Friendship Matters Less on a Rainy Day: Firm Outcomes and Relationship Bank Health

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Abstract

We examine the differential impacts of lending relationships on firm outcomes depending on individual bank health. We find that the information benefit dominates when the relationship bank is healthy but is swamped by hold up costs when it is not. We study this differential benefit of relationships on loan availability, loan terms, and firm outcomes. Our empirical strategy employs an instrument for endogenous relationships using heteroskedasticity of independent regressors and a new measure of bank health to overcome endogeneity of the standard measures. Results suggest that the decline of lending relationships in recent decades has conflicting effects on loan availability and terms due to the changing health of the relationship banks.

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1 Introduction

Firms, both small and large, have lending relationships with banks.[1] Of all public firms demanding credit in any quarter between 1990Q1 and 2012Q4, 48% took a loan from a top-50 bank(s) that they had transacted with in the previous five years. Over the past two decades, however, the concentration of banking relationships has declined. The average number of banks that our sample firms have a relationship with increased from 0.38 in 1990 to 2.09 in 2011, indicating that firms are entering repeat transactions with a larger set of banks over time. Similarly, as Figure 1 shows, the average share of any one bank in the total dollar value of bank loans taken by these firms over five years preceding a quarter has declined over the sample period from 80% in 1990Q1 to less than 50% in 2011Q4.[2] While a large literature shows the information benefits of relationships, several studies also document the negative effects. A developed firm bank relationship benefits the firm in that repeated exposure to the firm resolves some uncertainty about the firm for the lending bank. But this relationship creates a hold-up problem since the firm may be unable to switch to another bank, which can have negative consequences, especially when the relationship bank experiences a negative shock. Thus, it is unclear whether the steady fall in the prevalence of relationships has positive or negative implications for firm outcomes. In this paper, we argue that the answer depends systematically on bank health.

We show that lending relationships exacerbate the effect of bank health on the likelihood of obtaining a loan. An improvement in bank health is associated with a greater increase in the likelihood of obtaining a loan for a firm the stronger its relationship with the bank. On the other hand, a deterioration in bank health entails a negligibly higher likelihood of obtaining a loan for the firm that has a stronger relationship with that bank. We are the first to provide direct evidence of the information benefit coexisting with the hold-up problem in terms of loan availability. Further, by demonstrating the asymmetric effects of relationships during upturns and downturns, we are able to reconcile the large number of studies that argue that relationships are beneficial to firms with those that lament their existence during crises.

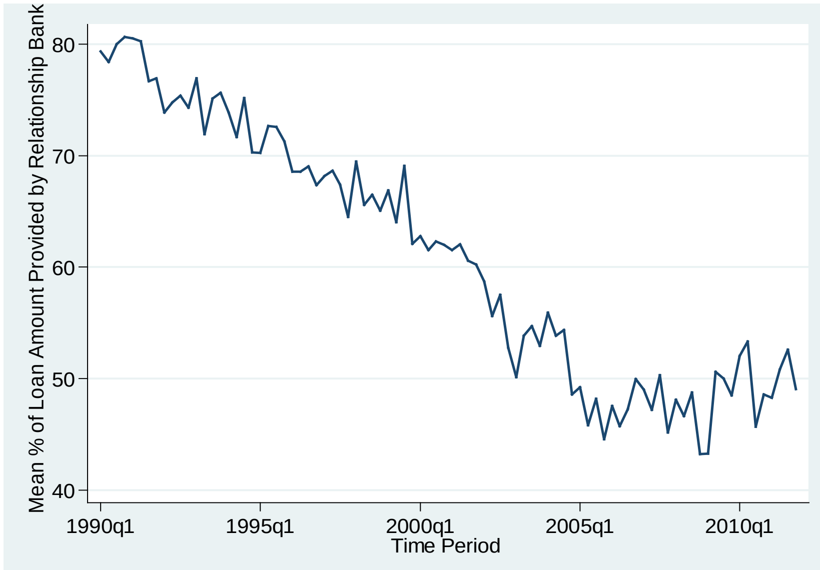
To the best of our knowledge, we are the first to provide direct evidence of the information benefit of lending relationships coexisting with the hold-up problem in terms of loan availability. When banks see an improvement in their health, it is willing to lend more to all firms that they deem credit worthy. In this case, there is little or no hold-up problem faced by firms with a relationship with the bank since they do not want to switch away from a healthy bank. With the hold-up cost decreased when bank health is good, the relationship benefit will be higher compared to when the hold-up cost is increased when bank health is poor. In the latter case,

[1] Relationship lending refers to lending decisions based on soft information that is gathered over multiple interactions between the bank and the firm (the relationship). This type of lending stands in contrast to transaction lending, in which lending decisions are based entirely on hard information which is easily transferred between parties and requires no previous interactions between firm and bank.

[2] This trend mirrors the decline of relationship lending to SMEs documented in several previous studies, including Petersen and Rajan [1995] and Berger [2003]. Just as in the case of SMEs, this decline may be attributable to changes in banking industry regulations and lending technologies.

we see the dominance of the hold-up effect so that the information benefit is all but eliminated. Essentially, the firm becomes so dependent on the relationship bank that it finds it too costly to switch to another bank.

Figure 1: Declining Strength of Bank-Firm Relationships[a]



[a]The figure plots the quarterly mean of the percentage of firms' total bank loans over the five years preceding a given quarter that came from any one bank. Firms in the sample are all publicly traded U.S. firms that obtain credit (either bank loans or public debt) in a given quarter. The sample includes top-50 banks by share of total bank loans supplied in a given quarter.

We use data on publicly traded firms (Compustat) and their debt, either as bank loans (LPC DealScan) or as bond issues (Thompson OneBanker). We measure relationships as the percentage provided by any one bank of the total number or total dollar amount of bank loans taken by firms within the preceding five years of a given quarter.[3] Following Becker and Ivashina [2014], we include only those firms that have positive credit demand in a quarter, measured as those who either issued public debt or obtained bank loans.[4] This enables us to isolate the impact of credit supply shocks on firm bank relationship benefits from concurrent effects of changes in credit demand. Our relationship measure is endogenous - a problem that has also plagued previous literature.[5] We overcome this issue by using a novel instrument for relationships based on the heteroskedasticity of independent regressors as proposed by Lewbel [2012].

Another methodological contribution of our paper is to use an exogenous measure of bank health. To measure bank health, we first define as a bank's borrower base the set of firms to

[3]These measures are similar to those used by Bharath et al. [2007]

[4]Consistent with Becker and Ivashina [2014], we also find that only a small fraction of firms both issue debt and obtain a bank loan in the same quarter.

[5]Distance between banks and firms has been used as an instrument but has become increasingly irrelevant over time, especially in the case of large banks lending to large firms.

which it issued loans in the five year period preceding the given quarter. Then, we consider the smaller subset of firms in this borrower base that demand debt in the current quarter. Our measure of bank health is then given by the percentage of these debt demanding firms that receive loans from the given bank in the given quarter. This yields a continuous, bank specific measure of credit supply.[6] It also overcomes the endogeneity of more standard bank health measures.

There are three main takeaways of our empirical results. (1) We find that both bank health and relationship strength are positively associated with firms' likelihood of obtaining a loan. While bank health is also associated with smaller loan spreads, relationships do not have a strong relation with loan spreads.[7] As expected, relationship effects are weaker for more informationally transparent firms. (2) Relationships exacerbate the effect of bank health on the likelihood of obtaining a loan. A firm at the 75th percentile of relationship strength is a whopping 23.1% more likely to get a loan than the one at the 25th percentile when the relationship bank's health is high (at its 75th percentile level). In contrast, a firm at the 75th percentile of relationship strength is only 5.68% more likely to get a loan than the one at the 25th percentile when the relationship bank's health is low (at its 25th percentile level). This result is robust across several definitions of changes in bank health. (3) The effects of relationships, both positive and negative, for various firm outcomes have become smaller in recent years, owing to the decline in relationships over time.

Our paper relates to the large literature on lending relationships. The information benefits and the hold-up problem of relationships have been discussed in theory (see Petersen and Rajan [1994],Petersen and Rajan [1995], and Boot [2000], among others). However, empirical evidence of the hold-up problem has largely been elusive. One paper that provides evidence of this is Petersen and Rajan [1994] who show that while the information benefit resulting from relationships does yield higher loan availability, it does not translate into lower interest rates. They argue that the latter result indicates rent extraction by relationship banks, i.e., the hold-up problem. Slovin et al. [1993] shows that firms with relationships with the troubled Continental Illinois Bank fared worse than firms not related to this bank during the banks near failure in 1984. We contribute to this literature by showing direct evidence of the hold up costs. We find empirical evidence for the channel through which bank health affects dependent firms by examining the effect of worsening bank health on loan availability, loan terms, firm employment, and firm output.

As mentioned earlier, conventional wisdom suggests that relationship lending is predominantly the mode for lending to SMEs that are often informationally opaque, requiring banks

[6]Our measure of bank health adapts the aggregate measure used by Becker and Ivashina [2014] to the level of an individual bank.

[7]Previous literature finds mixed results for whether relationships improve loan terms. For instance, while Petersen and Rajan [1994] find that relationships increase loan availability but not loan terms, Berger and Udell [1995] find that both loan availability and interest rates improve with relationships. However, most of these studies consider SMEs. Bharath et al. [2009] do find a reduction of 10-17 bps in loan spreads when large firms take loans repeatedly from the same lender.

to rely heavily on soft qualitative information (for instance, Petersen and Rajan [1994], Berger and Udell [1995] and Degryse and Van Cayseele [2000]). This information may be difficult to quantify and objectively communicate between different bank branches or loan officers, and includes such knowledge as subjective circumstances of the firm, reputation and credit history of the firm owner(s) or management, etc. Studies also argue that relationship lending to small firms is mainly provided by small banks that may have the flexibility to use such information (see Stein [2002] and Cole et al. [2004]). We show, however, that bank-firm relationships exist even between large firms and large banks, measured in terms of concentration or length of relationship. The importance of relationships for large, publicly traded firm outcomes that suffer much less from informational opacity than SMEs and have many sources of credit besides bank debt shows that soft information exists even for these firms.

We are not the first, however, to consider banking relationships in the context of large firms. Closest to our paper are two studies by Bharath et al. (2007. 2009). However, while Bharath et al. [2007] examine how banks benefit from having a relationship with firms, Bharath et al. [2009] show that loan spreads are reduced for firms with relationships with banks. They do not examine other firm outcomes that we consider - loan availability, employment, and output. Further, neither study examines how relationship effects vary with bank health. Chodorow-Reich [2014] showed that, during the Great Recession, deterioration in bank health had negative employment effects for relationship borrowers since they were unable to cheaply switch to healthier banks, suggesting that bank-firm relationships are "sticky." Our paper is different in three ways. First, we examine the impact of relationships not only when the bank health falls but also when it improves. This is significant because, as we show, the effects of relationships do not work in the same direction during upturns and downturns in bank health. Second, our measure of bank health allows us to look beyond nationwide financial crises. Instead, we are able to measure the health of individual banks which can fluctuate even when there is no macroeconomic crisis. Third, our measures of relationship focus more directly on firm dependence on banks as opposed to Chodorow-Reich [2014] who considers relationship borrowers as those who have taken previously taken a loan from the same bank. Ivashina and Kovner [2011] also consider relationships between large banks and firms but focus on an entirely different question. They examine how bank relationships influence syndicated loan terms for leveraged buyout firms. Their focus, in contrast to the focus of our paper, is on leveraged buyout firms. Further, they do not examine how relationships impact the effects of lenders' health, and do not focus on real outcomes like employment and output.

We continue to work on more results. In the next draft of our paper, we will also examine the impact of relationships on firm employment and output. Moreover, it is possible that even after controlling for bank, time, and industry fixed effects and including proxies for firm quality such as size, age, and credit rating, there may still be other unobservable aspects of firms that simultaneously determine relationship strength and our outcomes of interest, rendering our relationship variable endogenous. In our next draft, we will use an instrument for relationship strength which relies on the heteroskedasticity of independent regressors developed in Lewbel [2012]. Finally, we will also account for mergers and acquisitions of banks and firms over this time period.

The rest of the paper is organized as follows. Section 2 explains the empirical strategy. In section 3, we describe the data and present descriptive statistics. Section 4 discusses our main results. Section 5 concludes.

2 Empirical Methodology

2.1 Tests of Hypothesis 1

In this section, we will examine the effect of relationships on *the likelihood of obtaining a loan.* This section will describe the test of the following hypothesis:

Hypothesis 1 *H1. The likelihood of obtaining a loan from a bank increases with the strength of the relationship between the firm and the bank.*

Tests of Hypothesis 1.1

We further test how the effect of relationship on the likelihood of obtaining a loan *differs* given the health of the lending bank. Specifically, we examine the following hypothesis:

Hypothesis 1.1 *H1.1. The magnitude of the impact of relationship strength on the likelihood of obtaining a loan depends on the state of bank health.*

The first firm outcome of interest is the likelihood of a debt demanding firm receiving a loan from a given bank. We define the variable $(BankLoan)_{i,j,t}$ as an indicator variable taking the value one when bank j serves as a lead bank on a bank loan issued to firm i at time t. The variable takes the value of zero when firm i does not get a loan from bank j as a lead bank in quarter t. We focus on lead lenders because they are responsible for both setting the loan terms and monitoring the loan. Note that there can be multiple lead lenders on a given loan. We examine whether or not the likelihood of obtaining a bank loan depends on the relationship with the lead lender and how this dependence varies with the health of the bank. Specifically, to test hypothesis H1.1, we estimate the following model:

$$\begin{aligned}(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) \\ + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}\end{aligned} \tag{2.1}$$

where τ_t, η_i, and ν_j represent time, industry, and bank fixed effects, respectively. The coefficients of interest for evaluating hypothesis H1.1 are β_1 and β_3. Recall that firms with banking relationships face a tradeoff between the information benefits of a banking relationship and the hold-up costs. If the information effect dominates, we expect the coefficient β_1 to be positive, indicating that the presence of a relationship increases the likelihood of receiving a loan. This tradeoff becomes especially important in times of financial crisis for the lead bank. If in times of crisis, when $BH_{j,t}$ is low, the hold-up cost dominates, then we expect the coefficient β_3 to be positive, suggesting that a banking relationship decreases the likelihood of obtaining a loan in times of crisis relative to a firm with less of a relationship.

In order to test H1.1 using the model presented above, some attention is needed to defining the estimation universe. In order to examine the bank-firm pair choice *a priori*, we follow the methodology of Bharath et al. [2007] and create a choice set of 50 potential lenders for each firm in a given quarter. These possible lenders are identified as those lenders ranked in the top 50 by total dollar amount lent in a given quarter. This strategy, necessary to economize the size of the data set given that our unrestricted universe contains more than 11,000 unique bank and non-bank lenders, relies on the observation that a small number of commercial banks is responsible for a large percentage of overall lending. Note that with this strategy of generating all *a priori* firm - bank pairs, we are able to observe both firms with relationships and those without. In other words, if we were to condition only on observed bank-firm pairs, we would ignore the information in the choice of firms and banks not to match. We are able to exploit this information and contrast relationship and non-relationship firm-bank pairs.

Tests of Hypothesis 1.2

We further examine the tradeoff between information benefits and hold-up costs by examining the differential role of relationships in determining the likelihood of obtaining a loan for firms with varying levels of information asymmetry. Specifically, we examine the following hypothesis:

Hypothesis 1.2 *H1.2. The likelihood of obtaining a loan increases more with the strength of the relationship for informationally opaque firms on average and decreases less with the strength of the relationship when bank health is poor for informationally opaque firms*

We examine how the value of relationships varies with the informational opacity of the firm by estimating the following model

$$\begin{aligned}(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH)_{j,t} + \beta_4(IA_{i,t}) \\ + \beta_5(Rel_{i,j,t}) \times (IA_{i,t}) + \beta_6(Rel_{i,j,t}) \times (IA_{i,t}) \times (BH)_{j,t} \\ + \sum \beta_k(Control_k)_{i,t} \quad + \tau_t \quad + \eta_i \quad + \nu_j \quad + \epsilon_{i,j,t}\end{aligned} \tag{2.2}$$

where $(IA)_{i,t}$ represents a measure of information asymmetry for firm i at time t. We use the following variables as proxies for information asymmetry: firm size, firm age, availability of a credit rating, and investment grade credit rating for those firms with available credit ratings. Small firms, young firms, and firms with unrated debt are all less likely to be monitored by ratings agencies and the financial press and therefore are more likely to suffer more from informational asymmetries. Bharath et al. [2007] also argue that firms with lower credit ratings are also more likely to face information asymmetries. We use each of these measures of information asymmetry to evaluate the cost-benefit tradeoff of relationships.

We posit that the information benefit of relationships is greater for those firms suffering from greater information asymmetries. Assuming that an increase in $IA_{i,t}$ represents an increase (decrease) in information asymmetry, we would expect the coefficient β_5 to be positive (negative). Further, in times of crisis, when the informational benefit of relationships is reduced by the hold-up cost, we would expect this decrease to be smaller (larger) for firms with higher (lower) levels of information asymmetry. Then, when $IA_{i,t}$ represents an increase (decrease) in information asymmetry, we would expect the coefficient β_6 to be negative (positive).

The above models are estimated using a logistic regression. Bank, industry (2 digit SIC 1987 codes), and time fixed effects are included to account for time invariant bank and industry characteristics as well as economy wide time varying factors. Standard errors are clustered by time (quarter*year) and corrected for arbitrary heteroskedasticity.

2.2 Tests of Hypothesis 2

In this section, we will examine the effect of relationships on an additional firm outcome: *the interest rate charged on a loan, conditional on receipt of the loan.* This section will describe the test of the following hypothesis:

Hypothesis 2 *H2. The interest rate charged on a loan depends on the extent of the relationship between the firm and the bank.*

We examine the effects of a lending relationship on the firm's cost of funds by estimating the following model:

$$\begin{aligned}(AIS)_{i,j,t} = \beta_0 &+ \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \beta_4(IA_{i,t}) \\ &+ \beta_5(Rel_{i,j,t}) \times (IA_{i,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}\end{aligned} \tag{2.3}$$

where $AIS_{i,j,t}$ is the all-in-spread drawn, measuring overall loan cost, described in Section 3. In this analysis, a firm is paired with its lead lender(s) on observed loan transactions, recognizing that it is the lead lender(s) that determines the loan terms. With this specification, we examine the overall effect on lead lender relationships on loan rates as well as the *differential* effect on loan rates for firms with varying levels of information asymmetry. The coefficient β_1 represents the *average* effect of relationships on loan rates. The differential effect of relationships on loan rates *over time* is tested by examining the coefficient β_3. If relationships have different effects on loan rates in times of crisis, β_3 will differ significantly from zero. Finally, the differential effect of relationships on loan rates *across firms* is tested by examining the coefficient β_5. If the effect of relationships on loan rates depends on the level of information asymmetry in the firm, the coefficient β_5 will differ significantly from zero.

The above models are estimated using OLS regressions. Bank, industry (2 digit SIC 1987 codes), and time fixed effects are included to account for time invariant bank and industry characteristics as well as economy wide time varying factors. Standard errors are clustered by time (quarter*year) and are corrected for arbitrary heteroskedasticity.

3 Data and Sample Selection

To explore the impact of banking relationships on firm outcomes, we combine data from three primary sources. First, we obtain loan level data from a March 2015 extract of the Loan Pricing Corporation Dealscan (henceforth LPC). These data consist of loan contract information for dollar denominated private syndicated loans made to U.S. corporations over the period 1990 to 2012. The database covers 50% - 75% of the value of all commercial loans in the U.S. (Chava and Roberts [2008]). [8] Using this database, we obtain specific loan terms and construct our measures of banking relationships by observing a firm's borrowing history. Second, we obtain data on commercial bond issues from Thomson One Banker. The data consist of bond issue details for all U.S. public bond issues during the period 1990 to 2012. Combining the loan and bond data, we are able to identify the population of firms with non-zero demand for debt (either bank debt or public debt) in a given quarter. Finally, we obtain quarterly firm level data from Compustat, which covers all publicly traded firms. We then combine the firm level data with the loan contract data and the public bond issue data in order to observe the impact of relationship lending on firm outcomes. In all, our sample covers 585 unique lead bank lenders and 10,116 unique firms representing 64 unique (2 digit SIC 1987 codes) industries over the sample period 1990 to 2012. In order to evaluate our hypotheses relating bank relationships to the following firm outcomes: likelihood of obtaining a bank loan, loan interest rate, and employment, we require the following four dimensions of data: relationship measures, bank health measures, loan characteristics, and firm characteristics. In addition, we need to control for bank characteristics, and macroeconomic factors; this is done by including bank fixed effects and time fixed effects. Below, we discuss our measures for relationship, bank health, loan and firm characteristics.

3.1 Relationship Measures

Since a primary goal of this paper is to establish the net benefit of relationships to large firms, meaningful relationship measures are required. Traditional measures of relationship between firm i and bank j focus on 1) the distance between the borrower and lender and/or 2) the length of the relationship, defined as the total number of past loans granted to firm i by bank j or the length of time since the first loan by bank j to firm i. Each one of these types of relationship measures is problematic. Distance between bank and firm is 1) hard to define and 2) increasingly irrelevant to the contact between borrower and lender in the context of *large* public firms borrowing from *large* commercial banks due to changes in lending technologies

[8] Chava and Roberts [2008] report that coverage increased to include an even greater fraction of commercial loans from 1995 onward.

such as the spread in the use of credit scoring.[9] The time measures, while conveying relevant information about the extent of contact between firms and their lenders, are harder to measure accurately in a finite database. The starting point in time of the database rather than the true starting point of the relationship ultimately drives the magnitude of these time measures, unless the relationship began after the start of the data. Further, time based relationship measures are highly correlated with age making it hard to disentangle the effects of age from those of the relationship itself. We use a third type of relationship measure: concentration, measuring the *proportion* of firm debt supplied by a given bank. These concentration-based measures address the concerns stated above by providing time-independent measures that identify the extent of firm-bank contact without relying on geography.

To this end, we use relationship proxies developed in Bharath et al. [2007]. First, to measure the strength of a relationship between a given borrower and lender in a given quarter, we define a continuous measure as the percentage of the borrower's loans over the five year period prior to the given quarter accounted for by the given lender. We measure this percentage using both the number of loans granted and the loan amounts. We calculate these measures as:

$$REL(Number)_{i,j,t} = \frac{\text{Number of loans to borrower } i \text{ by bank } j \text{ over the period } t-20 \text{ to } t-1}{\text{Total Number of loans to borrower } i \text{ over the period } t-20 \text{ to } t-1} \tag{3.1}$$

where the index i refers to the borrower, j refers to the lender, and t refers to time measured in quarters. And

$$\begin{aligned} &REL(Amount)_{i,j,t} \\ &\quad = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } j \text{ over the period } t-20 \text{ to } t-1}{\text{Total \$ amount of loans to borrower } i \text{ over the period } t-20 \text{ to } t-1} \end{aligned} \tag{3.2}$$

where the index i refers to the borrower, j refers to the lender, and t refers to time measured in quarters as above.

In addition, we define a binary measure capturing the *existence* of a relationship, $REL(Dummy)_{i,j,t}$ which equals one if $REL(Number)_{i,j,t} > 0$ and zero otherwise.

3.2 Bank Health Measures

Critical to our examination is understanding how a relationship affects the likelihood of obtaining a loan *when a bank is in poor financial health.* To this end, we need a measure of the health of a bank at the time of the firm's demand for debt. In order to measure bank health, we adapt the novel aggregate bank health measure developed in Becker and Ivashina [2014] to the level of an individual bank. Becker and Ivashina [2014] separate the supply of bank credit from its demand by conditioning their examination of loan issuance on firms with positive debt

[9] Petersen and Rajan [2002] show that the "tyranny of distance" from banks is alleviated for small firms as a result of credit scoring. This allows them to take loans even from far off banks, reducing the need to invest in relationships with nearby banks. It is likely that such lending technologies reduce the importance of distance to an even greater extent for large firms and banks.

demand. They do this by examining the subset of firms which either received new bank loans or issued new debt in a given quarter; by revealed preferences these firms demonstrate a positive demand for debt. Conditional on issuing new debt, the authors interpret a debt demanding firm switching from loans to bonds as a contraction in bank-credit supply. Indeed, they find that firms are more likely to switch to bank debt in economic downturns. To measure the health of the aggregate banking sector, the authors then calculate the percentage of those firms receiving bank loans in the sample of total debt demanding firms in a given quarter. They find that this aggregate bank credit supply measure is pro-cyclical and has predictive power for bank borrowing by out-of-sample firms. We adapt the Becker and Ivashina [2014] bank credit supply measure to the level of an individual bank in order to measure the health of bank j in quarter t as follows. First, we define the (j,t) borrower base by identifying all firms that have borrowed from bank j over the five year period preceding quarter t. Of this borrower base, we identify the *debt demanding* subset as those firms with non-zero debt demand in quarter t defined as those firms issuing one form of debt (either bank loan or public bond) in quarter t. Next, we calculate the proportion of these debt demanding firms in the borrower base that was granted a loan by bank j. This is our measure of bank health. Formally, the health of bank j at time t, $(BH)_{j,t}$ is defined as

$$(BH)_{j,t} = \frac{\#\text{ of debt demanding firms in } (j,t) \text{ borrower base receiving loan from bank } j \text{ in quarter } t}{\#\text{ of debt demanding firms in borrower base of bank } j \text{ in quarter } t} \tag{3.3}$$

Note that this methodology gives us a continuous measure of bank health. The advantages of our adapted bank health measure extend beyond its ability to isolate the bank credit *supply side*. In addition, our measure is based on a *data driven* identification of the beginning and end of a given bank crisis and therefore does not require a subjective choice of crisis and non-crisis dates [10]. Similarly, the measure distinguishes financial crises, when the banking sector is affected, from market crises, where the economy is adversely affected by failures outside of the banking system. Finally, the major advantage of this bank health measure is the focus on the health of individual banks. Our bank health measure captures instances of bad health of individual banks even while the financial sector as a whole might not be in crisis. This distinction is important because it is precisely the inability of a firm to switch to a healthy bank when it's relationship bank is in crisis that drives the differential effect of relations on loan availability across banks.

[10] For example, Chodorow-Reich [2014] defines poor health of the banking sector by classifying all quarters in the 9-month period from October 2008 to June 2009 as crisis periods. The boundaries of this range of time were determined subjectively taking into account the levels of several financial indicators, such as key interest rate spreads, in conjunction with major events taking place in the financial sector such as the Lehman Brother's bankruptcy in September of 2008.

3.3 Loan Characteristics

To understand the impact of relationships on firm outcomes, we examine not only the incidence of a firm receiving a loan, but also the characteristics of the loan contract conditional on receiving a loan. Specifically, we examine the impact of bank relationships on the interest rate charged on the received loan. We use as loan rate the "drawn all-in spread" (henceforth AIS) reported for each loan in the LPC database. The AIS provides a standard measure of the overall cost of a loan and is expressed as a spread (in basis points) over the benchmark London interbank offering rate (LIBOR).[11] Our sample for loan terms analysis is restricted to variable rate loans with LIBOR as the base rate.

In addition to loan rates, we obtain data on other loan characteristics from the LPC database. Notably, we use loan maturity as a control variable in our loan rate regressions and we use the loan amount in our relationship measures. We also use the LPC database to identify the lead lenders for a given loan. To this end, we follow Bharath et al. [2009] and define a lead lender if at least one of the following conditions is met: 1) LeadArrangerCredit = "Yes" , 2)LenderRole = "Agent," "Admin agent," "Arranger," or "Lead Bank" and 3)the lender is the sole lender. Throughout our analysis, we measure the relationship between a firm and its *lead* lender(s).

3.4 Firm Characteristics

We are able to link firm data from the Compustat database to the loan data provided in the LPC database using the bridge file provided in Chava and Roberts [2008]. We include several firm level controls in our analysis using quarterly firm financial data. These firm level controls include firm size, measured by total assets; firm profitability, measured by return on equity; firm credit risk, measured by the S&P Domestic Long Term Issuer Credit Rating for the firm's total long term debt in quarters t; and firm age, measured as the time since firm IPO.[12] We also include industry fixed effects, based on the 2 digit SIC 1987 codes. We exclude all financial services firms (as borrowers) from our sample (SIC codes between 6000 and 6999).

3.5 Bank Characteristics and Macroeconomic Factors

In addition to the relationship measures, the bank health measure, and firm characteristics, we control for bank characteristics and macroeconomic factors through the use of bank and time fixed effects. Note that the inclusion of these bank fixed effects implies that bank health is identified from within bank variation over time.

[11] The AIS is defined as the coupon spread, plus any annual fee, plus any up-front fee divided by the maturity of the loan. See Berg et al. [2014] for a detailed explanation of the AIS spread and its merits as a measure of overall loan cost.

[12] Note that true age should be calculated from the date of incorporation, but this data is unavailable. Instead, we proxy age with time since IPO.

3.6 Descriptive Statistics

Table 1: Summary Statistics

Panel A: Firm Characteristics

Variable	Mean	Std. Deviation	Number of Observations
Total Firm Assets ($ Millions)	7,278.79	25,584.04	1,953,369
Firm Age (Years)	7.37	8.19	862,972
% Firms with Unrated Debt	0.49		1,953,369
% Firms with Investment Grade Debt	0.60		1,002,454

Panel B: Loan Characteristics

Variable	Mean	Std. Deviation	Number of Observations
Loan Amount ($ Millions)	279.44	766.48	119,843
All in drawn Spread (basis points)	149.99	131.281	59,002
Maturity (Months)	47.24	27.75	57,417
Number of Lenders per Loan	6.30	7.91	119,997
Number of Lead Lenders per Loan	1.91	2.60	119,997

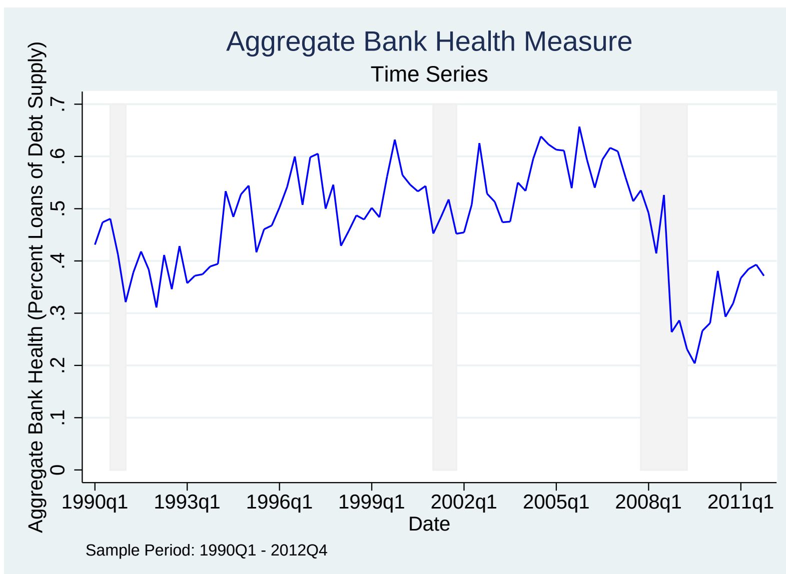
Panel C: Bank Health and Relationship Measures

Variable	Mean	Std. Deviation	Number of Observations
Bank Health Measure	0.24	0.21	1,953,369
Relationship Measure	0.009	0.08	1,953,369
Relation Measure (Conditional on Rel > 0)	.364	.340	53,724

This table presents summary statistics for firm, bank, and relationship characteristics. The sample period is 1990 - 2012. Mean and standard deviation are presented for each variable. Panel A presents summary statistics for the following firm characteristics: Total Assets of i at time t (in millions of dollars), Age of the firm (time in years since the IPO date of the firm), percentage of firms with Investment Grade Debt (long term debt credit ratings at BBB- or above), percentage of firms with unrated debt (no credit rating available for long term debt). Panel B presents summary statistics for the following loan characteristics: total loan facility amount (in millions of dollars), all-in-drawn spread (in basis points), the maturity of the loan (in months), the number of lenders per loan facility, and the number of lead lenders per loan facility. Panel C presents summary statistics for the relationship and bank health measures. The variable ($Rel_{i,j,t}$) is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. ($Rel_{i,j,t}$) is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. Unconditional summary statistics of the relationship measure are provided, as well as summary statistics conditional on a non-zero relationship measure. $BH_{j,t}$ is a continuous measure of the health of bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t.

Summary statistics for firm, loan, bank health, and relationship characteristics are presented in Table 1. The table shows that publicly traded firms in the U.S. included in our sample have, on average, $7,279 million in assets, and have existed for an average of 7 years post-IPO. These firms do differ in their informational opacity. While 50% of firms have some unrated debt, 60% of the rated firms have investment grade debt. These firms also take large syndicated loans with the loan amount averaging at nearly $280 million provided jointly by over six banks. The table also shows that bank health varies substantially across banks with the standard deviation as high as the mean. Also, firms that do have relationships (i.e., take loans from the same bank more than once over a five year window), take about 36% of their loan amount from the same bank.

Figure 2: Aggregate Bank Health[a]

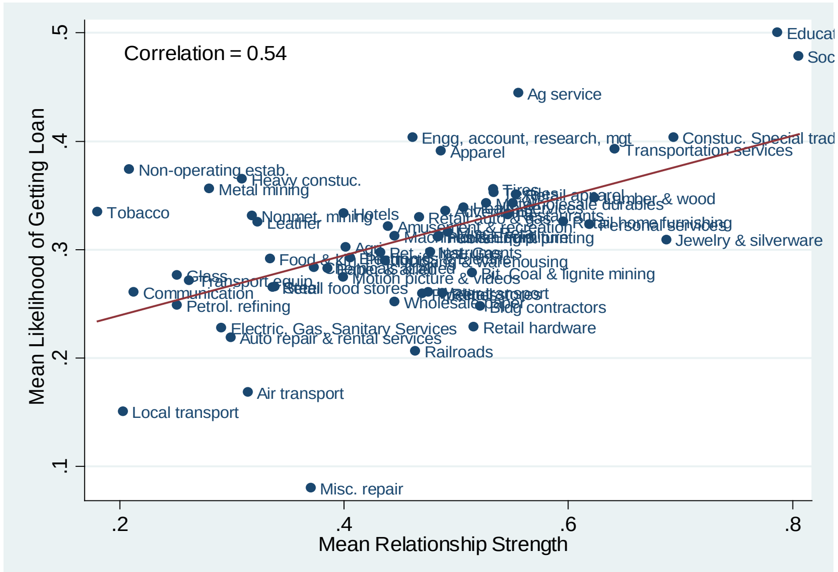


[a]Source: The figure plots the aggregate bank health over the sample period. Bank health is measured as the percentage of debt demanding firms in any quarter who obtain bank loans as opposed to issuing public debt.

We already showed the evolution of bank-firm relationship strength over time in the introduction (Figure 1). In Figure 2, we show the evolution of bank health in the aggregate over the sample period. This bank health measure is the percentage of all debt demanding publicly traded firms in a quarter that obtain bank loans instead of having to issue public debt. The higher this percentage the higher is the credit supply from banks and, hence, better is their financial health. The grey bars in Figure 2 indicate the three economic recessions in the U.S. economy over this period. The figure shows that bank health fluctuates considerably and can fall even when the economy is not in a recession. However, bank health has trended upwards since 1990. Although it plummeted during the Great Recession, it has been rising again since the end of the recession.

Figures 3 plots the average relationship strength (for firms with banking relationships) against the mean likelihood of them obtaining a loan from their relationship bank across all two

Figure 3: Loan Availability Positively Associated with Relationships[a]



[a]The figure plots the mean strength of bank-firm relationship against the mean likelihood of firms receiving a loan from that bank in a given quarter. The relationship variable is measured as percentage of firms' total bank loans over the five years preceding a given quarter that came from any one bank. The means are calculated over 1990Q1-2012Q4 for each two digit SIC 1987 industry code. Firms in the sample are all publicly traded U.S. firms that obtain credit (either bank loans or public debt) in a given quarter. The sample includes top-50 banks by share of total bank loans supplied in a given quarter.

digit industries (SIC 1987). We can see clearly that stronger relationships are associated with higher likelihood of getting a loan. The correlation is 0.54. Figure 4 shows that the likelihood of obtaining a loan is higher when the relationship banks are healthier. The correlation is 0.61.

4 Results

This section will describe the results of the tests of hypotheses H1, H1.1, and H1.2 as laid out in Section 2. First, Table 2 reports the results for the logit tests of H1. Recall that the dependent variable for these tests is the likelihood of firm i receiving a loan from bank j in quarter t. The three columns report the results for models with different control variables. The coefficient on the main relationship term is positive and highly statistically significant across the specifications. This is evidence that on average, relationships increase the likelihood of a firm obtaining a loan. The results presented in Table 2 are based on continuous measures of bank health and relationship as defined earlier. Specifically, $REL_{i,j,t}$ is defined as the percentage of loans made by bank j to firm i in the five year period preceding quarter t out of total loans obtained by firm i over the same five year period. Similarly, bank health is measured continuously and is defined as the percentage of bank j's debt demanding borrower base receiving loans from bank j at time t. Using the predicted probabilities, we can infer the economic magnitude of this effect. Holding constant the health of the bank at the median bank health level, we see that an

Table 2: The Effect of Relationships on the Likelihood of Obtaining a Bank Loan

Panel A: Coefficient Estimates

Variable	(1) Basic Specification	(2) Controls	(3) Controls W/Age
BH	1.293***	1.427***	1.530***
	(0.0899)	(0.109)	(0.121)
REL(Amount)	2.246***	1.951***	2.231***
	(0.137)	(0.164)	(0.196)
REL(Amount)xBH	6.105***	6.439***	6.740***
	(0.449)	(0.535)	(0.646)
DUM(Investment Grade)		0.166***	0.502***
		(0.0409)	(0.0702)
Roe		0.00274*	0.00455***
		(0.00166)	(0.00166)
Age			-0.0163***
			(0.00277)
Size		4.07e-06***	8.44e-06***
		(4.97e-07)	(6.86e-07)
Observations	2,052,060	980,699	297,009
Industry FE	YES	YES	YES
Bank FE	YES	YES	YES
Qtr*Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

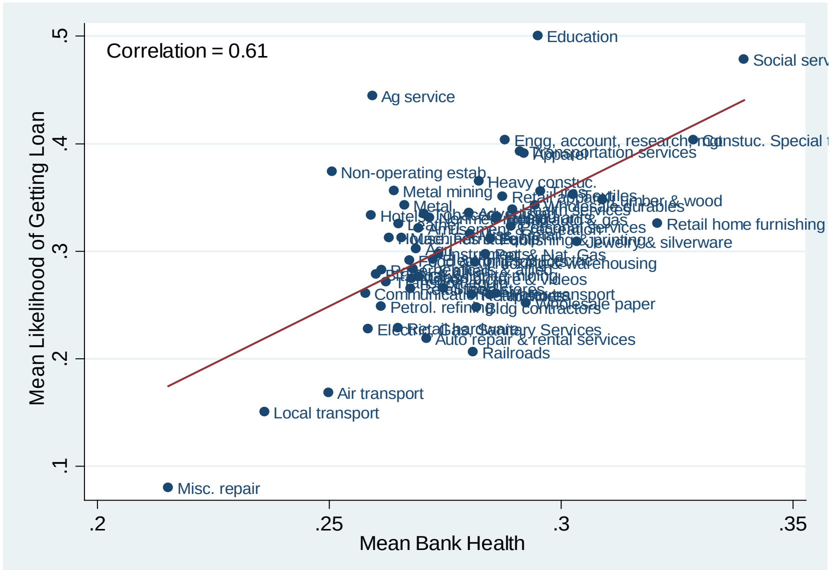
Panel B: Predicted Probabilities

	Sample Mean Predicted Probability of Obtaining a Loan			
	Bank Health			
Relationship	BH at P25	BH at P50	BH at P75	P75 - P25
REL at P25	2.92%	5.36%	8.55%	5.63%
REL at P50	4.97%	9.15%	16.50%	11.93%
REL at P75	10.65%	21.04%	39.60%	28.95%
P75 - P25	5.68%	11.85%	23.1%	

Panel A reports reports coefficient estimates from the logit regression of the following equation: $(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$ The dependent variable $(BankLoan)_{i,j,t}$ takes a value of one if firm i received a loan from bank j at time t (in quarters). Each firm with positive debt demand in a given quarter (identified by obtaining either a bank loan or issuing public bond debt) is paired with 50 potential lenders each quarter. These potential lenders represent the top 50 lenders by dollar amount in a given quarter. The variable $(Rel_{i,j,t})$ is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. $(Rel_{i,j,t})$ is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. $BH_{j,t}$ is a continuous bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. ROE represents the return on equity of firm i at time t. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. Age of the firm represents the time since the IPO date of the firm. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. In each cell, the first row represents the coefficient estimate; standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

Panel B presents predicted probabilities from the estimated logit model at three different levels of the variable REL and BH. The levels of each variable represent the 25th, 50th, and 75th percentile of the given variable. Predicted probabilities at the specified levels of the REL and BH measures are then averaged across the sample. For example, when BH is at its 25th percentile value and REL is also at its 25th percentile value, the average sample predicted probability of obtaining a loan is 2.92%. The difference between the 75th and 25th percentile probabilities are presented for each of the two dimensions (relationship and bank health). Note that the predicted probabilities are estimated using the specification in column (2).

Figure 4: Loan Availability Positively Associated with Bank Health[a]



[a]The figure plots the mean bank health against the mean likelihood of firms receiving a loan from that bank in a given quarter. Bank heath is measured as percentage of firms in a bank's borrower base demanding credit in a given quarter that obtained a loan from the same bank in that quarter. The means are calculated over 1990Q1-2012Q4 for each two digit SIC 1987 industry. Firms in the sample are all publicly traded U.S. firms that obtain credit (either bank loans or public debt) in a given quarter. The sample includes top-50 banks by share of total bank loans supplied in a given quarter.

increase in relationship from the 25th percentile to 75th percentile level increases the likelihood of obtaining a loan by 11.85%. Note that the model predicted probabilities are averaged over all observations at the given levels of relationship and bank health. In Table 3, an alternative measure of relationship is employed. Here, $Rel(Dummy)$ is an indicator variable taking the value one if the firm received at least one loan from bank j in the five year period preceding quarter j. We see again that the coefficient on the relationship main effect is positive and highly statistically significant. In terms of economic magnitude, we can infer from the predicted probabilities presented in Table 3 that holding constant bank health at its median level, a firm with a relationship is 21.91% more likely to obtain a loan than a firm without a relationship.

Our main result, however, is that this relationship effect varies *depending on the health of the lending bank*. Specifically, the coefficient on the relationship$\times$ bank health interaction is positive and highly statistically significant across all specifications. A positive interaction term means that the effect of bank health is amplified by relationships. In good times, when BH is high, relationships are even more valuable. In contrast, when BH is low, the value of relationships is reduced. This differential effect by bank health is consistent with the hold up effect reducing the net benefit of relationships more in crisis times then in good times. Using the predicted probabilities from the model estimated in column (2) of Table 2, we infer that an increase in relationship from its 25th percentile to 75th percentile level increases the likelihood of obtaining a loan by only 5.68% when bank health is low (at its 25th percentile level). In contrast, an increase in relationship from its 25th percentile to 75th percentile level increases the likelihood of obtaining a loan by 23.1% when bank health is high (at its 75th percentile level).

The results with the alternative relationship measure presented in Table 3 are consistent. The coefficient on the relationship × bank health interaction term is positive and highly statistically significant. Using the predicted probabilities from the model estimated in column (2) of Table 3, we infer that a having a relationship increases the likelihood of obtaining a loan by only 9.67% when bank health is low (at its 25th percentile). In contrast, having a relationship increases the likelihood of obtaining a loan by 41.3% when bank health is high (at its 75th percentile).

We further explore the robustness of this main result by examining different definitions of bank health. Table 4 presents two alternative measures of bank health which allow us to test whether the amplifying effect of relationships on the likelihood of obtaining a loan are symmetric in both increases and decreases in bank health. The introduction of these two new bank health measures allows us to isolate the effects of relationships in good times and crisis times (note that in the linear specification in Table 2 assumes an effect in both good times and crisis times). The alternate measures are constructed by first calculating the continuous variable $BH_{j,t}$ for each bank in each quarter as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t as previously defined. Then, the variables $DUM(BH = H)$ and $DUM(BH = L)$ are defined so that each indicates whether a given quarter is in the top 25% or bottom 25%, respectively, of quarters by BH for bank j. The model in column(1) uses this "level" measure of bank health. We see that the coefficients on the relationship main term is positive and statistically significant. Note further that the coefficient on the relationship × high bank health interaction term is positive and highly statistically significant while the coefficient on the relationship × low bank health interaction term is negative and highly statistically significant. This is evidence of the amplifying effect of relationships being present in both the good and bad states, consistent with the tradeoff between information benefits and hold-up costs differing across the two states. The hold-up costs are higher in crisis times, reducing the benefit of relationships in that state compared to the good state. Here a crisis is defined as a quarter with low bank health in absolute terms.

Also in Table 4,we use a bank health measure focusing on the difference in $BH_{j,t}$ over time (as opposed to its level). The variable $DUM(\Delta BH < 0)$ is an indicator variable taking on the value 1 if a given bank's BH level *decreased* from quarter $t-1$ to quarter t. In column (2), we again observe a positive and statistically significant coefficient on the relationship main term. We also observe a negative and highly statistically significant coefficient on the interaction term between relationship and the bank health change measure. This negative coefficient is consistent with relationships providing lower benefits in times of crisis, where crisis is now defined as a downturn over the quarter in bank health.

After establishing a differential effect of relationships across bank health, we now examine the differential effect of relationships across firms. Specifically, in H1.2, we test whether firms with higher degrees of information asymmetry benefit more from relationships. Recall that that the information benefit of relationships is greater for those firms suffering from greater information asymmetries. Thus, we would expect 1) to see higher relationship benefits for these firms, and 2) to see smaller *decreases* in relationship value in times of crisis for these firms. Table 5 presents coefficient estimates from a model that incorporates the degree of asymmetry. In each of the four columns, a different proxy for information asymmetry is used. In column (1), the size of the firm is tested, noting that *smaller* firms suffer from greater information asymmetry. In column (2), the age of the firm is used, noting that *younger* firms suffer from greater asymmetry. In column (3), the availability of a credit rating is used as the information asymmetry proxy, noting that if a firm's debt is not-rated (DUM(Not Rated = 1)), it suffers from greater information asymmetry. Finally, in column (4), the credit worthiness of a firm is used as the measure of information asymmetry, with lower rated firms (DUM(Investment Grade) = 0) suffering from greater asymmetry.

The results in Table 5 provide evidence that relationships matter more for firms with higher levels of asymmetry. Note that the coefficients on the interaction terms between information asymmetry and relationships is negative and statistically significant for Size and Investment Grade (although only weakly significant for Investment Grade). Note also that directionally, Age, Size, and Investment Grade all take on low values when information asymmetry is high, thus these coefficients are consistent with an increase in information asymmetry increasing the value of a relationship in securing a loan. Consistently, the coefficient on the interaction term between the indicator for unrated credit and relationships is positive and highly statistically significant. Recall that in contrast to the other three measures, DUM(Not Rated) takes on high values when information asymmetry is high. Thus, a positive coefficient on this interaction term suggests that relationships are more valuable in securing a loan for firms with higher information asymmetry.

Next we evaluate whether the *decreases* in relationship value in times of crisis are lower for firms with higher levels of information asymmetry. Recall that these firms have higher information benefits during crisis times. The triple interaction term in Table 5 between information asymmetry, relationship, and bank health is negative and statistically significant for size and Investment Grade (although only weakly statistically significant for Investment Grade). Note that directionally, Size and Investment Grade all take on low values when information asymmetry is high, thus these negative coefficients on the triple interaction term are consistent with a smaller decrease in relationship values in times of crisis for those firms with higher information asymmetry (in this case measured by size and credit rating of debt). Consistently, the triple interaction term with DUM(Not Rated) as the measure of information asymmetry is positive, although not statistically significant. Recalling that an increase in this variable represents an increase in information asymmetry, this positive triple interaction term is consistent with firms with higher information asymmetry (as measured by unrated debt), suffering less of a reduction in relationship value in crisis times. Overall, Table 5 provides evidence of firms with higher levels of information asymmetry deducing more value from relationships in general, but also suffering less of a reduction in relationship value in times of crisis.

An exception to this is the result using age as the information asymmetry proxy. The coefficients and their significance are inconsistent with the predictions and the results using the other proxies for information asymmetry. A possible explanation for this is that it is hard to completely disentangle the correlated effects of age and relationship. On the one hand, firms that are older suffer from less information asymmetry. On the other hand, firms that are older are likely to have longer relationships, i.e., more points of contact with the bank, simply by virtue of their longer existence. It is possible that in the context of the model estimated in Table 5, these two conflicting effects cannot be disentangled.

The final set of results addresses the effect of relationships on loan terms. Specifically, we test the effect of a lead bank relationship on the rate charged on an issued loan. We measure this loan rate using the "all-in drawn" spread, an accepted measure of the per period comprehensive cost of a loan. The models estimated in Tables 6 and 7 measure the effect of a relationship on loan spread 1)differentially by bank health (Table 6) and 2) differentially across firms with varying levels of information asymmetry (Table 7). In Table 6, columns (1) and (3) use the continuous bank health measure, while columns (2) and (4) use the indicator variable for relationships. In Table 7, each of the four columns uses a different proxy for information asymmetry. As in the analysis of H1.2, these proxies are: firm size, firm age, investment grade credit rating, and unrated debt. Examining the coefficients on the relationship variable, both the main terms as well as the interaction terms with bank health and information asymmetry, we see no evidence of an effect of relationships on loan spreads. All of the aforementioned coefficients are not statistically indistinguishable from zero. The only exception is the coefficient on the (indicator) relationship measure $\times$ bank health term in Table 6 column (2), which is positive and weakly statistically significant. Similarly, there is one exception in Table 7, which is the negative and highly statistically significant coefficient on the interaction term between investment grade debt and relationships. This negative coefficient suggests that spreads are reduced as the relationship increases for non-transparent firms (as measured by the lack of a credit rating). Our overall interpretation of the results presented in Tables 6 and 7 is that there is no effect of relationships on loan rates, neither across bank health nor across firms with varying levels of information asymmetry. It should be noted that our results of no effect of relationships on loan rates are consistent with Petersen and Rajan [1994], who reach a similar conclusion when evaluating relationship benefits for *small* firms. We find that this non-effect also holds true for large firms.

The results of hypothesis H2, taken together with the results of hypotheses H1.1 and H1.2, lead us to conclude that relationships increase the likelihood of getting a loan, although only when bank health is high, but have no effect on the interest charged once the loan is issued. This suggests that relationship benefits are derived through the credit rationing channel.

5 Conclusion

We show that, unlike conventional wisdom, relationship lending exists and matters beyond SMEs and small or community banks. Using data on large publicly traded firms that either issue public debt or take syndicated loans, we find that banking relationships are significantly and positively associated with the likelihood of firms obtaining loans from these banks. Importantly, we show that relationships impact firms through both reducing the information asymmetry between the lenders and borrowers as well as creating a hold-up problem for the borrowing firms. Results demonstrate that when a bank's health improves, firms with stronger relationships with the bank are at an advantage compared to those with weaker relationships, suggesting strong information benefits of relationships. However, when a bank's health deteriorates, firms with strong relationships are only marginally more likely to receive loans from the bank than those with weak relationships, suggesting a pronounced presence of the hold-up problem for firms with strong relationships.

This is a first and preliminary draft of the paper. In a future version, we will build on our current work in three significant ways. First, we will examine how banking relationships impact real outcomes including employment and output. Second, we will account for possible endogeneity of relationships using propensity score matching. Third, we will account for M&A activity of firms and banks that can be disruptive to lending relationships.

Table 3: The Effect of Relationships on the Likelihood of Obtaining a Bank Loan, Alternate Relationship Measure

Panel A: Coefficient Estimates

Variable	(1) Basic Specification	(2) Controls	(3) Controls W/Age
BH	0.988***	1.032***	1.082***
	(0.0905)	(0.113)	(0.127)
REL(Dummy)	1.680***	1.368***	1.288***
	(0.0680)	(0.0773)	(0.0985)
REL(Dummy)xBH	4.310***	4.407***	4.527***
	(0.200)	(0.218)	(0.232)
DUM(Investment Grade)		0.0297	0.311***
		(0.0364)	(0.0655)
Roe		0.00279*	0.00373***
		(0.00151)	(0.00129)
Age			-0.0110***
			(0.00236)
Size		1.75e-06***	4.03e-06***
		(4.94e-07)	(9.15e-07)
Observations	2,052,062	980,700	297,010
Industry FE	YES	YES	YES
Bank FE	YES	YES	YES
Qtr*Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Predicted Probabilities

	Mean Predicted Probability of Obtaining a Loan Bank Health			
Relationship	BH at P25	BH at P50	BH at P75	P75 - P25
0	0.89%	1.45%	1.81%	0.92%
1	10.56%	23.36%	42.94%	32.38%
(1) - (0)	9.67%	21.91%	41.13%	

Panel A reports reports coefficient estimates from the logit regression of the following equation: $(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$ The dependent variable $(BankLoan)_{i,j,t}$ takes a value of one if firm i received a loan from bank j at time t (in quarters). Each firm with positive debt demand in a given quarter (identified by obtaining either a bank loan or issuing public bond debt) is paired with 50 potential lead lenders each quarter. These potential lenders represent the top 50 lenders by dollar amount in a given quarter. The variable $(Rel_{i,j,t})$ is an indicator variable which takes on the value one if bank j has made a loan to firm i in the 5 year period preceding quarter t. $BH_{j,t}$ is a continuous bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. ROE represents the return on equity of firm i at time t. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. Age of the firm represents the time since the IPO date of the firm. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. In each cell, the first row represents the coefficient estimate; standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

Panel B presents predicted probabilities from the estimated logit model at two different levels of the variable REL (0 and 1) and three different levels of the variable BH. The 25th, 50th, and 75th percentile values of BH are used. Predicted probabilities at the specified levels of the REL and BH measures are then averaged across the sample. For example, when BH is at its 25th percentile value and REL is also at its 25th percentile value, the average sample predicted probability of obtaining a loan is .89%. The difference between the high and low values are presented for each of the two dimensions (relationship and bank health).

Table 4: The Effect of Relationships on the Likelihood of Obtaining a Loan: Alternative Bank Health Measures

variable	(1) BH (Level)	(2) ΔBH	(3) BH (Level)	(4) ΔBH
REL(Amount)	4.123***	4.289***	4.252***	4.384***
	(0.0502)	(0.0596)	(0.0757)	(0.0836)
DUM(BH = H)	0.320***		0.340***	
	(0.0264)		(0.0321)	
DUM(BH = L)	-0.383***		-0.367***	
	(0.0267)		(0.0351)	
REL(Amount)xDUM(BH = H)	0.629***		0.553***	
	(0.115)		(0.147)	
REL(Amount)xDUM(BH = L)	-1.196***		-1.183***	
	(0.107)		(0.142)	
DUM($\Delta BH < 0$)		-0.178***		-0.200***
		(0.0234)		(0.0275)
REL(Amount)xDUM($\Delta BH < 0$)		-0.556***		-0.471***
		(0.0943)		(0.128)
Size	5.63e-06***	5.73e-06***	1.08e-05***	1.08e-05***
	(4.56e-07)	(4.48e-07)	(6.36e-07)	(6.59e-07)
Age			-0.00425**	-0.00400*
			(0.00207)	(0.00226)
Roe	-3.56e-05***	9.33e-05***	-0.000401	-0.000345
	(5.52e-06)	(2.14e-05)	(0.000543)	(0.000551)
Observations	1,929,744	1,448,683	843,206	641,037
Industry FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Qtr*Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports reports coefficient estimates from the logit regression of the following equation: $(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$
The dependent variable $(BankLoan)_{i,j,t}$ takes a value of one if firm i received a loan from bank j at time t (in quarters). Each firm with positive debt demand in a given quarter (identified by obtaining either a bank loan or issuing public bond debt) is paired with 50 potential lead lenders each quarter. These potential lenders represent the top 50 lenders by dollar amount in a given quarter. The variable $(Rel_{i,j,t})$ is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. $(Rel_{i,j,t})$ is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. Two different measures of bank health are examined. First the continuous variable $BH_{j,t}$ is calculated for each bank in each quarter as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. Then, the variables $DUM(BH = H)$ and $DUM(BH = L)$ indicate whether a given quarter is in the top 25% or bottom 25%, respectively, of quarters by BH for bank j. The variable $DUM(\Delta BH < 0)$ is an indicator variable taking on the value 1 if a given bank's BH level *decreased* from quarter $t-1$ to quarter t. ROE represents the return on equity of firm i at time t. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. Age of the firm represents the time since the IPO date of the firm. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. The first row represents the coefficient estimate; standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

Table 5: The Differential Effect of Relationships on the Likelihood of Obtaining a Bank Loan by Information Asymmetry

	Information Asymmetry Proxy			
Variable	Size	Age	Not Rated	IGrade
REL(Amount)	2.119***	2.057***	1.985***	2.166***
	(0.163)	(0.334)	(0.168)	(0.217)
BH	1.416***	1.522***	1.321***	1.428***
	(0.109)	(0.121)	(0.0934)	(0.109)
REL(Amount)xBH	5.903***	5.486***	6.197***	6.223***
	(0.524)	(0.982)	(0.531)	(0.664)
Size	4.13e-06***	8.59e-06***	5.06e-06***	4.04e-06***
	(4.94e-07)	(6.82e-07)	(4.55e-07)	(4.96e-07)
REL(Amount)xSize	-1.72e-05***			
	(5.28e-06)			
BHxREL(Amount)xSize	5.77e-05***			
	(2.22e-05)			
Age		-0.0213***		
		(0.00278)		
REL(Amount)xAge		0.0141		
		(0.0221)		
BHxREL(Amount)xAge		0.165**		
		(0.0678)		
DUM(Not Rated)			-0.363***	
			(0.0313)	
REL(Amount)xDUM(Not Rated)			0.721***	
			(0.147)	
BHxREL(Amount)xDUM(Not Rated)			-0.857*	
			(0.442)	
DUM(Investment Grade)	0.165***	0.501***		0.191***
	(0.0405)	(0.0703)		(0.0410)
REL(Amount)xDUM(Investment Grade)				-0.368*
				(0.196)
BHxREL(Amount)xDUM(Investment Grade)				0.373
				(0.649)
Roe	0.00272	0.00447***	-4.49e-05***	0.00276*
	(0.00166)	(0.00165)	(5.79e-06)	(0.00166)
Observations	980,699	297,009	1,929,744	980,699
Industry FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Qtr*Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports reports coefficient estimates from the logit regression of the following equation: $(BankLoan)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \beta_4(IA_{i,t}) + \beta_5(Rel_{i,j,t}) \times (IA_{i,t}) + \beta_6(Rel_{i,j,t}) \times (IA_{i,t}) \times (BH)_{j,t} + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$ The dependent variable $(BankLoan)_{i,j,t}$ takes a value of one if firm i received a loan from bank j at time t (in quarters). Each firm with positive debt demand in a given quarter (identified by obtaining either a bank loan or issuing public bond debt) is paired with 50 potential lead lenders each quarter. These potential lenders represent the top 50 lenders by dollar amount in a given quarter. The variable $(Rel_{i,j,t})$ is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. $(Rel_{i,j,t})$ is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. $BH_{j,t}$ is a continuous bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. ROE represents the return on equity of firm i at time t. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $(IA_{i,t})$ is a proxy for information asymmetry for firm i at time t; four different proxies are tested. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. $DUM(NotRated)$ is an indicator variable taking on the value one if the long term debt of the firm at time t does not have a credit rating. Age of the firm represents the time since the IPO date of the firm. Size represents the total assets of the firm at time t in thousands of dollars. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. The first row represents the coefficient estimate: standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

Table 6: The Effect of Relationships on Loan Rates

Variable	(1)	(2)	(3)	(4)
Maturity	0.357***	0.352***	0.586***	0.580***
	(0.0456)	(0.0456)	(0.0399)	(0.0399)
BH	-9.543	-3.373	-12.34*	-6.922
	(7.784)	(8.238)	(6.825)	(7.106)
REL(Amount)	6.676		8.785	
	(10.65)		(8.132)	
REL(Amount)xBH	-31.51		-12.65	
	(28.81)		(21.52)	
DUM(REL)		1.678		-2.923
		(5.365)		(5.022)
DUM(REL)xBH		-27.53*		-17.18
		(14.44)		(13.37)
DUM(Investment Grade)	-143.0***	-142.6***		
	(2.377)	(2.373)		
DUM(Not Rated)			15.71***	15.29***
			(1.974)	(1.976)
Age	-0.691***	-0.693***	-1.932***	-1.909***
	(0.153)	(0.153)	(0.140)	(0.140)
Size	-7.44e-05***	-7.15e-05***	-0.000244***	-0.000241***
	(1.46e-05)	(1.46e-05)	(1.57e-05)	(1.57e-05)
Roe	-0.593*	-0.580*	-0.592**	-0.611**
	(0.307)	(0.306)	(0.284)	(0.284)
Observations	9,178	9,178	16,207	16,207
R-squared	0.564	0.564	0.312	0.313
Industry FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Qtr*Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports reports coefficient estimates from an OLS regression of the following equation: $(AIS)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$ The dependent variable $AIS_{i,j,t}$ represents the "all-in drawn" spread charged on a loan issued by lead bank j to firm i at time t (quarters). A given loan may have multiple lead lenders; each lead lender firm combination comprises a separate observation. The variable $(Rel_{i,j,t})$ is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. $(Rel_{i,j,t})$ is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. $BH_{j,t}$ is a continuous bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. $Maturity$ represents the maturity of the loan measured in years. ROE represents the return on equity of firm i at time t. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. Age of the firm represents the time since the IPO date of the firm. $DUM(NotRated)$ is an indicator variable taking on the value one if the long term debt of the firm at time t is unrated. Age of the firm represents the time since the IPO date of the firm. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. The first row represents the coefficient estimate; standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

Table 7: The Differential Effect of Relationships on Loan Rates by Information Asymmetry

Variable	(1) IGrade Debt	(2) Debt Not Rated	(3) Age	(4) Size
Maturity	0.358***	0.586***	0.357***	0.355***
	(0.0457)	(0.0399)	(0.0457)	(0.0456)
BH	-9.631	-12.42*	-9.543	-8.769
	(7.784)	(6.826)	(7.784)	(7.779)
REL(Amount)	3.628	10.84	6.733	12.33
	(10.93)	(8.694)	(11.53)	(10.73)
REL(Amount)xBH	-31.90	-12.00	-31.52	-33.29
	(28.81)	(21.54)	(28.81)	(28.79)
DUM(Investment Grade)	-144.2***		-143.0***	-142.0***
	(2.553)		(2.377)	(2.388)
REL(Amount)xDUM(Investment Grade)	9.820			
	(7.984)			
DUM(Not Rated)		16.31***		
		(2.168)		
REL(Amount)xDUM(Not Rated)		-3.901		
		(5.834)		
Age	-0.696***	-1.929***	-0.690***	-0.649***
	(0.153)	(0.140)	(0.163)	(0.153)
REL(Amount)xAge			-0.00725	
			(0.567)	
Size	-7.37e-05***	-0.000243***	-7.45e-05***	-6.68e-05***
	(1.46e-05)	(1.58e-05)	(1.46e-05)	(1.47e-05)
REL(Amount)xSize				-0.00128***
				(0.000315)
Roe	-0.600*	-0.591**	-0.593*	-0.577*
	(0.307)	(0.284)	(0.307)	(0.306)
Observations	9,178	16,207	9,178	9,178
R-squared	0.564	0.312	0.564	0.565
Industry FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Qtr*Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents coefficient estimates from an OLS regression of the following equation: $(AIS)_{i,j,t} = \beta_0 + \beta_1(Rel_{i,j,t}) + \beta_2(BH_{j,t}) + \beta_3(Rel_{i,j,t}) \times (BH_{j,t}) + \beta_4(IA_{i,t}) + \beta_5(Rel_{i,j,t}) \times (IA_{i,t}) + \sum \beta_k(Control_k)_{i,t} + \tau_t + \eta_i + \nu_j + \epsilon_{i,j,t}$
The dependent variable $AIS_{i,j,t}a$ represents the "all-in drawn" spread charged on a loan issued by lead bank j to firm i at time t (quarters). A given loan may have multiple lead lenders; each lead lender firm combination comprises a separate observation. The variable $(Rel_{i,j,t})$ is a continuous variable measuring the extent of a relationship between firm i and bank j in quarter t. $(Rel_{i,j,t})$ is equal to the percentage of loans granted to firm i by bank j in the five year period preceding time t out of total loans granted to firm i in the same five year period. $BH_{j,t}$ is a continuous bank j at time t. It is calculated as the percentage of bank j's debt demanding borrower base receiving a loan from bank j in quarter t. $Maturity$ represents the maturity of the loan measured in years. ROE represents the return on equity of firm i at time t. $AI_{i,t}$ represents a proxy for the degree of information asymmetry of firm i. The following four proxies are examined. $Size$ represents the total asset value of firm i at time t in thousands of dollars. $DUM(InvestmentGrade)$ is an indicator variable taking on the value one if the long term debt of the firm at time t has a credit rating of $BBB-$ or above. Age of the firm represents the time since the IPO date of the firm. $DUM(NotRated)$ is an indicator variable taking on the value one if the long term debt of the firm at time t is unrated. Age of the firm represents the time since the IPO date of the firm. Bank, industry (2 digit SIC 1987 codes), and time (year*quarter) fixed effects are included. The first row represents the coefficient estimate; standard errors, clustered by qtr*year, are in parentheses (***significant at the 1% level, **significant at the 5% level, *significant at the 1% level).

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