Consumer Search," *Review of Financial Economics*, 13, 2004, pp. 179-198.

Calem, Paul S. and Loretta J. Mester, "Consumer Behavior and the Stickiness of Credit Card Interest Rates," *American Economic Review*, 85(5), December 1995, pp. 1327-1336.

Crook, Jonathan, "Adverse Selection and Search in the Bank Credit Card Market," Credit Research Centre, University of Edinburgh, June 2002.

Durkin, Thomas A., "Credit Cards: Use and Consumer Attitudes, 1970-2000," *Federal Reserve Bulletin*, 86, September 2000, pp. 623-634.

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

Gross, David, and Nicholas Souleles, "An Empirical Analysis of Personal Bankruptcy and Delinquency," *Review of Financial Studies*, 15, Spring 2002, pp. 319-347.

Kennickell, Arthur B., "Revisions to the Variance Estimation Procedure for the SCF," Federal Reserve Board SCF Bibliography, October 2000, www.federalreserve.gov/pubs/oss/oss2/papers/variance.pdf.

Kennickell, Arthur B., "Imputation of the 1989 Survey of Consumer Finances: Stochastic Relaxation and Multiple Imputation," Federal Reserve Board SCF Bibliography, October 1991, www.federalreserve.gov/pubs/oss/oss2/papers/imp89.pdf.

Kennickell, Arthur B., "Multiple Imputation in the Survey of Consumer Finances," Federal Reserve Board SCF Bibliography, September 1998, www.federalreserve.gov/pubs/oss/oss2/papers/impute98.pdf and www.federalreserve.gov/pubs/oss/oss2/papers/impute98.fig.pdf.

Kerr, Sougata, and Lucia Dunn, "Consumer Search Behavior in the Changing Credit Card Market," Department of Economics, Ohio State University, September 2002.

Mester, Loretta J., "Why Are Credit Card Rates Sticky?" *Economic Theory*, 4, May 1994, pp. 505-530.

Stango, Victor, "Competition and Pricing in the Credit Card Market," *Review of Economics and Statistics* 82(3), August 2000, pp. 489-508.

Stango, Victor, "Pricing with Consumer Switching Costs: Evidence from the Credit Card Market," *Journal of Industrial Economics* 50(4), December 2002, pp. 475-492.

Table 1. Variable Definitions, Means, and Standard Deviations

All dollar amounts are in $1,000 units and expressed in 1989 constant dollars.

Variable	Definition	1989 No. obs = 2085 Mean (Std. Dev.)	1998 No. obs = 3135 Mean (Std. Dev.)	2001 No. obs = 3396 Mean (Std. Dev.)
TURNDOWN	1 if household is turned down for credit, in whole or in part, in past five years (credit constrained); 0 otherwise.	0.1367 (0.3435)	0.2063 (0.4046)	0.1910 (0.3931)
CCBAL	Household's bank credit card debt (after last payment), in $1000.	0.9555 (2.1217)	1.7475 (4.1657)	1.5475 (4.0101)
DELINQUENT	1 if household was sometimes behind or missed payments in past year; 0 otherwise.	0.1336 (0.3402)	0.1390 (0.3459)	0.1204 (0.3254)
MEXP_INC	Major monthly expenditures (rent, property fees, mortgage and home loan payments, home equity loan payments auto leases and auto loan payments) / Total household income.	0.2606 (0.9795)	0.2657 (0.9443)	0.2404 (0.3331)
CUREMP	Years head of household has been at current job; coded 0 if unemployed and 1 if employed less than one year.	7.9135 (9.4426)	7.7214 (9.3117)	8.3637 (10.2386)
CURADD	Years the household has lived at current address.	11.6418 (11.3908)	13.8329 (11.4003)	11.3914 (11.7482)
HOMEOWN	1 if household owns its home; 0 otherwise.	0.7320 (0.4429)	0.7236 (0.4472)	0.7313 (0.4433)
RACE	1 if nonwhite respondent; 0 otherwise.	0.1520 (0.3590)	0.1526 (0.3596)	0.1766 (0.3814)
EDU	Head of household=s highest grade of schooling completed (0-17, with 17 representing graduate school).	13.6362 (2.7648)	13.8573 (2.5192)	13.7770 (2.6138)
AVAILBAL	Total bank card credit line minus credit card balance (CCB).	6.2097 (15.1371)	12.1718 (19.7288)	13.4451 (32.0173)
ATT_INST	1 if respondent believes buying things on installment is a "bad idea"; 0 otherwise.	0.3054 (0.4606)	0.3189 (0.4661)	0.2734 (0.4457)
ATT_VACA	1 if respondent believes borrowing for a vacation trip is "not all right"; 0 otherwise.	0.8665 (0.3401)	0.8459 (0.3610)	0.8400 (0.3666)
ATT_JEWE	1 if respondent believes borrowing for a jewelry purchase is "not all right"; 0 otherwise.	0.9296 (0.2558)	0.9360 (0.2447)	0.9290 (0.2569)
LIQ	Total household liquid assets, which includes checking, savings, money market, and brokerage call accounts.	17.7954 (136.1364)	16.9173 (119.7808)	22.3983 (187.8333)
ln(LIQ)	*ln* of LIQ.	1.4724 (1.4097)	1.4987 (1.3820)	1.6013 (1.4636)

Variable	Definition	1989 No. obs = 2085 Mean (Std. Dev.)	1998 No. obs = 3135 Mean (Std. Dev.)	2001 No. obs = 3396 Mean (Std. Dev.)
NONLIQ	Total household non-liquid financial assets: which includes CD's, mutual funds, stocks, bonds, quasi-liquid retirement accounts (IRAs, thrift-type plans, future pensions), cash value of whole life insurance, cash value of life insurance, other financial assets (trusts, annuities, royalties, deferred compensation, loans, etc.).	82.9064 (368.3914)	135.5211 (835.5451)	165.3109 (883.6243)
ln(NONLIQ)	*ln* of NONLIQ.	2.5503 (1.9655)	2.9237 (2.0847)	2.9670 (2.2110)
INC	Total household income, in $1000.	55.1229 (211.5673)	55.1741 (237.3152)	62.6720 (197.4599)
ln(INC)	*ln* of INC.	3.5703 (0.8286)	3.5730 (0.8525)	3.6226 (0.9005)
DEBT_INC	Household non-housing and non-auto debt (excludes mortgages, home equity credit, other residential debt, and auto loans) divided by income.	0.1328 (0.5675)	0.2305 (1.6534)	0.1702 (0.8623)
ZERO_DEBT	1 if DEBT_INC is equal to 0; 0 otherwise.	0.3390 (0.4734)	0.3430 (0.4747)	0.3727 (0.4835)
NO_HEALTH_INS	1 if not everyone in the household has health insurance (public or private); 0 otherwise.	0.1098) (0.3127)	0.1466 (0.3537)	0.1371 (0.3439)
SELFEMP	1 if either respondent or spouse is self-employed; 0 otherwise.	0.1553 (0.3622)	0.1593 (0.3659)	0.1689 (0.3747)
HSIZE_M	Number of individuals in household if the head of household is married or living with a partner; 0 otherwise.	2.2688 (1.8783)	2.0773 (1.8065)	2.0559 (1.7949)
HSIZE_D	Number of individuals in household if the head of household is divorced or separated; 0 otherwise.	0.2270 (0.7066)	0.2328 (0.6945)	0.2571 (0.7573)
HSIZE_S	Number of individuals in household if the head of household is widowed or never married; 0 otherwise.	0.2896 (0.7934)	0.2971 (0.7671)	0.2994 (0.7599)
MAR_0034	1 if head of household is married or living with a partner and is 34 years old or younger; 0 otherwise.	0.1645 (0.3707)	0.1270 (0.3330)	0.1248 (0.3305)
MAR_3554	1 if head of household is married or living with a partner and is 35 to 54 years old; 0 otherwise.	0.3093 (0.4622)	0.3229 (0.4676)	0.3250 (0.4684)
MAR_5564	1 if head of household is married and living with a partner and is 55 to 64 years old; 0 otherwise.	0.1029 (0.3038)	0.0983 (0.2978)	0.0919 (0.2889)
DIV_0034	1 if head of household is divorced or separated and 34 years old or younger; 0 otherwise.	0.0162 (0.1263)	0.0157 (0.1242)	0.0135 (0.1154)
DIV_3554	1 if head of household is divorced or separated and 35 to 54 years old; 0 otherwise.	0.0754 (0.2641)	0.0806 (0.2723)	0.0857 (0.2799)
SNG_0034	1 if head of household is widowed or never married and 34 years old or younger; 0 otherwise.	0.0605 (0.2383)	0.0590 (0.2357)	0.0633 (0.2436)

Variable	Definition	1989 No. obs = 2085 Mean (Std. Dev.)	1998 No. obs = 3135 Mean (Std. Dev.)	2001 No. obs = 3396 Mean (Std. Dev.)
SNG_3554	1 if head of household is widowed or never married and 35 to 54 years old; 0 otherwise.	0.0334 (0.1798)	0.0540 (0.2260)	0.0506 (0.2191)
NMAR_5564	1 if head of household is not married and not living with a partner and 55 to 64 years old; 0 otherwise.	0.0411 (0.1985)	0.0468 (0.2112)	0.0464 (0.2103)
NMAR_65	1 if head of household is not married and not living with a partner and 65 years or older; 0 otherwise.	0.0847 (0.2784)	0.0827 (0.2754)	0.0726 (0.2595)
RATE	For households with revolving credit card balance, interest rate on card with largest balance; otherwise, interest rate on most recently acquired card; in basis points	N/A	1446.549 (450.544)	1433.324 (504.593)
SHOP	1 if respondent/household does more than a moderate amount of shopping when making major decisions about credit or borrowing (i.e., if respondent answers 4 or 5 to SCF question); 0 if hardly any to moderate shopping (i.e., if respondent answers 1, 2, or 3 to SCF question).	0.395 (0.489)	0.373 (0.478)	0.392 (0.485)
SCORE	SCF respondent's pseudo credit score, imputed using a regression equation estimated with credit bureau data.	723.331 (55.988)	723.967 55.479	715.376 (59.351)
AGE_3554	1 if head of household is 35 to 54 years old; 0 otherwise.	0.418 (0.498)	0.457 0.499	0.461 (0.499)
AGE_5564	1 if head of household is 55 to 64 years old; 0 otherwise.	0.144 (0.398)	0.145 0.384	0.138 (0.381)
AGE_65	1 if head of household is 65 years or older; 0 otherwise.	0.197 (0.409)	0.196 (0.405)	0.199 (0.401)

Table 2. Relationship Between Credit Card Balances and the Likelihood of Being Turned Down For Credit for 1989, 1998, and 2001

Dependent Variable: TURNDOWN = Turned Down for Credit in the Last 5 Years

Dollar amounts measured in $1,000 and in 1989 constant dollars (based on the GDP chain-weighted price deflator). Estimated using population-weighted data. Includes respondents with at least one bank credit card.

	1989 N = 2085				1998 N = 3135				2001 N = 3396			
Variable		**Estimate**	**Std Error**	**T-Stat**		**Estimate**	**Std Error**	**T-Stat**		**Estimate**	**Std Error**	**T-Stat**
Intercept	***	−2.4353	0.4379	−5.5612	***	−0.9864	0.3085	−3.1970	***	−1.5313	0.2931	−5.2238
CCBAL	*	0.0270	0.0161	1.6792	***	0.0352	0.0068	5.1633	***	0.0266	0.0069	3.8529
DELINQUENT	***	0.3698	0.1068	3.4628	***	0.5126	0.0755	6.7897	***	0.5494	0.0759	7.2356
MEXP_INC		0.0478	0.0310	1.5397		0.0424	0.0707	0.5995	***	0.3514	0.0913	3.8476
CUREMP	***	−0.0160	0.0056	−2.8415	***	−0.0103	0.0040	−2.6092	**	−0.0076	0.0036	−2.0883
CURADD	*	−0.0100	0.0057	−1.7408	***	−0.0128	0.0045	−2.8324	***	−0.0143	0.0043	−3.2818
HOMEOWN	*	−0.1772	0.1025	−1.7280	***	−0.2080	0.0739	−2.8147	***	−0.2430	0.0706	−3.4408
RACE	***	0.5157	0.0984	5.2392		0.0303	0.0769	0.3941		−0.0058	0.0736	−0.0789
EDU	**	0.0369	0.0174	2.1216		−0.0174	0.0136	−1.2722		0.0201	0.0137	1.4674
AVAILBAL	**	−0.0125	0.0061	−2.0623	***	−0.0086	0.0027	−3.1927	**	−0.0064	0.0025	−2.5265
ATT_INST		0.0147	0.0891	0.1648		−0.0343	0.0666	−0.5148		0.0756	0.0665	1.1362
ATT_VACA		0.0024	0.1173	0.0208	***	−0.2454	0.0792	−3.1002		−0.1080	0.0766	−1.4102
ATT_JEWE		0.1301	0.1518	0.8572		0.0513	0.1157	0.4433		0.0343	0.1113	0.3085
ln(LIQ)		−0.0475	0.0408	−1.1636	**	−0.0771	0.0344	−2.2425	***	−0.1497	0.0307	−4.8798
ln(NONLIQ)		−0.0486	0.0330	−1.4718	**	−0.0443	0.0206	−2.1460	***	−0.0714	0.0200	−3.5746
ln(INC)	**	0.1812	0.0783	2.3139	**	0.1182	0.0584	2.0252	***	0.2394	0.0587	4.0810
DEBT_INC	***	0.4360	0.1095	3.9831		0.0351	0.0451	0.7800		0.0140	0.0581	0.2408
ZERO_DEBT	***	−0.3918	0.1162	−3.3705	***	−0.4931	0.0919	−5.3647	***	−0.4613	0.0810	−5.6978
NO_HEALTH_INS		0.0863	0.1154	0.7477		0.0263	0.0810	0.3246		0.1028	0.0858	1.1982
SELFEMP	***	0.4266	0.1083	3.9379	***	0.2299	0.0822	2.7963		0.0777	0.0838	0.9270
HSIZE_M		−0.0399	0.0372	−1.0727	***	0.0765	0.0293	2.6114		0.0073	0.0291	0.2501
HSIZE_D		0.1031	0.0841	1.2260	***	0.1822	0.0665	2.7403		−0.0361	0.0586	−0.6168
HSIZE_S		0.0105	0.0725	0.1442		0.0157	0.0585	0.2679		0.0293	0.0581	0.5035
MAR_0034	***	0.6506	0.2463	2.6419	***	0.6457	0.1790	3.6074	*	0.2916	0.1502	1.9418
MAR_3554	**	0.5562	0.2393	2.3245	**	0.4064	0.1664	2.4423		0.1674	0.1393	1.2022
MAR_5564		0.3530	0.2528	1.3965	**	0.4232	0.1793	2.3605		0.1150	0.1699	0.6766
DIV_0034		−0.4911	0.5035	−0.9754	***	0.8583	0.2905	2.9545	*	0.4788	0.2755	1.7379
DIV_3554		0.3100	0.3232	0.9592	**	0.5562	0.2283	2.4364	*	0.3759	0.2068	1.8176
SNG_0034		0.1913	0.3311	0.5777	***	0.9640	0.2265	4.2562		0.2974	0.2069	1.4376
SNG_3554		0.0886	0.3398	0.2607	***	0.5965	0.2283	2.6124		0.2181	0.2141	1.0189
NMAR_5564	*	0.5931	0.3083	1.9238	**	0.4736	0.2293	2.0654		0.3064	0.2018	1.5183
NMAR_65		−0.1042	0.3229	−0.3225		−0.3088	0.2742	−1.1264		−0.3608	0.2454	−1.4702

Significantly different from zero at significance level: *10%, **5%, ***1%

Table 3. Coefficient on Credit Card Balances (CCBAL) for Full Sample and for Subsamples of Households for 1989, 1998, and 2001

Dependent Variable: TURNDOWN = Turned Down for Credit in the Last 5 Years

Dollar amounts measured in $1,000 and in 1989 constant dollars (based on the GDP chain-weighted price deflator). Estimated using population-weighted data. Includes respondents with at least one bank credit card.

	1989					1998					2001				
		Coeff on CCBAL					Coeff on CCBAL					Coeff on CCBAL			
	No. of Obs.		Estimate	Std Error	T-Stat	No. of Obs.		Estimate	Std Error	T-Stat	No. of Obs.		Estimate	Std Error	T-Stat
Full Sample	2085	*	0.0270	0.0161	1.679	3135	***	0.0352	0.0068	5.163	3396	***	0.0266	0.0069	3.853
Homeowners	1696	*	0.0325	0.0174	1.870	2405	***	0.0290	0.0081	3.591	2596	***	0.0300	0.0073	4.083
Households with yearly income of $30,000 or more	1524	***	0.0727	0.0191	3.807	2297	***	0.0253	0.0080	3.151	2474	**	0.0178	0.0076	2.357
Households with stock and bond holdings of $2,000 or more	974	***	0.0938	0.0312	3.010	1378		0.0200	0.0165	1.210	1432	***	0.0232	0.0089	2.596
Households that applied for credit within the past 5 years (this is available only in the 1998 and 2001 surveys)						2197	***	0.0334	0.0075	4.482	2356	***	0.0235	0.0070	3.340

Significantly different from zero at significance level: *10%, **5%, ***1%

Table 4. Interest Rate Regressions

Non-revolvers

RATE = $\gamma_0 + \gamma_1$SHOP + SCORE × $\boldsymbol{\beta_1 Y} + \gamma_2$SCORE^2 + $\boldsymbol{\delta Z} + \varepsilon$ (2)

Parameter	Variable		1998 n=1867 Estimate	Std Error	T-Stat		2001 n=2006 Estimate	Std Error	T-Stat
γ_0	Intercept	*	6088.5970	3292.4832	1.8492		−935.9888	1945.4029	−0.4811
γ_1	SHOP		−527.3563	487.2155	−1.0824		−617.1571	416.6157	−1.4814
β_{11}	SCORE×SHOP		−12.0037	9.1445	−1.3127		7.2973	5.5041	1.3258
β_{12}	SCORE×(1−SHOP)		−12.6693	9.0897	−1.3938		6.5226	5.5038	1.1851
γ_2	SCORE^2		0.0088	0.0063	1.3825		−0.0046	0.0039	−1.1783
δ_1	*ln*(INC)		−23.6646	14.4380	−1.6391		10.8249	14.5110	0.7460
δ_2	EDU	*	7.4366	4.4104	1.6862		−2.9325	5.1118	−0.5737
δ_3	AGE_3554	*	60.3627	35.8299	1.6847		−3.1289	38.7530	−0.0807
δ_4	AGE_5564	**	92.9645	45.5156	2.0425		74.8815	61.8253	1.2112
δ_5	AGE_65		78.0862	50.6560	1.5415		17.3119	52.8904	0.3273
	Adjusted R^2 =			0.0140				0.0054	

Revolvers

RATE = $\gamma_0 + \gamma_1$SHOP + SCORE×$\boldsymbol{\beta_1 Y}$ + CCBAL×$\boldsymbol{\beta_2 Y} + \gamma_2$SCORE^2 + γ_3SCORE×CCBAL
+ CCBAL^2×$\boldsymbol{\beta_3 Y} + \gamma_4$SCORE×CCBAL^2 + $\boldsymbol{\delta Z} + \varepsilon$ (3)

Parameter	Variable		1998 n=1265 Estimate	Std Error	T-Stat		2001 n=1390 Estimate	Std Error	T-Stat
γ_0	Intercept		−65.5972	1724.9426	−0.0380		472.6754	1673.9713	0.2824
γ_1	SHOP	***	1073.3659	369.7840	2.9027		−45.8841	367.4816	−0.1249
β_{11}	SCORE×SHOP		5.2827	5.2049	1.0149		7.3644	5.0105	1.4698
β_{12}	SCORE×(1−SHOP)		6.9002	5.1352	1.3437		7.4758	4.9453	1.5117
β_{21}	CCBAL×SHOP	***	0.2448	0.0764	3.2062		0.1179	0.0718	1.6421
β_{22}	CCBAL×(1−SHOP)	***	0.2568	0.0756	3.3949	*	0.1273	0.0686	1.8537
γ_2	SCORE^2		−0.005656	0.003793	−1.4912	*	−0.006862	0.003724	−1.8426
γ_3	SCORE×CCBAL	***	−0.0004018	0.0001122	−3.5799	*	−0.0001896	0.0001041	−1.8222
β_{31}	CCBAL^2×SHOP	**	-7.5485×10^{-6}	2.9522×10^{-6}	−2.5569	*	-3.2795×10^{-6}	1.753×10^{-6}	−1.8710
β_{32}	CCBAL^2×(1−SHOP)	***	-7.6448×10^{-6}	2.8972×10^{-6}	−2.6386	**	-3.3936×10^{-6}	1.693×10^{-6}	−2.0046
γ_4	SCORE×CCBAL^2	***	1.23×10^{-8}	4.5×10^{-9}	2.7602	**	5.1×10^{-9}	2.6×10^{-9}	1.9801
δ_1	*ln(*INC)	*	−33.8362	20.1906	−1.6758	***	−68.1592	21.1262	−3.2263
δ_2	EDU	*	−11.0859	5.9897	−1.8508	**	−15.7189	6.5692	−2.3928
δ_3	AGE_3554		30.7368	34.4412	0.8924		52.1658	37.5835	1.3880
δ_4	AGE_5564	**	119.6250	50.7668	2.3564		31.7622	52.5001	0.6050
δ_5	AGE_65		93.8584	63.1564	1.4861	*	165.7024	95.6139	1.7330
	Adjusted R^2			0.0940				0.0960	

Significantly different from zero at significance level: *10%, **5%, ***1%
Adjusted R^2s are the average across the five estimations corresponding to the five implicates.

Table 5. Derivatives of the Interest Rate Regressions

Mean values and standard errors of the means in each subgroup

Panel A. Derivative of credit card interest rate with respect to credit score

		Non-revolvers: $\frac{\partial \text{RATE}}{\partial \text{SCORE}} = \beta_{11}\text{SHOP} + \beta_{12}(1-\text{SHOP}) + 2\gamma_2\text{SCORE}$		**Revolvers**: $\frac{\partial \text{RATE}}{\partial \text{SCORE}} = \beta_{11}\text{SHOP} + \beta_{12}(1-\text{SHOP}) + 2\gamma_2\text{SCORE} + \gamma_3\text{CCBAL} + \gamma_4\text{CCBAL}^2$	
		1998	**2001**	**1998**	**2001**
Shoppers	Est	1.162*	0.5225	−3.256***	−2.478***
	Std err	0.6301	0.5788	0.4831	0.5055
	T-stat	1.849	0.903	−6.739	−4.902
Non-shoppers	Est	0.5814	−0.3217	−1.765***	−2.141***
	Std err	0.6370	0.5298	0.3633	0.3477
	T-stat	0.913	−0.607	−4.859	−6.159

Panel B. Derivative of credit card interest rate with respect to shopping propensity

		Non-revolvers: $\frac{\partial \text{RATE}}{\partial \text{SHOP}} = \gamma_1 + (\beta_{11} - \beta_{12})\text{ SCORE}$		**Revolvers**: $\frac{\partial \text{RATE}}{\partial \text{SHOP}} = \gamma_1 + (\beta_{11} - \beta_{12})\text{ SCORE} + (\beta_{21} - \beta_{22})\text{ CCBAL} + (\beta_{31} - \beta_{32})\text{ CCBAL}^2$	
		1998	**2001**	**1998**	**2001**
Shoppers and Non-shoppers	Est	−25.49	−38.65	−90.80***	−146.8***
	Std err	23.91	24.42	29.72	31.59
	T-stat	−1.066	−1.582	−3.055	−4.648

Panel C. Derivative of credit card interest rate with respect to credit card balance for three score categories

Revolvers: $\frac{\partial \text{RATE}}{\partial \text{CCBAL}} = \beta_{21}\text{SHOP} + \beta_{21}(1-\text{SHOP}) + 2\beta_{31}\text{SHOP}\times\text{CCBAL} + 2\beta_{32}(1-\text{SHOP})\times\text{CCBAL} + \gamma_3\text{SCORE} + 2\gamma_4\text{SCORE}\times\text{CCBAL}$

		1998			**2001**		
		Score = Low	**Score = Mid**	**Score = High**	**Score = Low**	**Score = Mid**	**Score = High**
Shoppers	Est	−0.0011	−0.0217***	−0.0417***	−0.0008	−0.0097	−0.0201**
	Std err	0.0079	0.0064	0.0084	0.0083	0.0065	0.0086
	T-stat	−0.140	−3.394	−4.942	−0.097	−1.497	−2.333
Non-shoppers	Est	0.0105	−0.0102*	−0.0345***	0.0105	−0.0017	−0.0119
	Std err	0.0079	0.0058	0.0094	0.0073	0.0057	0.0097
	T-stat	1.333	−1.764	−3.671	1.440	−0.297	−1.224

Panel D. Cross-derivative of credit card interest rate

		Revolvers: $\frac{\partial \text{RATE}}{\partial \text{CCBAL}\,\partial \text{SCORE}} = \gamma_3 + \gamma_4\text{CCBAL}$	
		1998	**2001**
Shoppers and Non-shoppers	Est	−0.00031***	−0.00015*
	Std err	0.000085	0.000090
	T-stat	−3.649	−1.722

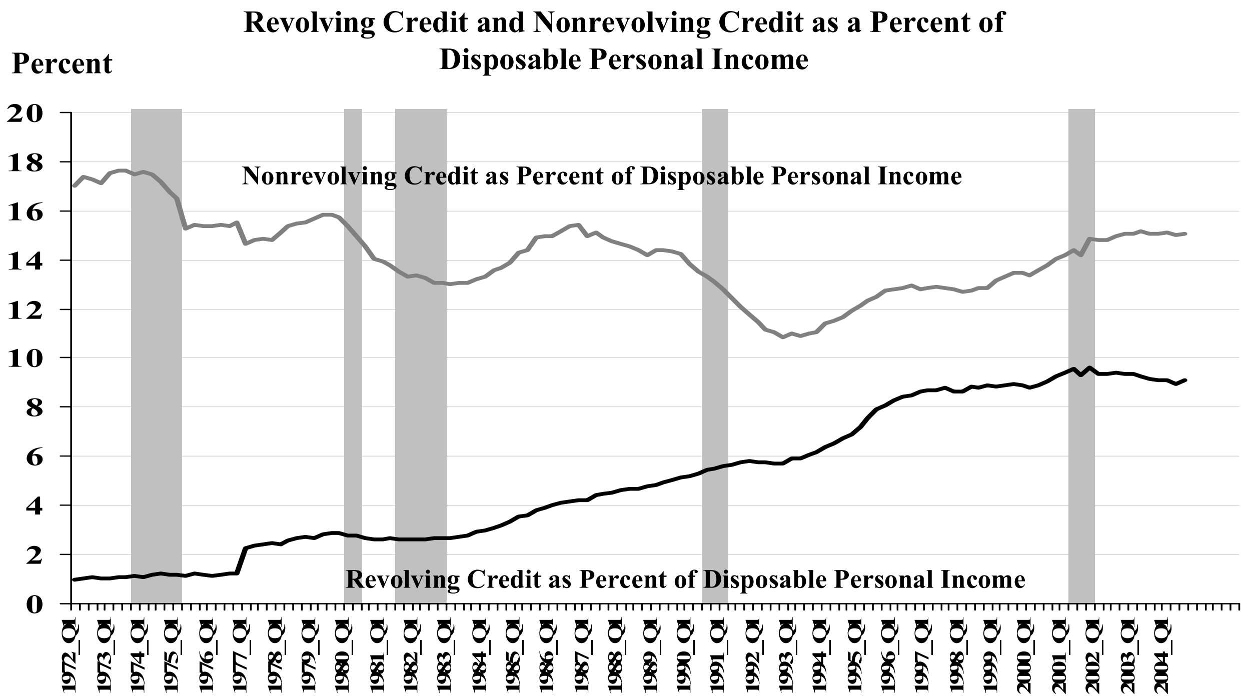
Significantly different from zero at significance level: *10%, **5%, ***1%

Categories: Score low is $0 \le$ Score < 660; Score mid is $660 \le$ Score < 700; Score high is $700 \le$ Score.

Derivative is evaluated for each observation in the subgroup using values of all variables for that observation. Mean of the derivative is calculated for all observations in the subgroup, and standard error of the mean is calculated. Means and standard errors are reported in the table

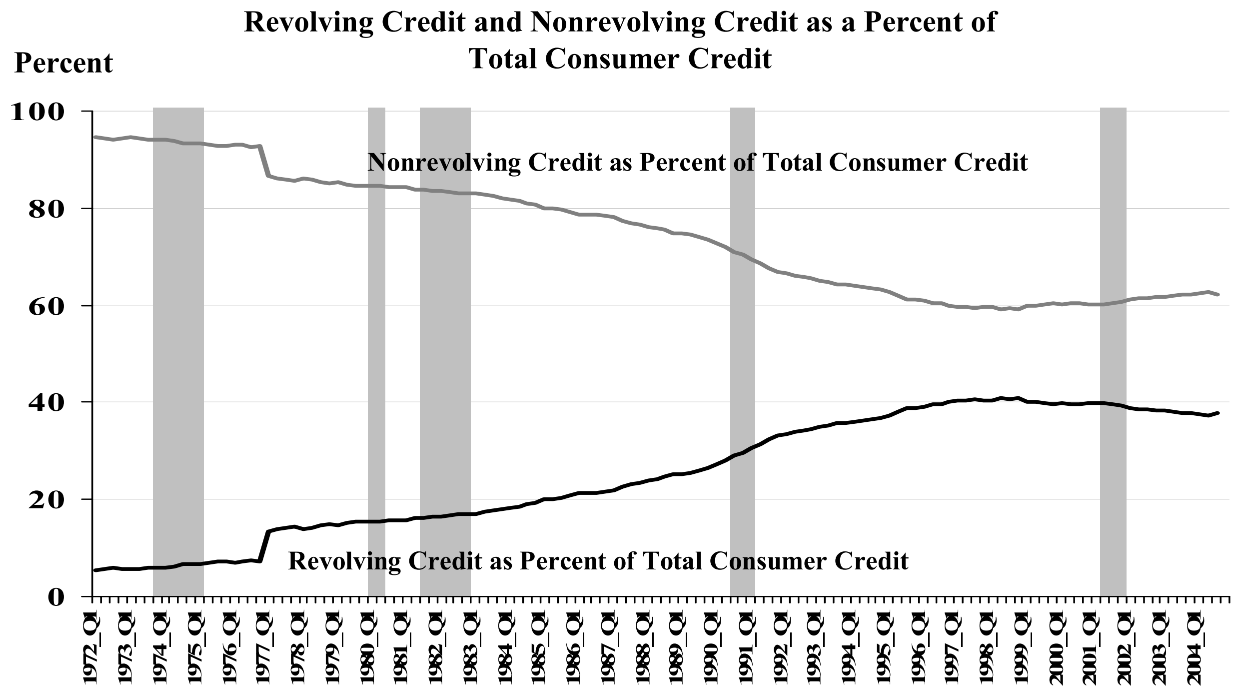
RATE is measured in basis points.

Figure 1



Note: Shaded areas represent economic recessions.
Source: Federal Reserve Board and Bureau of Economic Analysis

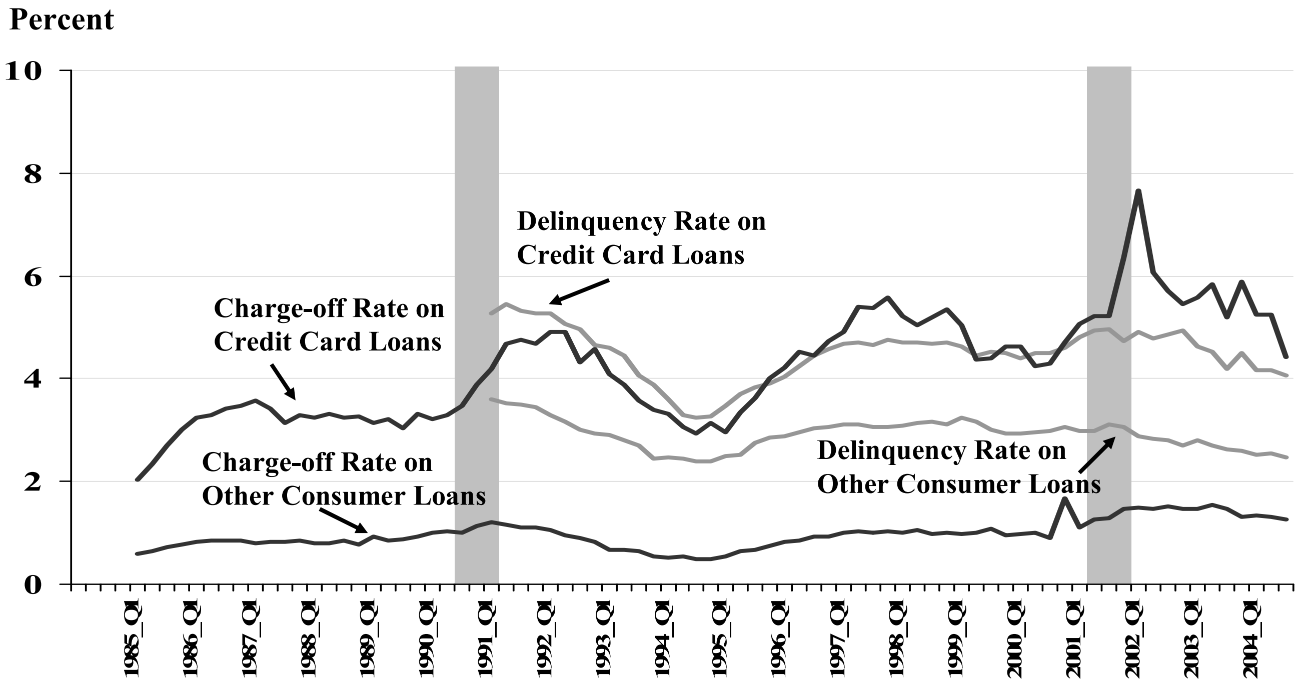
Figure 2



Note: Shaded areas represent economic recessions.
Source: Federal Reserve Board and Bureau of Economic Analysis

Figure 3

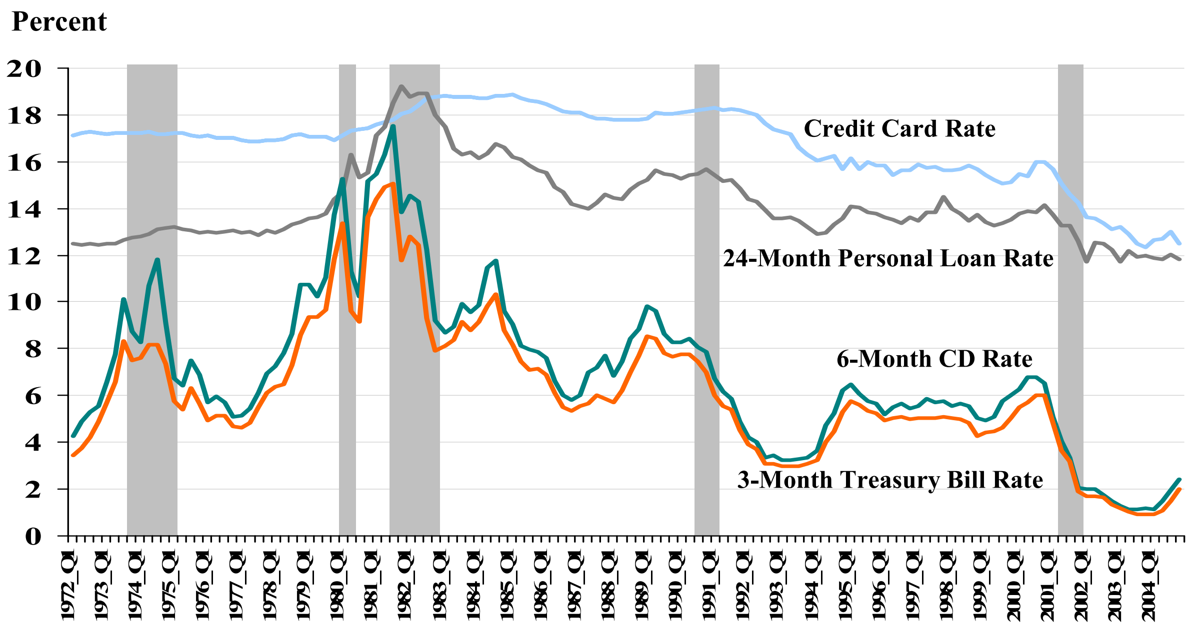
Delinquency and Charge-off Rates on Credit Cards and Other Consumer Debt



Note: Shaded areas represent economic recessions.
Source: Federal Reserve Board

Figure 4

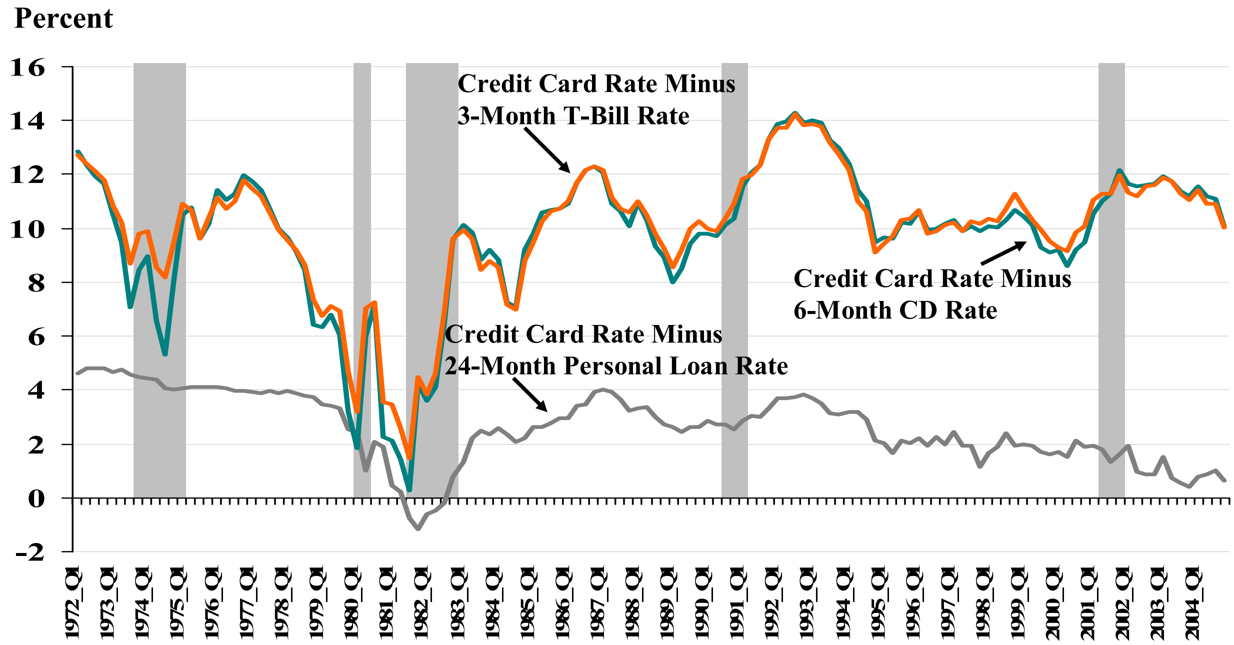
**Credit Card Rates, Personal Loan Rate,
6-Month CD Rate, and 3-Month Treasury Bill Rate**



Note: Shaded areas represent economic recessions.
Source: Commercial Bank Interest Rates: Credit Card Plans:All Accounts (NSA,%), 24-Month Personal Loan Rate (NSA, %), 6-Month CD Rate, Secondary Market (%), 3-Month Treasury Bill Rate, Secondary Market (%), Federal Reserve Board and Haver Analytics

Figure 5

Spread Between Credit Card Rate and Personal Loan Rate, 6-Month CD Rate, and 3-Month Treasury Bill Rate



Note: Shaded areas represent economic recessions.
Source: Commercial Bank Interest Rates: Credit Card Plans: All Accounts (NSA,%), 24-Month Personal Loan Rate (NSA, %), 6-Month CD Rate, Secondary Market (%), 3-Month Treasury Bill Rate, Secondary Market (%), Federal Reserve Board and Haver Analytics

Figure 6
Relationship Between Credit Card Interest Rate and Credit Card Balance by Shopper Type and Credit Score
1998 SCF data

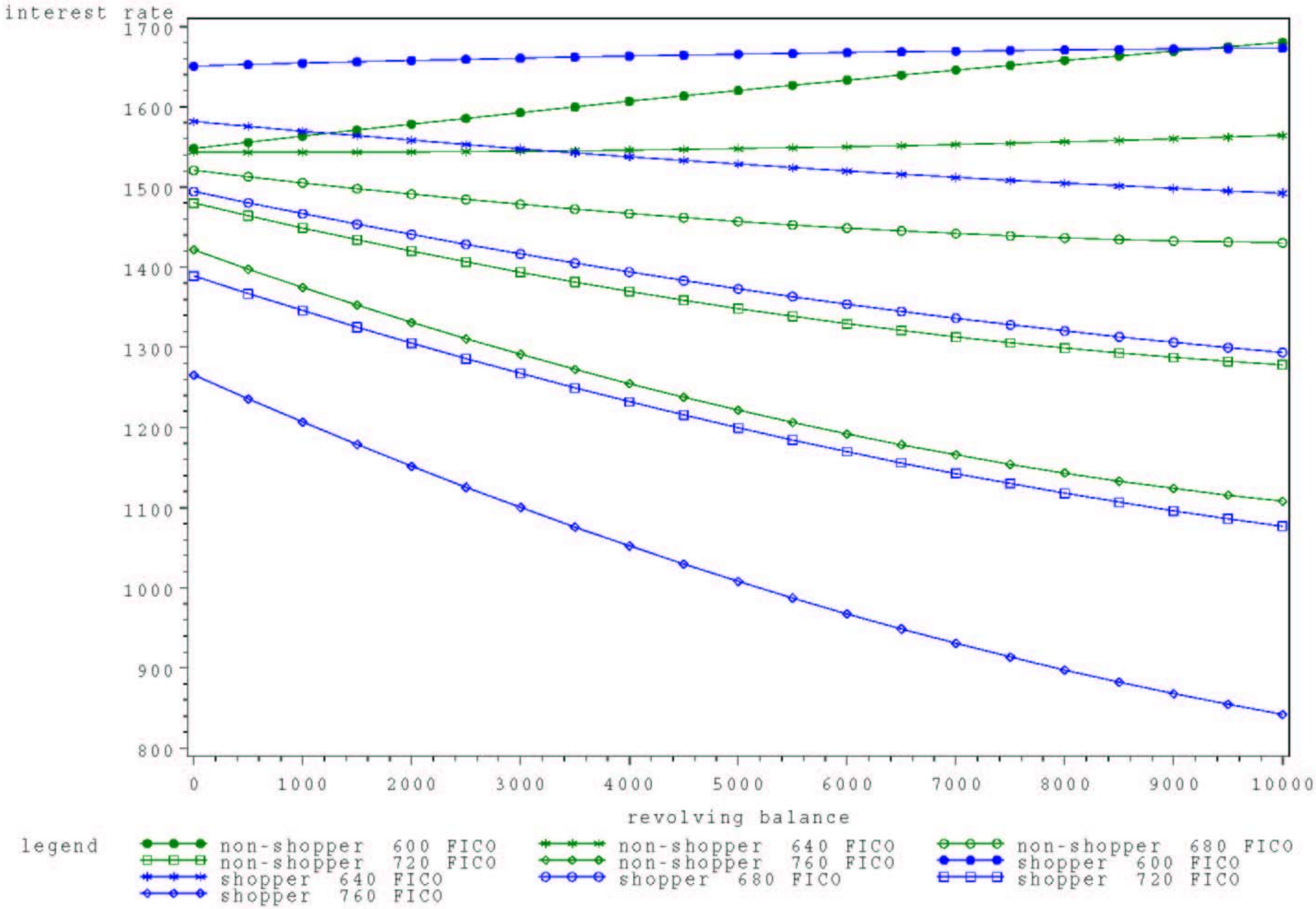


Figure 7
Relationship Between Credit Card Interest Rate and Credit Card Balance by Shopper Type and Credit Score
2001 SCF data