Benefits of Relationship Banking: Evidence from Consumer Credit Markets*

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September 2017

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, and length. 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. To investigate the mechanisms, we show that the observed results are not due to selection or higher perceived default costs. Our results are consistent with monitoring explanation: the information that the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used in some way to mitigate credit risk on the credit card account. These results imply significant potential benefits of relationship banking to banks in the retail credit market.

JEL Classification: G21, D14
Key Words: Relationship Banking; Credit Cards, Consumer Credit, Deposits, Investments; Household Finance.

* For helpful comments, we would like to thank Gene Amromin, Robert Hauswald, Bert Higgins, Wenli Li, Wenlan Qian, Anjan Thakor, and seminar participants at the ASSA meetings, the Bank Structure Conference at the Federal Reserve Bank of Chicago, the Conference on Research in Economic Theory and Econometrics, and the Federal Reserve Bank of Philadelphia. We also thank Jim Papadonis and Joanne Maselli for their support of this research project. We are grateful to Diana Andrade, Ron Kwolek, and Greg Pownell for excellent research assistance. The views expressed in this paper are those of the authors alone, not those of the Office of the Comptroller of the Currency.
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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. (e.g., Billett et al., 1985; Slovin et al., 1993; Petersen and Rajan 1994; Berger and Udell, 1995; Chakravarty and Scott, 1999; Ongena and Smith, 2001). There has been limited empirical research on the underlying benefits of relationships to banks. The review by Boot (2000) concludes that "existing empirical work is virtually silent on identifying the precise sources of value in relationship banking." Mester, Nakamura, and Renault (2007) study a sample of 100 Canadian small-business borrowers, and 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

[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).

collateral. In another paper, Bharath, Dahiya, Saunders, and Srinivasan (2007) find that bank–firm lending relationships are important to the bank in gaining future loan business and winning future debt and equity underwriting business from the same borrower.

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.[3]

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 2010s, 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 (2013 SCF). Aggregate credit card balances are large, currently amounting to about $700 billion (Federal Reserve Board 2015). 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. Issuers generally rely very heavily on credit-risk scores (e.g., Moore, 1996), which are the issuers' own summary statistics for the default risk and profitability of each account. They use external score for ex ante screening and internal score for

[3] One exception is Puri and Rocholl (2008), who subsequent to study analyze the importance of retail banking relationships to banks by examining cross-selling, and find evidence of banks benefiting from an increase in both brokerage accounts as well as other retail products from their depositors.

ex post monitoring. 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. 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.

One advantage of our paper is that we use administrative panel data so that we can measure actual relationship from various dimensions. 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), and the depth of the relationships (balances in dollars). Moreover, our data is longitudinal so that we can measure 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.

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 previous 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, Norden and Weber 2010). 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 (breadth, depth, and length). 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.

We further investigate the potential mechanisms that drive the main results. There are three possible explanations: selection, higher perceived default costs, and monitoring. To test the explanation of selection, we apply the method of propensity score matching. The results from the matched sample are largely consistent with the main results in terms of directions and magnitudes.

Moreover, the relationship variables are not correlated with credit terms (APR and limit) or changes in borrowers' FICO score in the 12 and 24 months after the lender issued the credit card. These results suggest that our results are unlikely due to selection.

The explanation of higher perceived default costs implies that relationship accounts would deliberately avoid default on their credit card debt with the lender even facing adverse economic or financial shocks. We construct a subsample including those accounts who experienced severe deterioration ex post in the credit quality. We find no significant difference between the two groups in terms of defaults.

We explore the dynamic information of our data to study the monitoring explanation. We find that changes in the credit scores, declines in checking account balances, and transfers to and from checking and savings accounts predict default rates, attrition rates, and utilization rates. These results are consistent with monitoring explanation: the information that the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used in some way to mitigate credit risk on the credit card account.

Our paper adds to the existing literature in several ways. First, we contribute to the literature on the benefit of relationship retail banking. Previous literature suggest that the benefit of relationship banking is through soft information that was developed overtime in a relationship. For example, local banks have information advantage to screen loans to higher risk borrowers more accurately based on unobservable soft information, thereby resulting in better loan outcomes (Petersen and Rajan 2002; Agarwal and Hauswald 2010; Ergungor and Moulton 2014). Our paper shows that credit card borrowers' other account activities with the same lenders can predict borrower defaults, attrition and credit card utilizations. It suggest the benefit of relationship banking might also come from hard information instead of soft information. Norden and Weber

(2010), which came subsequent to our work, finds that borrowers that default are likely to exhibit abnormal patterns in their checking accounts approximately 12 months before the default event. Banks can use these information to predict future borrower defaults, findings suggest that relationship lender can benefit the most out of these information. Puri, Steffen and Sascha (2011), also a paper subsequent to our work, shows that loans of retail customers, who have a relationship with their savings bank prior to applying for a loan, default significantly less than customers with no prior relationship in Germany. Our results are consistent with these findings. This paper is also related to economies of scope in retail banking with multiple financial services. Economies of scope in retail banking usually come from the fact that offering multiple services together allow a bank to spread the cost of branches, staffs, and ATMs. We document another benefit from a "supermarket" style of banking that leads to economies of scope. Offering multiple financial service together to the same person might generate private information that lead to lower ex ante screening and ex post monitoring costs for banks. The reduction of default, attrition and the increase of utilization might increase the profit of retail banking. Second, we explore the richness and dynamics of our data to investigate why we observe the benefit of relationship banking. Our analysis show that the observed results are not due to selection or higher perceived default costs. Instead, our results support the monitoring explanation. The results are consistent with the implication of Norden and Weber (2010), suggesting that relationship lender can benefit from monitoring the dynamics of borrowers' checking accounts.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the empirical methodology and results. Section 4 analyzes possible explanations and Section 5 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. Observing debt helps us to learn about their debt and credit risk. For instance, banks report the balance to the credit bureaus but do not report the debt to the bureaus. We control for debt in our main specification to make our estimation of the effect of relationship more precise.

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 is the industry-standard FICO score, which is public information for all potential lenders. The external score is estimated based on the credit bureau data available for each consumer. The "internal" credit score is an account-specific behavioral score, which is private information only to the specific lender. The internal 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

[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).

updated annually. The dataset also includes the self-reported level of account-holder income when available from the account application. 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. Moreover, the dataset includes 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.[7]

The sample includes credit card accounts that were open as of the start of the sample period in October 2001. 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. 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.

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%). Of the relationship accounts, 34% have one other relationship, and 24%, 19%, 11%, 8%, and 3% have two to six-or-more relationships, respectively. Among the accounts with one other relationship, 47% have a checking account, 29% a savings account, 12% a mortgage, and 12% a home equity loan or line. None of these accounts has just a CD or mutual

[7] The dataset also includes some additional account-holder demographic data, such as age, marital status, and house ownership status. However, these demographic variables are sparsely populated, so we do not include them in our main specification. Nevertheless, the main conclusions below are robust to including these variables.

fund relationship; evidently, it is not until a customer already has one other relationship that he/she typically opens an investment relationship. 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.

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.[8] 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:

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

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

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. $MacroDemog_{i,t-6}$ represents the macroeconomic and demographic characteristics, such as the local unemployment rate, plus the account-holder specific estimates of income and wealth. $LoanPerformance_{i,t-6}$ 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. $CreditBureau_{i,t-6}$ represents the external credit score and the other variables from the credit bureaus, such as total balances on credit cards, Helocs, and mortgages.[9]

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 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.

[9] 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.

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 combines the previous measures simultaneously. These relationship variables measure the relationship breadth.

We further measure the relationship depth. 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). 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). R8 considers the effect of *changes* in the various types of balances (for convenience, between months *t-6* and *t-5*). R9 considers the volatility of balances. (In light of the available sample period, it uses the standard deviation between *t-1* and *t-12*.) R10 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*). R11 focuses more specifically on checking balances, using an indicator for whether these balances have fallen below $2000.

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 R11 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 considers simultaneously the previous measures of relationship, specifically relationship breadth, type, and length. 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-R6, relationship accounts have lower probabilities of default. Similar measures of relationships have been considered in the previous literature on corporate lending. These relationship variables from R1-R6 measure the relationship breadth. We further measure the relationship depth.

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 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.

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 R8 focuses on the change in relationship balances (in addition to the level of balances from R7 and the indicators from R4).[10] 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 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% - 16% declines. These results show the value of relationships specifically in the ongoing monitoring of loans.

R9 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% - 13%. R10 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. R11 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

[10] Since our sample excludes relationships opened subsequent to the credit card account, these results are driven by changes in the intensive margin of balances. R8 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.

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.

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). Larger relationship balances (R7 and R11) and increases in relationship balances (R8) are also associated with lower attrition rates, but more (and increased) volatility in the balances is associated with higher attrition rates (R9 and R10).

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.[11] 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 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.[12]

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.,

[11] 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.
[12] 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.

the average difference of 7 p.p. is substantial.[13] 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.

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 R8, 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 credit and credit card lines of credit. Under R9 and R10, higher (and increased) volatility of balances is associated with lower utilization.

Under R11, given the level of checking balances (R7), the indicator for low balances is not significant. 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. Possible Explanations

[13] 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.

Our main results from above sections demonstrate that on average relationship accounts exhibit lower probabilities of default and attrition, and have higher utilization rates, compared to non-relationship accounts. Though the results are consistent with the presence of relationship banking effects, we recognize that multiple hypotheses could explain the above relations. There are three possible explanations: selection, higher perceived default costs, and monitoring. In this section, we conduct several tests to investigate these alternative explanations.

The first hypothesis is that our results could have been driven primarily by selection mechanisms. Specifically, there are two issues associated with selections. The first one is whether the lender treated credit card applications differently at origination. If the lender was in fact using cross-account information (relationships) in its underwriting decisions by offering better credit card terms such as lower APRs or higher credit limits to customers (borrowers) with prior relationships, we should not be surprised to observe different behaviors in using credit cards between the relationship and non-relationship accounts. The unconditional summary statistics in Table 1 report a lower average APR and higher credit line limit for relationship accounts relative to non-relationship accounts, indicating that the lender might use the relationship information in its underwriting decisions. To address the issue, we estimate empirical specifications with the credit card APR and credit line limit as dependent variables and a set of variables used in the lender's underwriting process as independent variables. We also include the relationship variable in the regressions to test if it is playing a significant role in determining credit terms (APR and limit). Results are reported in Table 5. Coefficients of the relationship variable are insignificant in both regressions, implying that the bank was not using the cross-account information to set credit terms.

The second issue associated with selection is the effects of the relationship banking as a reflection of the self-selection. If a borrower who deals primarily with one bank is intrinsically less risky than a borrower who deals with multiple banks, or if the credit card offerings with inferior credit terms are more likely to attract those risky borrowers without prior relationships with the issuer, the better performance of the relationship accounts relative to non-relationship accounts cannot be contributed the banking relationships. Instead, the difference in performances between relationship borrowers and non-relationship borrowers is linked to their riskiness at origination. To investigate the existence of self- selection effect, we conduct two types of analysis. First, we rely on the approach of the propensity score matching to construct a matched sample to ensure the group of relationship accounts is paired with a comparable group of non-relationship accounts. The matched non-relationship accounts are selected by the nearest-neighbor algorithm without replacement based on the computed propensity scores. We first test whether the relationship and non-relationship accounts are comparable. Compared to non-relationship accounts, the relationship accounts in the matched sample have similar APRs and credit limits. Moreover, there is little difference in the matched account's characteristics and his or her creditworthiness as represented by FICOs. Overall, the relationship and non-relationship accounts are mostly comparable to each other. The results of propensity score matching are shown in Table 6. We find that, for relationship accounts, the marginal probabilities of default and attrition are about 12% and 13% lower than those of accounts without other relationships, ceteris paribus. Relationship accounts have a 7 percentage point higher utilization rate compared to non-relationship accounts, ceteris paribus. The results from the matched sample are largely consistent with the main results in terms of directions and magnitudes. In other measures of relationship, the relationship accounts

also have lower default and attrition, but higher utilization rate compared to accounts without other relationships. These results suggest that our results are unlikely due to selection.

Although we use a matching approach to make sure the relationship and non-relationship groups are comparable, the selection can also be an unobserved risk type. To address this issue, we run the second test by comparing changes in accounts' credit quality after booking between borrowers with and without prior relationships with the bank. Specifically, we assess the extent to which a borrower's FICO score changed in the 12 and 24 months after the lender issued the credit card to the borrower. We use FICO score to measures the relative credit quality of an individual account (given that a FICO score comes from the credit bureaus and reflects the account-holder's credit and debt repayment activities across all credit products he/she holds, it can be informative of the extent to which the borrower faced adverse economic hardships that hindered his/her ability to make the minimum payment on other held credit cards or on other loans). FICO is also not related to the borrower's relationship with the lender (or other lenders). If non-relationship accounts are inherently more risky than relationship accounts in our sample, we expect a more severe deterioration ex post in the credit quality (FICO score) of the non-relationship accounts relative to the relationship accounts. Table 7 reports the regression results on changes in FICO scores of accounts at 12 and 24 months since their origination. The results show that between the relationship and non-relationship account groups, changes in FICO scores at the 12 or 24 months subsequent to origination remain similar. Hence, there was no (economically or statistically) significant deterioration in the credit quality of the non-relationship accounts relative to the relationship accounts. These results also support no self-selection effect.

The second potential explanation is related the higher perceived default costs associated with the relationship accounts. Borrowers with prior relationships are more likely to build loyalty

towards the lender, and thus become more reluctant to default on credit card debt. The results on the breadth of relationships (R2), length of relationships (R5), and depth of relationships (R7), are consistent with the causal mechanism that has to do with building loyalty. Alternatively, borrowers with prior relationships may view that defaulting on credit card debt is more costly when the lender also holds some of their other debt and/or assets, as they are perhaps fearful that in the event of a default, the lender would have much more information about their balance sheets, and thus, would be more likely to obtain successful deficiency judgements. The results on the type of relationships (R4) are consistent with a mechanism related to the fear of lender recourse in the event of a default. According to Table 2 the largest marginal effects are associated with brokerage, CD, mutual fund, checking, and savings accounts, which of course all have to do with investing, while the smallest effects are associated with borrowing (home equity loans and mortgages). These patterns are consistent with borrowers who have significant asset positions in accounts managed by the lender perceiving higher default costs. As a result, the better performance of the relationship accounts relative to non-relationship accounts could be contributed their relative higher perceived default costs. Does the relationship accounts have higher perceived default costs compared to non-relationship accounts? If it is the case, we expect that relationship accounts would deliberately avoid default on their credit card debt with the lender even facing adverse economic/financial shocks. With this reasoning, we construct a subsample including those accounts who experienced severe deterioration ex post in the credit quality (for example, accounts who's FICOs dropped by 20% or 50 pints). Using the subsample, we compare the difference in default probabilities between relationship and non-relationship accounts. Table 8 presents the results. We find no significant difference between the two groups. We take this as evidence of not higher perceived default costs associated with the relationship accounts.

We explore the dynamic information of our data to study the monitoring explanation. An advantage of our panel data is that we can measure 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. In our analysis of dynamic information (R8-R10), we find that changes in the credit scores, declines in checking account balances, and transfers to and from checking and savings accounts predict default rates, attrition rates, and utilization rates. These results are consistent with monitoring explanation: the information that the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used in some way to mitigate credit risk on the credit card account. In our dataset, we do not have measures about lenders' direct interventions after observing these changes in borrowers' other accounts. In practice, when banks observe that borrowers' credit scores drop suddenly, they might raise interest rate, cut credit lines, or even freeze the credit line. Typical credit card contracts specify that if credit quality changes the lender has discretion to alter the pricing and quantity of credit. We find some examples of credit card agreement in CFPB credit card agreement database.[14] For example, credit card agreement from Bank of America says "we reserve the right to amend this Agreement at any time." The reasons they may amend the agreement include: "changes related to your individual credit history, such as: your risk profile, your payment or transaction patterns, balance patterns, the utilization levels of this and other accounts, credit bureau information including the age, history and type of other accounts, and the measure of risk associated with each." We verified with the lender and they do tell us that they will use their discretion to alter the contract terms upon deterioration in the credit scores.

[14] https://www.consumerfinance.gov/credit-cards/agreements/

In sum, we show that the observed results are not due to selection or higher perceived default costs. Our results are consistent with monitoring explanation: the information that the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used in some way to mitigate credit risk on the credit card account.

5. 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. We show that the observed results are not due to selection or higher perceived default costs. Our results are consistent with monitoring explanation: the information that the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used in some way to mitigate credit risk on the credit card account.

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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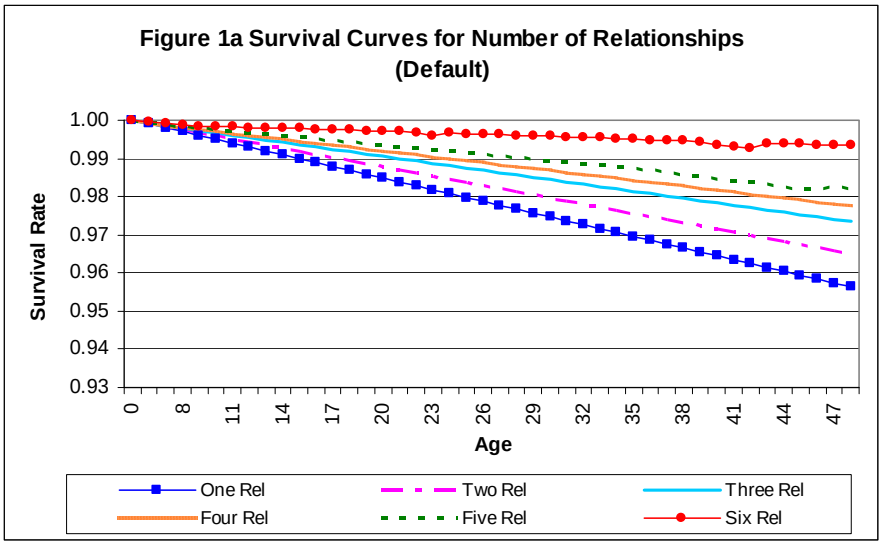
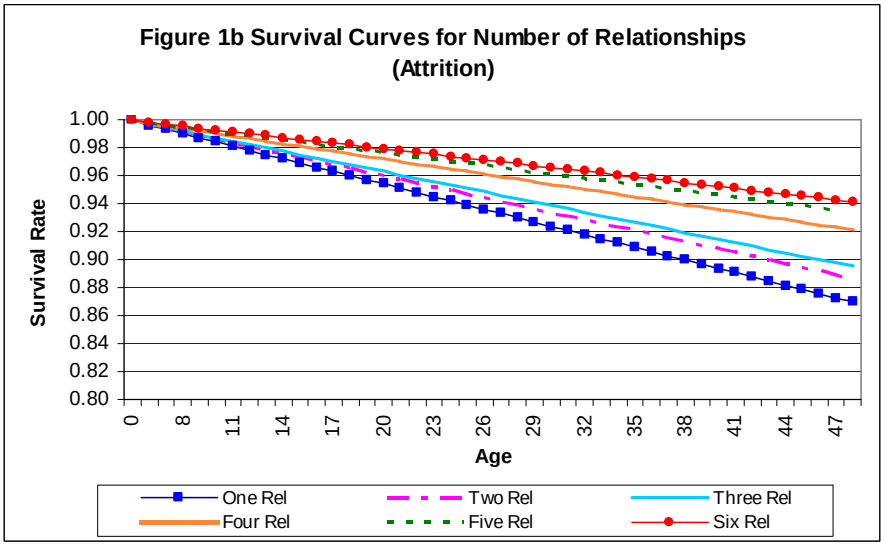
Figure 1 Survival Curves for Different Number of Relationships





Notes: Figure 1a shows the survival curves for different number of relationships. The horizontal axis shows the age in months since opening. The vertical axis shows the survial rate. Figure 1a shows the survival curves for (lack of) defaul. Figure 1b shows the survival curves for (lack of) attrition.

Table 1: Descriptive Statistics

Variable	Non-Relationship Accounts		Relationship Accounts	
	Mean	Std dev	Mean	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 %	5.60%		3.90%	
Attrition %	15.50%		12.00%	
Utilization rate	0.188		0.239	
Number of Accounts	40944	43.70%	52750	56.30%

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

	Default			
Variable	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. 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 * State Branch	-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)

	Default			
Variable	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. 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 9. 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 10. 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 11. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.6999	0.1675	<.0001	12.7%
Controls	Yes			
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.) 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 use dummy variables identifying the types of relationships, broadly and narrowly defined. R5 measures the length of the relationships (age in months since opening). R6 considers simultaneously the previous measures of relationship, specifically relationship breadth, type, and length. R7 measures the balances of the relationship categories (relationship depth, using ln(balances +1)), and R8 measures the changes in the balances. R9 measures the volatility of balances over the prior 12 months, and R10 measures the change in the volatility of balances over the prior two 6-month periods. R11 uses a dummy variable for whether checking balances have fallen below $2000. 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. 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 * State Branch	-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 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. 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 9. 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 10. 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 11. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.5386	0.1412	<.0001	13.0%
Controls	Yes			
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

	Utilization Rate		
Variable	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. 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 * State Branch	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)

	Utilization Rate		
Variable	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. 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 9. 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 10. 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 11. Low Checking Balances (& R7 & R4)			
Indicator(Balance < $2000)	-0.0567	0.0590	0.8322
Controls	Yes		
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.

Table 5: Correlation between Relationships, APR and Credit Limit

	APR			Credit Limit		
Variable	Coeff	Std Err	P-value	Coeff	Std Err	P-value
R 1. Relationship						
Relationship Indicator	-0.0360	0.1425	0.7819	12.7424	41.1555	0.8283
Controls	Yes			Yes		
Number of Obs	93694			93694		

Note: This table shows the correlation between the relationship variable, the credit card APR, and credit line limit. 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. The relationship variables are defined in Table 2. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

Table 6. Propensity Score Matching

	Default			Attrition			Utilization Rate		
Relationship Variable	Coeff	P-value	Marg Eff	Coeff	P-value	Marg Eff	Coeff	SE	P-value
R 1. Any Relationship									
Relationship Indicator	-0.318	0.0004	12%	-0.599	<.0001	13%	0.070	0.010	<.0001
R 2. Breadth (#) of Relations									
1	-0.243	<.0001	4%	-0.817	<.0001	3%	0.023	0.003	<.0001
2	-0.220	<.0001	6%	-0.753	<.0001	5%	0.027	0.003	<.0001
3	-0.317	0.000	10%	-0.704	<.0001	11%	0.052	0.003	<.0001
4	-0.256	0.000	12%	-0.901	<.0001	16%	0.068	0.003	<.0001
5	-0.650	0.028	16%	-0.966	<.0001	17%	0.097	0.003	<.0001
6+	-0.599	0.028	19%	-0.628	<.0001	22%	0.134	0.003	<.0001
R 3. Type of Relations (Broad)									
Deposit Relationships	-0.226	<.0001	10%	-0.108	<.0001	12%	0.072	0.001	<.0001
Investment	-0.327	<.0001	21%	-0.278	<.0001	13%	0.098	0.001	<.0001
Loan	-0.031	<.0001	5%	-0.230	<.0001	9%	0.032	0.007	<.0001
R 4. Type of Relations (Narrow)									
Checking	-0.115	<.0001	7%	-0.144	<.0001	10%	0.094	0.001	<.0001
Savings	-0.267	<.0001	12%	-0.127	<.0001	7%	0.055	0.001	<.0001
Brokerage	-0.240	<.0001	16%	-0.634	<.0001	2%	0.087	0.002	<.0001
CD	-0.441	<.0001	22%	-0.227	<.0001	6%	0.068	0.002	<.0001
Mutual Fund	-0.360	<.0001	20%	-0.100	<.0001	13%	0.028	0.003	<.0001
Home Equity Line	-0.015	<.0001	8%	-0.272	<.0001	5%	0.046	0.003	<.0001
Home Equity Loan	-0.010	<.0001	2%	-0.200	<.0001	2%	0.033	0.003	<.0001
Mortgage Loan	-0.016	<.0001	3%	-0.200	<.0001	3%	0.035	0.009	<.0001
Controls	Yes			Yes			Yes		
Number of Obs	837212			837212			837212		

Note: This table shows the effects of relationships on credit card default, attrition and utilization rates (balances/limit), estimating eq. (1) with the method of propensity score matching. 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 R1 to R4; each panel represents a separate specification. The relationship variables are defined in Table 2. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

Table 7. Change in Credit Quality since Origination

	12 Months Change in Fico Score			24 Months Change in Fico Score		
Variable	Coeff	Std Err	t-stst	Coeff	Std Err	t-stst
External Risk Score	0.617	2.444	0.252	0.486	2.293	0.212
Rel Indicator	0.104	0.485	0.215	0.100	0.447	0.224
External Risk Score * Rel Indicator	0.063	0.194	0.326	0.047	0.156	0.298
Controls	Yes			Yes		
Number of Obs	93694			93694		

Note: This table shows the correlation between the relationship variable and the changes in FICO scores of accounts at 12 and 24 months since their origination. The explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

Table 8: Perceived Default Costs

Relationship Variable	Coeff	Default P-value	Marg Eff
R 1. Any Relationship			
Relationship Indicator	-0.021	0.2816	-2%
R 2. Breadth (#) of Relations			
1	-0.003	0.3602	0%
2	-0.003	0.3319	0%
3	-0.013	0.3569	-2%
4	-0.028	0.3500	-2%
5	-0.020	0.3732	-3%
6+	-0.036	0.3251	-5%
R 3. Type of Relations (Broad)			
Deposit Relationships	-0.015	0.2883	-2%
Investment	-0.023	0.3932	-4%
Loan	-0.003	0.2716	0%
R 4. Type of Relations (Narrow)			
Checking	-0.013	0.2887	-1%
Savings	-0.079	0.3710	-2%
Brokerage	-0.061	0.3871	-2%
CD	-0.029	0.2597	-3%
Mutual Fund	-0.039	0.3607	-3%
Home Equity Line	-0.007	0.2594	0%
Home Equity Loan	-0.001	0.3540	-1%
Mortgage Loan	-0.008	0.3653	-1%
Controls	Yes		
Number of Obs / Default	14912	392	

Note: 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). We restrict our sample to those accounts who experienced severe deterioration ex post in the credit quality (for example, accounts who's FICOs dropped by 20% or 50 points). 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 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.

Appendix: Robustness Check and External Validity

We have presented the main results and discuss the possible explanations. In this section, we discuss robustness check and external validity of our study.

In the main specification, we use Cox proportional hazard models to estimate the effect of relationship on default and attrition separately. We also conduct the robustness analysis using multinomial logit to jointly model default and ordinary account closures. The results are consistent with those in our hazard specifications. In fact, the coefficient on the relationship variables is only different at the first decimal point. If needed we can include then in the online appendix.

In the main specification, we take income as continuous variable and include it as one of the control variables. In the robustness analysis, we estimated a model with missing income as a separate dummy and creating income bins for the rest of the sample as opposed to incorporating income as a continuous variable. Our results are quantitatively and qualitatively very similar. For instance, the coefficient on relationship dummy in R1 changed from -0.3208 to -0.3196.

In the main specification, we take FICO score as continuous variable and include it as one of the control variables. In the robustness analysis, we estimated the model by making the scores discrete in 20 point buckets. The results are virtually the same. For instance, the coefficient on relationship dummy in R1 changed from -0.3208 to -0.3217. Just as robustness we also estimated the model with have a quadratic and a cubic term for the two scores. Once again the coefficient on relationship dummy in R1 changed from -0.3208 to -0.3213.

One concern of our study is the external validity. The data we use is from late 2001 to late 2003. It is possible that limitations in computing technology available in the early 2000s explains why the lender did not use cross account information at the time. With the technology advance in the last 15 years, do lenders use this information now?

We provide two pieces to evidence to show that our study have strong external validity. First, in a subsequent study to our work, using data from Germany, Puri, Steffen and Sascha (2011) show that loans of retail customers, who have a relationship with their savings bank prior to applying for a loan, default significantly less than customers with no prior relationship. The results are consistent with our main findings.

Second, to understand the recent industry patterns, we supplement our analysis with a new credit card dataset in Singapore from 2010 to 2012. The dataset is from Agarwal and Qian (2014), and it is proprietary dataset obtained from the leading bank in Singapore that has more than four million customers, or 80 percent of the entire population in Singapore. As the largest bank in Singapore, it has more than twice the number of branches and over four times the number of automatic teller machines (ATMs) than the other major banks in Singapore. It also pioneers the application the computing technology into banking industry.

Our sample contains consumer financial transactions data of more than 180,000 individuals, which is a random, representative sample of the bank's customers, in a 24-month period between April 2010 and March 2012. For each individual in our sample period, we have monthly statement information about each of their credit cards, debit cards, and checking accounts with the bank, including balance, total debit and credit amount (for checking accounts), spending (for credit and debit cards), credit card limit, credit card payment, and debt.

We create a dummy that equals 1 if the credit card account holder has a checking account. The dummy is similar to our measurement R1 in the paper. We run a simple logit regression to study the relationship between the relationship variable and default, attrition and credit card utilization. Appendix Table 4 presents the results. The coefficient of the relationship variable is negative and significant in the default regression. This implies that relationship accounts have a

lower probability of default than non-relationship accounts, ceteris paribus. The coefficient for relationship variable is not significant in the attrition regression. This implies that relationship accounts have similar attrition rates to the non-relationship accounts. The coefficient of the relationship variable is positive and significant in the utilization regression. Hence relationship accounts have higher utilization rates than non-relationship accounts, ceteris paribus.

This results using Singapore data from 2010 to 2012 shows similar patterns to US data from 2001 to 2003 on default and credit card utilization. It seems that with 10 years of application of computer technology in banking industry, a leading bank in a developed country still had not used the cross account information to credit card account holders.

Appendix Table 1: Baseline Results for Default

	Default			
Variable	Coeff	Std Err	P-value	Marg Eff
External Risk Score	-0.0041	0.0002	<.0001	14.60%
Internal Risk Score	-0.0055	0.0002	<.0001	16.30%
Debt	0.3479	0.0129	<.0001	1.60%
Purchase	-0.0457	0.0354	0.2351	1.10%
Payments	-0.1722	0.0124	<.0001	2.80%
Credit line	-0.2880	0.0134	<.0001	4.80%
APR	0.0385	0.0050	<.0001	0.70%
Total number of bankcards	0.0625	0.0082	<.0001	2.50%
Total bankcard credit limits	-0.0032	0.0106	0.7139	4.70%
Total bankcard balances	0.1441	0.0364	<.0001	3.40%
Total number of non-bank cards	0.0070	0.0027	0.0224	0.40%
Total non-bank card balances	0.0553	0.0156	<.0001	1.10%
Total home equity line limits	-0.0032	0.0018	0.0474	3.50%
Total home equity line balance	0.1222	0.0469	<.0001	1.80%
Total mortgage loan balance	-0.0020	0.0004	<.0001	3.10%
Total auto loan balance	-0.0049	0.0032	0.1370	5.10%
Total student loan balance	-0.0084	0.0043	0.0413	2.70%
Unemployment rate	0.5891	0.2780	0.0354	3.00%
% w/o health insurance	-0.0290	0.0220	0.2246	2.90%
D(House prices)	-0.3833	0.0398	<.0001	8.20%
State income	-0.0842	0.0945	0.5916	3.80%
Application income	-0.0486	0.0579	0.9271	2.70%
Application inc missing	0.1790	0.0427	<.0001	2.40%
Wealth = low	0.3277	0.2466	0.1023	1.20%
= medium	0.2703	0.3670	0.4606	2.00%
R1 = Any Relationship	-0.3208	0.0859	<.0001	10.10%
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

	Default			
Variable	Coeff	Std Err	P-value	Marg Eff
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 Defaults	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

	Default		
Variable	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	0.22
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.

Appendix Table 4: Singapore Credit Card Data from 2010 to 2012

	Default			Attrition			Utilization		
Variable	Coeff	T-stat	P-value	Coeff	T-stat	P-value	Coeff	T-stat	P-value
R 1. Relationship									
Relationship Indicator	-0.4830	12.0400	<0.01	-0.0050	0.7800	>0.1	0.0130	12.1800	<0.01
Controls	Yes			Yes			Yes		
Year-month FE	Yes			Yes			Yes		
Number of Obs	3,917,767			3,917,767			3,916,868		

Note: This table shows the effects of relationships in predicting credit card default (bankruptcy or three months delinquency), using logit regression. We use credit card date from a large Singapore bank from 2010 to 2012. The explanatory variables include macro-demographic and relationship variables, in addition to month dummies. The table reports only the results for the relationship variables. The relationship variables are defined in Table 2. The standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.