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Benefits of relationship banking: Evidence from consumer credit markets☆

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ABSTRACT

Using a unique panel dataset that contains comprehensive information about the relationships between a large bank and its credit card customers, we show that relationship accounts exhibit lower probabilities of default and attrition, and have higher utilization rates, than non-relationship accounts. Dynamic information about changes in the behavior of a customer's other accounts at the same bank helps predict the behavior of the credit card account over time. These results imply that relationship banking offers significant potential benefits to banks: information the lender has at its disposal can be used to mitigate credit risk on the credit card account.

1. Introduction

According to recent theories of financial intermediation, one of a bank's main roles is to serve as a relationship lender.[1] Relationships offer banks comparative advantages in lending through the accumulation of private information, which can arise from the length of the relationship over time and its breadth across multiple products. In turn, relationships benefit bank customers through increased credit availability, such as greater amounts of and lower prices for credit (Boot and

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

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Thakor 1994).[2] Empirical studies of the benefits of relationship banking have largely focused on the benefits to customers, and corporate customers in particular.[3]

Only limited empirical research has been conducted on the benefits of relationships to banks. In his review of relationship banking literature, Boot (2000) concludes that “existing empirical work is virtually silent on identifying the precise sources of value in relationship banking.” Mester et al. (2007) study a sample of 100 Canadian small-business borrowers, and find that information about customers’ collateral, and their inventory and accounts receivable in particular—which might not be available to banks outside of a relationship—is useful for loan monitoring. Also, changes in transaction account balances are informative about changes in this collateral. In subsequent work, Puri et al. (2017) provide external validation to our work and show that retail customers in Germany who have a relationship with their savings bank prior to applying for a loan default significantly less often than customers with no prior relationship.

This paper studies the economic benefits of relationship banking to banks in the context of retail banking.[4] Credit cards provide a good setting for analyzing retail relationship banking, since it is easier to identify the information actually used by credit card issuers to manage their accounts. Specifically, our paper examines the implications of bank relationships for key aspects of credit card behavior, such as default, attrition, and utilization rates.[5] We use a unique, representative dataset of about 100,000 credit card accounts that are linked to information about other relationships account holders have with the bank that issued the card. Our dataset includes “public” credit bureau information that is available to all potential lenders, lenders’ “private” within-account (as opposed to cross-account) information about past behavior of the accounts at issue, and lenders’ “private” cross-account relationship information. Given the information used by banks to manage their accounts, this paper can more cleanly test whether additional information—in this case, relationship information—provides *additional* predictive power.

The key contribution of this study is our use of 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, such as credit card default, attrition, and utilization rates. One advantage of our paper is that the administrative panel data can help to measure an actual relationship along various dimensions. The cross-account relationship information 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 are longitudinal, so we can measure some relationship information that is inherently dynamic, such as high-frequency changes in the level and volatility of balances in other relationships. To our knowledge, this is the first comprehensive analysis of relationships in the retail banking market.

Previewing the main results, our paper shows substantial potential benefits from relationship lending, through lower default risk, lower attrition, and increased utilization. Using Cox proportional hazard models, relationship information is found to significantly help predict default and attrition, above and beyond all other variables used by the bank—i.e., 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, respectively, than those of accounts without other relationships, ceteris paribus. More generally, benefits to the bank tend to increase with various measures of the strength of the relationship (breadth, depth, and length). Further, explicitly dynamic information about *changes* in the behavior of 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, in addition to other advantages that have been discussed in the literature, is that they can improve the monitoring of borrowers over time. Relationship banking is also associated with higher utilization rates. For instance, utilization rates for relationship accounts are 7 percentage points higher than non-relationship accounts, ceteris paribus.

Previous literature has proposed several reasons why such relationship information can be informative, but it is difficult to empirically distinguish between these explanations. Some emphasize the selection mechanism; for example, banks might be better at screening credit card applications by existing relationship customers. Or perhaps customers with multiple relationships differ from non-relationship customers in ways that are difficult to observe, such as being wealthier or having higher perceived default costs. Our strategy is to apply the method of propensity score matching to control for selection on observables. The results from our matched sample are largely consistent with the main results in terms of directions and magnitudes. Moreover, relationship variables are not correlated with credit terms (APR and limit) or changes in bor-

[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; Bolton and Scharfstein, 1996). Relationship lending can also potentially create a hold-up problem, giving the bank an information monopoly that could allow it to price contracts on noncompetitive terms (Sharpe, 1990; Rajan, 1992; and Wilson, 1993).

[3] The literature that focuses on the benefits of relationship banking for customers includes, but is not limited to, Billett et al. (1995), Slovin et al. (1993), Petersen and Rajan (1994), Berger and Udell (1995), Chakravarty and Scott (1999), Ongena and Smith (2001), Degryse and Ongena (2005), Yasuda (2005), Bharath et al. (2011), Ivashina and Kovner (2011), and Kysucky and Norden (2016).

[4] One exception is Puri and Rocholl (2008), who analyze the importance of retail banking relationships to banks by examining cross-selling, and find evidence that banks benefit from an increase in both brokerage accounts and other retail products by their depositors. Agarwal et al. (2017) also study the role of relational contracts in the mortgage market.

[5] Attrition is account closing without default.

rowers' FICO score in the 12 and 24 months after the lender issues the credit card. In addition, if relationship customers have higher perceived default costs, they would deliberately avoid default on their credit card debt to the lender, even when facing adverse economic shocks. Our strategy is to study a subsample that includes those accounts that experienced severe deterioration ex post in credit quality. The results show no significant difference between the two groups in terms of default. Therefore, our results do not support the selection mechanism.

Other explanations in the literature tend to emphasize more dynamic mechanisms related to information production over time and ongoing monitoring of loans. This implies that there are information benefits to monitoring such relationship balances over time. We explore the dynamic information in our data to study the private information mechanism, and find that changes in 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 the private information mechanism: Information the lender has 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 literature in several ways. First, this study demonstrates the benefits of relationship retail banking. Previous studies suggest that the benefit of relationship banking is through soft information developed over time in a relationship. For example, local banks have an information advantage when screening loans to higher risk borrowers based on unobservable soft information, which results in better loan outcomes (Petersen and Rajan 2002; Agarwal and Hauswald 2008 and 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, and suggests that the benefits of relationship banking might arise from hard information instead of soft information. The paper is also related to economies of scope in retail banking with multiple financial services. We show that private information generated by multiple financial services offers another benefit from a "supermarket" style of banking that leads to economies of scope.

Second, this paper explores the richness and dynamics of our data to investigate the mechanisms of the benefits of relationship banking. Our analysis shows that the observed results are not due to selection mechanism; instead, they support the private information mechanism. Norden and Weber (2010) find that borrowers who default are likely to exhibit abnormal patterns in their checking accounts approximately 12 months before defaulting. Banks can use this information to predict future borrower defaults, and study results suggest that relationship lenders can benefit the most from such information. Our results are consistent with Norden and Weber's, suggesting that relationship lenders 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

This paper uses 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 100,000 open accounts as of October 2001, which we follow monthly for the next 24 months.

The dataset includes key information the bank uses to manage its credit card accounts, such as the main billing information listed on each account's monthly statement, which includes total payments, spending, balances, and debt, as well as the credit limit and APR. It is important to distinguish between accounts characterized by revolving debt and accounts in which the borrower fully pays the outstanding balance each month. Since banks report the balance but not revolving debt to credit bureaus, observing revolving debt provides additional information about account holders' credit risk. Our main specification controls for debt to render our estimation of the effect of relationship more precise.

The dataset also includes 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 and estimated based on available credit bureau data for each consumer. The "internal" credit score is an account-specific behavioral score estimated by lenders using private, in-house information, and is only available three months after the credit card has been issued. Traditionally, that information has been limited to the behavior of the individual account in question and does not include other accounts or relationships the account holder has at the same bank. This is the case with our sample. 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 the bank has directly collected from the credit bureaus: the total number of bankcards held by the account holder across all lenders and the cards' balances and limits; number of 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. Credit bureau variables are updated quarterly.

These data are augmented by a number of other data sources. First, and most importantly for our purposes, the dataset was linked to a systematic summary of other accounts credit card account holders have at the bank. Specifically, the data contains information about the following types of deposit, investment, and loan relationships: checking, savings, CDs, mutual

Table 1
Descriptive statistics.

Variable	Non-relationship accounts		Relationship accounts	
	Mean	Std	Mean	Std
Unemployment rate	5.3	0.9	5.2	0.8
% w/o health insurance	12.5	3.7	12.7	3.3
State income	$36,083	$4588	$36,428	$4507
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	$1979	$3912	$1836	$3238
Payments	$308	$774	$389	$903
Purchase	$229	$923	$274	$669
APR	16.99	5.46	15.50	5.08
Credit line	$8283	$3737	$9491	$3804
Total number of bankcards	6	6	5	6
Total bankcard credit limits	$27,984	$24,902	$23,027	$27,639
Total bankcard balances	$7023	$14,066	$7569	$17,122
Total number of non-bank cards	11	10	13	14
Total non-bank card balances	$18,553	$9324	$16,103	$7975
Total home equity line amount	$7394	$28,922	$5866	$25,241
Total home equity line balance	$4857	$18,651	$3909	$14,074
Total mortgage loan balance	$43,092	$81,893	$44,745	$87,208
Total auto loan balance	$3377	$6098	$2891	$6544
Total student loan balance	$1183	$6893	$1115	$7696
Default	5.6%		3.9%	
Attrition	15.5%		12.0%	
Utilization	18.8%		23.9%	
Number of Accounts	40,944	43.7%	52,750	56.3%

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

funds, brokerage, mortgages, home equity loans (second mortgages), and HELOCs.[6] For each relationship type, the data includes the length of the relationship (age in months) and its depth (balances in dollars). This relationship information is updated monthly over the sample period.[7]

Second, credit data are augmented by macroeconomic and geographic-average demographic information based on each account holder's location, including the state's unemployment rate, average state income, fraction of people in the state who lack healthcare coverage, and local house prices.[8] Some of these variables are updated monthly, and others annually. The dataset also includes the self-reported level of account holder income, when available, from the account application; slightly less than half of the accounts in our sample include this variable. To avoid reducing sample size, a dummy variable is created to indicate when application income is missing, and in those cases the value of income is set 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 account origination.[9]

The dataset includes open credit card accounts and accounts closed due to attrition or default. In the analysis, accounts that were closed before the start of the sample period in October 2001 are excluded; thus, our study sample only includes credit card accounts that were open as of the start of the sample period. Furthermore, to simplify our hazard analysis of account age, in the reported results only accounts that originated after October 1999 are included. Also, to focus on the effects of relationships and minimize potential endogeneity, for credit card account holders with other relationships, account holders who initiated new relationships in our sample period subsequent to opening the credit card account are also excluded.

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

[6] As noted previously, the dataset does not include several 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 we use.

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

[8] Unemployment and income data are from the Bureau of Labor Statistics. We use FHFA MSA-level house prices when available; otherwise, we use average prices for the state. In preliminary work, we also considered additional variables, such as the state divorce rate (which is not available for some states, such as California) and bankruptcy exemption levels in the state (which are subsumed by our state dummies).

[9] 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.

"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 of credit. No account has only a CD or mutual fund relationship; evidently, a customer typically opens an investment relationship only after establishing at least one other relationship. On average, relationship account holders have higher income and higher wealth. They also have less debt on their accounts and higher internal and external credit scores. Overall, based on public and private within-account information, relationship accounts generally appear to be less risky than non-relationship accounts. (Credit scores are calibrated such that higher scores correspond to lower probabilities of default.) Consistently, relationship accounts received higher credit limits and lower APRs. Turning to their performance over the sample period, relationship accounts do in fact have lower default rates, as well as lower attrition rates and higher utilization rates, on average. The open question is whether these results can be explained by differences in their other (non-relationship) characteristics, rather than by their relationships.

3. Empirical results

This section presents the empirical results on the effect of relationship banking on credit card default, attrition, and credit card utilization.

3.1. Relationship banking and credit card default and attrition

To test whether relationship banking can assist banks in assessing default and attrition risk for credit card loans, we estimate Cox proportional hazard models for default and attrition.[10] Default is defined as going bankrupt or being three months delinquent, whichever comes first. Attrition is account closing without default.

The Cox model allows for a nonparametric baseline hazard rate, as well as potentially time-varying explanatory variables. The main specification is the following Cox model:

$$\lambda(t|X_i) = \lambda_0(t)e^{(\beta X_i)} \tag{1}$$

where $\beta X_i = \beta_1 Time_t + \beta_2 State_i + \beta_3 MacroDemog_{i,t-6} + \beta_4 LoanPerformance_{i,t-6} + \beta_5 CreditBureau_{i,t-6} + \beta_6 Relationship_{i,t-6}$ and $\lambda(t|X_i)$ is the hazard function for default or attrition of account i at time t with covariates X_i.

The main explanatory variables are grouped into six categories: $Time_t$ represents a complete set of month dummies, with one for each month in the sample period. $State_i$ represents a set of dummy variables that correspond to the state in which account holder i lives. $MacroDemog_{i,t\text{-}6}$ represents macroeconomic and demographic characteristics, such as the local unemployment rate and account holder–specific estimates of income and wealth. $LoanPerformance_{i,t\text{-}6}$ includes internal measures of the performance of the sample credit card account over the sample period—including monthly purchases, payments, and debt—and the account's credit limit, interest rate, and internal credit-risk score. $CreditBureau_{i,t\text{-}6}$ represents the external credit score and other credit bureau variables, such as total balances on credit cards, HELOCs, and mortgages.[11]

Such variables have been studied before. For instance, using related duration models, Gross and Souleles (2002) show that external scores are powerful predictors of consumer default. Even given these scores, internal scores are also 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 holder's relationships. The baseline relationship measure labeled R1 simply uses a dummy variable to identify 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 (1–6+, omitting 0 relationships). R3 focuses on the types of relationship, which are grouped into three broad categories (again using dummy variables): deposit relationships, investment relationships, and loan relationships. R4 identifies the types of relationships more finely (eight 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 relationship breadth.

This paper further measures relationship depth. R7 does this using the balance of each of the relationship categories (in addition to controlling for the presence of each relationship, as in R4). In an effort to distinguish more specifically the potential benefits of relationships in the ongoing monitoring of loans, we also consider more dynamic relationship

[10] The results using a multinomial logit model were qualitatively similar.

[11] 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 three months delinquent, its credit score would have already declined sharply, essentially creating a mechanical relationship with the dependent variable.

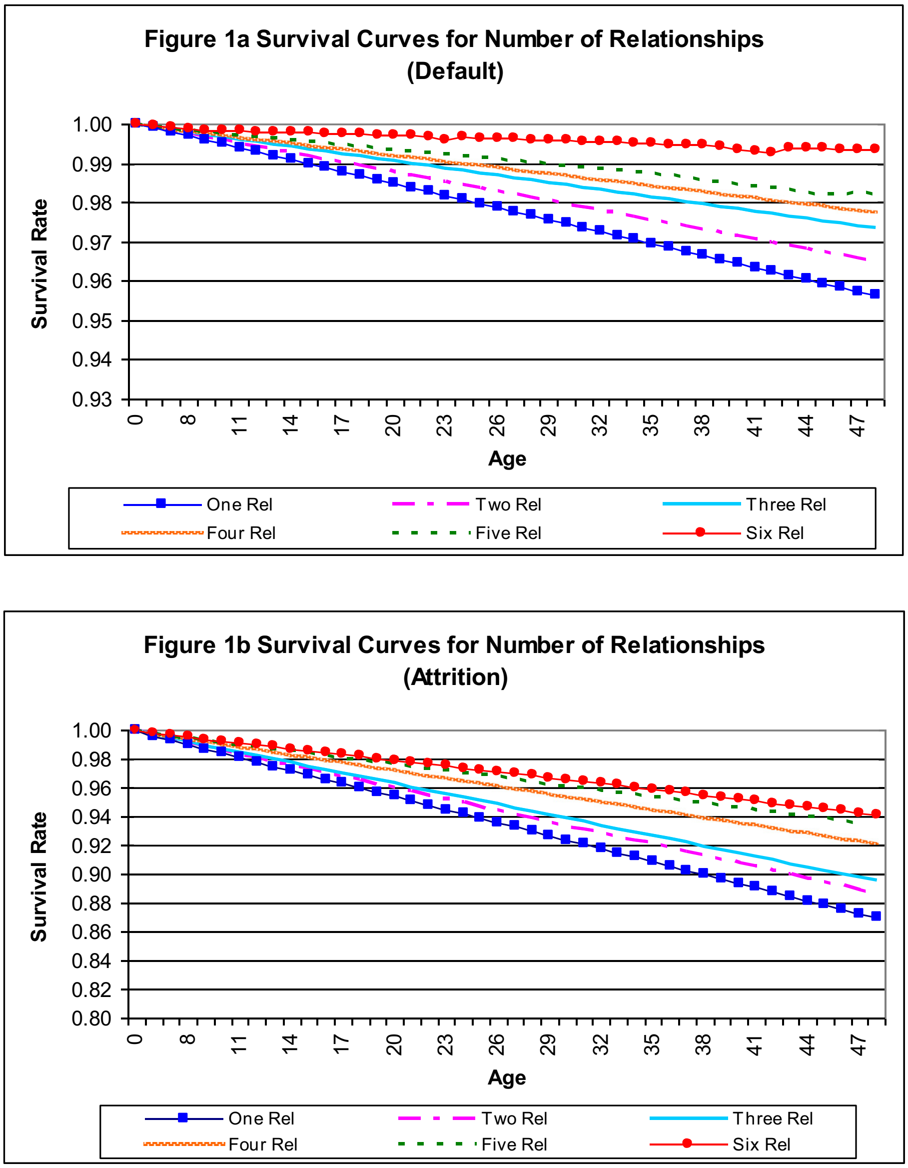

Fig. 1. Survival curves for different numbers of relationships.
Notes: (a) shows survival curves for different numbers of relationships. The horizontal axis shows the age in months since opening. The vertical axis shows the survival rate. (a) shows survival curves for (lack of) default. (b) shows survival curves for (lack of) attrition.

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 $2,000.

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

This paper first presents how baseline hazard rates from the Cox model vary with the number of relationships, without controlling for other covariates. Fig. 1(a) shows the associated survival curves for (lack of) default, which 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 rises significantly, to about 99%. Conversely, the probability of default monotonically declines with the number of relationships. Fig. 1(b) shows the analogous survival curves for (lack of) attrition. Again, the curves substantially and monotonically increase with the number of relationships.

Our paper then estimates the full multivariate Cox model, following Eq. (1), first for default. We begin by briefly discussing results for the non-relationship variables for our baseline specification R1 (for brevity, reported in Appendix Table 1). Starting with credit variables, external and internal scores have negative and significant coefficients. As expected, higher scores are predictive of lower probabilities of default. 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 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 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 negative coefficients overall. In sum, public information from credit bureaus is predictive of default; even given this information, however, 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 instance—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 results for relationship information. Given the large sample size, the coefficients of all relationship measurements are statistically significant at the 1% level. In the following discussion, only coefficients and marginal effects will be discussed. The baseline relationship measure R1 simply uses an indicator variable for having another relationship; the omitted group is non-relationship accounts. According to the marginal effect, relationship accounts have a 10% lower probability of default than non-relationship accounts, ceteris paribus. This is an economically significant effect (and larger than the marginal effects of all other covariates, with the exception of credit scores). Given the rich set of covariates, including both public information and the issuer's private within-account information, 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–R11 separately. (For brevity, only 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 Fig. 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. R3 considers the effects of different types of relationships. The probability of default decreases by 14% with investment relationships, versus 9% for deposit relationships and 4% for loan relationships. R4 uses a finer partition of relationship types. Within investment accounts, CD relationships have the largest (negative) marginal effects. All of the other relationship types also have significant, albeit smaller, negative effects. 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 a one-standard-deviation increase in age, the probability of default decreases by 3%–13%, with the largest effect arising from the age of a CD relationship. R6 simultaneously considers the previous measures of relationship, specifically relationship breadth, type, and length. The general pattern of results is similar to that described above.

Overall, under all measures of relationships R1–R6, which measure relationship breadth, relationship accounts have lower probabilities of default. Similar measures of relationships have been considered in previous literature on corporate lending.

This paper further measures relationship depth in R7, using ln (balances+\$1). (The specification also includes 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, marginal effects range from 7% to 20%. 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 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.

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	<0.0001	10.1%
R 2. Breadth of Relationships				
Number of Bank Relationships = 1	−0.2628	0.0356	<0.0001	1.6%
=2	−0.2307	0.0416	<0.0001	3.1%
=3	−0.3258	0.1270	<0.0001	6.3%
=4	−0.2539	0.1221	<0.0001	9.4%
=5	−0.6404	0.3151	<0.0001	10.6%
=6+	−0.6253	0.2465	<0.0001	17.9%
R 3. Type of Relationships (Broad)				
Deposit Relationships	−0.2410	0.0672	<0.0001	9.3%
Investment Relationship	−0.3366	0.1199	<0.0001	14.1%
Loan Relationship	−0.0303	0.0129	<0.0001	4.2%
R 4. Type of Relationships (Narrow)				
Checking Dummy	−0.1217	0.0391	<0.0001	6.6%
Savings Dummy	−0.2743	0.0697	<0.0001	8.0%
Brokerage Dummy	−0.2534	0.0891	<0.0001	10.5%
CD Dummy	−0.4579	0.1237	<0.0001	16.6%
Mutual Fund Dummy	−0.3714	0.0320	<0.0001	14.9%
Home Equity Line Dummy	−0.0162	0.0047	<0.0001	7.4%
Home Equity Loan Dummy	−0.0107	0.0047	<0.0001	2.8%
Mortgage Loan Dummy	−0.0167	0.0052	<0.0001	3.6%
R 5. Length of Relationships				
Age of Checking Relationship	−0.0013	0.0002	<0.0001	3.4%
Age of Savings Rel	−0.0061	0.0004	<0.0001	5.8%
Age of Brokerage Rel	−0.0108	0.0009	<0.0001	9.8%
Age of CD Rel	−0.0213	0.0054	<0.0001	13.2%
Age of Mutual Fund Rel	−0.0163	0.0015	<0.0001	6.3%
Age of Home Equity Line Rel	−0.0009	0.0009	<0.0001	11.5%
Age of Home Equity Loan Rel	−0.0018	0.0009	<0.0001	9.4%
Age of Mortgage Loan Rel	−0.0059	0.0021	<0.0001	10.0%
R 6. Combined Relationship Measures				
Number of Bank Relationships = 1	−0.2551	0.0354	<0.0001	0.1%
=2	−0.2292	0.0409	<0.0001	1.8%
=3	−0.3129	0.1262	<0.0001	4.7%
=4	−0.2453	0.1200	<0.0001	7.0%
=5	−0.6307	0.3054	<0.0001	10.1%
=6+	−0.6189	0.2458	<0.0001	17.0%
Checking Dummy	−0.1169	0.0376	<0.0001	4.3%
Savings Dummy	−0.2573	0.0649	<0.0001	5.3%
Brokerage Dummy	−0.2417	0.0840	<0.0001	7.8%
CD Dummy	−0.4231	0.1195	<0.0001	13.1%
Mutual Fund Dummy	−0.3658	0.0308	<0.0001	11.7%
Home Equity Line Dummy	−0.0150	0.0045	<0.0001	4.2%
Home Equity Loan Dummy	−0.0098	0.0045	<0.0001	0.5%
Mortgage Loan Dummy	−0.0160	0.0048	<0.0001	0.7%
Age of Checking Relationship	−0.0012	0.0002	<0.0001	2.6%
Age of Savings Rel	−0.0059	0.0004	<0.0001	5.1%
Age of Brokerage Rel	−0.0108	0.0009	<0.0001	8.9%
Age of CD Rel	−0.0212	0.0052	<0.0001	11.7%
Age of Mutual Fund Rel	−0.0156	0.0015	<0.0001	6.2%
Age of Home Equity Line Rel	−0.0009	0.0009	<0.0001	11.0%
Age of Home Equity Loan Rel	−0.0017	0.0008	<0.0001	8.6%
Age of Mortgage Loan Rel	−0.0058	0.0021	<0.0001	8.8%
State with Branch Indicator	−0.2674	0.0749	<0.0001	3.0%
Relationship * State Branch	−0.1222	0.0507	<0.0001	1.8%
Checking Balance	−0.0604	0.0137	<0.0001	12.5%
Savings Balance	−0.0720	0.0182	<0.0001	5.7%
CD Balance	−0.0749	0.0208	<0.0001	9.0%
Mutual Fund Balance	−0.1767	0.0421	<0.0001	18.4%
Home Equity Line Balance	−0.1147	0.0327	<0.0001	4.0%
Home Equity Loan Balance	−0.0788	0.0339	<0.0001	4.2%
Mortgage Loan Balance	−0.1974	0.0756	<0.0001	2.1%

(*continued on next page*)

Table 2 (*continued*)

Variable	Default Coeff	Std Err	*P*-value	Marg Eff
R 7. Depth of Relationships (ln(Bal) & R4)				
Checking Balance	−0.0612	0.0139	<0.0001	13.2%
Savings Balance	−0.0731	0.0188	<0.0001	7.2%
CD Balance	−0.0780	0.0210	<0.0001	10.6%
Mutual Fund Balance	−0.1806	0.0433	<0.0001	19.8%
Home Equity Line Balance	−0.1173	0.0333	<0.0001	3.1%
Home Equity Loan Balance	−0.0817	0.0344	<0.0001	5.8%
Mortgage Loan Balance	−0.1984	0.0776	<0.0001	3.3%
R 8. Change in Balances (ln(Bal) & R7 & R4)				
D(Checking Balance)	−0.0307	0.0032	<0.0001	6.1%
D(Savings Balance)	−0.0285	0.0011	<0.0001	13.0%
D(Mutual Fund Balance)	−0.0655	0.0014	<0.0001	10.0%
D(Home Equity Line Balance)	−0.0042	0.0015	0.0002	6.5%
D(External Score)	−0.4479	0.0262	<0.0001	16.0%
D(Internal Score)	−0.3854	0.0683	<0.0001	12.3%
R 9. Volatility of Balances (sd(12) & R7 & R4)				
sd(Checking Balance)	1.1014	0.0209	<0.0001	5.2%
sd(Savings Balance)	0.7945	0.0616	<0.0001	11.9%
sd(Mutual Fund Balance)	1.2133	0.0638	<0.0001	10.2%
sd(Home Equity Line Balance)	1.1366	0.0867	<0.0001	11.3%
sd(External Score)	0.7706	0.2233	<0.0001	13.1%
sd(Internal Score)	0.4569	0.2118	<0.0001	7.5%
R 10. Change in Volatility (D(sd(6)) & R7 & R4)				
D(sd(Checking Balance))	1.0136	0.0227	<0.0001	6.8%
D(sd(Savings Balance))	0.5563	0.0509	<0.0001	12.9%
D(sd(Mutual Fund Balance))	0.9448	0.0669	<0.0001	11.3%
D(sd(Home Equity Line Balance))	0.9608	0.0733	<0.0001	13.5%
D(sd(External Score))	0.5999	0.2104	<0.0001	14.9%
D(sd(Internal Score))	0.5903	0.2174	<0.0001	8.8%
R 11. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.6999	0.1675	<0.0001	12.7%
Controls	Yes			
Number of Obs / Number Default	1,132,182	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). Explanatory variables include macro-demographic, loan-performance, credit bureau and relationship variables, in addition to month and state dummies. The table reports only results for relationship variables; each panel represents a separate specification. (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 simultaneously considers previous measures of relationship, specifically relationship breadth, type, and length. R7 measures balances of the relationship categories (relationship depth, using ln(balances + 1)), and R8 measures changes in the balances. R9 measures the volatility of balances over the prior 12 months, and R10 measures changes in the volatility of balances over the two prior 6-month periods. R11 uses a dummy variable for whether checking balances have fallen below $2000. Standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts. Marginal effects for continuous covariates show the effects of a one-standard-deviation change in covariates.

To distinguish the specifically dynamic notions of the benefits of relationships, the following specifications consider the dynamic measures of relationship information more explicitly.

Relationship measure R8 focuses on the change in relationship balances (in addition to the level of balances from R7 and indicators from R4),[12] and includes corresponding changes in external and internal credit scores. For a one-standard-deviation increase in relationship balance, the probability of default decreases by 6%–16%. These results demonstrate the value of relationships, and specifically in the ongoing monitoring of loans. R9 measures the volatility of balances across the

[12] Since our sample excludes relationships opened subsequent to the credit card account, these results are driven by changes in the intensive margin of balances. R8 does not include the (high-frequency) changes in CD and mortgage and home equity loan balances, since these mostly reflect interest and regular amortization, and so are a priori not as informative.

prior 12 months, and includes the volatility of 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 marginal effects ranging between 5% and 13%. R10 considers, instead, changes in the volatility of balances over the two previous six-month periods, and coefficients are again significantly positive. Increases in volatility are also associated with higher default risk. 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 discrete increase in risk associated with low balances per se. Low checking balances are associated with a 13% marginal increase in the probability of default.

Table 3 presents the results of estimating Eq. (1) instead for attrition, again focusing on relationship measures. (For brevity, non-relationship results are left to the appendix.) In general, the pattern of relationship results is qualitatively similar to that in Table 2 (and so our discussion of them will accordingly be brief). That is, the same relationship information 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 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 in our data, including dynamic measures, relationship accounts have lower probabilities of default and attrition, ceteris paribus.

3.2. Relationship banking and credit card utilization

This section studies 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, the same covariates are used as in Eq. (1), but the dependent variable $Y_{i,t}$ is replaced with the utilization rate of account i in month t.[13] The specification is estimated using OLS, allowing for heteroscedasticity across accounts and serial correlation within accounts.

We begin by briefly noting some of the results for non-relationship variables, which are shown 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, which suggests 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.[14]

Table 4 reports results for the relationship variables. The coefficient on relationship measure R1 is significantly positive; hence relationship accounts have higher utilization rates than non-relationship accounts, ceteris paribus. Relative to an average utilization rate of about 20 p.p., the average difference of 7 p.p. is substantial.[15] Using measure R2, utilization significantly and monotonically increases with the number of relationships. The utilization rate is 2 p.p. higher for accounts with one other relationship, and 14 p.p. higher for accounts with at least six other 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, 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, 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.

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

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

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

Table 3
Implications of relationships for attrition.

Variable	Attrition			
	Coeff	Std Err	*P*-value	Marg Eff
R 1. Relationship				
Relationship Indicator	−0.5607	0.0950	<0.0001	11.6%
R 2. Breadth of Relationships				
Number of Bank Relationships = 1	−0.8552	0.0764	<0.0001	3.2%
=2	−0.7798	0.0696	<0.0001	3.8%
=3	−0.7196	0.0807	<0.0001	10.6%
=4	−0.9266	0.0968	<0.0001	14.6%
=5	−0.9731	0.1146	<0.0001	18.4%
=6+	−0.6895	0.0799	<0.0001	21.4%
R 3. Type of Relationships (Broad)				
Deposit Relationships	−0.1067	0.0474	<0.0001	11.3%
Investment Relationship	−0.2889	0.0396	<0.0001	13.3%
Loan Relationship	−0.2457	0.1294	<0.0001	7.8%
R 4. Type of Relationships (Narrow)				
Checking Dummy	−0.1537	0.0295	<0.0001	10.3%
Savings Dummy	−0.1251	0.0500	<0.0001	6.4%
Brokerage Dummy	−0.6333	0.0759	<0.0001	2.4%
CD Dummy	−0.2469	0.0764	<0.0001	5.7%
Mutual Fund Dummy	−0.1103	0.0698	<0.0001	12.6%
Home Equity Line Dummy	−0.2772	0.1006	<0.0001	5.0%
Home Equity Loan Dummy	−0.2178	0.0623	<0.0001	2.1%
Mortgage Loan Dummy	−0.2079	0.1172	<0.0001	1.2%
R 5. Length of Relationships				
Age of Checking Relationship	−0.0004	0.0002	<0.0001	5.0%
Age of Savings Rel	−0.0005	0.0003	<0.0001	5.9%
Age of Brokerage Rel	−0.0064	0.0016	<0.0001	5.5%
Age of CD Rel	−0.0009	0.0002	<0.0001	1.7%
Age of Mutual Fund Rel	−0.0008	0.0002	<0.0001	4.9%
Age of Home Equity Line Rel	−0.0014	0.0001	<0.0001	3.5%
Age of Home Equity Loan Rel	−0.0015	0.0002	<0.0001	1.7%
Age of Mortgage Loan Rel	−0.0021	0.0009	<0.0001	0.9%
R 6. Combined Relationship Measures				
Number of Bank Relationships = 1	−0.8500	0.0755	<0.0001	1.8%
= 2	−0.7809	0.0693	<0.0001	2.0%
= 3	−0.7103	0.0806	<0.0001	9.6%
= 4	−0.9212	0.0952	<0.0001	13.9%
= 5	−0.9648	0.1138	<0.0001	18.2%
= 6+	−0.6864	0.0796	<0.0001	20.5%
Checking Dummy	−0.1535	0.0292	<0.0001	8.2%
Savings Dummy	−0.1246	0.0499	<0.0001	5.9%
Brokerage Dummy	−0.6256	0.0756	<0.0001	1.7%
CD Dummy	−0.2458	0.0751	<0.0001	5.3%
Mutual Fund Dummy	−0.1103	0.0687	<0.0001	11.8%
Home Equity Line Dummy	−0.2722	0.1005	<0.0001	4.9%
Home Equity Loan Dummy	−0.2146	0.0620	<0.0001	1.0%
Mortgage Loan Dummy	−0.2070	0.1162	<0.0001	0.6%
Age of Checking Relationship	−0.0004	0.0002	<0.0001	3.6%
Age of Savings Rel	−0.0005	0.0003	<0.0001	4.7%
Age of Brokerage Rel	−0.0064	0.0016	<0.0001	4.1%
Age of CD Rel	−0.0009	0.0002	<0.0001	0.9%
Age of Mutual Fund Rel	−0.0008	0.0002	<0.0001	3.2%
Age of Home Equity Line Rel	−0.0014	0.0001	<0.0001	1.6%
Age of Home Equity Loan Rel	−0.0015	0.0002	<0.0001	0.9%
Age of Mortgage Loan Rel	−0.0020	0.0009	<0.0001	0.1%
State with Branch Indicator	−0.9645	0.0798	<0.0001	2.9%
Relationship * State Branch	−0.8644	0.1034	<0.0001	1.4%
Checking Balance	−0.0240	0.0100	<0.0001	8.8%
Savings Balance	−0.0391	0.0139	<0.0001	5.5%
CD Balance	−0.0595	0.0158	<0.0001	5.0%
Mutual Fund Balance	−0.0497	0.0278	<0.0001	5.5%
Home Equity Line Balance	−0.0184	0.0209	<0.0001	5.5%
Home Equity Loan Balance	−0.0720	0.0495	<0.0001	5.6%

(*continued on next page*)

Table 3 (*continued*)

Variable	Attrition			
	Coeff	Std Err	*P*-value	Marg Eff
Mortgage Loan Balance	−0.1565	0.2358	<0.0001	1.1%
R 7. Depth of Relationships (ln (Bal + $1) & R4)				
Checking Balance	−0.0242	0.0101	<0.0001	9.3%
Savings Balance	−0.0392	0.0140	<0.0001	6.5%
CD Balance	−0.0601	0.0159	<0.0001	5.1%
Mutual Fund Balance	−0.0506	0.0283	<0.0001	5.9%
Home Equity Line Balance	−0.0187	0.0210	<0.0001	6.9%
Home Equity Loan Balance	−0.0724	0.0497	<0.0001	5.8%
Mortgage Loan Balance	−0.1596	0.2396	<0.0001	1.4%
R 8. Change in Balances (ln(Bal) & R7 & R4)				
D(Checking Balance)	−0.6195	0.0552	<0.0001	5.3%
D(Savings Balance)	−0.3557	0.0018	<0.0001	5.8%
D(Mutual Fund Balance)	−0.4797	0.1071	<0.0001	2.1%
D(Home Equity Line Balance)	−0.1510	0.0057	<0.0001	2.5%
D(External Score)	−0.8771	0.2081	<0.0001	13.5%
D(Internal Score)	−0.4872	0.2255	<0.0001	14.5%
R 9. Volatility of Balances (sd(12) & R7 & R4)				
sd(Checking Balance)	0.8699	0.1779	<0.0001	12.4%
sd(Savings Balance)	0.3015	0.0512	<0.0001	3.8%
sd(Mutual Fund Balance)	0.8418	0.2345	<0.0001	3.1%
sd(Home Equity Line Balance)	0.4405	0.1275	<0.0001	8.7%
sd(External Score)	0.7632	0.2051	<0.0001	10.9%
sd(Internal Score)	0.7232	0.3451	<0.0001	16.9%
R 10. Change in Volatility (D(sd(6)) & R7 & R4)				
D(sd(Checking Balance))	0.4981	0.0454	<0.0001	5.2%
D(sd(Savings Balance))	0.4849	0.1062	<0.0001	14.4%
D(sd(Mutual Fund Balance))	0.7144	0.2951	<0.0001	11.7%
D(sd(Home Equity Line Balance))	0.7132	0.1934	<0.0001	11.9%
D(sd(External Score))	0.8707	0.1991	<0.0001	16.4%
D(sd(Internal Score))	0.9569	0.0943	<0.0001	12.8%
R 11. Low Checking Balances (& R7 & R4)				
Indicator(Balance < $2000)	0.5386	0.1412	<0.0001	13.0%
Controls	Yes			
Number of Obs / Number Attrition	1,132,182	12,649		

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

4. Possible explanations

Our main results demonstrate that on average, relationship accounts exhibit lower probabilities of default and attrition and have higher utilization rates, compared to non-relationship accounts. Though results are consistent with the presence of relationship banking effects, multiple hypotheses could explain the above relations. There are two main explanations in the literature: the selection mechanism and the private information mechanism. This section conducts several tests to investigate these alternative explanations.

The first hypothesis is that our results could have been driven primarily by the selection mechanism. Specifically, two issues are associated with selection. The first 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 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 relationship information in its underwriting decisions. To address this issue, our strategy is to estimate empirical specifications with the credit card's APR and credit line limit when the account was opened as dependent variables and a set of variables used in the lender's underwriting process as independent variables. The relationship variable is also included in the regressions to test whether it plays a significant

Table 4
Implications of relationships for utilization.

Variable	Utilization rate		
	Coeff	Std Err	P-value
R 1. Relationship			
Relationship Indicator	0.0680	0.0109	<0.0001
R 2. Breadth of Relationships			
Number of Bank Relationships = 1	0.0241	0.0027	<0.0001
=2	0.0292	0.0029	<0.0001
=3	0.0517	0.0029	<0.0001
=4	0.0690	0.0030	<0.0001
=5	0.0954	0.0031	<0.0001
=6+	0.1378	0.0031	<0.0001
R 3. Type of Relationships (Broad)			
Deposit Relationships	0.0730	0.0012	<0.0001
Investment Relationship	0.1032	0.0011	<0.0001
Loan Relationship	0.0324	0.0073	<0.0001
R 4. Type of Relationships (Narrow)			
Checking Dummy	0.0931	0.0011	<0.0001
Savings Dummy	0.0576	0.0013	<0.0001
Brokerage Dummy	0.0930	0.0025	<0.0001
CD Dummy	0.0755	0.0017	<0.0001
Mutual Fund Dummy	0.0297	0.0027	<0.0001
Home Equity Line Dummy	0.0484	0.0026	<0.0001
Home Equity Loan Dummy	0.0334	0.0030	<0.0001
Mortgage Loan Dummy	0.0373	0.0089	<0.0001
R 5. Length of Relationships			
Age of Checking Relationship	0.0002	0.0000	<0.0001
Age of Savings Rel	0.0003	0.0000	<0.0001
Age of Brokerage Rel	0.0007	0.0000	<0.0001
Age of CD Rel	0.0001	0.0000	<0.0001
Age of Mutual Fund Rel	0.0009	0.0000	<0.0001
Age of Home Equity Line Rel	0.0007	0.0000	<0.0001
Age of Home Equity Loan Rel	0.0001	0.0001	<0.0001
Age of Mortgage Loan Rel	0.0003	0.0001	<0.0001
R 6. Combined Relationship Measures			
Number of Bank Relationships = 1	0.0230	0.0026	<0.0001
= 2	0.0290	0.0027	<0.0001
= 3	0.0490	0.0028	<0.0001
= 4	0.0662	0.0028	<0.0001
= 5	0.0935	0.0030	<0.0001
= 6+	0.1368	0.0029	<0.0001
Checking Dummy	0.0910	0.0011	<0.0001
Savings Dummy	0.0563	0.0013	<0.0001
Brokerage Dummy	0.0871	0.0024	<0.0001
CD Dummy	0.0722	0.0016	<0.0001
Mutual Fund Dummy	0.0289	0.0025	<0.0001
Home Equity Line Dummy	0.0462	0.0025	<0.0001
Home Equity Loan Dummy	0.0318	0.0029	<0.0001
Mortgage Loan Dummy	0.0349	0.0087	<0.0001
Age of Checking Relationship	0.0002	0.0000	<0.0001
Age of Savings Rel	0.0003	0.0000	<0.0001
Age of Brokerage Rel	0.0007	0.0000	<0.0001
Age of CD Rel	0.0001	0.0000	<0.0001
Age of Mutual Fund Rel	0.0009	0.0000	<0.0001
Age of Home Equity Line Rel	0.0006	0.0000	<0.0001
Age of Home Equity Loan Rel	0.0001	0.0001	<0.0001
Age of Mortgage Loan Rel	0.0003	0.0001	<0.0001
State with Branch Indicator	0.0456	0.0031	<0.0001
Relationship * State Branch	0.0436	0.0033	<0.0001
Checking Balance	0.0331	0.0004	<0.0001
Savings Balance	0.0824	0.0005	<0.0001
CD Balance	0.0228	0.0005	<0.0001
Mutual Fund Balance	0.0225	0.0007	<0.0001
Home Equity Line Balance	0.0573	0.0006	<0.0001
Home Equity Loan Balance	0.0140	0.0022	<0.0001
Mortgage Loan Balance	0.0636	0.0080	<0.0001

(*continued on next page*)

Table 4 (*continued*)

Variable	Utilization rate		
	Coeff	Std Err	*P*-value
R 7. Depth of Relationships (ln (Bal + $1) & R4)			
Checking Balance	0.0341	0.0004	<0.0001
Savings Balance	0.0822	0.0005	<0.0001
CD Balance	0.0231	0.0005	<0.0001
Mutual Fund Balance	0.0231	0.0007	<0.0001
Home Equity Line Balance	0.0594	0.0007	<0.0001
Home Equity Loan Balance	0.0138	0.0023	<0.0001
Mortgage Loan Balance	0.0652	0.0080	<0.0001
R 8. Change in Balances (ln(Bal) & R7 & R4)			
D(Checking Balance)	0.0185	0.0000	<0.0001
D(Savings Balance)	0.0162	0.0001	<0.0001
D(Mutual Fund Balance)	0.0029	0.0003	<0.0001
D(Home Equity Line Balance)	−0.0175	0.0001	<0.0001
D(External Score)	0.0178	0.0089	<0.0001
D(Internal Score)	0.0200	0.0077	<0.0001
R 9. Volatility of Balances (sd(12) & R7 & R4)			
sd(Checking Balance)	−0.0157	0.0018	<0.0001
sd(Savings Balance)	−0.0338	0.0023	<0.0001
sd(Mutual Fund Balance)	−0.0631	0.0009	<0.0001
sd(Home Equity Line Balance)	−0.0240	0.0051	<0.0001
sd(External Score)	−0.0161	0.0001	<0.0001
sd(Internal Score)	−0.0560	0.0243	<0.0001
R 10. Change in Volatility (D(sd(6)) & R7 & R4)			
D(sd(Checking Balance))	−0.0004	0.0001	<0.0001
D(sd(Savings Balance))	−0.0002	0.0003	<0.0001
D(sd(Mutual Fund Balance))	−0.0030	0.0002	<0.0001
D(sd(Home Equity Line Balance))	−0.0004	0.0000	<0.0001
D(sd(External Score))	−0.0012	0.0015	<0.0001
D(sd(Internal Score))	−0.0007	0.0001	<0.0001
R 11. Low Checking Balances (& R7 & R4)			
Indicator(Balance < $2000)	−0.0567	0.0590	0.8322
Controls	Yes		
Number of Obs	1,132,182		

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

role in determining credit terms (APR and limit). Results are reported in Appendix Table 4. Coefficients of the relationship variable are insignificant in both regressions, implying that the bank was not using cross-account information to set credit terms.

The second issue associated with selection is the effect of relationship banking as a reflection of 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 credit card offerings with inferior credit terms are more likely to attract risky borrowers without a prior relationship with the issuer, the better performance of relationship accounts relative to non-relationship accounts cannot be attributed to the banking relationship. Instead, the difference in performance between relationship borrowers and non-relationship borrowers is linked to their riskiness at origination. To investigate the presence of a self-selection effect, our strategy is to use propensity-score matching to control for selection on observables and use changes in borrowers' credit score after credit card issuance to study selection on unobservables. First, a matched sample is constructed using propensity-score matching to ensure that the group of relationship accounts is paired with a comparable group of non-relationship accounts. Matched non-relationship accounts are selected by the nearest-neighbor algorithm without replacement, based on the computed propensity scores. We first test whether relationship and non-relationship accounts are comparable. Compared to non-relationship accounts, 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, relationship and non-relationship accounts are mostly comparable to each other. The results of propensity score matching are shown in Table 5. For relationship accounts, the marginal probabilities of default and attrition are about 12% and 13% lower, respectively, than those of accounts without other relationships, ceteris paribus. Relationship accounts have a 7 per-

Table 5
Propensity score matching.

Relationship variable	Default			Attrition			Utilization rate		
	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	<0.0001	13%	0.070	0.010	<0.0001
R 2. Breadth (#) of Relations									
1	−0.243	<0.0001	4%	−0.817	<0.0001	3%	0.023	0.003	<0.0001
2	−0.220	<0.0001	6%	−0.753	<0.0001	5%	0.027	0.003	<0.0001
3	−0.317	0.000	10%	−0.704	<0.0001	11%	0.052	0.003	<0.0001
4	−0.256	0.000	12%	−0.901	<0.0001	16%	0.068	0.003	<0.0001
5	−0.650	0.028	16%	−0.966	<0.0001	17%	0.097	0.003	<0.0001
6+	−0.599	0.028	19%	−0.628	<0.0001	22%	0.134	0.003	<0.0001
R 3. Type of Relations (Broad)									
Deposit Relationships	−0.226	<0.0001	10%	−0.108	<0.0001	12%	0.072	0.001	<0.0001
Investment	−0.327	<0.0001	21%	−0.278	<0.0001	13%	0.098	0.001	<0.0001
Loan	−0.031	<0.0001	5%	−0.230	<0.0001	9%	0.032	0.007	<0.0001
R 4. Type of Relations (Narrow)									
Checking	−0.115	<0.0001	7%	−0.144	<0.0001	10%	0.094	0.001	<0.0001
Savings	−0.267	<0.0001	12%	−0.127	<0.0001	7%	0.055	0.001	<0.0001
Brokerage	−0.240	< 0.0001	16%	−0.634	<0.0001	2%	0.087	0.002	< 0.0001
CD	−0.441	<0.0001	22%	−0.227	<0.0001	6%	0.068	0.002	<0.0001
Mutual Fund	−0.360	<0.0001	20%	−0.100	<0.0001	13%	0.028	0.003	<0.0001
Home Equity Line	−0.015	<0.0001	8%	−0.272	<0.0001	5%	0.046	0.003	<0.0001
Home Equity Loan	−0.010	<0.0001	2%	−0.200	<0.0001	2%	0.033	0.003	<0.0001
Mortgage Loan	−0.016	<0.0001	3%	−0.200	<0.0001	3%	0.035	0.009	<0.0001
Controls	Yes			Yes			Yes		
Number of Obs	837,212			837,212			837,212		

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. Explanatory variables include macro-demographic, loan-performance, credit-bureau, and relationship variables, in addition to month and state dummies. The table reports only results for relationship variables R1–R4; each panel represents a separate specification. Relationship variables are defined in Table 2. Standard errors are adjusted for heteroscedasticity across accounts and serial correlation within accounts.

centage points higher utilization rate than non-relationship accounts, ceteris paribus. Results from the matched sample are largely consistent with the main results in terms of directions and magnitudes. In other relationship measures, relationship accounts also have lower default and attrition, but higher utilization rates compared to accounts without other relationships. These results suggest that our results are unlikely to be due to selection.

Although a matching approach is used to ensure that the relationship and non-relationship groups are comparable, selection can also be an unobserved risk type. To address this issue, our strategy is to run a second test by comparing changes in accounts' credit quality, after booking, between borrowers with and without prior relationships with the bank. Specifically, our analysis assesses 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. The FICO score measures the relative credit quality of an individual account (given that a FICO score comes from credit bureaus and reflects the account holder's credit and debt repayment activities across all credit products he/she holds, it can be informative regarding 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 other loans). The FICO score 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, there should be a more severe deterioration ex post in the credit quality (FICO score) of non-relationship accounts relative to relationship accounts. Appendix Table 5 reports regression results on changes in FICO scores of accounts at 12 and 24 months after origination. The results show that between the relationship and non-relationship account groups, changes in FICO scores at 12 or 24 months subsequent to origination remain similar. Hence, there was no (economically or statistically) significant deterioration in the credit quality of non-relationship accounts relative to relationship accounts. These results also fail to support a self-selection effect.

Another type of selection might be the higher perceived default costs associated with relationship accounts. Borrowers with prior relationships are more likely to build loyalty for the lender, and thus become more reluctant to default on credit card debt. Alternatively, borrowers with prior relationships may believe 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 judgments. If relationship accounts have higher perceived default costs compared to non-relationship accounts, relationship accounts would deliberately avoid default on their credit card debt with the lender, even when facing adverse economic/financial shocks. With this reasoning, we construct a subsample that includes accounts that experienced severe deterioration ex post in credit quality. For our analysis, an account is defined to experience severe deterioration ex post if the FICO score dropped by 50 points, controlling for initial FICO scores. In this subsample, our analysis compares the difference in default probabilities between relationship and non-relationship accounts. Appendix Table 6 presents the results. The results show no significant difference between the two groups. The evidence suggests that no higher perceived default costs are associated with relationship accounts.

This paper also explores our data's dynamic information to study the private information mechanism. Our panel data can measure some relationship information that is inherently dynamic, such as high-frequency changes in the level and volatility of the balances in other relationships. In our analysis of dynamic information (R8–R10), changes in 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 the private information mechanism: information the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used to mitigate credit risk on the credit card account. Our dataset does not have measures that identify lenders' direct interventions after observing these changes in borrowers' other accounts. In practice, when banks observe that a borrower's credit score drops suddenly, they might raise the interest rate, cut the credit line, or even freeze the credit line. Typical credit card contracts specify that if credit quality changes, the lender has the discretion to alter the pricing and quantity of credit. There are relevant examples in the CFPB credit card agreement database.[16] For instance, the Bank of America's credit card agreement says, "We reserve the right to amend this Agreement at any time." Reasons 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 this with the lender of our data which confirmed that it will alter contract terms upon deterioration in credit scores at its discretion.

In sum, the observed results are not due to selection or higher perceived default costs, but rather are consistent with a monitoring explanation. Information the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used to mitigate credit risk on the credit card account.

5. Conclusion

This study provides direct evidence of the potential benefits of relationship banking to retail banks. 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 and 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, as one of the 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. They are, however, consistent with a monitoring explanation: Information the lender has at its disposal on the dynamics of the relationship borrower's other accounts can be used to mitigate credit risk on the credit card account.

These results imply that relationship information is valuable in a predictive sense, but exactly how banks should use this information requires additional consideration. The optimal use of information and optimal contract design, both from the bank's point of view and socially, is an important but difficult question that is beyond the scope of this paper. First, banks must consider how consumers and their competitors would respond to use of the information. Second, government policies can restrict the use of certain 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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2018.02.005.

References

Agarwal, S., Hauswald, R., 2008. The Choice between arm's-length and relationship debt: evidence from Eloans. FRB of Chicago Working Paper No. 2008–10. Available at SSRN: https://ssrn.com/abstract=1306455.
Agarwal, S., Hauswald, R., 2010. Distance and private information in lending. Rev. Financ. Stud. 23, 2757–2788.
Agarwal, S., Song, C., Yao, V., 2017. Relational contracts, reputational concerns, and appraiser behavior: evidence from the housing market. Georgetown McDonough School of Business Research Paper No. 3076944. Available at SSRN: https://ssrn.com/abstract=3076944.
Berger, A.N., Udell, G.F., 1995. Relationship lending and lines of credit in small firm finance. J. Busin. 68, 351–381.
Bharath, S., Dahiya, S., Saunders, A., Srinivasan, A., 2011. Lending relationships and loan contract terms. Rev. Financ. Stud. 24, 1141–1203.
Billet, M.T., Flannery, M.J., Garfinkel, J.A., 1995. The effect of lender identity on a borrowing firm's equity return. J. Finance 50, 699–718.
Bolton, P., Scharfstein, D.S., 1996. Optimal debt structure and the number of creditors. J. Polit. Econ. 104, 1–25.
Boot, A., 2000. Relationship banking: What do we know. J. Financ. Interm. 9, 7–25.
Boot, A., Thakor, A.V., 1994. Moral hazard and secured lending in an infinitely repeated credit market game. Int. Econ. Rev. 35, 899–920.
Chakravarty, S., Scott, J.S., 1999. Relationships and rationing in consumer loans. J. Busin. 72, 523–544.
Degryse, H., Ongena, S., 2005. Distance, lending relationships, and competition. J. Finance 60, 231–266.

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

Dewatripont, M., Maskin, E., 1995. Credit and efficiency in centralized and decentralized economies. Rev. Econ. Stud. 62, 541–555.
Ergungor, O.E., Moulton, S., 2014. Beyond the transaction: banks and mortgage default of low-income homebuyers. J. Money Credit Bank. 46, 1721–1752.
Gross, D., Souleles, N.S., 2002. An empirical analysis of personal bankruptcy and delinquency. Rev. Financ. Stud. 15, 319–347.
Ivashina, V., Kovner, A., 2011. The private equity advantage: leveraged buyout firms and relationship banking. Rev. Financ. Stud. 24, 2462–2498.
Kysucky, V., Norden, L., 2016. The benefits of relationship lending in a cross-country context: a meta-analysis. Manag. Sci. 62, 90–110.
Mester, L.J., Nakamura, L.I., Renault, M., 2007. Transactions accounts and loan monitoring. Rev. Financ. Stud. 20, 529–556.
Musto, D., Souleles, N.S., 2006. A portfolio view of consumer credit. J. Monet. Econ. 53, 59–84.
Norden, L., Weber, M., 2010. Credit line usage, checking account activity, and default risk of bank borrowers. Rev. Financ. Stud. 23, 3665–3699.
Ongena, S., Smith, D., 2001. Empirical evidence on the duration of banking relationships. J. Financ. Econ. 61, 449–475.
Petersen, M.A., Rajan, R.G., 1994. The benefits of lending relationships: evidence from small business data. J. Finance 49, 3–37.
Petersen, M.A., Rajan, R.G., 2002. Does distance still matter? The information revolution in small business lending. J. Finance 57, 2533–2570.
Puri, M., Rocholl, J., 2008. On the importance of retail banking relationships. J. Financ. Econ. 89, 253–267.
Puri, M., Rocholl, J., Steffen, S., 2017. What do a million observations have to say about loan defaults? Opening the black box of relationships. J. Financ. Intermed. 1–15.
Rajan, R.G., 1992. Insiders and outsiders: The choice between informed and arm's-length debt. J. Finance 47, 1367–1400.
Sharpe, S., 1990. Asymmetric information, bank lending and implicit contracts: a stylized model of customer relationships. J. Finance 45, 1069–1366.
Slovin, M.B., Sushka, M.E., Polocheck, J.A., 1993. The value of bank durability: borrowers as bank stakeholders. J. Finance 48, 247–266.
Wilson, P.F., 1993. The pricing of loans in a bank–borrower relationship. Working Paper, Indiana University.
Yasuda, A., 2005. Do bank relationships affect the firm's underwriter choice in the corporate-bond underwriting market. J. Finance 60, 1259–1292.