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Benefits of Relationship Banking: Evidence from Consumer Credit Markets

Sumit Agarwal, Souphala Chomsisengphet, Chunlin Liu, and Nicholas S. Souleles

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Sumit Agarwal[a], Souphala Chomsisengphet[b], Chunlin Liu[c], and Nicholas S. Souleles[d]

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Abstract

This paper empirically examines the benefits of relationship banking to banks, in the context of consumer credit markets. Using a unique panel dataset that contains comprehensive information about the relationships between a large bank and its credit card customers, we estimate the effects of relationship banking on the customers' default, attrition, and utilization behavior. We find that relationship accounts exhibit lower probabilities of default and attrition, and have higher utilization rates, compared to non-relationship accounts, ceteris paribus. Such effects become more pronounced with increases in various measures of the strength of the relationships, such as relationship breadth, depth, length, and proximity. Moreover, dynamic information about changes in the behavior of a customer's other accounts at the bank, such as changes in checking and savings balances, helps predict and thus monitor the behavior of the credit card account over time. These results imply significant potential benefits of relationship banking to banks in the retail credit market.

JEL Classification:
Key Words: Relationship Banking; Credit Cards, Consumer Credit, Deposits, Investments; Household Finance.

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Corresponding author: Nicholas Souleles at *souleles@wharton.upenn.edu*
[a] Federal Reserve Bank of Chicago
[b] Office of the Comptroller of the Currency
[c] Finance Department, University of Nevada - Reno
[d] Finance Department, The Wharton School, University of Pennsylvania and NBER

1. Introduction

According to recent theories of financial intermediation, one of the main roles of a bank is serving as a relationship lender.[1] As a bank provides more services to a customer, it creates a stronger relationship with the customer and gains more private information about him or her. Such relationships can potentially benefit both banks and their customers. For instance, relationship banking can help banks in monitoring the default risk of borrowers, providing the banks with a comparative advantage in lending. Relationship banking can also lower banks' cost of information gathering over multiple products. Depending on the competitiveness of the banking sector, such benefits to banks can lead to increased credit supply to customers, through either greater quantities and/or lower prices of credit (e.g., Boot and Thakor, 1994).[2]

Empirical studies of the benefits of the relationship banking have largely focused on the benefits to customers, corporate customers in particular. Early studies documented that the existence of a bank relationship increases the value of a firm (e.g., Billett et al., 1985; Slovin et al., 1993). Subsequent studies have sought to measure the effects of relationships on credit supply to firms. These studies have emphasized different aspects of relationships, such as their breadth (e.g., number of services provided), depth, length, and proximity. However, the results of the studies have been mixed. For example, Petersen and Rajan (1994) find that relationship lending affects the quantity of credit more than the price, while other studies find that customers get either lower future contract prices (e.g., Burger and Udell, 1995; Chakravarty and Scott, 1999) or higher future contract prices (e.g., Ongena and Smith, 2002).

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[1] Boot (2000) provides an excellent review of the literature on relationship banking.

[2] There can also be costs to relationship lending. For example, it can potentially create a "soft budget-constraint" problem, in which the customer exploits the relationship in bad times (Dewatripont and Maskin, 1995; and Bolton and Scharfstein, 1996). Or, relationship lending can potentially create a hold-up problem, providing a bank with an information monopoly that could allow it to price contracts at non-competitive terms (Sharpe, 1990; Rajan, 1992; and Wilson, 1993).

There has been limited empirical research on the underlying benefits of relationships to banks.[3] One exception is Mester, Nakamura, and Renault (2005), who use a sample of 100 Canadian small-business borrowers to investigate the benefits of particular relationship information in monitoring the risk of corporate loans. They find that information about customers' collateral, in particular their inventory and accounts receivable, which might not be available to banks outside of a relationship, is useful for loan monitoring. Also, changes in transaction account balances are informative about changes in this collateral.

While the above studies analyze relationship banking in the context of firm-lender relationships, it can also potentially matter for consumer-lender relationships. Using the Survey of Consumer Finance [SCF], Chakravarty and Scott (1999) conclude that relationship lending not only lowers the probability of credit rationing but also lowers the price of credit for consumer loans. While this study provides evidence that banks pass on some the benefits of relationship lending to consumers, it does not directly measure the underlying benefit to the banks in the first place. We fill this gap in the literature by analyzing the economic benefits of relationship banking to banks, in the context of retail banking.

Credit cards provide a good setting for analyzing retail relationship banking. Credit cards are consumers' most important source of unsecured credit, in addition to being one of the most important means of payment. By the late 1990s, almost three-fourths of U.S. households had at least one credit card, and of these households about three-fifths were borrowing on their cards (1998 SCF). Aggregate credit card balances are large, currently amounting to about $900 billion (Federal Reserve Board 2007).

[3] The review by Boot (2000) concludes that "existing empirical work is virtually silent on identifying the precise sources of value in relationship banking."

One important advantage of studying the credit card market, as opposed to most other credit markets, is that it is easier to identify the information actually used by credit card issuers in managing their accounts. This is because the issuers rely on "hard" information. Since they have millions of accounts to manage, the issuers use automated decision rules that are functions of a given set of variables. A special feature of our dataset is that it contains the variables used to manage the credit card accounts in our sample. While different issuers can use somewhat different sets of such variables, issuers generally rely very heavily on credit-risk scores (e.g., Moore, 1996). The scores can be thought of as the issuers' own summary statistics for the default risk and profitability of each account. As we discuss below, there are two main types of scores, based on different sets of information available to the issuers, both public and private. Hence we can use the scores to conveniently summarize the public and private information traditionally used by credit card issuers.

Such comprehensive summaries of banks' information have not been available in previous studies of bank lending, especially in markets where unobserved "soft" information can be important. Given the information used by banks to manage their accounts, we can more cleanly test whether additional information, in this case relationship information, provides *additional* predictive power.

Specifically, we examine the implications of bank relationships for key aspects of credit card behavior, such as default, attrition and utilization rates. We use a unique, representative dataset of about a hundred thousand credit card accounts, linked to information about the other relationships that the account-holders have with the bank that issued their credit card accounts. Previous studies (Gross and Souleles, 2002) have analyzed the usefulness of other, non-relationship types of information in predicting consumer default, including macroeconomic and geographic-average demographic variables, “public” credit bureau information that is available to all potential lenders, and lenders’ “private” within-account (as opposed to across-account) information about the past behavior of the accounts at issue. The key contribution of this study is to use cross-account relationship information, to test whether a bank’s private information regarding the behavior of the *other* accounts held by a customer at the bank provides additional predictive power regarding the account at issue. Since our dataset samples credit card accounts, we focus on predicting credit card behavior.

The cross-account relationship information that we use is rich and comprehensive. It includes measures of the breadth of the relationships (number of relationships), the types of relationships (e.g., deposit, investment, and loan accounts), the length of the relationships (age in months), the proximity of the relationships (distance from a branch), and the depth of the relationships (balances in dollars).

The previous corporate literature has discussed a number of different explanations as to why such relationship information could be informative, but it is difficult to empirically distinguish between these explanations. Some explanations tend to emphasize what can roughly be thought of as selection mechanisms. For example, when considering loan applications, banks might be better at screening applications from existing relationship customers. Or, perhaps customers with multiple relationships are different in otherwise-hard-to-observe ways than non-relationship customers. (E.g., relationship customers might be wealthier or more sophisticated, or might face larger costs of switching to another lender.) By contrast, other explanations in the literature tend to emphasize more dynamic mechanisms related to information production over time and the ongoing monitoring of loans. While multiple explanations might simultaneously be at work, we will consider some relationship information that is inherently dynamic, such as high-frequency changes in the level and in the volatility of the balances in other relationships. That is, are there informational benefits to monitoring such relationship balances over time? Such dynamic relationship information has not generally been available in the previous literature. While dynamic information is potentially available from any relationship, some authors have noted the potential value of checking relationships in particular (e.g. Black 1975, Fama 1985). Accordingly, we consider extensions regarding checking balances, such as the implications of very low checking balances and of recent transfers in and out of checking.

Our data allows us to estimate some of the most important potential benefits of relationship information to retail banks. First, we examine if the various measures of relationships can help banks better predict the default behavior of credit card accounts. Second, we also examine the implications of relationships for attrition and utilization rates. To our knowledge, this is the first comprehensive analysis of relationships in the retail banking market.

Previewing the main results, we find substantial potential benefits from relationship lending, through lower default risk, lower attrition, and increased utilization. Using Cox proportional hazard models, the relationship information is found to significantly help predict default and attrition, above and beyond all the other variables used by the bank – both public information and private non-relationship information based only on the behavior of the credit card account. For example, for credit card accounts with at least one other relationship with the bank, the marginal probabilities of default and attrition are about 10% and 12% lower than those of accounts without other relationships, ceteris paribus. More generally, the benefits to the bank tend to increase with various measures of the strength of the relationships, including measures analogous to those used in the prior corporate literature, such as relationship breadth, depth, length, and proximity. Further, explicitly dynamic information about *changes* in the behavior of the account-holders' other relationships at the bank, such as changes in checking and savings balances, help predict the behavior of the credit card account over time. This suggests that one important advantage of relationships, among the various other advantages that have been discussed in the literature, is that they can help improve the monitoring of borrowers over time. Also, we find that relationship banking is associated with higher utilization rates. For instance, relationship accounts have a 7 percentage point higher utilization rate compared to non-relationship accounts, ceteris paribus.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the empirical methodology and results. Section 4 concludes.

2. Data

We use a unique, proprietary panel dataset of credit card accounts, with associated relationship information, from a large, national financial institution. The dataset contains a representative sample of about a hundred thousand accounts open as of October 2001, followed monthly for the next 24 months.

The dataset includes the key information used by the bank in managing its credit card accounts. The dataset contains the main billing information listed on each account's monthly statement, including total payments, spending, balances, and debt, as well as the credit limit and APR.

The dataset also includes the two key credit-risk scores for each account, which are lenders' traditional summary statistics for the risk and profitability of the account. The "external" credit score (the industry-standard FICO score) is estimated based on the credit bureau data available for each consumer. While the credit bureaus contain some information about the full range of a consumer's credit relationships, across all lenders, the individual lenders report only a subset of their own information about each relationship to the bureaus. The external scores summarize this "public" information, which is available to all potential lenders. The "internal" credit score is estimated by the lenders using their private, in-house information. Traditionally (and true for our sample), that information has been limited to the behavior of the individual account in question -- here the sample credit card accounts -- not the other accounts or relationships the account-holder has at the same bank. Thus the two scores conveniently summarize the non-relationship (private within-account and public) information used by banks in managing credit cards.

In addition to the external credit score, the dataset also includes the subset of the underlying credit bureau information that the bank directly collected from the credit bureaus: the total number of bankcards held by the account-holder, across all lenders, and the balances and limits on those cards; the number and balances on other, non-bank credit cards (such as store cards); total balances and limits on home equity lines of credit (Helocs); total mortgage balances (including both first and second mortgages); and total balances on student loans and auto loans. The credit bureau variables are updated quarterly.

This data has been augmented with a number of other data sources. First, and most importantly for our purposes, the dataset was linked to a systematic summary of the other accounts the credit card account-holders have at the bank. Specifically, we have information about the following types of deposit, investment, and loan relationships: checking; savings; CD's; mutual funds; brokerage; mortgages; home equity loans (second mortgages); and home equity lines of credit.[4] For each relationship type, we know the length of the relationship (age in months) and the depth of the relationship (balances in dollars). This relationship information is updated monthly over the sample period.[5]

Second, this credit data is also augmented with macroeconomic and geographic-average demographic information based on each account-holder's location, including: the state unemployment rate, average state income, the fraction of people in the state lacking healthcare coverage, and local house prices.[6] Some of these variables are updated monthly while others are updated annually. The dataset also includes the self-reported level of account-holder income when available from the account application[7], as well as an account-holder specific estimate of wealth (based on marketing/geographic data, and coded as "high", "medium", or "low") as of the time of the origination of the account.

The sample includes credit card accounts that were open as of the start of the sample period in October 2001.[8] To focus on the effects of relationships and minimize any potential endogeneity, for credit card account-holders with other relationships, in the reported results we require that these other relationships have been opened before the credit card account; that is, we exclude account-holders that initiated new relationships within our sample period subsequent to opening the credit card account.

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[4] The dataset does not include a few smaller relationships, such as student loans, personal loans, and auto loans. Thus our results represent a lower bound on the total possible value of relationships, though some of this information (student and auto loans) will be partly captured by the credit bureau data that we use.

[5] The exception is that balances information is not available for brokerage accounts.

[6] We use the OFHEO MSA-level house prices when available; otherwise we use the state average prices. In preliminary work, we also considered additional variables, such as the state divorce rate (which however is not available for some states, such as California) and the bankruptcy exemption levels in the state (which are subsumed by our state dummies).

[7] This income variable is available for slightly under half of the accounts. To avoid reducing the sample size, we include a dummy variable indicating when application income is missing, and in those cases set the value of income to zero.

[8] That is, accounts that are closed at the start of the sample, due to attrition or default, have been excluded. Furthermore, to simplify the hazard analysis of account age, in the reported results we focus on accounts originated after October 1999.

Table 1 provides summary statistics for the key variables used below, averaged over the two years of the sample period. The table distinguishes "relationship accounts," which have at least one other relationship (56% of the sample), and "non-relationship accounts," which have no other relationships (44%). The relationship account-holders have higher income and higher wealth on average. They also have less debt on their account and higher internal and external credit scores. Overall, based on the public and private within-account information, the relationship accounts generally appear to be less risky than the non-relationship accounts. (The credit scores are calibrated such that higher scores correspond to lower probabilities of default.) Consistently, the relationship accounts received higher credit limits and lower APRs. Turning to their performance over the sample period, the relationship accounts do in fact have lower default rates, and also lower attrition rates and higher utilization rates, on average. The open question is whether these results can be explained by the differences in their other (non-relationship) characteristics, as opposed to their relationships.

The next section undertakes a multivariate analysis of the accounts' behavior, emphasizing the role of the private, cross-account relationship variables, conditional on controlling for the other characteristics like the credit scores.

3. Empirical Results

3.1 Relationship Banking and Credit Card Default and Attrition

3.1.1 Methodology

To test if relationship banking can help banks in assessing the default and attrition risk of credit card loans, we estimate Cox proportional hazard models for default and for attrition.[9] We use a standard industry definition of default as going bankrupt or three months delinquent, whichever comes first (e.g., as in Gross and Souleles, 2002). Attrition is based on account closing without default.

The Cox model allows for a non-parametric baseline hazard rate as well as potentially time-varying explanatory variables. We estimate specifications of the following form:

$$Y_{i,t} = \beta_1 Time_t + \beta_2 StateDummies_i + \beta_3 MacroDemog_{i,t-6} + \beta_4 LoanPerformance_{i,t-6} + \beta_5 CreditBureau_{i,t-6} + \beta_6 Relationship_{it-6} + \varepsilon_{it} \qquad (1),$$

where $Y_{i,t}$ is a dummy variable indicating whether account i defaulted (or attrited) in month t.

We group the main explanatory variables into six categories: $Time_t$ represents a complete set of month dummies, one for each month in the sample period. $StateDummies_i$ represents a set of dummy variables corresponding to the state in which account-holder i lives. $MacroDemog_{i,t\text{-}6}$ represents the macroeconomic and demographic characteristics, such as the local unemployment rate, plus the account-holder specific estimates of income and wealth. $LoanPerformance_{i,t\text{-}6}$ includes the internal measures of the performance of the sample credit card account over the sample period, including monthly purchases, payments, and debt, and the credit limit, interest rate, and internal credit-risk score. $CreditBureau_{i,t\text{-}6}$ represents the external credit score and the other variables from the credit bureaus, such as total balances on credit cards, Helocs, and mortgages.[10]

Such variables have been studied before. Using related duration models, Gross and Souleles (2002) show that the external scores are very powerful predictors of consumer default. Even given these scores, the internal scores are also very powerful predictors, which implies that credit card issuers' private within-account information is valuable. Nonetheless, even given the

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[9] We also estimated the baseline results using a multinomial logit model, and the results were qualitatively similar.

[10] Unless stated otherwise, the time-varying variables in *MacroDemog*, *LoanPerformance*, *CreditBureau*, and *Relationship* are generally lagged by six months to minimize endogeneity, as in Gross and Souleles (2002). For instance, by the time an account is already three months delinquent, its credit score would have already severely deteriorated, creating essentially a mechanical relationship with the dependent variable.

two scores, macroeconomic and demographic characteristics are also predictive, albeit less so quantitatively. This result suggests that lenders do not necessarily use all potentially available information (perhaps due to regulatory or reputational concerns).

The key innovation of this study comes in assessing the incremental predictive power of *Relationship*, which represents a broad array of measures of the account-holders' relationships. The baseline relationship measure labeled R1 simply uses a dummy variable to identify the credit card account-holders who have at least one other relationship at the bank at origination. (The omitted, baseline category is non-relationship accounts). R2 measures the breadth of the relationship, using dummy variables for the number of relationships (1 to 6+, omitting 0 relationships). R3 focuses on the types of relationship, grouping the relationships into three broad categories (again using dummy variables): deposit relationships, investment relationships, and loan relationships. R4 identifies the types of relationships more finely (8 categories): checking and savings accounts (deposit relationships); CDs, brokerage, and mutual fund accounts (investment relationships); and mortgages, home equity loans, and home equity lines (loan relationships). R5 measures the length of the relationships (age in months since opening), for each of the eight relationship categories separately. R6 focuses on the proximity of the relationship, using interacted dummy variables to distinguish account-holders that have a relationship and reside in states with bank branches. R7 measures the depth of the relationships by the balances of each of the relationship categories (in addition to controlling for the presence of each relationship as in R4). R8 combines the previous measures simultaneously.

To try to distinguish more specifically the potential benefits of relationships in the ongoing monitoring of loans, we also consider more dynamic relationship information (controlling for the level and presence of balances using R4 and R7). R9 considers the effect of *changes* in the various types of balances (for convenience, between months *t-6* and *t-5*). R10 considers the volatility of balances. (In light of the available sample period, it uses the standard deviation between *t-1* and *t-12*.) R11 uses instead the change in the volatility of balances (the standard deviation between *t-1* and *t-6*, minus the standard deviation between *t-7* and *t-12*). R12 focuses more specifically on checking balances, using an indicator for whether these balances have fallen below $2000. R13 uses instead indicator variables for whether there were matching balance transfers between the checking account and the other accounts.

In all specifications, the standard errors are clustered to adjust for heteroscedasticity across accounts and serial correlation within accounts.

3.1.2 Results

We first show how the baseline hazard rates from the Cox model vary with the number of relationships, without controlling for other covariates. Figure 1a shows the associated survival curves for (lack of) default. The survival curves are monotonically increasing with the number of relationships. For example, for accounts with just one other relationship, the probability of not defaulting within 48 months is about 96%. But for accounts with six or more relationships, that probability significantly rises, to about 99%. Conversely, the probability of default monotonically declines with the number of relationships. Figure 1b shows the analogous survival curves for (lack of) attrition. Again, the curves substantially and monotonically increase with the number of relationships.

We now estimate the full multivariate Cox model, following equation (1), first for default. We begin by briefly discussing the results for the non-relationship variables, for our baseline specification R1 (for brevity, reported in Appendix Table 1). Starting with the credit variables, the external and internal scores have negative and significant coefficients. As expected, higher scores are predictive of lower probabilities of default. The marginal effects for continuous covariates like the scores show the effects of a one standard-deviation increase in the covariates. A one standard-deviation larger external (internal) score is associated with a 15% (16%) reduction in the probability of credit card default relative to the baseline default rate, ceteris paribus. These are economically significant effects.

Many of the other credit variables are also significant, though their marginal effects are much smaller. The probability of default significantly increases with the amount of debt on the credit card account. It also increases with the total number of credit cards held by the account-holder (both bankcard and non-bankcard), and the balances on those cards. A larger credit limit or a lower APR on the account is associated with a lower probability of default. As discussed in the prior literature, this likely reflects the endogeneity of credit supply: on average issuers extended better credit terms to borrowers that were less risky. Hence the results for such covariates should not be interpreted as causal. For our purposes it is conservative to control for such variables, since they are in the issuer's (non-relationship) information set. Similarly for Helocs, where one can also distinguish credit demand (balances) and credit supply (credit limits), larger balances are associated with more default, but larger limits are associated with less default. Other credit balances where one cannot so readily distinguish credit supply and demand, such as mortgage balances, have overall negative coefficients. In sum, the public information from the credit bureaus is predictive of default, and even given this information the bank's private within-account information is also predictive.

Turning to the macroeconomic-demographic variables, adverse local economic conditions are generally associated with more default. Higher local unemployment and lower house price growth are associated with significantly higher default rates, even given the state and month dummies. A one standard-deviation increase in unemployment (decrease in house price growth rates) corresponds to a 3% increase (8% increase) in the probability of default. Higher income and wealth are associated with less default, though these results are not statistically significant. (This could reflect measurement error in these estimates of income and wealth. "Low-doc" accounts, for which income was not collected at the time of application, have significantly higher default rates.) Overall, these (non-relationship) results are generally consistent with prior research (Gross and Souleles, 2002).

We now focus on the results for the relationship information. The baseline relationship measure R1 simply uses an indicator variable for having another relationship. The omitted group is non-relationship accounts. The relationship variable has a significant negative coefficient. This implies that relationship accounts have a lower probability of default than non-relationship accounts, ceteris paribus. According to the marginal effect, the probability of default is 10% lower on average. This is an economically significant effect (and larger than the marginal effects of all the other covariates apart from the credit scores). Given the rich set of covariates, including both the public information and private within-account information of the issuer, this result demonstrates the predictive value of cross-account relationship information.

Table 2 considers the other measures of relationships. Each horizontal panel in the table shows the results from the Cox model for separate specifications using each of the relationship measures R1 to R13 separately. (For brevity, only the relationship results are reported. For reference, the table repeats the results for R1.) R2 measures relationship breadth according to the number of relationships. As in Figure 1, the probability of default significantly and monotonically declines with the number of relationships. According to the marginal effects, the probability of default decreases by 2% for the first relationship, and by 18% for the sixth (or more) relationship.

Relationship measure R3 considers the effects of different types of relationships. The presence of each of the three broad relationship types is associated with lower probabilities of default. The magnitude of the effect is largest for investment relationships. The probability of default decreases by 14% with investments relationships, versus 9% for deposit relationships and 4% for loan relationships. R4 uses a finer partition of the relationship types. Within investment accounts, CD relationships have the largest (negative) marginal effects. All the other relationship types also have significant, albeit smaller, negative effects.

Measure R5 focuses on the length of the other relationships (age in months, distinct from the age of the credit card account which is separately taken into account in the Cox model). For each relationship type, the probability of default significantly declines with the age of the relationship. The marginal effects range in size from 3% to 13% declines (for a one standard-deviation increase in age), with the largest effect arising from the age of a CD relationship.

R6 focuses on the proximity of the relationship, using an indicator for account-holders that reside in states with bank branches, and the interaction of this variable with the indicator (R1) for having a relationship.[11] The interaction term is significantly negative. This implies that the (negative) effect of relationships on default risk is stronger when account-holders reside closer to branches. Thus, even given the other controls for local conditions, proximity to the bank matters (as in Petersen and Rajan, 2002).

R7 focuses instead on relationship depth, using ln(balances + \$1). (The specification also includes the indicator variables for having the corresponding relationship, as in R4.) For all

[11] This specification requires dropping the state dummies in equation (1). Accordingly we focus on the interaction term, not the non-interacted indicator for proximity.

relationships, larger balances at the bank are associated with smaller probabilities of default. For asset balances, the marginal effects range from 7% to 20%. The marginal effects are much smaller in magnitude for credit balances, though still negative. Recall that the specification controls for *total* credit balances for each of the credit relationship types using the credit bureau data, as well as (a more coarse measure of) wealth. Hence, these results can be interpreted as indicating that the larger the *share* of an account-holder's various balances at this particular bank, the lower the probability of default on the credit card from the bank.

R8 considers simultaneously the previous measures of relationship, specifically relationship breadth, type, length, proximity, and depth. Not surprisingly, the marginal effects are often smaller, but nonetheless the general pattern of results is similar to that above. All of the relationship measures retain their significant negative coefficients.

Overall, under all the measures of relationship R1-R7, relationship accounts have lower probabilities of default. Similar measures of relationships have been considered in the previous literature on corporate lending. To try to distinguish the specifically dynamic notions of the benefits of relationships, the subsequent specifications consider more explicitly dynamic measures of relationship information.

Relationship measure R9 focuses on the change in relationship balances (in addition to the level of balances from R7 and the indicators from R4).[12] The specification also includes the corresponding changes in the external and internal credit scores. Increases in the scores have negative, statistically and economically significant effects. As expected, upwards revisions in the scores reflect the arrival of information indicating a reduction in default risk. Even controlling

[12] Since our sample excludes relationships opened subsequent to the credit card account, these results are driven by changes in the intensive margin of balances. R9 does not include the (high-frequency) changes in the CD and mortgage and home equity loan balances, since these mostly reflect interest and regular amortization, and so are a priori not as informative.

for this, the changes in balances also have significant negative coefficients. Thus increases over time in relationship balances are associated with declines in default risk, ceteris paribus. The marginal effects are substantial, ranging from 6%-13% declines. These results show the value of relationships specifically in the ongoing monitoring of loans.

R10 measures the volatility of balances, across the prior 12 months. The specification also includes the volatility of the credit scores. Accounts with more volatile scores have higher probabilities of default (consistent with Musto and Souleles, 2006). In addition, more volatile relationship balances are also associated with higher default risk, with the marginal effects ranging between 5% - 12%. R11 considers instead the change in the volatility of the balances, over the prior two six-month periods. The coefficients are again significantly positive. Increases in volatility are also associated with higher default risk.

The remaining relationship measures focus on checking balances in particular. R12 uses an indicator for whether checking balances fall to a low level, here below $2000. Since the specification also includes the overall level of checking balances (R7), this indicator reflects the discrete increase in risk associated with low balances per se. The estimated coefficient is significantly positive. Low checking balances are associated with a 13% marginal increase in the probability of default. Finally, R13 uses an indicator that identifies matching balance transfers between the checking account and the other accounts. The first indicator identifies whether balances were moved *to* checking from the other accounts. The coefficient is significantly positive. Further analysis shows that this result is driven mostly by transfers from the savings and investment accounts. Thus, when account-holders appear to dissave, the probability of default is higher. This is consistent with their having faced a negative shock. Conversely, the negative coefficient on the second indicator implies that when account-holders save, transferring balances from checking to the other accounts, the probability of default is lower. This is consistent with a positive shock. The marginal effect is much larger for dissaving, implying a 13% increase in the probability of default.

Table 3 presents the results of estimating equation (1) instead for attrition, again focusing on the relationship measures. (For brevity, the non-relationship results are left to the appendix.) In general the pattern of the relationship results is qualitatively similar to that in Table 2 (and so our discussion of them will be brief). That is, the same relationship information that is associated with lower default rates is also generally associated with lower attrition rates.

For example, using the baseline measure R1, relationship accounts have on average a 12% lower probability of attrition than non-relationship accounts, ceteris paribus. This result is statistically and economically significant. The effect on attrition is again monotonic with the number of relationships (R2), ranging from a 3% decline in attrition probability for the first relationship to a 21% decline for the sixth relationship. The effect is significant for all of the relationship types (R3 and R4), especially investment and deposit relationships. The probability of attrition significantly declines with the length of the relationships (R5). The (negative) effect of relationships on attrition is stronger with proximity (R6). Larger relationship balances (R7 and R12) and increases in relationship balances (R9) are also associated with lower attrition rates, but more (and increased) volatility in the balances is associated with higher attrition rates (R10 and R11). Under R13, balance transfers from checking (i.e., saving) are associated with lower attrition, but transfers to checking (i.e., dissaving) are associated with higher attrition, with the marginal effect being larger for the latter.

In sum, across the entire rich array of relationship measures that we have considered, including the dynamic measures, relationship accounts have lower probabilities of default and attrition, ceteris paribus.

3.2 *Relationship Banking and Credit Card Utilization*

3.2.1 Methodology

In this section we consider the implications of relationships on a standard measure of account usage, the account utilization rate (i.e., account balances relative to the account limit). For consistency, we generally use the same covariates as in equation (1), but replace the dependent variable $Y_{i,t}$ with the utilization rate of account *i* in month *t*.[13] We estimate by OLS, allowing for heteroscedasticity across accounts and serial correlation within accounts.

3.2.2 Results

We begin by briefly noting some of the results for the non-relationship variables, which appear in Appendix Table 3 for the baseline specification using R1. Higher credit scores are correlated with lower utilization rates. This is not surprising, since the scores are known to take utilization into account negatively. Credit balances (total bankcard, non-bankcard, home equity line, mortgage and auto balances, with the exception of student loan balances) come in with significant negative coefficients, suggesting some substitutability with balances on the sample credit cards, though the magnitudes of the effects are small. Higher unemployment is associated with significantly greater utilization, though higher house price growth (and higher income) is also associated with significantly greater utilization, which is indicative of a wealth effect. The

[13] Unlike equation (1), we exclude the account limit, debt, payment and purchase amounts as independent variables, since they are closely related to the dependent variable.

effect of house prices is substantial: Each percentage point increase in house price growth is associated with a 2.4 percentage point (p.p.) increase in the utilization rate.[14]

Table 4 reports the results for the relationship variables. The coefficient on relationship measure R1 is significantly positive. Hence relationship accounts have higher utilization rates than non-relationship accounts, ceteris paribus. Relative to an average utilization rate of about 20 p.p., the average difference of 7 p.p. is substantial.[15] Using measure R2, utilization significantly and monotonically increases with the number of relationships. The utilization rate is 2 p.p. higher for accounts with one other relationship, and 14 p.p. higher for accounts with at least six relationships. Under measures R3 and R4, utilization increases with each type of relationship, especially checking and brokerage relationships (by about 9 p.p.). Under R5, utilization also increases with the length of each type of relationship.

Under R6, interacting the relationship indicator (R1) with the indicator for proximity leads to a significant positive coefficient. Thus the effect of relationships on utilization is larger when account-holders live near a bank branch.

Using R7, the coefficients on relationship balances are significantly positive. Hence, given total balances, larger shares of balances at the bank are associated with greater usage of the credit card from the bank. Using R9, changes in relationship balances also generally have positive effects. The notable exception is that an increase in Heloc balances has a significant negative effect. This is consistent with a degree of substitutability between home equity lines of

[14] This result, as well as the results for the other variables in the table, is similar using debt normalized by the limit as the dependent variable.

[15] The conclusion is the same using debt normalized by the limit as the dependent variable, even though *unconditionally* relationship accounts have lower debt and higher limits than non-relationship accounts. For debt, the coefficient on R1 is accordingly somewhat smaller at .033, but still statistically and economically significant.

credit and credit card lines of credit. Under R10 and R11, higher (and increased) volatility of balances is associated with lower utilization.

Under R12, given the level of checking balances (R7), the indicator for low balances is not significant. However, under R13, transfers of balances to checking from other accounts (in particular savings and investment accounts, i.e., dissaving) are associated with significantly higher credit card utilization, by about 10 p.p. on average. Conversely, transfers from checking to the other accounts (i.e., saving) are associated with significantly lower utilization, by about 8 p.p. on average. These results are suggestive of the arrival of negative and positive shocks, respectively, consistent with the previous results for R13 for default and attrition. More generally, the various results regarding checking relationships imply that dynamic information from checking accounts in particular can be useful in the ongoing monitoring of loans. Changes in the behavior of checking accounts can provide indirect information about shocks and other factors that otherwise are hard for a bank to observe directly.

4. Conclusion

This study provided direct evidence of the potential benefits of relationship banking to retail banks. The results indicate that, even controlling for traditional sources of bank information (both public information and private, within-account information) and other variables, credit card account-holders with other relationships at a bank tend to have higher utilization rates yet lower default and attrition rates. In particular, dynamic information about changes in the behavior of an account-holder's other relationships helps predict the behavior of the credit card account over time. This is consistent with the view that, among the various potential benefits of relationship banking, relationships can help banks better monitor their loans over time.

These results imply that relationship information is valuable in a predictive sense, but how exactly banks should use this information requires additional considerations. The optimal use of information and optimal contract design, both from the point of view of the bank and socially, is an important but difficult question that is beyond the scope of this paper. First, banks need to consider how consumers and their competitors would respond to the use of the information. Second, government policies can restrict certain uses of information, including cross-account information. In addition to considering the benefits of such restrictions, a comprehensive analysis of such policies should also consider the potential efficiency loss from excluding information that is predictive.

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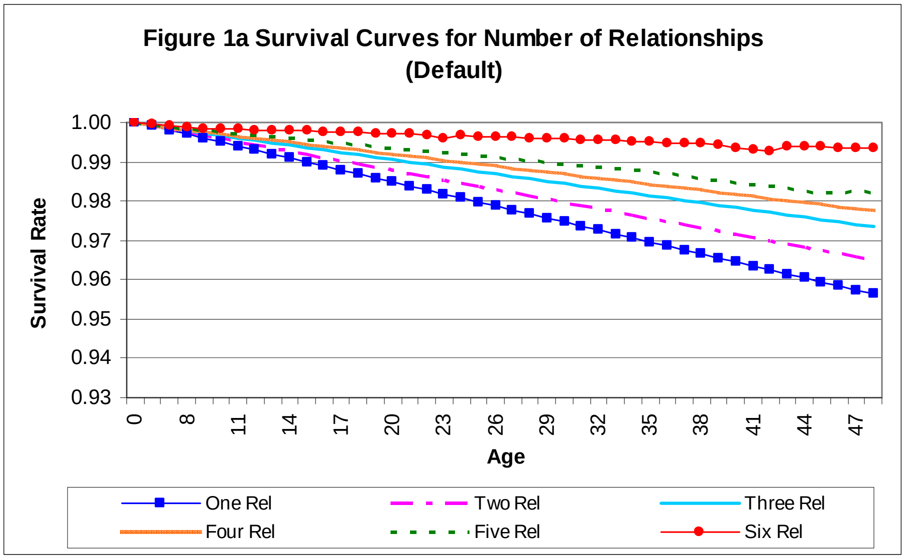
Figure 1a Survival Curves for Number of Relationships (Default)
1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
Survival Rate
0
8
11
14
17
20
23
26
29
32
35
38
41
44
47
Age
One Rel
Two Rel
Three Rel
Four Rel
Five Rel
Six Rel

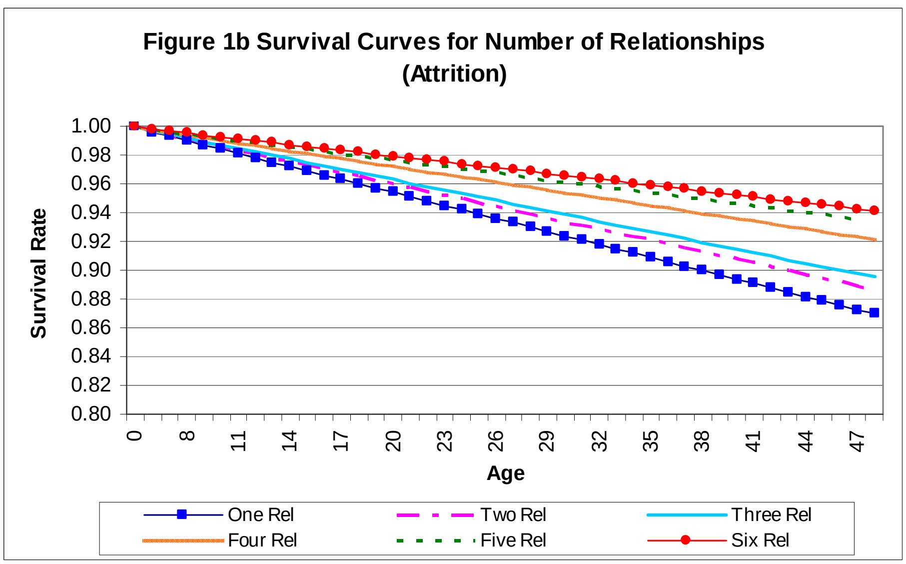
Figure 1b Survival Curves for Number of Relationships (Attrition)
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0.80
Survival Rate
0
8
11
14
17
20
23
26
29
32
35
38
41
44
47
Age
One Rel
Two Rel
Three Rel
Four Rel
Five Rel
Six Rel

Table 1: Descriptive Statistics

Variable	Non-Relationship Accounts Mean	Non-Relationship Accounts Std dev	Relationship Accounts Mean	Relationship Accounts Std dev
Unemployment rate (%)	5.3	0.9	5.2	0.8
% w/o health insurance	12.5	3.7	12.7	3.3
House prices %	7.3	0.8	7.4	0.9
State income ($1000)	36.083	4.588	36.428	4.507
Application income	41.074	12.627	44.123	16.029
Wealth = low	32%		27%	
= medium	57%		55%	
= high	11%		17%	
External Risk Score	735	71	743	66
Internal Risk Score	716	46	720	33
Debt	1.979	3.912	1.836	3.238
Payments	0.308	0.774	0.389	0.903
Purchase	0.229	0.923	0.274	0.669
APR	16.99	5.46	15.50	5.08
Credit line	8.283	3.737	9.491	3.804
Total number of bankcards	6	6	5	6
Total bankcard credit limits	27.984	24.902	23.027	27.639
Total bankcard balances	7.023	14.066	7.569	17.122
Total number of non-bank cards	11	10	13	14
Total non-bank card balances	18.553	9.324	16.103	7.975
Total home equity line limits	7.394	28.922	5.866	25.241
Total home equity line balance	4.857	18.651	3.909	14.074
Total mortgage loan balance	43.092	81.893	44.745	87.208
Total auto loan balance	3.377	6.098	2.891	6.544
Total student loan balance	1.183	6.893	1.115	7.696
Default %	5.6%		3.9%	
Attrition %	15.5%		12.0%	
Utilization rate	0.188		0.239	
Number of Accounts	40944	43.7%	52750	56.3%

Notes:
Values are averaged over the sample period. Dollar amounts in $1000 units.
(Default and attrition rates are total rates over the sample period.)

Table 2: Implications of Relationships for Default

Variable	Default			
	Coeff	Std Err	P-value	Marg Eff
R 1. Relationship				
Relationship Indicator	-0.3208	0.0859	<.0001	10.1%
R 2. Breadth of Relationships				
Number of Bank Relationships=1	-0.2628	0.0356	<.0001	1.6%
=2	-0.2307	0.0416	<.0001	3.1%
=3	-0.3258	0.1270	<.0001	6.3%
=4	-0.2539	0.1221	<.0001	9.4%
=5	-0.6404	0.3151	<.0001	10.6%
=6+	-0.6253	0.2465	<.0001	17.9%
R 3. Type of Relationships (Broad)				
Deposit Relationships	-0.2410	0.0672	<.0001	9.3%
Investment Relationship	-0.3366	0.1199	<.0001	14.1%
Loan Relationship	-0.0303	0.0129	<.0001	4.2%
R 4. Type of Relationships (Narrow)				
Checking Dummy	-0.1217	0.0391	<.0001	6.6%
Savings Dummy	-0.2743	0.0697	<.0001	8.0%
Brokerage Dummy	-0.2534	0.0891	<.0001	10.5%
CD Dummy	-0.4579	0.1237	<.0001	16.6%
Mutual Fund Dummy	-0.3714	0.0320	<.0001	14.9%
Home Equity Line Dummy	-0.0162	0.0047	<.0001	7.4%
Home Equity Loan Dummy	-0.0107	0.0047	<.0001	2.8%
Mortgage Loan Dummy	-0.0167	0.0052	<.0001	3.6%
R 5. Length of Relationships				
Age of Checking Relationship	-0.0013	0.0002	<.0001	3.4%
Age of Savings Rel	-0.0061	0.0004	<.0001	5.8%
Age of Brokerage Rel	-0.0108	0.0009	<.0001	9.8%
Age of CD Rel	-0.0213	0.0054	<.0001	13.2%
Age of Mutual Fund Rel	-0.0163	0.0015	<.0001	6.3%
Age of Home Equity Line Rel	-0.0009	0.0009	<.0001	11.5%
Age of Home Equity Loan Rel	-0.0018	0.0009	<.0001	9.4%
Age of Mortgage Loan Rel	-0.0059	0.0021	<.0001	10.0%
R 6. Proximity of Relationship				
Relationship Indicator	-0.3041	0.0812	0.000	6.0%
State with Branch Indicator	-0.2728	0.0762	<.0001	7.6%
Relationship * Branch State	-0.1231	0.0510	<.0001	3.0%

Table 2: Implications of Relationships for Default (ctd)

Variable	Default			
	Coeff	Std Err	P-value	Marg Eff
R 7. Depth of Relationships (ln(Bal) & R4)				
Checking Balance	-0.0612	0.0139	<.0001	13.2%
Savings Balance	-0.0731	0.0188	<.0001	7.2%
CD Balance	-0.0780	0.0210	<.0001	10.6%
Mutual Fund Balance	-0.1806	0.0433	<.0001	19.8%
Home Equity Line Balance	-0.1173	0.0333	<.0001	3.1%
Home Equity Loan Balance	-0.0817	0.0344	<.0001	5.8%
Mortgage Loan Balance	-0.1984	0.0776	<.0001	3.3%
R 8. Combined Relationship Measures				
Number of Bank Relationships=1	-0.2551	0.0354	<.0001	0.1%
=2	-0.2292	0.0409	<.0001	1.8%
=3	-0.3129	0.1262	<.0001	4.7%
=4	-0.2453	0.1200	<.0001	7.0%
=5	-0.6307	0.3054	<.0001	10.1%
=6+	-0.6189	0.2458	<.0001	17.0%
Checking Dummy	-0.1169	0.0376	<.0001	4.3%
Savings Dummy	-0.2573	0.0649	<.0001	5.3%
Brokerage Dummy	-0.2417	0.0840	<.0001	7.8%
CD Dummy	-0.4231	0.1195	<.0001	13.1%
Mutual Fund Dummy	-0.3658	0.0308	<.0001	11.7%
Home Equity Line Dummy	-0.0150	0.0045	<.0001	4.2%
Home Equity Loan Dummy	-0.0098	0.0045	<.0001	0.5%
Mortgage Loan Dummy	-0.0160	0.0048	<.0001	0.7%
Age of Checking Relationship	-0.0012	0.0002	<.0001	2.6%
Age of Savings Rel	-0.0059	0.0004	<.0001	5.1%
Age of Brokerage Rel	-0.0108	0.0009	<.0001	8.9%
Age of CD Rel	-0.0212	0.0052	<.0001	11.7%
Age of Mutual Fund Rel	-0.0156	0.0015	<.0001	6.2%
Age of Home Equity Line Rel	-0.0009	0.0009	<.0001	11.0%
Age of Home Equity Loan Rel	-0.0017	0.0008	<.0001	8.6%
Age of Mortgage Loan Rel	-0.0058	0.0021	<.0001	8.8%
State with Branch Indicator	-0.2674	0.0749	<.0001	3.0%
Relationship * Branch State	-0.1222	0.0507	<.0001	1.8%
Checking Balance	-0.0604	0.0137	<.0001	12.5%
Savings Balance	-0.0720	0.0182	<.0001	5.7%
CD Balance	-0.0749	0.0208	<.0001	9.0%
Mutual Fund Balance	-0.1767	0.0421	<.0001	18.4%
Home Equity Line Balance	-0.1147	0.0327	<.0001	4.0%
Home Equity Loan Balance	-0.0788	0.0339	<.0001	4.2%
Mortgage Loan Balance	-0.1974	0.0756	<.0001	2.1%

Table 2: Implications of Relationships for Default (ctd)

Variable	Default			
	Coeff	Std Err	P-value	Marg Eff
R 9. Change in Balances (ln(Bal) & R7 & R4)				
D(Checking Balance)	-0.0307	0.0032	<.0001	6.1%
D(Savings Balance)	-0.0285	0.0011	<.0001	13.0%
D(Mutual Fund Balance)	-0.0655	0.0014	<.0001	10.0%
D(Home Equity Line Balance)	-0.0042	0.0015	0.0002	6.5%
D(External Score)	-0.4479	0.0262	<.0001	16.0%
D(Internal Score)	-0.3854	0.0683	<.0001	12.3%
R 10. Volatility of Balances (sd(12) & R7 & R4)				
sd(Checking Balance)	1.1014	0.0209	<.0001	5.2%
sd(Savings Balance)	0.7945	0.0616	<.0001	11.9%
sd(Mutual Fund Balance)	1.2133	0.0638	<.0001	10.2%
sd(Home Equity Line Balance)	1.1366	0.0867	<.0001	11.3%
sd(External Score)	0.7706	0.2233	<.0001	13.1%
sd(Internal Score)	0.4569	0.2118	<.0001	7.5%
R 11. Change in Volatility (D(sd(6)) & R7 & R4)				
D(sd(Checking Balance))	1.0136	0.0227	<.0001	6.8%
D(sd(Savings Balance))	0.5563	0.0509	<.0001	12.9%
D(sd(Mutual Fund Balance))	0.9448	0.0669	<.0001	11.3%
D(sd(Home Equity Line Balance))	0.9608	0.0733	<.0001	13.5%
D(sd(External Score))	0.5999	0.2104	<.0001	14.9%
D(sd(Internal Score))	0.5903	0.2174	<.0001	8.8%
R 12. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.6999	0.1675	<.0001	12.7%
R 13. Transfers of Balances (&R7 & R4)				
To Checking	0.5954	0.1953	<.0001	12.8%
From Checking	-0.7100	0.1918	<.0001	3.2%
Number of Obs / Number Default	1132182	4322		

Notes: This table shows the effects of relationships in predicting credit card default (bankruptcy or three months delinquency), using Cox proportional hazard models following eq. (1). The explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports only the results for the relationship variables; each panel represents a separate specification. (The other variables appear in the appendix for specification R1.) In the first panel, R1 is a dummy variable identifying credit card accounts that have another relationship. R2 uses dummy variables for the number of relationships (relationship breadth). R3 and R4 uses dummy variables identifying the types of relationships, broadly and narrowly defined. R5 measures the length of the relationships (age in months since opening). R6 uses dummy variables to distinguish account-holders that have a relationship and reside close to bank branches (i.e., reside in states with bank branches). R7 measures the balances of the relationship categories (relationship depth, using ln(balances +1)), and R9 measures the changes in the balances. R10 measures the volatility of balances over the prior 12 months, and R11 measures the change in the volatility of balances over the prior two 6-month periods. R12 uses a dummy variable for whether checking balances have fallen below $2000. R13 uses dummy variables for whether there were matching balance transfers between the checking account and the other accounts. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts. The marginal effects for continuous covariates show the effects of a one standard-deviation change in the covariates.

Table 3: Implications of Relationships for Attrition

	Attrition			
Variable	Coeff	Std Err	P-value	Marg Eff
R 1. Relationship				
Relationship Indicator	-0.5607	0.0950	<.0001	11.6%
R 2. Breadth of Relationships				
Number of Bank Relationships=1	-0.8552	0.0764	<.0001	3.2%
=2	-0.7798	0.0696	<.0001	3.8%
=3	-0.7196	0.0807	<.0001	10.6%
=4	-0.9266	0.0968	<.0001	14.6%
=5	-0.9731	0.1146	<.0001	18.4%
=6+	-0.6895	0.0799	<.0001	21.4%
R 3. Type of Relationships (Broad)				
Deposit Relationships	-0.1067	0.0474	<.0001	11.3%
Investment Relationship	-0.2889	0.0396	<.0001	13.3%
Loan Relationship	-0.2457	0.1294	<.0001	7.8%
R 4. Type of Relationships (Narrow)				
Checking Dummy	-0.1537	0.0295	<.0001	10.3%
Savings Dummy	-0.1251	0.0500	<.0001	6.4%
Brokerage Dummy	-0.6333	0.0759	<.0001	2.4%
CD Dummy	-0.2469	0.0764	<.0001	5.7%
Mutual Fund Dummy	-0.1103	0.0698	<.0001	12.6%
Home Equity Line Dummy	-0.2772	0.1006	<.0001	5.0%
Home Equity Loan Dummy	-0.2178	0.0623	<.0001	2.1%
Mortgage Loan Dummy	-0.2079	0.1172	<.0001	1.2%
R 5. Length of Relationships				
Age of Checking Relationship	-0.0004	0.0002	<.0001	5.0%
Age of Savings Rel	-0.0005	0.0003	<.0001	5.9%
Age of Brokerage Rel	-0.0064	0.0016	<.0001	5.5%
Age of CD Rel	-0.0009	0.0002	<.0001	1.7%
Age of Mutual Fund Rel	-0.0008	0.0002	<.0001	4.9%
Age of Home Equity Line Rel	-0.0014	0.0001	<.0001	3.5%
Age of Home Equity Loan Rel	-0.0015	0.0002	<.0001	1.7%
Age of Mortgage Loan Rel	-0.0021	0.0009	<.0001	0.9%
R 6. Proximity of Relationship				
Relationship Indicator	-0.8123	0.0539	<.0001	9.4%
State with Branch Indicator	-0.9686	0.0805	<.0001	3.7%
Relationship * Branch State	-0.8668	0.1056	<.0001	2.1%

Table 3: Implications of Relationships for Attrition (ctd)

Variable	Attrition			
	Coeff	Std Err	P-value	Marg Eff
R 7. Depth of Relationships (ln (Bal+$1) & R4)				
Checking Balance	-0.0242	0.0101	<.0001	9.3%
Savings Balance	-0.0392	0.0140	<.0001	6.5%
CD Balance	-0.0601	0.0159	<.0001	5.1%
Mutual Fund Balance	-0.0506	0.0283	<.0001	5.9%
Home Equity Line Balance	-0.0187	0.0210	<.0001	6.9%
Home Equity Loan Balance	-0.0724	0.0497	<.0001	5.8%
Mortgage Loan Balance	-0.1596	0.2396	<.0001	1.4%
R 8. Combined Relationship Measures				
Number of Bank Relationships=1	-0.8500	0.0755	<.0001	1.8%
=2	-0.7809	0.0693	<.0001	2.0%
=3	-0.7103	0.0806	<.0001	9.6%
=4	-0.9212	0.0952	<.0001	13.9%
=5	-0.9648	0.1138	<.0001	18.2%
=6+	-0.6864	0.0796	<.0001	20.5%
Checking Dummy	-0.1535	0.0292	<.0001	8.2%
Savings Dummy	-0.1246	0.0499	<.0001	5.9%
Brokerage Dummy	-0.6256	0.0756	<.0001	1.7%
CD Dummy	-0.2458	0.0751	<.0001	5.3%
Mutual Fund Dummy	-0.1103	0.0687	<.0001	11.8%
Home Equity Line Dummy	-0.2722	0.1005	<.0001	4.9%
Home Equity Loan Dummy	-0.2146	0.0620	<.0001	1.0%
Mortgage Loan Dummy	-0.2070	0.1162	<.0001	0.6%
Age of Checking Relationship	-0.0004	0.0002	<.0001	3.6%
Age of Savings Rel	-0.0005	0.0003	<.0001	4.7%
Age of Brokerage Rel	-0.0064	0.0016	<.0001	4.1%
Age of CD Rel	-0.0009	0.0002	<.0001	0.9%
Age of Mutual Fund Rel	-0.0008	0.0002	<.0001	3.2%
Age of Home Equity Line Rel	-0.0014	0.0001	<.0001	1.6%
Age of Home Equity Loan Rel	-0.0015	0.0002	<.0001	0.9%
Age of Mortgage Loan Rel	-0.0020	0.0009	<.0001	0.1%
State with Branch Indicator	-0.9645	0.0798	<.0001	2.9%
Relationship * Branch State	-0.8644	0.1034	<.0001	1.4%
Checking Balance	-0.0240	0.0100	<.0001	8.8%
Savings Balance	-0.0391	0.0139	<.0001	5.5%
CD Balance	-0.0595	0.0158	<.0001	5.0%
Mutual Fund Balance	-0.0497	0.0278	<.0001	5.5%
Home Equity Line Balance	-0.0184	0.0209	<.0001	5.5%
Home Equity Loan Balance	-0.0720	0.0495	<.0001	5.6%
Mortgage Loan Balance	-0.1565	0.2358	<.0001	1.1%

Table 3: Implications of Relationships for Attrition (ctd)

	Attrition			
Variable	Coeff	Std Err	P-value	Marg Eff
R 9. Change in Balances (ln(Bal) & R7 & R4)				
D(Checking Balance)	-0.6195	0.0552	<.0001	5.3%
D(Savings Balance)	-0.3557	0.0018	<.0001	5.8%
D(Mutual Fund Balance)	-0.4797	0.1071	<.0001	2.1%
D(Home Equity Line Balance)	-0.1510	0.0057	<.0001	2.5%
D(External Score)	-0.8771	0.2081	<.0001	13.5%
D(Internal Score)	-0.4872	0.2255	<.0001	14.5%
R 10. Volatility of Balances (sd(12) & R7 & R4)				
sd(Checking Balance)	0.8699	0.1779	<.0001	12.4%
sd(Savings Balance)	0.3015	0.0512	<.0001	3.8%
sd(Mutual Fund Balance)	0.8418	0.2345	<.0001	3.1%
sd(Home Equity Line Balance)	0.4405	0.1275	<.0001	8.7%
sd(External Score)	0.7632	0.2051	<.0001	10.9%
sd(Internal Score)	0.7232	0.3451	<.0001	16.9%
R 11. Change in Volatility (D(sd(6)) & R7 & R4)				
D(sd(Checking Balance))	0.4981	0.0454	<.0001	5.2%
D(sd(Savings Balance))	0.4849	0.1062	<.0001	14.4%
D(sd(Mutual Fund Balance))	0.7144	0.2951	<.0001	11.7%
D(sd(Home Equity Line Balance))	0.7132	0.1934	<.0001	11.9%
D(sd(External Score))	0.8707	0.1991	<.0001	16.4%
D(sd(Internal Score))	0.9569	0.0943	<.0001	12.8%
R 12. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.5386	0.1412	<.0001	13.0%
R 13. Transfers of Balances (&R7 & R4)				
To Checking	0.5262	0.2624	<.0001	14.9%
From Checking	-0.9530	0.3027	<.0001	3.2%
Number of Obs / Number Attrition	1132182	12649		

Notes: This table shows the effects of relationships in predicting credit card attrition, using Cox proportional hazard models following eq. (1). The explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports only the results for the relationship variables; each panel represents a separate specification. (The other variables appear in the appendix for specification R1.) The relationship variables are defined in Table 2. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts. The marginal effects for continuous covariates show the effects of a one standard-deviation change in the covariates.

Table 4: Implications of Relationships for Utilization

Variable	Utilization Rate		
	Coeff	Std Err	P-value
R 1. Relationship			
Relationship Indicator	0.0680	0.0109	<.0001
R 2. Breadth of Relationships			
Number of Bank Relationships=1	0.0241	0.0027	<.0001
=2	0.0292	0.0029	<.0001
=3	0.0517	0.0029	<.0001
=4	0.0690	0.0030	<.0001
=5	0.0954	0.0031	<.0001
=6+	0.1378	0.0031	<.0001
R 3. Type of Relationships (Broad)			
Deposit Relationships	0.0730	0.0012	<.0001
Investment Relationship	0.1032	0.0011	<.0001
Loan Relationship	0.0324	0.0073	<.0001
R 4. Type of Relationships (Narrow)			
Checking Dummy	0.0931	0.0011	<.0001
Savings Dummy	0.0576	0.0013	<.0001
Brokerage Dummy	0.0930	0.0025	<.0001
CD Dummy	0.0755	0.0017	<.0001
Mutual Fund Dummy	0.0297	0.0027	<.0001
Home Equity Line Dummy	0.0484	0.0026	<.0001
Home Equity Loan Dummy	0.0334	0.0030	<.0001
Mortgage Loan Dummy	0.0373	0.0089	<.0001
R 5. Length of Relationships			
Age of Checking Relationship	0.0002	0.0000	<.0001
Age of Savings Rel	0.0003	0.0000	<.0001
Age of Brokerage Rel	0.0007	0.0000	<.0001
Age of CD Rel	0.0001	0.0000	<.0001
Age of Mutual Fund Rel	0.0009	0.0000	<.0001
Age of Home Equity Line Rel	0.0007	0.0000	<.0001
Age of Home Equity Loan Rel	0.0001	0.0001	<.0001
Age of Mortgage Loan Rel	0.0003	0.0001	<.0001
R 6. Proximity of Relationship			
Relationship Indicator	0.0530	0.0113	<.0001
State with Branch Indicator	0.0458	0.0033	<.0001
Relationship * Branch State	0.0455	0.0035	<.0001

Table 4: Implications of Relationships for Utilization (ctd)

Variable	Utilization Rate Coeff	Std Err	P-value
R 7. Depth of Relationships (ln (Bal+$1) & R4)			
Checking Balance	0.0341	0.0004	<.0001
Savings Balance	0.0822	0.0005	<.0001
CD Balance	0.0231	0.0005	<.0001
Mutual Fund Balance	0.0231	0.0007	<.0001
Home Equity Line Balance	0.0594	0.0007	<.0001
Home Equity Loan Balance	0.0138	0.0023	<.0001
Mortgage Loan Balance	0.0652	0.0080	<.0001
R 8. Combined Relationship Measures			
Number of Bank Relationships=1	0.0230	0.0026	<.0001
=2	0.0290	0.0027	<.0001
=3	0.0490	0.0028	<.0001
=4	0.0662	0.0028	<.0001
=5	0.0935	0.0030	<.0001
=6+	0.1368	0.0029	<.0001
Checking Dummy	0.0910	0.0011	<.0001
Savings Dummy	0.0563	0.0013	<.0001
Brokerage Dummy	0.0871	0.0024	<.0001
CD Dummy	0.0722	0.0016	<.0001
Mutual Fund Dummy	0.0289	0.0025	<.0001
Home Equity Line Dummy	0.0462	0.0025	<.0001
Home Equity Loan Dummy	0.0318	0.0029	<.0001
Mortgage Loan Dummy	0.0349	0.0087	<.0001
Age of Checking Relationship	0.0002	0.0000	<.0001
Age of Savings Rel	0.0003	0.0000	<.0001
Age of Brokerage Rel	0.0007	0.0000	<.0001
Age of CD Rel	0.0001	0.0000	<.0001
Age of Mutual Fund Rel	0.0009	0.0000	<.0001
Age of Home Equity Line Rel	0.0006	0.0000	<.0001
Age of Home Equity Loan Rel	0.0001	0.0001	<.0001
Age of Mortgage Loan Rel	0.0003	0.0001	<.0001
State with Branch Indicator	0.0456	0.0031	<.0001
Relationship * Branch State	0.0436	0.0033	<.0001
Checking Balance	0.0331	0.0004	<.0001
Savings Balance	0.0824	0.0005	<.0001
CD Balance	0.0228	0.0005	<.0001
Mutual Fund Balance	0.0225	0.0007	<.0001
Home Equity Line Balance	0.0573	0.0006	<.0001
Home Equity Loan Balance	0.0140	0.0022	<.0001
Mortgage Loan Balance	0.0636	0.0080	<.0001

Table 4: Implications of Relationships for Utilization (ctd)

Variable	Utilization Rate		
	Coeff	Std Err	P-value
R 9. Change in Balances (ln(Bal) & R7 & R4)			
D(Checking Balance)	0.0185	0.0000	<.0001
D(Savings Balance)	0.0162	0.0001	<.0001
D(Mutual Fund Balance)	0.0029	0.0003	<.0001
D(Home Equity Line Balance)	-0.0175	0.0001	<.0001
D(External Score)	0.0178	0.0089	<.0001
D(Internal Score)	0.0200	0.0077	<.0001
R 10. Volatility of Balances (sd(12) & R7 & R4)			
sd(Checking Balance)	-0.0157	0.0018	<.0001
sd(Savings Balance)	-0.0338	0.0023	<.0001
sd(Mutual Fund Balance)	-0.0631	0.0009	<.0001
sd(Home Equity Line Balance)	-0.0240	0.0051	<.0001
sd(External Score)	-0.0161	0.0001	<.0001
sd(Internal Score)	-0.0560	0.0243	<.0001
R 11. Change in Volatility (D(sd(6)) & R7 & R4)			
D(sd(Checking Balance))	-0.0004	0.0001	<.0001
D(sd(Savings Balance))	-0.0002	0.0003	<.0001
D(sd(Mutual Fund Balance))	-0.0030	0.0002	<.0001
D(sd(Home Equity Line Balance))	-0.0004	0.0000	<.0001
D(sd(External Score))	-0.0012	0.0015	<.0001
D(sd(Internal Score))	-0.0007	0.0001	<.0001
R 12. Low Checking Balances (& R7 & R4)			
Indicator(Balance < $2000)	-0.0567	0.0590	0.8322
R 13. Transfers of Balances (&R7 & R4)			
To Checking	0.0958	0.0240	<.0001
From Checking	-0.0812	0.0382	<.0001
Number of Obs	1132182		

Notes: This table shows the effects of relationships on credit card utilization rates (balances/limit), estimating eq. (1) by OLS. The explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports only the results for the relationship variables; each panel represents a separate specification. (The other variables appear in the appendix for specification R1.) The relationship variables are defined in Table 2. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

Appendix Table 1: Baseline Results for Default

Variable	Default Coeff	Std Err	P-value	Marg Eff
External Risk Score	-0.0041	0.0002	<.0001	14.6%
Internal Risk Score	-0.0055	0.0002	<.0001	16.3%
Debt	0.3479	0.0129	<.0001	1.6%
Purchase	-0.0457	0.0354	0.2351	1.1%
Payments	-0.1722	0.0124	<.0001	2.8%
Credit line	-0.2880	0.0134	<.0001	4.8%
APR	0.0385	0.0050	<.0001	0.7%
Total number of bankcards	0.0625	0.0082	<.0001	2.5%
Total bankcard credit limits	-0.0032	0.0106	0.7139	4.7%
Total bankcard balances	0.1441	0.0364	<.0001	3.4%
Total number of non-bank cards	0.0070	0.0027	0.0224	0.4%
Total non-bank card balances	0.0553	0.0156	<.0001	1.1%
Total home equity line limits	-0.0032	0.0018	0.0474	3.5%
Total home equity line balance	0.1222	0.0469	<.0001	1.8%
Total mortgage loan balance	-0.0020	0.0004	<.0001	3.1%
Total auto loan balance	-0.0049	0.0032	0.1370	5.1%
Total student loan balance	-0.0084	0.0043	0.0413	2.7%
Unemployment rate	0.5891	0.2780	0.0354	3.0%
% w/o health insurance	-0.0290	0.0220	0.2246	2.9%
D(House prices)	-0.3833	0.0398	<.0001	8.2%
State income	-0.0842	0.0945	0.5916	3.8%
Application income	-0.0486	0.0579	0.9271	2.7%
Application inc missing	0.1790	0.0427	<.0001	2.4%
Wealth = low	0.3277	0.2466	0.1023	1.2%
= medium	0.2703	0.3670	0.4606	2.0%
R1 = Any Relationship	-0.3208	0.0859	<.0001	10.1%
State dummies	Yes			
Month dummies	Yes			
Number of Obs / Number Defaults	1132182	4322		

Notes: This table reports the results from Cox models of credit card default (bankruptcy or three months delinquency), as a function of the explanatory variables in eq. (1): macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports the results for the baseline relationship measure R1, which is a dummy variable identifying credit card accounts that have another relationship. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts. The marginal effects for continuous covariates show the effects of a one standard-deviation change in the covariates.

Appendix Table 2: Baseline Results for Attrition

Variable	Coeff	Std Err	P-value	Marg Eff
	Default			
External Risk Score	0.0033	0.0001	<.0001	8.7%
Internal Risk Score	0.0034	0.0003	<.0001	9.8%
Debt	0.0783	0.0065	<.0001	1.8%
Purchase	-0.2904	0.0227	<.0001	4.5%
Payments	0.1245	0.0065	<.0001	1.8%
Credit line	0.0890	0.0061	<.0001	6.2%
APR	0.0483	0.0041	<.0001	8.4%
Total number of bankcards	-0.0180	0.0086	<.0001	8.0%
Total bankcard credit limits	-0.0078	0.0012	<.0001	7.7%
Total bankcard balances	-0.0013	0.0048	<.0001	4.0%
Total number of non-bank cards	0.0180	0.0023	<.0001	0.4%
Total non-bank card balances	-0.0322	0.0283	<.0001	2.5%
Total home equity line limits	-0.0071	0.0087	0.9141	3.3%
Total home equity line balance	-0.0033	0.0076	<.0001	2.7%
Total mortgage loan balance	0.0013	0.0023	<.0001	0.4%
Total auto loan balance	0.0020	0.0035	0.5291	3.1%
Total student loan balance	-0.0031	0.0021	0.8290	4.6%
Unemployment rate	-0.2604	0.7240	<.0001	5.5%
% w/o health insurance	0.0038	0.0133	0.7768	3.1%
D(House prices)	-0.1427	0.0426	<.0001	4.7%
State income	-0.0209	0.0550	0.9636	1.4%
Application income	-0.0359	0.0645	0.9778	3.4%
Application inc missing	0.3041	0.1992	<.0001	0.7%
Wealth = low	-0.1064	0.0476	0.0534	6.5%
= medium	-0.1076	0.0674	0.1177	7.9%
R1 = Any Relationship	-0.5607	0.0950	<.0001	11.6%
State dummies	Yes			
Month dummies	Yes			
Number of Obs / Number Attritions	1132182	12649		

Notes: This table reports the results from Cox models of credit card attrition, as a function of the explanatory variables in eq. (1): macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports the results for the baseline relationship measure R1, which is a dummy variable identifying credit card accounts that have another relationship. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts. The marginal effects for continuous covariates show the effects of a one standard-deviation change in the covariates.

Appendix Table 3: Baseline Results for Utilization

Variable	Default Coeff	Std Err	P-value
External Risk Score	-0.0147	0.0043	<.0001
Internal Risk Score	-0.0008	0.0000	<.0001
APR	-0.0016	0.0000	<.0001
Total number of bankcards	0.0001	0.0000	0.0380
Total bankcard credit limits	0.0223	0.0017	<.0001
Total bankcard balances	-0.0005	0.0000	<.0001
Total number of non-bank cards	-0.0016	0.0001	<.0001
Total non-bank card balances	-0.0001	0.0000	<.0001
Total home equity line limits	-0.0013	0.0001	<.0001
Total home equity line balance	-0.0007	0.0000	<.0001
Total mortgage loan balance	-0.0002	0.0001	<.0001
Total auto loan balance	-0.0003	0.0001	<.0001
Total student loan balance	0.0014	0.0002	<.0001
Unemployment rate	0.0148	0.0015	<.0001
% w/o health insurance	-0.0009	0.0000	0.0217
D(House prices)	0.0239	0.0064	<.0001
State income	0.0051	0.0012	<.0001
Application income	0.0032	0.0006	<.0001
Application inc missing	0.0396	0.0045	<.0001
Wealth = low	-0.0002	0.0014	0.8520
= medium	-0.0019	0.0017	0.2200
R1 = Any Relationship	0.0680	0.0109	<.0001
cons	0.3198	0.0652	<.0001
State dummies	Yes		
Month dummies	Yes		
Number of Obs	1132182		

Notes: This table shows the results of estimating eq. (1) for credit card utilization rates (balances/limit), by OLS. The explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports the results for the baseline relationship measure R1, which is a dummy variable identifying credit card accounts that have another relationship. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

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