Why do firms switch banks?

Radhakrishnan Gopalan
Olin School of Business, Washington University

Gregory F. Udell
Kelley School of Business, Indiana University

Vijay Yerramilli
Kelley School of Business, Indiana University

July 2007

Abstract

Using 30,466 bank loan deals originated during 1990-2005, we examine why firms switch to new banks for their repeat loans instead of staying with their relationship banks. Employing a variety of measures to proxy for firms' informational transparency, we find that the soft information hypothesis, which states that informationally opaque firms are more likely to stay with their relationship banks, does not hold uniformly across the information spectrum; the most opaque firms and the most transparent firms in our sample are most likely to stay with their relationship banks. Further, firms that switch banks are more likely to switch from small banks to large banks, and from small bank markets to large bank markets. We also find that firms obtain higher loan amounts, undertake higher capital expenditure, and experience an increase in leverage after they switch to a new bank. Thus, overall, our findings are supportive of the graduation hypothesis which states that firms that face borrowing constraints at their relationship banks are more likely to switch to larger banks in order to better meet their growing need for credit.

JEL Classification: G21, G24, G34

1 Introduction

A large and growing literature in finance shows that firms benefit by borrowing from their relationship banks.[1] It is argued that these benefits arise mainly because of the relationship bank's ability to generate "soft" information about the borrowing firm – information that cannot be easily observed by or transferred to outsiders – that it can use to make better credit decisions than outside lenders.[2] On the other hand, there could also be costs to the firm of borrowing from its relationship banks, that might cause it to switch to a new bank. For instance, the relationship banks may be small and unable to meet the firm's growing credit needs; the relationship bank may informationally capture the firm and charge a higher interest rate; etc. When a firm has a repeat need for private credit, it is likely to trade-off the benefits and costs of borrowing from its relationship banks in deciding whether to switch to a new bank or not.[3] Although the benefits of banking relationships are well understood in the existing literature, the costs are not. Our objective in this paper is to shed light on both the costs and benefits of borrowing from relationship banks by identifying the factors that impact a firm's propensity to switch to a new bank for its repeat loans. Our approach is to treat a firm's banking relationships as endogenous, and to understand how these relationships evolve over time.

We obtain our loan data from the Reuters Loan Pricing Corporation's(LPC) Dealscan database. Dealscan provides detailed loan information, including the identity of the borrower and the lender, on loans originated during the period 1986-2005 – a period sufficiently long to allow us to analyze how lending relationships evolve over time. We conduct our analysis using an extensive data set of 30,466 loan deals originated by 850 U.S. banks to 13,788 borrowers in the United States. We define a firm's banking relationship as the pairing between the firm and the lead bank in the loan syndicate providing the firm with financing. This is because prior research has shown that the lead lender is the one responsible for monitoring borrowers (Sufi (2006)). We examine firms' repeat loan deals, and our main variable of interest is whether a firm switches to a new lead lender for its repeat deal or not. We combine the loan data with firm-level data from Compustat and bank-level data from the Call Reports to analyze how firm characteristics and bank characteristics influence the firm's decision to switch to a new bank for its repeat loan.

[1] Please see our Section 2 for a detailed discussion of this literature.

[2] Such soft information could include information about the firm's position in its product markets, management quality, etc; as against this, an outside lender may only have access to hard information such as the firm's financials. There is an extensive theoretical and empirical literature which shows that banks are specialists in information production (Leland and Pyle (1977), Diamond (1984), Fama (1985), Boyd and Prescott (1986), etc.) and that information-problematic firms benefit from such monitoring (Diamond (1991), Hadlock and James (2002), etc.)

[3] As evidence that the costs of staying with existing banks could be significant, we show that it is very common for firms to switch to new banks for their repeat loans; 44% of the repeat loans in our sample involve new bank-borrower relationships.

The soft information hypothesis predicts that firms that are informationally opaque and firms that are in poor financial health benefit by staying with their relationship banks. As per this hypothesis, the propensity of a firm to switch to a new bank must be increasing in measures of the firm's informational transparency and financial health. On the other hand, there could also be costs of staying with existing banks, that might cause firms to switch to new banks. It is well known that the banking industry is highly segmented, and that small and large borrowers specialize in lending to different categories of firms (Stein (2002), Berger et al. (2005), Kano et al. (2006)); small banks have a better ability to process soft information and are more likely to lend to informationally problematic borrowers, while large banks specialize in syndicated lending to larger firms. Moreover, small banks may not be able to meet the growing credit needs of their borrowers because of regulator-imposed and self-imposed lending limitson the extent of exposure to individual borrowers. This suggests that as firms grow and their information quality improves, they are more likely to want to build new relationships with larger banks in order to better meet their increasing needs for credit and other capital market services. This can be viewed as a "graduation hypothesis" similar to firms graduating to more reputable investment banks, auditors, etc. (see Krigman et al. (2001) for instance). As per the graduation hypothesis, a firm should be more likely to switch to a new bank if all its existing relationships are with small banks; moreover, the firm should also be more likely to switch to a large bank.

Interestingly, in contrast to the soft information hypothesis, the graduation hypothesis does not predict an increasing relationship between a firm's informational transparency and its propensity to switch to a new bank. Since smaller and less transparent firms are more likely to have existing relationships with small banks, the graduation hypothesis predicts that these should be more likely to switch to new banks; on the other hand, large transparent firms that already have existing relationships with large banks should be less likely to switch. More importantly, the graduation hypothesis offers testable predictions regarding the motivations of firms in switching to new banks. Since firms graduate to a large bank when their credit needs increase beyond what can be provided by their current relationship bank, they should be more likely to switch when the amount of their most recent loan was "abnormally" low and should be able to obtain a higher loan amount after they switch to a new bank. Moreover, the ability to borrow more by switching banks should also likely result in higher capital expenditures and higher leverage in these firms. We examine the influence of firm, bank and bank market characteristics on a firm's propensity to switch to a new bank to distinguish between these hypotheses.[4] By way of preview, our main findings are as follows:

We find that the soft information hypothesis – that informationally opaque firms are

[4]As we explain in our "Hypotheses" section, there could also be other supply side factors like competition in the bank market, deposit growth at banks, and merger and acquisition activity involving existing banks that might influence a firm's propensity to switch to a new bank.

more likely to stay with their existing banks – does not hold uniformly across the information spectrum. Consistent with the soft information hypothesis, we find that firms for which financial data is not available in the Compustat database – "non-Compustat" firms which may be thought of as much more informationally opaque than "Compustat" firms – are 12% less likely to switch banks than the Compustat firms. However, among the sub-sample of Compustat firms, the informationally opaque firms (small firms, firms without a credit rating, firms tracked by fewer analysts) are more likely to switch banks. This finding is robust to a variety of specifications, and is economically and statistically significant; for instance, a one standard deviation increase in firm size lowers the probability of switching by 8.2%. Thus overall in our sample, the most opaque firms (non-Compustat firms) and the most transparent firms (the large Compustat firms) are less likely to switch banks. This non-monotonic relationship between information quality and a firm's propensity to switch to a new bank is consistent with the graduation hypothesis.

Consistent with the graduation hypothesis, we find that firms are more likely to switch from small banks to large banks, from small bank markets to large bank markets, from markets in which large banks have a lower market share to markets dominated by large banks. This evidence is also consistent with the notion that as firms grow and become more transparent, they have less need for small banks that specialize in lending to informationally problematic firms.[5] Interestingly, the non-Compustat firms in our sample are not only less likely to switch to new banks, but are also less likely to switch to large banks and large bank markets. This evidence suggests that the firms that are very opaque find it difficult to graduate to large banks and potentially overcome borrowing constraints at their existing bank.

Further support for the graduation hypothesis is obtained from our results that firms are more likely to switch to a new bank if the amount of their most recent loan was "abnormally" low,[6] and that they obtain a larger loan amount after they switch to a new bank. Furthermore, examining the sub-sample of Compustat firms for which we have detailed financial information, we find that firms that switched to new banks undertook higher capital expenditure (i.e., invested more in new property plant and equipment) and experienced an increase in leverage following the switch. Interestingly, this effect is stronger for the smaller firms, which presumably face tighter borrowing constraints at their relationship banks. Taken together, these findings offer strong support to the graduation hypothesis that firms switch to new banks in order to escape borrowing constraints at their relationship banks.

To summarize, while most of the empirical literature has highlighted the benefits of

[5] Scott (2004), Cole et al. (2004), and Berger et al. (2005) provide evidence that small banks are better at producing soft information and delivering relationship lending.

[6] We measure "abnormal" loan amount as the difference between the actual loan amount and a predicted loan amount, obtained from a predictive model that includes firm, loan, bank and bank market characteristics along with time effects.

banking relationships, we highlight both the benefits and costs of banking relationships by focussing on the determinants of banking relationships. While banking relationships can benefit opaque borrowers by enabling banks to reuse soft information, our paper highlights that there are attendant costs too, especially if the existing relationship is with a small bank that may not be able to meet a firm's growing borrowing needs. These borrowing constraints may induce firms to switch to larger banks in order to improve their access to credit and other capital market services. The benefits of borrowing from relationship banks may dominate the costs for the very small and informationally opaque borrowers, such as the small non-Compustat firms in our sample. However, information considerations do not prevent larger firms – many of which are traded publicly, have debt ratings and are tracked by financial analysts – from switching to new banks. For these firms, the borrowing constraints with current relationship banks outweigh the information benefits of continuing current relationships. This, we believe, is the main contribution of our paper to the literature on banking relationships.

The remainder of our paper is organized as follows: We present a discussion of the related literature in Section 2. Our main hypothesis are outlined in Section 3. We describe our data and summary statistics in Section 4. Our main results are presented in Section 5. Section 6 concludes the paper.

2 Related Literature

Our paper complements the large and growing literature that documents the benefits of strong banking relationships to firms, both within the United States and outside. In terms of international evidence, there is a large body of research that shows that firms that are either related to or have close ties to their banks are less liquidity constrained and obtain financing on better terms than firms without such close connections (see Hoshi et al. (1990), Elsas and Krahnen (1998), Harhoff and Korting (1998), La Porta et al. (2003), Charumilind et al. (2006), Park et al. (2006), etc.). In the United States, several researchers have documented that the existence or renewal of a banking relationship or a loan commitment is a positive signal to the stock market (James (1987), Lummer and McConnell (1989), Shockley and Thakor (1992), Billet et al. (1995), etc.), offering indirect evidence that even publicly-listed firms benefit from banking relationships.

More direct evidence is provided by Petersen and Rajan (1994) and Cole (1998) who show that banking relationships lead to increased availability of credit for small businesses, and by Berger and Udell (1995) who show that relationship banks are less likely to demand collateral from small businesses. Berlin and Mester (1998) show that relationship banks also benefit their borrowers by smoothing loan prices across multiple loans in response to interest rate shocks. A more recent study that examines whether large US firms derive any benefits from strong banking relationships is Bharath et al. (2006). Using a sample similar to ours, Bharath et al document that borrowing from a relationship bank translates into lower interest rates of 5 to 15 basis points, higher loan amounts and lower collateral requirements.

The main difference between our paper and the papers mentioned above is that we treat a firm's banking relationships as endogenous, and examine why firms enter into new banking relationships at all. Our paper focuses on both the benefits and costs of relationship banking, and demonstrates that these can vary depending on firm characteristics and bank characteristics. In other words, relationship building through accumulation of soft information is not as valuable to large, publicly traded and transparent firms as it is to small and opaque firms; moreover, for firms with growing credit needs, relationships with larger banks that have expertise in syndicated lending could be more valuable than relationships with small banks that have expertise in lending to informationally problematic borrowers.

Our paper also differs from Petersen and Rajan (1994), Berger and Udell (1995), Berlin and Mester (1998) and Cole (1998) in two other crucial respects. First, our sample consists of loan deals made by medium- to large-size US banks to medium- to large-size US firms, while their sample consists only of small banks making loans to small privately-owned firms, which are likely to find banking relationships most useful. A second crucial difference is that our sample, which spans a long period of time, offers us a dynamic view of firms' banking relationships, while their sample only offers a static snapshot.[7] The greater variation in firm characteristics and bank characteristics in our sample and the longer time span allow us to better understand the choice a firm faces between borrowing from its relationship bank versus switching to a new bank.

Our paper is related to two recent papers that examine the issue of firms switching to new banks for their repeat loans. Using a panel data set of the banking relationships of Norwegian firms, Ongena and Smith (2001) find that firms that maintain multiple-bank relationships are more likely to end a bank relationship than single-bank firms. Consistent with our results from the US private debt market, Ongena and Smith find that small, highly-leveraged "growth" firms are more likely to end a bank relationship than large, low-leveraged "value" firms. Using a detailed data set of Bolivian loans, Ioannidou and Ongena (2006) show that borrowers switch to new banks mainly in order to obtain a lower rate on their loans; however, once the borrower is informationally locked in with the new bank, the new bank starts hiking the interest rate. Apart from the fact that our analysis is conducted on US loan data, there are other important differences between our paper and these two papers. First, we find that US firms switch to new banks mainly in order to obtain higher loan amount; we do not find any evidence of lower loan yields following a switch. This is in contrast to the finding in Ioannidou and Ongena (2006) and the prediction in Von

[7] These papers use the data from the Federal Reserve Board's National survey of Small Business Finances (NSSBF).

Thadden (2004).[8] Second, we examine the impact of the borrower's information quality, bank characteristics and bank market characteristics on the borrower's propensity to switch to a new bank. This leads to our main finding that firms attempt to graduate from small banks to large banks, and from small bank markets to large bank markets.

Finally, our paper also contributes to recent research that documents that bank characteristics and bank market characteristics impact credit availability to small businesses (Berger et al. (2007)) and deposit interest rates (Rosen (2003)). Most of this literature has been motivated by the consolidation of the banking industry in the last few decades, and the consequent impact on the structure and organization of the industry. We extend this literature by showing that bank characteristics and bank market characteristics also influence the propensity of firms to form new banking relationships.

3 Hypothesis

Our primary objective is to determine how firms choose between a relationship bank and a non-relationship bank for their repeat borrowing needs. Here we outline the main hypotheses that have predictions relevant for this choice.

Theoretical literature highlights that banks in the course of their interaction with borrowers collect information about the borrower. Such information, say about the borrower's position in its product markets, management quality, etc., is referred to as "soft information" and is typically not observed by outside lenders. If a firm chooses a relationship bank for its repeat borrowing, then the bank can use the soft information to make a more informed credit decision. As against this a non-relationship bank may only have access to hard information such as the firm's financials. Thus borrowing from relationship banks is likely to be especially beneficial for informationally opaque firms that lack "hard" public information.

On a related note, firms in financial distress may be concerned about the bank's ability to make the "right" liquidation versus continuation decision (Chemmanur and Fulghieri (1994)). Such firms may also benefit by borrowing from better-informed relationship banks. It is also possible that borrowers with poor financials may repeatedly borrow from their relationship lenders in order to acquire a reputation for being "good" borrowers (Diamond (1989)). Summarizing, the soft information hypothesis predicts that informationally opaque firms and firms in poor financial health are more likely to borrow from their relationship banks.

Testing the soft information hypothesis with the Dealscan database is made difficult by

[8] Examining a data set of small business loans in the United States, Black (2006) finds evidence that when small firms seek an additional (outside) lender, new lender rates are generally higher than existing lender rates, implying that outside rates are higher than inside rates.

the fact that financial information on borrowers involved in about 65% of the loans is not available in the Compustat database. This precludes the use of variables such as firm size as proxies for a firm's information environment. Typically the firms not in Compustat are the smaller, private firms which are likely to be informationally more opaque. We use this fact and identify the presence of financial information in Compustat as indicating greater information transparency. Thus our first proxy for a firm's information environment is a dummy variable indicating presence of financial information in Compustat. For firms that are covered by the Compustat database, we use the firm's size measured in terms of the book value of total assets, presence of unsecured debt rating and the number of analysts following the firm as additional proxies for the firm's information quality. We also use the firm's leverage, measured as the ratio of total debt over total assets (*Leverage*) and Altman Z-score as measures of a firm's financial health.[9]

We now outline the "graduation hypothesis" of how firms choose between a relationship and a non-relationship bank for their repeat loans. The banking literature highlights that the industry is heterogenous and has a mix of large and small banks. These banks possess unique strengths and are argued to specialize in lending to different classes of borrowers (Stein (2002), Berger et al. (2005), Kano et al. (2006)); small banks are argued to have a better ability to process soft information and hence more likely to lend to informationally problematic small borrowers, while large banks are argued to specialize in syndicated lending to larger firms. It is also well known that bank regulators in order to promote portfolio diversification, impose exposure limits for individual borrowers based on the size of the bank's capital. The presence of such limits implies that small banks may not be able to meet the growing credit needs of their borrowers.[10] So as firms' credit needs increase they are more likely to want to build relationships with larger banks. If the firms have existing relationships with small banks then they are more likely to want to form new relationships with large banks. This process may be more pronounced for firms with a better information environment as large banks are more likely to be willing to lend to them. We call this the "graduation hypothesis."

The graduation hypothesis predicts that firms that do not have existing relationships with large banks are not only more likely to switch banks, but are also more likely to switch to a large bank. Since large and small banks populate different markets, this is also likely to result in firms switching from small, non-metropolitan bank markets to large, metropolitan bank markets. Furthermore, this effect should be less pronounced for the informationally opaque firms. Interestingly, in contrast to the soft information hypothesis, the graduation hypothesis does not predict a positive relationship between a firm's information transparency and its propensity to switch. Firms that are very small and informationally

[9] The Z-score is defined as 3.3*(pre-tax income/total assets)+ 0.999*(sales/total assets)+ 1.4*(retained earnings/total assets)+ 1.2*(working capital/total assets)+ 0.6*(Equity/Debt).

[10] Loan syndication is one way banks can overcome these limits. But interestingly it is the large banks that are more active in the syndication market.

opaque may find it difficult to graduate to large banks as these banks may be unwilling to lend to them. As firms grow and their information environment improves, not only are these firms likely to be more attractive to large banks but the costs of switching are also likely to go down. Hence if these firms have existing relationships with small banks, then they should be more likely to switch to new large banks. On the other hand, large transparent firms that already have existing relationships with large banks should be less likely to switch banks. Thus the graduation hypothesis predicts a non-monotonic relationship between a firm's information environment and its propensity to form new banking relationships. The most opaque and the most transparent firms are less likely to switch in comparison to firms in the middle of the information spectrum.

Since firms graduate to a large bank when their credit needs increase beyond what can be provided by their current relationship bank, they are more likely to switch when the amount of their most recent loan was "abnormally" low and are likely to obtain a higher loan amount when they switch.[11] Moreover, the ability to borrow more by switching banks is also likely to result in higher capital expenditures and leverage in these firms. We test all these predictions of the graduation hypothesis.

Apart from the soft information and the graduation hypotheses, a firm's decision to borrow from relationship vs non-relationship banks can also be driven by other supply side factors such as competition in the bank market, bank's deposit growth, and bank mergers. Bank-borrower relationships are under constant threat from competing lenders that may provide a superior product or a lower price (Petersen and Rajan (1995) and Boot and Thakor (2000)). So the probability of a firm switching to a non-relationship bank should be higher if the firm borrows from competitive bank markets. Banks that experiences a high deposit growth may be more aggressive in courting new firms. So we expect the probability of a firm borrowing from a non-relationship bank to be positively related to the bank's deposit growth. Finally, firms may also switch to a non-relationship bank due to changes at their relationship banks such as mergers, restructuring etc. Bank merger may change the characteristics of a bank and consequently a firm's willingness to continue borrowing from the bank (Berger et al. (1998)). Since informationally opaque firms are likely to face a higher cost of switching, we expect these effects to be weaker for information problematic firms. We now outline the data we use to test these predictions.

[11] Apart from meeting the increased future credit needs, such a switch may also enable potential access to other capital market products and services offered by larger banks. It is also possible that firms switch to new banks so as to escape the hold-up problem highlighted in Rajan (1992) and Sharpe (1990). Rajan argues that a relationship bank might exploit its informational advantage over outside uninformed lenders to extract rents from the borrower. It is possible that small and opaque borrowers, anticipating such future hold-up, switch to new banks so as to not be informationally captured by their relationship bank. Empirical evidence on the hold-up problem associated with relationship lending, however, is quite mixed (e.g., Petersen and Rajan (1995), Zarutskie (2006), and Carbó-Valverde et al. (2006)).

4 Data Description and Summary Statistics

4.1 Sample Construction

We obtain the data on individual loan contracts from a 2006 extract of the Loan Pricing Corporation's (LPC) Dealscan database. Dealscan provides information on loans made to medium and large sized US and foreign firms. According to LPC, the data is collected from a variety of sources – detailed SEC filings, self reporting by lenders, etc. We extract information on all dollar-denominated loans made by US lenders to US borrowers during the 1990–2006 period. We exclude borrowers that are in the financial services sector, i.e., borrowers with SIC codes between 6000 and 6500.

Dealscan provides information on deals or loan packages obtained by borrowers. For the purpose of our study, the unit of observation will be the deal. Each deal or loan package could consist of multiple loans, which are contracted simultaneously. The loans could be financed either by a single lender or by a syndicate of lenders. When the loan is financed by a syndicate, Dealscan allows us to identify the lead lender for the loan.[12] We also obtain the loan contract terms such as the total loan amount, yield,[13] maturity, loan type, purpose of the loan, information on security and loan covenants from Dealscan.

We use the Compustat database to obtain detailed financial information regarding the borrowers in our sample. To avoid errors, we manually match the Dealscan data with Compustat using firm name. For the borrowers in Compustat, we obtain the borrower's financial information at the end of the financial year in which the deal was originated.

We obtain detailed information on the lead banks from the Call Report Data from the website of the Chicago Federal Reserve. Here again to avoid error, we manually match the call report data with Dealscan using the name of the lead bank. From the call reports, we obtain information on the bank size, location of the bank, specifically, the metropolitan statistical area (MSA) code or the county code in which the bank is located. We use the bank location to calculate bank market characteristics such as market size, concentration, etc.

4.2 Empirical Specification and Key Variables

In our empirical analysis we are mainly concerned with the firm's choice between a relationship bank and a non-relationship bank for its repeat borrowing. To analyze this choice,

[12]Specifically, we identify the lead lender using the "LeadArrangerCredit" (which is a dummy variable) and "BankAllocation" (which denotes the fraction of loan amount contributed by the lender) variables. For a syndicated loan, we identify a lender as lead lender if LeadArrangerCredit=1 or BankAllocation=100.

[13]Specifically, Dealscan provides a variable called "all-in-drawn spread" which denotes the cost to the borrower per dollar of loan amount withdrawn. The all-in-drawn spread is provided as a basis-point spread above the London Interbank Offer Rate (LIBOR).

we estimate panel logit regressions that are variants of the following form:

$$y_{it} = F(\beta_0 + \beta_1 * X_i + \beta_2 * X_b + \beta_3 * X_d + \mu_t + \mu_i), \quad (1)$$

where the subscript 'i' indicates the borrower, subscript 't' indicates the deal number for a particular borrower, subscript 'b' indicates the bank and/or the bank market and subscript 'd' indicates the deal. In all specifications that we estimate, the standard errors are robust and clustered at individual borrower level.

The dependent variable y_{it} is *New Relationship*, a dummy variable that identifies instances when the borrower borrows from a non-relationship bank. To construct *New Relationship*, we use all the previous deals of the borrower in our sample and code *New Relationship* equal to 1 if the lead lender in the current deal has never been a lender in the past (after adjusting for mergers and acquisitions). Note that *New Relationship*=0 indicates that the firm borrows from a relationship bank. Since, we look at past deals to code *New Relationship*, we construct this variable only from the borrower's 2^{nd} deal onwards.

Since Dealscan is not a comprehensive listing of all US private debt deals, firms may have borrowings which are not covered in Dealscan.[14] Since we identify new borrower-lead lender relationships based on the past loans in Dealscan, absence of loan information in Dealscan is likely to result in misclassification of repeat relationships as new-relationships. This misclassification is likely to reduce the difference between new- and repeat-relationship deals and is only likely to attenuate our results. To partly control for this misclassification, we repeat most of our analysis on sub-samples of deals originated during the time period 1995-2005, when Dealscan significantly increased its coverage. A couple of additional comments on the definition of *New Relationship* are in order. First, we do not impose any time restriction in defining this variable. Instead, we define a variable called *Time between deals* to measure the time since the previous deal and include it as a control in our regressions. Second, we classify a deal as involving a repeat relationship (i.e., *New Relationship*=0) even if the lead lender in the current deal was a syndicate participant in any of the borrower's previous deals. There are only 175 such instances in our data.

Since *New Relationship* is only available from the borrower's 2^{nd} deal onwards, we drop the first deal in our regressions. We also drop all deals beyond the borrower's 4^{th} deal. We do this because their inclusion may bias our results. Since we look at the borrower's past deals to identify new-relationships, the probability of borrowing from a relationship bank is likely to mechanically increase with the number of past deals of the borrower. For robustness, we repeat all our tests after including all loans of borrowers (other than the first) with controls for the deal number and obtain similar results.

[14] According to Carey and Hrycray (1999), the database contains between 50% and 75% of all commercial loans in the US during the early 1990s. From 1995 onwards, Dealscan contains the "large majority" of sizeable commercial loans.

Among the borrower characteristics (X_i) that we use, *Non Compustat* is a dummy variable that takes a value 1 for borrowers not present in the Compustat database. These firms are expected to be informationally opaque. For borrowers with financial information in Compustat, we use *Size*, *Rated* and *Analysts* as alternative measures of the firm's information quality: *Size* is the log of the book value of total assets, *Rated* is a dummy variable that identifies firms with unsecured long term credit rating, and *Analysts* is the number of security analysts following the firm's stock. Larger firms, firms with credit ratings and firms with greater analyst following are likely to be informationally transparent. We also use *Leverage*, the ratio of book value of total debt to book value of total assets as a measure of firm leverage. We use *Industry Leverage*, the median *Leverage* of all Compustat firms in the same 4-digit SIC code as the borrower, as an exogenous measure of expected firm leverage. We measure all the borrower financial ratios at the end of the financial year in which the deal is originated.

Among the bank characteristics (X_b) that we use, *Large Bank* is a dummy variable that identifies banks with book value of total assets greater than the 95^{th} percentile among all banks during the quarter in which the loan was originated.[15] *Deposit Growth* denotes the rate of growth of deposits for the lead lender during the quarter preceding the loan origination. As is standard in the banking literature, we define a lead lender's local market as the metropolitan statistical area (MSA) in which the lead lender is located; if the lead lender is not located in a metropolitan area, we use the county as the local market. Among the bank market characteristics that we use, *Bank Mkt. Size* is the logarithm of the sum of the book value of assets of all banks in the local market. *Large Bank Dep Share* is the share of deposits of large banks (as identified using *Large Bank*) in the lead lender's local market. *Deposits Herfindahl* is the sum of the squares of the deposit market shares of all banks in the local market in which the lead lender is located. We use *Deposits Herfindahl* as a measure of concentration (or as an inverse measure of competition) in the lead lender's local market. The higher the Herfindahl index, the more concentrated is the local bank market. It must be mentioned that *Large Bank Dep Share* and *Deposits Herfindahl* are highly positively correlated with *Bank Mkt. Size*. This is not surprising because larger bank markets tend to be dominated by large banks.

Among the deal characteristics (X_d) that we control for, *Short Term* is a dummy variable that identifies deals with average maturity of less than 1 year, *Medium Term* identifies deals with maturity between 1 and 5 years, and *Long Term* identifies deals with maturity over 5 years. Since maturity is reported at the individual loan level, we compute deal maturity as the weighted average maturity of all loans within a deal, with the weights equal to the loan amounts. We also use dummy variables *Repayment*, *Takeover* and *Working Capital* to identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital respectively.

[15] In the year 2000, the 95 percentile size corresponded to book value of assets of around \$1.2 billion.

The graduation hypothesis predicts that firms are likely to switch banks if borrowers obtain adverse terms on their most recent past loan. To test this prediction we model the terms on a loan using the following panel model:

$$y_{it} = \beta_0 + \beta_1 * X_i + \beta_2 * X_d + \beta_3 * X_b + \mu_t, \tag{2}$$

where the dependent variable y is either *Log(Amount)*, the logarithm of the deal amount, or *Log(Yield)* the logarithm of the deal yield. We define deal yield as the weighted average all-in-drawn spread (see footnote 13) on all loans in the deal package, weighted by loan amounts. We estimate the model with borrower (X_i), deal (X_d), and bank (X_b), characteristics mentioned earlier and use the model to predict the amount or yield on a deal.[16] We then obtain a measure of the "abnormal" amount (yield), which we call *Excess Amount* (*Excess Yield*), as the difference between the actual amount (yield) on the deal and the predicted amount (yield) estimated from model (2); to estimate the impact of previous deal terms on a borrower's propensity to form new-relationships, we re-estimate regression (1) after including lagged values of *Excess Amount* and *Excess Yield*.

The graduation hypothesis also predicts that firms that switch to a new bank obtain more favorable borrowing terms, undertake higher capital expenditures, and experience an increase in leverage compared to firms that do not switch. To test these predictions, we estimate panel regressions that are variants of following form:

$$y_{it} = \beta_0 + \beta_1 * \text{New Relationship}_d + \beta_2 * X_i + \beta_3 * X_d + \beta_4 * X_b + \mu_t + \mu_i, \tag{3}$$

where the dependent variable y is either a deal characteristic or a firm characteristic. The deal characteristics we model include, *Log(Amount)*, *Log(Yield)*, *Secured* a dummy variable identifying secured deals, and *Financial Covenants*, a dummy variable that identifies deals with financial covenants. The firm characteristics we model include *Log(Capex)*, the logarithm of the firm's capital expenditure, and *Leverage*. Since we have financial information only for firms with Compustat data, the sample for the firm characteristics regressions are confined to the Compustat firms.

4.3 Summary Statistics

We provide the descriptive statistics for our full sample in Panel A of Table I. These pertain to all loan deals in which the lead lender is identified as a US bank and which are either the 2^{nd}, 3^{rd} or the 4^{th} deal of a firm; there are 12,278 deals which meet these conditions. The average deal amount is about $275 million, whereas the median is $100 million. The average yield is 129 basis points over the LIBOR. 3,487 (28%) of these deals involve only a single bank, whereas the remaining 8,791 deals (72%) involve more than one bank in the

[16] We do not include borrower fixed effects in this regression because of look-ahead bias.

syndicate. We have covenant and security data for only around half of the sample. Within the sub-sample of deals for which we have security data, 73% of the deals are secured. Similarly, within the sub-sample of deals for which we have data on covenants, financial covenants are present in 86% of the deals.

The median firm in our sample borrows approximately every 16 months (or 1.35 years). However, 25% of our sample involves firms that borrow as frequently as every 10 months. As can be seen, about 40% of these repeat deals involve new borrower-lead lender relationships. We use dummy variables to identify the purpose of the deal. Around 59% of the deals identify financing working capital, 21% identify repayment of previous debt, and around 13% identify financing a takeover as the main purpose of the deal. Deals involving firms without Compustat data constitute about 65% of our sample. Among the deals to Compustat firms, only around 38% involve firms that had unsecured debt ratings. Among our Compustat firms, the average firm had total book assets of $4.25 billion and the median firm has book assets of $544 million.

Our next set of variables measure lead bank and bank market characteristics and are constructed by matching Dealscan data with bank data from the Call Reports. We are able to match the lead banks of 8,832 deals with their financial information from the most recent quarter. As can be seen, around 86% of the lead lenders in our sample are large banks, although large banks by definition constitute only 5% of the overall population of banks. This shows that lead lenders are typically large banks and the majority of the smaller banks confine themselves to participating in the syndicates. Further, as mentioned earlier, in our sample of 30,466 deals, there are only 175 instances where a syndicate participant goes on to became a lead lender on a latter deal involving the same borrower. This offers further evidence that lead lenders and participants are fundamentally different, and offers justification for defining bank-borrower relationships at the lead lender level. We use the dummy variable *Non MSA Bank* to identify lead lenders not located in a Metropolitan Statistical Area. As can be seen, less than 3% of the lead lenders in our sample are located in a non-metropolitan area. Hence we do not use this variable in our subsequent analysis.

4.4 Univariate Tests

In Panel B of Table I, we provide the mean values of the key variables in the two sub-samples identified based on whether or not the deal involves a new bank-borrower relationship. From the table we can see that deals involving new relationships are for smaller amounts, carry a higher yield, are more likely to include financial covenants, are for shorter maturities and involve fewer lenders. Further, deals involving new relationships are more likely to finance takeovers and are less likely to finance working capital investment. This evidence suggests that riskier borrowers are more likely to enter into new banking relationships; or, it could be that these borrowers are perceived to be risky by their new banks that know very little about them.

We can also see from Panel B that borrowers involved in new relationships are more likely to be Compustat firms. This is consistent with the soft information hypothesis that predicts that informationally transparent firms are more likely to form new relationships. However, among Compustat firms, we find that firms that enter into new banking relationships are likely to be smaller, less likely to have credit rating, and are likely to be followed by fewer security analysts. Thus among Compustat firms, the firms that switch to new banks are the less transparent firms. This is inconsistent with the soft information hypothesis. On the other hand, this is consistent with our earlier observation that new relationship deals are in general riskier than those involving repeat relationships.

From the last set of variables in Panel B, we find that banks involved in new relationships, i.e., the banks to which firms switch to, are smaller, located in smaller banking markets, are more likely to be located in non-MSA counties, and are in more competitive banking markets as measured by the deposits Herfindahl index. Since these differences do not control for other firm characteristics, we should exercise caution in interpreting them. As we show presently, after controlling for firm characteristics, we find that firms are more likely to switch to larger banks and larger banking markets.

In Panel C of Table I, we provide the mean values of the key variables in the two sub-samples identified based on whether or not the borrower has Compustat data. Not surprisingly, borrowing firms without Compustat data borrow smaller amounts but borrow more frequently and pay a higher yield on their loans. The fact that non-Compustat firms borrow smaller amounts more frequently may indicate credit constraints imposed on them by their banks. One surprising result is that these firms are less likely to have financial covenants in their loan agreements; one potential explanation is that this reflects the poor quality of their financial statements. The number of lenders involved in loans to the non-Compustat firms is also smaller. Further we find that the non-Compustat firms are less likely to borrow from a large bank, are more likely to borrow from a non-MSA bank, and are more likely to borrow in a less competitive banking market.

Panel A of Table II provides the correlations between the key loan variables and lead bank variables for all the firms in our sample. From this table it is clear that smaller loans are associated with a higher yield. We also find that many of the bank and bank market characteristics are highly correlated. Clearly, large banks are typically found in large bank markets, in highly concentrated bank markets, and are less likely to be located in non-MSA counties. To avoid problems of multi-collinearity, in our regressions we include the bank and bank market characteristics one at a time.

In Panel B of Table II we provide the correlations between the key variables for the sub-sample of firms with Compustat data. From the table it is clear that larger firms, more profitable firms, firms with a credit rating, and firms with higher market to book ratios have a lower yield. It is also clear that the larger firms typically borrow from the larger bank markets.

We now proceed to formal multivariate tests of our hypotheses.

5 Empirical Results

5.1 Informational transparency and New Banking Relationships

In this section, we test the soft information hypothesis by estimating the relationship between information quality and the propensity of a firm to borrow from a non-relationship bank. Since we have detailed borrower financial information for only around 35% of our sample, we begin our analysis with *Non Compustat* as our measure of information quality. In Panel A of Table III, we first estimate the panel logit regression (1) for all the firms in our sample with *Non Compustat* as the main independent variable. As per the soft information hypothesis, the coefficient on *Non Compustat* should be negative and significant.

In Column (1), we estimate the model without any controls. The negative coefficient on *Non Compustat* is in line with the soft information hypothesis and confirms our earlier observation from Table I that firms without Compustat data are less likely to form new banking relationships. In Column (2), we repeat the regression with important deal characteristics as controls. To partially control for firm size, we include the logarithm of the lagged loan amount; *Repayment*, *Working Capital*, and *Takeover* to control for loan purpose; *Short Term* and *Long Term* to control for deal maturity; and *Syndicate* to identify deals with more than one lender. Finally, to control for the time since the last deal for the borrower, we include, *Time Bet. Deals*, a dummy variable that takes a value 1 if the time since the last deal is above the sample median. We are unable to control for other firm characteristics because the sample includes firms for which there is no financial data in Compustat.

The results in Column (2) indicate that the coefficient on *Non Compustat* remains negative and its magnitude is unaffected by the inclusion of the additional control variables. The coefficients on the control variables show that firms are more likely to form new-relationships when the prior loan amount is small, the main purpose of the deal is to finance takeovers, when the deal has an average maturity greater than 1 year, when the syndicate has only one lender and when a long time has elapsed since the last borrowing by the firm. These results are consistent with the univariate results from Table I. The negative coefficient on *Log(Amount)* either indicates that firms that switch lenders borrow smaller amounts. The positive coefficient on *Takeover* is in line with our earlier observation that deals involving new bank-borrower relationships are likely to be more risky. The positive co-efficient on *Time Bet. Deals* may indicate the fact that if a long time has elapsed since the borrower's last deal, then the incremental benefits of borrowing from the relationship bank may be small.

As mentioned earlier in Section 4.2, the accuracy of our definition of *New Relationship* (i.e., our classification of a borrower's repeat loans as new relationships or repeat relationships) depends on the comprehensiveness of the Dealscan coverage. Since Dealscan coverage improved significantly post 1995, in Column (3), we repeat the regression after confining the sample to the deals originated after 1995. The results are significantly stronger in this sub-sample indicating that any potential misclassification of existing relationships as a new relationship is only biasing our coefficient on *Non Compustat* downward. In Column (4), we repeat the regression on the sub-sample of deals financed by a single bank, i.e., the non-syndicated deals. We do this because non-syndicated deals are more likely to involve smaller firms and confining the sample to non-syndicated deals is likely to diminish the distortions introduced by not controlling for other firm characteristics. As can be seen, our results in Column (4) are qualitatively similar to those in other columns.

In Column (5), we repeat the regression on a balanced panel, i.e., we only include firms which have at least 4 deals reported in Dealscan. We do this to ensure that our results are not driven by firms with a higher number of repeat deals. The results in Column (5) once again confirm that firms with no coverage in Compustat are less likely to switch to new banks. Finally, in Column (6), we repeat the regression with firm fixed effects and a linear probability model. The results again confirm that firms without Compustat data are less likely to switch to a new bank. Since this is a linear probability model, the coefficient is equal to the marginal effect. The coefficient indicates that when a firm without Compustat data changes status, the probability of switching to a new bank increases by more than 12%. This indicates that our results are economically significant.[17]

Overall, the results in Panel A suggest that the most informationally opaque firms in our sample, i.e., the non-Compustat firms, are less likely to switch to a new bank for their repeat deals. This result is consistent with the soft information hypothesis and also with the graduation hypothesis.

In Panel B of Table III, we repeat regression (1) on the sub-sample of borrowers for which we have financial data in the Compustat database. This enables us to use alternate proxies for a firm's information environment and also to better control for other firm characteristics. In Column (1) we use *Size* as the proxy for a firm's information environment. Since larger firms are less likely to suffer from asymmetric information problems, the soft information hypothesis predicts a positive coefficient on *Size*. In these regressions we also control for

[17] As against this, the coefficient in Column (2) indicates that without controlling for unobserved firm level heterogeneities, a firm without Compustat data is about 3% less likely to switch to a new bank than a firm with Compustat data.

a firm's investment opportunities with the *Market to Book Ratio* and the firm's expected leverage as measured by *Industry Leverage*.

The negative coefficient on *Size* in Column (1) indicates that smaller firms are more likely to form new banking relationships. This is consistent with the univariate results presented in Section 4.4, and contradicts the soft information hypothesis. The coefficients on the other control variables are similar to those obtained with the full sample in Panel A. In Column (2), we repeat the regression after limiting the sample to loans originated after 1995 and obtain consistent results. In unreported tests, we repeat the regression after limiting the sample to single lender loans, to borrowers with a minimum of four deals. In all sub-samples, we obtain results that indicate that larger firms are more likely to stay with their relationship banks, whereas smaller firms are more likely to form new banking relationships.

In Column (3), we repeat the regression with an alternative measure of information quality; instead of firm size, we use the dummy variable, *Rated*. Since firms without a bond rating are likely to have lesser information in the public domain, the soft information hypothesis would predict a positive coefficient on *Rated*. However, as with *Size*, we observe a negative and statistically significant coefficient on *Rated*. In Column (4), we repeat the regression with *Analysts* as a measure of a firm's information transparency and obtain similar results.

Overall, the results in Panel B indicate that among the firms with financial data in Compustat, the larger firms, firms with bond ratings, and firms with a greater analyst following are more likely to borrow from their relationship bank. These results are inconsistent with the soft information hypothesis. Our results are both statistically and economically significant. The coefficient on *Size* in Column (1) indicates that a one standard deviation increase in *Size*, reduces the probability of switching to a new bank by 8.2%.

In Columns (5) and (6) we test if firms in poor financial position are more likely to borrow from relationship banks. In Column (5) we use *Leverage* as a measure of financial health. Note that since we control for *Industry Leverage* a higher value of *Leverage* should indicate a worse financial position. In Column (6) we use *Altman Z-Score* as a measure of the firm's financial position. The results indicate that neither variable is a significant predictor of a firm's tendency to form new relationships.

To summarize, our findings so far indicate that the soft information hypothesis does not hold uniformly across the information spectrum. Consistent with the soft information hypothesis, we do find that non-Compustat firms, are more likely to stay with their relationship banks. However, among the sub-sample of Compustat firms, the informationally opaque firms (small firms, firms without a credit rating, firms tracked by fewer analysts) are more likely to switch banks. Thus overall in our sample, the most opaque firms (non-

Compustat firms) and the most transparent firms (the large Compustat firms) are less likely to switch banks. This non-monotonic relationship between information quality and a firm's propensity to switch to a new bank is consistent with the graduation hypothesis. As mentioned earlier, the smallest firms may find it difficult to switch banks as the new banks may be reluctant to take them on. On the other hand, the largest firms may not have any need to graduate as they may already have relationship with large banks. The first missing link between our results and the graduation hypothesis is to identify the type of banks that firms switch to. This we now proceed to do.

5.2 Are firms graduating to larger banks?

In this section we estimate the impact of bank and bank market characteristics on a firm's choice to form new-relationships. The graduation hypothesis predicts that firms are more likely to form new relationships with large banks especially in cases where they have no existing relationships with large banks. To test this prediction, in Table IV, we estimate regression (1) on the full sample after including bank and bank market characteristics.[18] We include characteristics of both the lead bank for the current loan and also those of the borrower's past relationship bank.

In Column (1), we estimate regression (1) after including two new variables, *Large Bank* and *Prev Large Bank*. *Large Bank* is a dummy variable that identifies whether or not the lead bank on the current loan deal is a large bank; recall that we define a bank as large if its size exceeds the 95^{th} percentile of all banks in the most recent quarter preceding the loan origination. *Prev Large Bank* is a dummy variable that takes a value 1 if the firm has had a previous relationship with a large bank. Consistent with the graduation hypothesis, the significant negative coefficient on *Prev Large Bank* in Column (1) indicates that a firm is less likely to switch to a new bank if it has an existing relationship with a large bank.

In Column (2), we repeat the regression after including interaction terms between *Non Compustat* and *Large Bank* and *Prev Large Bank*. The results indicate that firms without Compustat data are not only less likely to switch to a new bank (negative coefficient on *Non Compustat*), but they are also less likely to switch to a *Large Bank* (negative coefficient on the interaction term *Large Bank**Non Compustat*). Moreover, on average, firms are more likely to switch to a large bank, as seen from the positive and statistically significant coefficient on *Large Bank*. Our results are broadly consistent with the graduation hypothesis and also indicate that informationally opaque firms– the non-Compustat firms– find it difficult to graduate to large banks.

In Column (3), we repeat the regression after including proxies for bank market size,

[18] We also perform the tests on our smaller sub-sample of Compustat firms, where we were able to control for other firm characteristics. The results are similar to those reported.

Bank Mkt. Size and *Prev Bank Mkt. Size*. As mentioned in section 4.4, we include the bank market characteristics in our regressions one at a time because they are highly correlated with each other. *Bank Mkt. Size* measures the size of the local market in which the current lead lender is located, and *Prev Bank Mkt. Size* is defined as the maximum of *Bank Mkt. Size* for all the previous deals of the borrower. The results in Column (3) indicate that borrowers are more likely to switch to a bank in a larger bank market. Furthermore, borrowers who are already borrowing from banks in large bank markets are less likely to form new banking relationships. In Column (4), we repeat this regression after including interaction terms between *Non Compustat* and *Bank Mkt. Size* and *Prev Bank Mkt. Size* and obtain results similar to those in Column (2): non-Compustat firms are not only less likely to switch to new banks, but they are also less likely to switch to banks in large bank markets.

In Columns (5) and (6), we repeat the regressions after replacing *Bank Mkt. Size* with *Large Bank Dep Share*; recall that this variable measures how dominant large banks are in the local bank market. It measures the share of deposits of large banks (as identified using the *Large Bank* dummy) in the lead lender's local market. The results in Column (5) and (6) show that firms are more likely to switch into markets dominated by large banks, and are less likely to switch if they are already borrowing from large-bank dominated markets.

Overall, the results in Panel A of Table IV are consistent with the graduation hypothesis. We now proceed to evaluate the motives for why firms graduate to large banks.

5.3 Do firms forms new banking relationships to improve access to credit?

The graduation hypothesis indicates that firms switch to new banks to relax borrowing constraints at their current relationship bank and to potentially increase the amount they can borrow. We now proceed to test this prediction.

We begin by relating the terms on the borrowers past deal to its propensity to switch banks. The graduation hypothesis predicts that a firm is more likely to switch to a new bank if the amount on its most recent loan deal was abnormally low. We test this prediction in two stages. In the first stage, we estimate the normal amount for any loan by estimating (2) on all loans. We then take the difference between the actual amount and the predicted amount. We call this difference *Excess Amount*. In the next stage, we re-estimate (1) with lagged values of *Excess Amount* as an additional regressor. The graduation hypothesis predicts a negative coefficient on *Excess Amount*. The results of this analysis are presented in Panel A of Table V.

Column (1) presents the results of the cross-sectional regression (2), estimated on all loans with *Log(Amount)* as the dependent variable.[19] We find that loan deals from large banks involve larger amounts. Also, not surprisingly, non-Compustat firms borrow lower amounts. We use the results of the regression in Column (1) to compute *Excess Amount* for all deals. We then re-estimate (1) with lagged *Excess Amount* as an additional independent variable. Additional controls include all the variables that are significant predictors of a firm's propensity to switch to a new bank. The negative and significant coefficient on *Excess Amount* indicates that borrowers are more likely to switch to a new bank if they obtain an abnormally low amount on their most recent loan. In Column (3), we confine the sample to deals originated after 1995; in Column (4), we confine the sample to single lender loans; and in Column (5), we repeat the regression on a balanced panel of firms, i.e., we limit the sample to firms which have a minimum of four loans reported in Dealscan. The results in all sub-samples are consistent with the graduation hypothesis and highlight that firms are more likely to switch banks if they face borrowing constraints at their relationship banks in the form of lower loan amounts.

Borrowing constraints at relationship banks can also take the form of a higher loan yield. To see if loan yields at relationship banks impact a firm's decision to switch to a new bank, in Panel B we estimate *Excess Yield* on any loan. As before, we first model the yield on a deal using (2) with *Log(Yield)* as the dependent variable; the results of this regression are given in Column (1). We use these results to compute *Excess Yield*. We then re-estimate (1) after including lagged values of *Excess Yield* as an additional regressor. The positive and significant coefficient on *Excess Yield* indicates that firms are more likely to switch if they obtain a high yield on their most recent loan. In Column (2), we estimate the model on only the 2^{nd} deal of the borrower. In Column (3), we confine the sample to deals originated after 1995, in Column (4) we confine the sample to single lender loans and in Column (5) we limit the sample to borrowers who have a minimum of four loans. The results in all specifications are consistent.

Our results have two interpretations. The first one, consistent with the graduation hypothesis is that firms switch banks when they face high yields at their relationship banks. The second interpretation is that our model for deal yield estimated in Column (1) misprices risky borrowers and hence these borrowers are likely to have positive values of *Excess Yield*. Hence the positive coefficient on *Excess Yield* is merely a reflection of the fact that riskier borrowers are more likely to switch to a new bank. We try to disentangle these two predictions when we compare the yield on loan deals involving new relationships with those involving repeat relationships in Table VI.

To examine if firms benefit from new relationships, we compare the amount and yield on deals involving new relationships with those involving repeat relationships. Formally, we estimate the panel model (3) with *Log(Amount)* and *Log(Yield)* as dependent variables,

[19] Once again, our results are qualitatively similar when we repeat this analysis on the smaller sub-sample of Compustat firms.

and *New Relationship* as the key regressor. We control for deal, bank, and bank market characteristics. The results of our estimation are summarized in Panel A of Table VI. The dependent variable y is *Log(Amount)* in Columns (1) through (4), and *Log(Yield)* in Columns (5) through (7).

The results in Column (1) show that the amount in deals involving new bank-borrower relationships are smaller than those involving repeat relationships. Note that we have not controlled for unobserved firm level heterogeneities in this specification. So this result could arise even if borrowers who switch to new banks are smaller in size than those that do not switch. Therefore, in Column (2), we repeat the regression with firm fixed effects. The results indicate that after controlling for firm fixed effects, the deals involving new relationships are not associated with a lower amount. One problem with firm fixed effects is that in removing the average borrower effect, it also includes the amounts on future deals of a borrower. This introduces a look ahead bias. To control for this, and also to examine the impact of the first instance when a borrower switches to a new bank, we repeat the regression after confining the sample to deals till the first time a borrower switches to a new bank. The results in Column (3) show that the amount on the deal when the borrower first switches to a new bank is significantly more. This offers strong support for the graduation hypothesis. In Column (4), we estimate a first-differences procedure as an alternative to firm fixed effects. In this specification we include all deals since a first difference procedure is not subject to look ahead bias. The positive and significant coefficient on *New Relationship* indicates that firms that switch to a new bank obtain higher loan amounts. This offers evidence that firms benefit from new banking relationships.

In Columns (5) to (7), we repeat the analysis with *Log(Yield)* instead of *Log(Amount)* as the dependent variable. The results in Column (5) show that deals involving new bank-borrower relationships carry higher yields. But after controlling for firm fixed effects in Column (6) we find that the deals involving new relationships are not associated with a higher yield. In Column (7) we confine the sample till the first time a borrower switches to a new bank and get similar results. Our results indicate that borrowers do not benefit in terms of a lower yield when they switch to a new bank.

We also examine if firms that form new banking relationships obtain better deal terms in terms of lower collateral requirements and fewer financial covenants. Our findings are summarized in Panel B of Table VI. After controlling for unobserved firm-level effects, we do not find any evidence that firms that switch to new banks benefit through lower collateral requirements or fewer financial covenants.

So far, our results suggest that firms obtain higher loan amounts when they switch to new banks. This result is consistent with the graduation hypothesis that argues that firms switch to new banks in order to escape borrowing constraints at their relationship banks. Relaxation of borrowing constraints should also reflect in an increase in firms' capital expenditures and leverage ratios. To see if firms experience such increases when they form new banking relationships, in Table VII we re-estimate (3) with *Log(Capex)* and *Leverage* as dependent variables and *New Relationship* as the main regressor.

The dependent variable in Columns (1) and (2) is *Log(Capex)*. Since we do not normalize capital expenditure with firm size, we include lagged firm size as an additional control. In these regressions we also control for the amount of loan the firm borrows. This ensures that our results are not an automatic result of higher loan amounts involved in new-relationship deals. Our results in Column (1) indicate that firms invest more in new PP&E after they switch to a new bank. This finding offers further support to the graduation hypothesis. To see if this effect is stronger for smaller firms which are likely to experience tighter borrowing constraints at relationship banks, we repeat the estimation after including an interaction term between *New Relationship* and *Size*. As predicted, the coefficient on the interaction term, *New Relationship*Size*$_{t-1}$, is negative and highly significant. This suggests that, after controlling for firm characteristics, bigger firms experience a smaller increase in PP&E investment when they switch to a new bank. Our results are also economically significant: the positive coefficient in Column (2) corresponds to a 4% increase in capital expenditure in the year following the switch to a new bank. In Columns (3) and (4) we repeat our panel regression with *Leverage* as the dependent variable. As can be seen from Column (4), firms experience an increase in leverage following a switch to a new bank. Moreover, this effect is lesser for bigger firms, that presumably face lesser borrowing constraints than the smaller firms.

Overall, our findings in Tables V, VI and VII indicate that firms switch banks when they experience abnormally low loan amounts (Table V) and when they switch banks, they borrow higher amounts (Table VI) and such borrowing results in higher capital expenditure and leverage (Table VII). These results are consistent with and offer support for the graduation hypothesis.

5.4 Impact of other supply side factors on a firm's propensity to switch to a new bank

In this section we investigate how supply side factors such as the competitiveness of the banking market, bank deposit growth rate and bank mergers affect a firm's propensity to switch to a new bank. To do this, in Table IV we estimate (1) after including these additional supply side variables as regressors.

In Columns (1) and (2), we estimate the regression with measures of bank market concentration, *Deposits Herfindahl* and *Prev Deposits Herfindahl*. *Deposits Herfindahl* measures the level of concentration (or alternatively the inverse of the level of competition) in the current lead bank's local market. *Prev Deposits Herfindahl* is a measure of the extent of competition in the markets where the firm has previously borrowed. We define *Prev Deposits Herfindahl* as the *minimum* of *Deposits Herfindahl* on all previous loans involving the borrower. The results in Column (1) show that borrowers are more likely to switch lenders if they are borrowing from a bank market with a low deposits Herfindahl index, i.e., a competitive bank market. The results in Column (2) indicate that this effect is stronger for non-Compustat firms. Thus these results highlight the role of bank market competition in enabling firms to switch banks. In Column (3), we estimate the regression after including a dummy variable *Merger*, which takes a value 1 if any of the firm's relationship banks undergoes a merger. The positive coefficient on *Merger* in Column (3) indicates that firms are more likely to switch banks if one of their relationship banks undergoes a merger. This result supports the hypothesis that mergers have an adverse effect on bank-borrower relationships.

In Column (4), we examine if the borrower's decision to switch to a new bank is influenced by the deposit growth at the new bank. We do this by repeating our regression after including *Deposit Growth* as an additional regressor. *Deposit Growth* measures the rate of growth of deposits for the current lead lender during the quarter preceding the loan origination. The positive and significant coefficient on *Deposit Growth* in Column (4) indicates that firms are more likely to switch to banks which experience a higher deposit growth. The negative coefficient on the interaction term *Non Compustat*Deposit Growth* in Column (6) suggests that even in the face of high deposit growth, banks are less likely to solicit *Non Compustat* firms to form new relationships.

6 Concluding Remarks

In this paper, we examine a large dataset of loan deals contracted over the period 1990–2005 to understand how firms choose between a relationship bank and a non-relationship bank for their repeat borrowing needs. In the introduction, we had outlined two main hypothesis to explain this choice: the soft information hypothesis and the graduation hypothesis. The soft information hypothesis states that informationally opaque firms are more likely to stay with their relationship banks. On the other hand, the graduation hypothesis states that borrowers that face borrowing constraints at their relationship banks are more likely to switch to larger banks in order to better meet their growing need for credit and other capital market services. We examine the impact of firm, bank and bank market characteristics on firms' propensity to switch to a non-relationship bank, in order to distinguish between these hypotheses.

We find that the soft information hypothesis does not hold uniformly across the information spectrum. Consistent with the soft information hypothesis, we do find that our non-Compustat firms, which may be thought of as highly opaque, are significantly less likely to switch banks than the Compustat firms. However, among the sub-sample of Compustat firms, the informationally opaque firms (small firms, firms without a credit rating, firms tracked by fewer analysts) are more likely to switch banks. In other words, information considerations do not prevent such firms from switching to new banks. Thus overall in our sample, the most opaque firms (non-Compustat firms) and the most transparent firms (the large Compustat firms) are less likely to switch banks. This non-monotonic relationship between information quality and firm's propensity to switch to a new bank is consistent with the graduation hypothesis.

Consistent with the graduation hypothesis, we also find that firms that switch banks mainly switch from small banks to large banks, and from small bank markets to large bank markets. Interestingly, firms that are highly opaque are not only less likely to switch banks, but are also less likely to switch to a large bank. Moreover, firms that switch to new banks obtain larger loan amounts, invest more in new PP&E, and experience an increase in leverage following the switch. Interestingly, this effect is stronger for the smaller firms, which presumably face tighter borrowing constraints at their relationship banks. Taken together, these findings offer strong support to the graduation hypothesis that firms switch to larger banks in order to escape borrowing constraints at their relationship banks.

Our findings suggest avenues for future research. One possible avenue is to examine whether switching to a new bank, in addition to loosening a firm's borrowing constraints, also improves the firm's access to other capital market services. Another possible avenue is to examine how firms and relationship banks smooth loan contract terms over repeat interactions.[20] For instance, it is plausible that firms switch to new banks in anticipation of long-term future benefits, such as fewer financial constraints, access to a wider array of banking services, etc. In other words, the benefits of switching to a new bank might not be realized immediately following the switch. If this is true, it might explain why we do not find evidence of lower yields immediately following a switch to a new bank. On the other hand, it is also possible that banks offer attractive terms to entice new borrowers with the hope of extracting a higher price in the future. This is an open question which we plan to address in our future research.

References

Berger, A. N., N. Miller, M. Petersen, R. Rajan, and J. Stein (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics 76*, 237–269.

[20]Berlin and Mester (1998) and Ioannidou and Ongena (2006) examine this question with small business lending in the US and with Bolivian loan data, respectively. However, it is not well understood how larger borrowers in the US and their banks smooth out loan contract terms over repeat interactions.

Berger, A. N., R. J. Rosen, and G. F. Udell (2007). The effect of market size structure on competition: The case of small business lending. *Journal of Banking and Finance 31*, 11–33.

Berger, A. N., A. Saunders, J. M. Scalise, and G. F. Udell (1998, December). The effect of bank mergers and acquisitions on small business lending. Working Paper, Board of Governors of the Federal Reserve System.

Berger, A. N. and G. F. Udell (1995). Relationship lending and lines of credit in small business finance. *Journal of Business 68*, 351–381.

Berlin, M. and L. J. Mester (1998). On the profitability and cost of relationship lending. *Journal of Banking and Finance 22*, 873–897.

Bharath, S., S. Dahiya, A. Saunders, and A. srinivasan (2006). Lending relationships and loan contract terms; Does size matter? Working Paper.

Billet, M., M. Flannery, and J. Garfinkel (1995). The effect of lender identity on a borrowing firm's equity return. *Journal of Finance 50*, 699–718.

Black, L. (2006). An empirical analysis of insider rates vs. outsider rates in bank lending. Working paper.

Boot, A. W. and A. V. Thakor (2000). Can relationship banking survive competition? *Journal of Finance 55*, 679–713.

Boyd, J. H. and E. C. Prescott (1986). Financial intermediary-coalitions. *Journal of Economic Theory 38*(2), 211–232.

Carbó-Valverde, S., F. Rodriquez-Fernandez, and G. F. Udell (2006). Bank market power and SME financing constraints. Indiana University working paper.

Carey, M. and M. Hrycray (1999). Credit flow, risk, and the role of private debt in capital structure. Working paper, Federal Reserve Board.

Charumilind, C., R. Kali, and Y. Wiwattanakantang (2006). Connected lending: Thailand before the financial crisis. *Journal of Business 79*(1), 181–217.

Chemmanur, T. and P. Fulghieri (1994). Reputation, renegotiation, and the choice between bank loans and publicly traded debt. *Review of Financial Studies 7*(4), 475–506.

Cole, R. A. (1998, August). The importance of relationships to the availability of credit. *Journal of Banking and Finance 22*, 959–977.

Cole, R. A., L. G. Goldberg, and L. J. White (2004). Cookie-cutter versus character: The microstructure of small business lending by large and small banks. *Journal of Financial and Quantitative Analysis 39*, 227–251.

Diamond, D. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies 51*, 394–414.

Diamond, D. (1989). Reputation acquisition in debt markets. *Journal of Political Economy 97*(4), 826–862.

Diamond, D. (1991). Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy 99*, 688–721.

Elsas, R. and J. Krahnen (1998). Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking and Finance 22*, 1283–1316.

Fama, E. F. (1985). What's different about banks? *Journal of Monetary Economics 15*, 29–39.

Hadlock, C. J. and C. James (2002). Do banks provide financial slack? *Journal of Finance 57*, 1383–1419.

Harhoff, D. and T. Korting (1998). Lending relationships in Germany - Empirical evidence from survey data. *Journal of Banking and Finance 22*(10), 1317–1353.

Hoshi, T., A. Kashyap, and D. Scharfstein (1990). The role of banks in reducing the costs of financial distress in japan. *Journal of Financial Economics 27*, 67–88.

Ioannidou, V. and S. Ongena (2006). "Time for a change": Loan conditions and bank behavior when firms switch. Working Paper, Tilburg University and CEPR.

James, C. (1987). Some evidence on the uniqueness of bank loans. *Journal of Financial Economics 19*, 217–235.

Kano, M., H. Uchida, G. Udell, and W. Watanabe (2006). Information verifiability, bank organization, bank competition and bank-borrower relationships. RIETI discussion paper 06-E-003, The Research Institute of Economy, Trade, and Industry.

Krigman, L., W. Shaw, and K. Womack (2001). Why do firms switch underwriters? *Journal of Financial Economics 60*, 245–284.

La Porta, R., F. Lopez-De-Silanes, and G. Zamarripa (2003, February). Related lending. *Quarterly Journal of Economics 118*(1), 231–268.

Leland, H. E. and D. H. Pyle (1977, May). Informational assymetries, financial structure and financial intermediation. *Journal of Finance 32*.

Lummer, S. and J. McConnell (1989). Further evidence on the bank lending process and the capital market response to bank loan agreements. *Journal of Financial Economics 25*, 99–122.

Ongena, S. and D. C. Smith (2001). The duration of bank relationships. *Journal of Financial Economics 61*, 449–475.

Park, S., B. Shin, and G. Udell (2006). Lending relationships, credit availability and banking crises. Working paper.

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance 49*(1), 3–37.

Petersen, M. A. and R. G. Rajan (1995). The effect of credit market competition on lending relationships. *Quarterly Journal of Economics 110*, 407–443.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance 47*(4), 1367–1400.

Rosen, R. J. (2003, November). Banking market conditions and deposit interest rates.

Scott, J. A. (2004). Small business and value of community financial institutions. *Journal of Financial Services Research 25*, 207–230.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance 45*(4), 1069–1087.

Shockley, R. and A. Thakor (1992). Information content of commitments to lend in the future: Theory and evidence on the gains from relationship banking. Working paper, Indiana University.

Stein, J. (2002). Information production and capital allocation: Decentralized versus hierarchial firms. *Journal of Finance 57*(5), 1891–1921.

Sufi, A. (2006). Information asymmetry and financing arrangements: Evidence from syndicated loans. *Journal of Finance 62*(2), 629–668.

Von Thadden, E.-L. (2004). Asymmetric information, bank lending, and implicit contracts: The winner's curse. *Finance Research Letters 1*, 11–23.

Zarutskie, R. (2006). Evidence on the effects of bank competition on firm borrowing and investment. *Journal of Financial Economics 81*(3), 503–537.

Table I: Summary Statistics

This table reports the summary statistics for key variables in our sample. Panel A summarizes the full sample. Panel B reports the means for the two sub-samples involving new borrower-lead lender relationship and those involving repeat relationships, while Panel C reports the means for the two sub-samples identified based on availability of Compustat data for the borrower. Under deal characteristics, *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise; *Deal Amount* is the size of the deal in $ Million; *Yield* is the weighted-average basis point spread over LIBOR for all the loans within the deal; *Secured* is a dummy variable that takes a value 1 if the deal is secured and 0 otherwise; *Financial Covenants* is a dummy variable that takes a value 1 if the deal included financial covenants and 0 otherwise; *Deal Maturity* is the weighted-average maturity (in months) of all the loans within the deal; *Short Term*, *Medium Term* and *Long Term* are dummy variables that identify deals with *Deal Maturity* less than 1 year, between 1 and 5 years, and greater than 5 years, respectively; *No. of Lenders* is the number of lenders in the syndicate; *Time Between Deals* is the time in years between the current deal and the most recent deal of the same borrower; *Repayment*, *Takeover* and *Working Capital* are dummy variables that identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital, respectively. Under borrower characteristics, *Non Compustat* is a dummy variable that identifies borrowing firms for which financial data is not available in Compustat; *Assets* is the book value of total assets of the borrower (in $ million), while *Size* is the log of *Assets*; *Rated* is a dummy variable that identifies borrowers who have an unsecured long term credit rating; *Analysts* is the number of security analysts following the borrower's stock; *R&D/TA* is the ratio of the R&D expenditure to the total assets of the borrower; *Market to Book* is the ratio of the market value of total assets to the book value of total assets of the borrower; *EBITDA* is the borrower's earnings before interest, tax, depreciation and amortization (in $ million); *Profits* is the log of *EBITDA*; *Industry Leverage* is the median *Leverage* for all firms in the same 4-digit SIC code as the borrower, where *Leverage* is the ratio of the book value of total debt to the book value of total assets. We measure all the borrower financial ratios at the end of the financial year in which the deal was originated. Under bank and bank market characteristics, *Large Bank* is a dummy variable that identifies lead banks with book value of total assets greater than the 95^{th} percentile among all banks during the quarter in which the deal was originated; *Bank Market Size* is the log of the sum of the book value of assets of all banks in the local market (county or MSA) in which the lead bank is located; *Non-MSA Bank* is a dummy variable that identifies lead banks located in a non-metropolitan area; *Large Bank Dep Share* is the share of deposits of large banks (as identified using *Large Bank*) in the lead bank's local market; *Deposits Herfindahl* is the sum of the squares of the deposit market shares of all the banks in the lead bank's local market. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial data on borrowers is from Compustat and data on analyst following is from IBES database. Financial information on banks is obtained from the Call Reports Data.

Panel A: Summary Statistics

Variable	N	Mean	Min	P25	P50	P75	Max.
Deal Characteristics							
Deal Amount (in $ million)	12278	275.707	0.05	37.372	100	270	13000
Yield (bps over LIBOR)	12278	129.188	0	30	112.5	200	1300
Secured	6653	0.733	0	0	1	1	1
Financial Covenants	5511	0.858	0	1	1	1	1
Deal Maturity (Months)	11589	39.381	1.000	19	36	60	240
No. of Lenders	12278	4.417	1	1	3	6	283
Time Bet. Deals (Years)	12278	1.938	0	0.844	1.356	2.542	14.964
New Relationship	12264	0.394	0	0	0	1	1
Short Term	12278	0.237	0	0	0	0	1
Long Term	12278	0.129	0	0	0	0	1
Repayment	12278	0.212	0	0	0	0	1
Takeover	12278	0.128	0	0	0	0	1
Working Capital	12278	0.584	0	0	1	1	1
Borrower Characteristics							
Non Compustat	12278	0.645	0	0	1	1	1
Assets (in $ million)	4360	4245.73	1.65	159.09	544.91	2137.53	668,641
Rated	4385	0.382	0	0	0	1	1
Analysts	3389	9.112	1	3	7	13	48
R&D/ Total Assets	2298	0.114	0	0	0.012	0.045	137.121
Market to Book	4755	1.492	0.005	0.796	1.126	1.706	61.379
EBITDA (in $ million)	4500	502.06	-2424.40	18.61	73.02	302.24	45639
Industry Leverage	3948	0.179	0.002	0.079	0.169	0.268	0.482
Bank and Bank Market Characteristics							
Large Bank	8792	0.858	0	1	1	1	1
Bank Market Size	8832	26.223	17.687	24.997	26.715	27.946	28.583
Non-MSA Bank	8832	0.027	0	0	0	0	1
Large Bank Dep Share	8832	0.865	0	0.816	0.968	0.987	0.998
Deposits Herfindahl	8832	0.363	0.019	0.208	0.327	0.545	1

Panel B: Univariate Tests

Variable	Existing Relationship	New Relationship	Difference
Deal Characteristics			
Deal Amount (in $ million)	319.396	208.500	110.896***
Yield (in bps over LIBOR)	120.564	142.302	-21.738***
Secured	0.701	0.772	-0.071***
Financial Covenants	0.836	0.886	-0.05***
Deal Maturity (Months)	38.926	40.06	-1.13***
No. of Lenders	4.767	3.876	0.892***
Time between deals	1.604	2.452	-0.85***
Repayment	0.209	0.217	-0.01
Takeover	0.112	0.152	-0.04***
Working Capital	0.604	0.553	0.05***
Borrower Characteristics			
Non Compustat	0.659	0.623	0.04***
Size	20.588	19.756	0.831***
Rated	0.458	0.277	0.18***
Analysts	10.218	7.487	2.73***
R&D/ Total Assets	0.150	0.054	0.10
Market to Book	1.471	1.52	-0.05
Profits	0.136	0.134	0.00
Industry Leverage	0.184	0.173	0.01***
Bank and Bank Market Characteristics			
Large Bank	0.869	0.839	0.03***
Bank Market Size	26.294	26.093	0.20***
Non-MSA Bank	0.024	0.032	-0.01***
Large Bank Dep Share	0.874	0.850	0.02***
Deposits Herfindahl	0.372	0.347	0.02***

Panel C: Univariate Tests

Variable	Compustat Firms	Non-Compustat Firms	Difference
Deal Characteristics			
New Relationship	0.418	0.381	0.037***
Deal Amount (in $ million)	330.033	245.792	84.241***
Yield (bps over LIBOR)	114.445	137.307	-22.863***
Secured	0.646	0.796	-0.150***
Financial Covenants	0.882	0.838	0.044***
Deal Maturity (Months)	37.106	40.633	-3.528***
No. of lenders	4.925	4.137	0.788***
Time between deals (Years)	2.094	1.852	0.243***
Repayment	0.244	0.194	0.0497***
Takeover	0.127	0.128	-0.001
Working Capital	0.589	0.581	0.008
Borrower Characteristics			
Size	20.209		
Rated	0.383		
Analysts	9.104		
R&D/ Total Assets	0.114		
Market to Book	1.49		
Profits	0.135		
Industry Leverage	0.179		
Bank and Bank Market Characteristics			
Large Bank	0.876	0.849	0.0266***
Bank Market Size	26.214	26.228	-0.014
Non-MSA Bank	0.02	0.03	-0.01***
Large Bank Dep Share	0.869	0.864	0.005
Deposits Herfindahl	0.353	0.369	-0.016***

Table II: Sample Correlations

This table reports the correlation coefficients between the key variables in our sample. Panel A reports the correlations for the full sample while Panel B reports the correlations for the sub-sample of deals for which we have borrower financial data from Compustat. Under deal characteristics, *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise; *Deal Amount* is the size of the deal in $ Million; *Yield* is the weighted-average basis point spread over LIBOR for all the loans within the deal. Under borrower characteristics, *Non Compustat* is a dummy variable that identifies borrowing firms for which financial data is not available in Compustat; *Size* is the log of the book value of total assets of the borrower; *Rated* is a dummy variable that identifies borrowers who have an unsecured long term credit rating; *Market to Book* is the ratio of the market value of total assets to the book value of total assets of the borrower; *Profits* is the log of the borrower's earnings before interest, tax, depreciation and amortization; *Industry Leverage* is the median *Leverage* for all firms in the same 4-digit SIC code as the borrower, where *Leverage* is the ratio of the book value of total debt to the book value of total assets. We measure all the borrower financial ratios at the end of the financial year in which the deal was originated. Under bank and bank market characteristics, *Large Bank* is a dummy variable that identifies lead banks with book value of total assets greater than the 95^{th} percentile among all banks during the quarter in which the deal was originated; *Bank Market Size* is the log of the sum of the book value of assets of all banks in the local market (county or MSA) in which the lead bank is located; *Non-MSA Bank* is a dummy variable that identifies lead banks located in a non-metropolitan area; *Large Bank Dep Share* is the share of deposits of large banks (as identified using *Large Bank*) in the lead bank's local market; *Deposits Herfindahl* is the sum of the squares of the deposit market shares of all the banks in the lead bank's local market. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial data on borrowers is from Compustat and data on analyst following is from IBES database. Financial information on banks is obtained from the Call Reports Data.

Panel A: Correlations for Key Variables (All Firms)

	New Relationship	Yield	Deal Amount	Non Compustat	Size	Large Bank
New Relationship	1.000					
Yield (bps over LIBOR)	0.148	1.000				
Deal Amount	-0.087	-0.201	1.000			
Non Compustat	-0.024	0.194	-0.063	1.000		
Size	-0.157	-0.427	0.441	-0.246	1.000	
Large Bank	-0.010	-0.079	-0.007	-0.060	0.038	1.000
Bank Market Size	-0.025	-0.051	0.112	-0.021	0.169	0.631
Deposits Herfindahl	-0.022	0.078	-0.002	0.026	-0.033	0.321
Non-MSA Bank	0.000	-0.007	-0.006	0.041	0.004	-0.081
Large Bank Dep Share	-0.030	-0.035	0.033	-0.032	0.081	0.724

Panel B: Correlations for Key Variables (Compustat Firms)

	New Relationship	Yield	Deal Amount	Size	Industry Leverage	Profits	Market to Book	Rated	Large Bank
New Relationship	1.000								
Yield (bps over LIBOR)	0.185	1.000							
Deal Amount	-0.104	-0.203	1.000						
Size	-0.246	-0.476	0.432	1.000					
Industry Leverage	-0.056	-0.019	0.100	0.141	1.000				
Profits	0.009	-0.217	0.006	0.041	-0.147	1.000			
Market to Book	0.020	-0.154	-0.006	0.004	-0.243	0.463	1.000		
Rated	-0.176	-0.274	0.294	0.543	0.266	-0.051	-0.074	1.000	
Large Bank	0.010	-0.073	-0.005	0.039	-0.033	0.014	0.034	0.004	1.000
Bank Market Size	-0.008	-0.129	0.141	0.257	0.017	-0.003	0.008	0.287	0.600
Deposits Herfindahl	0.030	0.106	-0.068	-0.094	-0.036	-0.047	-0.015	-0.064	0.257
Non-MSA Bank	0.010	0.035	-0.036	-0.054	0.004	-0.022	-0.001	-0.057	-0.268
Large Bank Dep Share	-0.020	-0.073	0.044	0.114	0.001	-0.010	0.017	0.112	0.725

Table III: New Relationships and Firm Characteristics

This table reports the results of a panel logit regression relating the probability of a new borrower-lead lender relationship to firm and deal characteristics. Specifically, in Panel A, we estimate the following logit regression on the 2^{nd} to 4^{th} deals of all borrowers in our sample:

$$y_{it} = F(\beta_0 + \beta_1 * NonCompustat_i + \beta_2 * X_d),$$

where y is *New Relationship*, a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. The main independent *Non Compustat* is a dummy variable that identifies borrowing firms for which financial data is not available in Compustat. Among the deal characteristics (X_d) that we control for, *Log(Amount)*$_{t-1}$ is the log of the deal amount on the borrower's most recent deal; *Repayment*, *Takeover* and *Working Capital* are dummy variables that identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital, respectively; *Short Term* and *Long Term* are dummy variables that identify deals with average maturity less than 1 year and greater than 5 years, respectively; *Syndicate* is a dummy variable that takes a value 1 if more than one lender is involved in the deal and 0 otherwise; *Long Time Bet. Deals* is a dummy variable that takes a value 1 if the time between the current deal the most recent deal for the same borrower is above the sample median. In Column 3, we limit the sample to the period 1995-2006. In Column 4, we limit the sample to single lender loan deals. In Column 5, we run the regression on a balanced panel of borrowers, i.e., we limit the sample to those borrowers which have a minimum of 4 deals reported on Dealscan. In Column 6, we run a linear probability model with borrower fixed effects. In all the specifications, the standard errors are robust and clustered at the individual borrower level. The data on loan deals is from Dealscan and covers deals originated during 1990-2005.

Panel A: New Relationships and Firm Characteristics (All Firms)

	Pr(New Relationship)					
	(1)	(2)	(3)	(4)	(5)	(6)
Non Compustat	-.156	-.195	-.268	-.180	-.185	-.126
	(.042)***	(.043)***	(.047)***	(.078)**	(.055)***	(.029)***
Log(Amount)$_{t-1}$		-.203	-.189	-.197	-.205	-.039
		(.014)***	(.015)***	(.021)***	(.019)***	(.007)***
Repayment		-.156	-.279	-.240	-.218	-.060
		(.081)*	(.089)***	(.152)	(.110)**	(.028)**
Working Capital		-.127	-.192	-.018	-.122	-.032
		(.074)*	(.081)**	(.141)	(.103)	(.026)
Takeover		.218	.149	-.120	.097	.007
		(.088)**	(.096)	(.175)	(.118)	(.030)
Short Term		-.161	-.193	-.283	-.145	.010
		(.052)***	(.057)***	(.082)***	(.067)**	(.018)
Long Term		-.033	.036	.060	.020	.040
		(.061)	(.069)	(.123)	(.081)	(.023)*
Syndicate		-.308	-.310		-.314	-.002
		(.049)***	(.055)***		(.066)***	(.019)
Long Time Bet. Deals		.740	.837	.640	.706	.126
		(.041)***	(.045)***	(.073)***	(.053)***	(.013)***
Obs.	12264	12087	9963	3424	7306	12087
Pseudo R^2 or R^2	.001	.06	.067	.047	.054	.623

This Panel reports the results of a logit regression similar to that in Panel A, relating the probability of a new borrower-lead lender relationship to firm and deal characteristics. Specifically, we estimate the following logit regression on the 2^{nd} to 4^{th} deals of only those borrowers for which we have financial information available on Compustat:

$$y_{it} = F(\beta_0 + \beta_1 * Size_{it} + \beta_2 * X_i + \beta_3 * X_d),$$

where y is *New Relationship*, and *Size* is the log of the book value of total assets of the borrower. Among the borrower characteristics (X_i) that we control for, *Industry Leverage* is the median *Leverage* for all firms in the same 4-digit SIC code as the borrower, where *Leverage* is the ratio of the book value of total debt to the book value of total assets; *Altman Z-Score* is computed as 3.3*(pre-tax income/total assets)+ 0.999*(sales/total assets)+ 1.4*(retained earnings/total assets)+ 1.2*(working capital/total assets)+ 0.6*(Equity/Debt); *Market to Book* is the ratio of the market value of total assets to the book value of total assets of the borrower; *Profits* is the log of the borrower's earnings before interest, tax, depreciation and amortization. We also control for all the deal characteristics mentioned in Panel A. In Column 2, we limit the sample to deals originated during the period 1995-2006. In Column 3, we limit the sample to single lender loans, while in Column 4, we run the regression on a balanced panel of borrowers, i.e., we limit the sample to those borrowers which have a minimum of 4 deals reported on Dealscan. In Columns 5, we repeat the estimation in Column 1 with *Rated* substituted in place of *Size*, where *Rated* is a dummy variable that takes a value 1 if the borrower has an unsecured long term credit rating. In Columns 6, we repeat the estimation in Column 1 with *Analysts* substituted in place of *Size*, where *Analysts* is the number of security analysts following the borrower's stock. The data on loan deals is from Dealscan and covers deals originated during 1990-2006. Financial data on borrowers is from Compustat and data on analyst following is from IBES database.

Panel B: New Relationships and Firm Characteristics (Compustat Firms)

	Pr(New Relationship)					
	(1)	(2)	(3)	(4)	(5)	(6)
Size	-.200	-.201			-.197	-.210
	(.026)***	(.028)***			(.027)***	(.028)***
Rated			-.563			
			(.083)***			
Analysts				-.036		
				(.006)***		
Leverage					-.248	
					(.208)	
Altman Z-Score						.014
						(.011)
Market to Book	-.012	-.012	-.009	.029	-.012	-.040
	(.021)	(.020)	(.020)	(.025)	(.021)	(.034)
Industry Leverage	.502	.580	.283	-.036	.668	.142
	(.318)	(.342)*	(.313)	(.358)	(.350)*	(.378)
Repayment	-.450	-.666	-.423	-.421	-.439	-.300
	(.171)***	(.193)***	(.171)**	(.204)**	(.172)**	(.181)*
Takeover	-.182	-.365	-.140	-.159	-.169	-.021
	(.186)	(.207)*	(.186)	(.221)	(.187)	(.197)
Working Capital	-.270	-.360	-.264	-.249	-.262	-.152
	(.167)	(.188)*	(.166)	(.198)	(.167)	(.176)
Short Term	-.174	-.280	-.242	-.232	-.182	-.161
	(.089)*	(.096)***	(.086)***	(.096)**	(.089)**	(.094)*
Long Term	-.226	-.159	-.187	-.264	-.209	-.219
	(.122)*	(.137)	(.122)	(.141)*	(.123)*	(.129)*
Syndicate	-.311	-.239	-.491	-.412	-.305	-.189
	(.088)***	(.098)**	(.079)***	(.092)***	(.088)***	(.093)**
Long Time Bet. Deals	.714	.772	.758	.755	.712	.725
	(.071)***	(.078)***	(.071)***	(.081)***	(.071)***	(.077)***
Obs.	3943	3259	3943	3019	3943	3469
Pseudo R^2	.064	.071	.059	.057	.064	.067

Table IV: New Relationships and Bank Characteristics

This table reports the results of a panel logit regression relating the probability of a new bank-borrower relationship to bank and bank market characteristics. Specifically we estimate the following logit regression on the 2^{nd} to 4^{th} deals of all the borrowers in our sample:

$$y_{it} = F(\beta_0 + \beta_1 * X_b + \beta_2 * X_i + \beta_3 * X_d),$$

where where y is *New Relationship*, X_b represents various bank and bank market characteristics, X_i represents borrower characteristics, and X_d represents deal characteristics. *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. Among the bank and bank market characteristics that we analyze, *Large Bank* is a dummy variable that identifies lead banks with book value of total assets greater than the 95^{th} percentile among all banks during the quarter in which the deal was originated; *Prev Large Bank* is the maximum of *Large Bank* over all of the borrower's past deals, i.e., *Prev Large Bank* takes a value 1 if the borrower has ever borrowed from a *Large Bank* in the past and 0 otherwise; *Bank Market Size* is the log of the sum of the book value of assets of all banks in the local market (county or MSA) in which the lead bank is located; *Prev Bank Mkt. Size* is the maximum of *Bank Mkt. Size* for all of the borrower's previous deals; *Large Bank Dep Share* is the share of deposits of large banks (as identified using *Large Bank*) in the lead bank's local market; *Prev Large Bank Dep Share* is the maximum of *Large Bank Dep Share* over all of the borrower's previous deals. Since we estimate this regression on our entire sample of repeat deals, the only firm characteristic that we can control for is *Non Compustat*, a dummy variable that identifies borrowing firms for which financial data is not available in Compustat. Among the deal characteristics (X_d) that we control for, *Short Term* and *Long Term* are dummy variables that identify deals with average maturity less than 1 year and greater than 5 years, respectively; *Repayment*, *Takeover* and *Working Capital* are dummy variables that identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital, respectively; *Long Time Bet. Deals* is a dummy variable that takes the value 1 if the time between the current deal and the most recent deal of the borrower is greater than the sample median. In all the specifications, the standard errors are robust and clustered at the individual borrower level. The data on loan deals is from Dealscan and covers deals originated during 1990-2006. Financial information on banks is obtained from the Call Reports Data.

New Relationships and Bank Characteristics (All Firms)

	Pr(New Relationship)					
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank	-.006	.333				
	(.107)	(.186)*				
Prev. Large Bank	-.400	-.448				
	(.099)***	(.153)***				
Large Bank* Non Compustat		-.508				
		(.226)**				
Prev. Large Bank* Non Compustat		.084				
		(.200)				
Bank Market Size			.130	.223		
			(.023)***	(.039)***		
Prev. Bank Market Size			-.208	-.236		
			(.022)***	(.034)***		
Bank Market Size* Non Compustat				-.144		
				(.048)***		
Prev. Bank Market Size* Non Compustat				.047		
				(.044)		
Large Bank Dep Share					.368	.682
					(.174)**	(.287)**
Prev. Large Bank Dep Share					-1.314	-1.278
					(.156)***	(.248)***
Large Bank Dep Share* Non Compustat						-.500
						(.361)
Prev. Large Bank Dep Share* Non Compustat						-.031
						(.318)
Non Compustat	-.193	.170	-.167	-.177	-.195	-.199
	(.058)***	(.168)	(.058)***	(.058)***	(.058)***	(.058)***
Obs.	7453	7453	7510	7510	7510	7510
Pseudo R^2	.043	.045	.055	.057	.05	.05

Table V: New Relationships and Prior Deal Characteristics

Table V reports the results of logit regressions relating the probability of a new borrower-lead lender relationship to the amount (in Panel A) and the yield (in Panel B) on the borrower's most recent loan deal. In Column (1) of Panel A we estimate a cross-sectional regression to predict the amount on a deal using the model

$$y_{it} = \beta_0 + \beta_1 * X_i + \beta_2 * X_d + \beta_3 * X_b + \mu_t,$$

where y is Log(Amount), X_i denotes borrower characteristics, X_d denotes deal characteristics, and X_b denotes bank and bank market characteristics. We estimate this regression on our entire sample of loan deals and control for time fixed effects; the standard errors are robust and clustered at the individual borrower level. Since we estimate this regression on our entire sample of loan deals, the only borrower characteristic we control for is *Non Compustat*, a dummy variable that identifies borrowing firms for which financial data is not available in Compustat. Among the deal characteristics that we control for, *Short Term* and *Long Term* are dummy variables that identify deals with average maturity less than 1 year and greater than 5 years, respectively; *Repayment*, *Takeover* and *Working Capital* are dummy variables that identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital, respectively; *Syndicate* is a dummy variable that identifies deals financed by more than one lender. Among the bank and bank market characteristics that we control for, *Large Bank* is a dummy variable that identifies lead banks with book value of total assets greater than the 95^{th} percentile among all banks during the quarter in which the deal was originated; *Bank Market Size* is the log of the sum of the book value of assets of all banks in the local market (county or MSA) in which the lead bank is located; *Large Bank Dep Share* is the share of deposits of large banks (as identified using *Large Bank*) in the lead bank's local market; *Deposits Herfindahl* is the sum of the squares of the deposit market shares of all the banks in the lead bank's local market. In Columns 2-5, we estimate the following logit regression on the 2^{nd} to 4^{th} deals of all the borrowers in our sample:

$$y_{it} = F(\beta_0 + \beta_1 * LagExcessAmount + \beta_2 * X_i + \beta_3 * X_d + \beta 4 * X_b),$$

where y is *New Relationship*, a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. *Lag Excess Amount* is the difference between the actual amount and the predicted amount according to the model in Column (1) on the borrower's most recent loan deal. We control for firm characteristics (*Non Compustat*), deal characteristics (*Short Term*, *Long Term*, *Repayment*, *Takeover*, *Working Capital*, *Syndicate*, *Long Time Bet. Deals*), and bank and bank market characteristics (*Large Bank*, *Prev. Large Bank*, *Bank Market Size*, *Prev. Bank Market Size*, *Large Bank Dep Share*, *Prev. Large Bank Dep Share*). In Column 3, we limit the sample to the period 1995-2006, and in Column 4, we limit the sample to single lender deals. In Column 5, we run the logit regression on a balanced panel of firms, i.e., we limit the sample to those borrowers which have a minimum of 4 deals reported on Dealscan. In all the specifications, the standard errors are robust and clustered at the individual borrower level. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial information on banks is obtained from the Call Reports Data.

Panel A: Likelihood of New Relationships and Previous Deal Amount

	Log(Amount)	Pr(New Relationship)			
	(1)	(2)	(3)	(4)	(5)
Lag Excess Amount		-.168	-.117	-.129	-.209
		(.041)***	(.047)**	(.064)**	(.049)***
Large Bank	.190	-.562	-.705	-.288	-.664
	(.036)***	(.163)***	(.197)***	(.223)	(.222)***
Prev. Large Bank		.450	.478	.105	.826
		(.170)***	(.193)**	(.228)	(.256)***
Non Compustat	-.495	-.127	-.249	-.225	-.089
	(.034)***	(.064)**	(.072)***	(.116)*	(.082)
Debt Repayment	.308	.046	-.195	-.080	-.020
	(.043)***	(.125)	(.143)	(.219)	(.172)
Takeover	.591	.334	.224	-.125	.249
	(.045)***	(.134)**	(.151)	(.250)	(.181)
Working Capital	.248	.147	.026	.164	.179
	(.039)***	(.113)	(.127)	(.201)	(.160)
Long Term Loan	.448	-.093	-.049	-.041	.049
	(.031)***	(.093)	(.113)	(.177)	(.121)
Short Term Loan	.135	-.225	-.217	-.367	-.228
	(.034)***	(.076)***	(.086)**	(.118)***	(.098)**
Syndicate	1.985	-.592	-.507		-.585
	(.029)***	(.068)***	(.081)***		(.094)***
Obs.	22189	6847	5390	1876	4170
Pseudo R^2 or R^2	.364	.06	.077	.04	.052

This panel reports the results of a logit regression relating the probability of a new borrower-lead lender relationship to the yield on the borrower's most recent loan deal. In Column (1), we estimate a cross-sectional regression on our entire sample of loan deals to predict the yield on a deal using the model

$$y_{it} = \beta_0 + \beta_1 * \text{Non Compustat} + \beta_2 * X_d + \beta_3 * X_b + \mu_t,$$

where y is Log(Yield). X_d includes deal characteristics like *Short Term*, *Long Term*, *Repayment*, *Takeover*, *Working Capital*, and *Syndicate*; and X_b includes bank and bank market characteristics like *Large Bank*, *Bank Market Size*, and *Large Bank Dep Share*. In Columns 2-5, we estimate the following logit regression on the 2^{nd} to 4^{th} deals of all the borrowers in our sample:

$$y_{it} = F(\beta_0 + \beta_1 * \text{Lag Excess Yield} + \beta_2 * X_i + \beta_3 * X_d + \beta_4 * X_b),$$

where y is *New Relationship* and *Lag Excess Yield* is the difference between the actual yield and the predicted yield according to the model in Column (1) on the borrower's most recent loan deal. The controls and the sample are similar to Panel A. In Column 3, we limit the sample to the period 1995-2006, and in Column 4, we limit the sample to single lender deals. In Column 5, we run the logit regression on a balanced panel of firms, i.e., we limit the sample to those borrowers which have a minimum of 4 deals reported on Dealscan. In all the specifications, the standard errors are robust and clustered at the individual borrower level.

Panel B: Likelihood of New Relationships and Previous Deal Yield

	Log(Yield)	Pr(New Relationship)			
	(1)	(2)	(3)	(4)	(5)
Lag Excess Yield		.259	.256	.221	.227
		(.090)***	(.100)**	(.210)	(.084)***
Large Bank	-.173	-.599	-.860	-.061	-1.010
	(.020)***	(.217)***	(.239)***	(.463)	(.325)***
Non Compustat	.327	-.184	-.265	-.301	-.273
	(.020)***	(.075)**	(.082)***	(.189)	(.105)***
Debt Repayment	-.077	-.124	-.297	-1.074	-.364
	(.022)***	(.153)	(.172)*	(.403)***	(.241)
Takeover	.094	.302	.178	-.511	.137
	(.021)***	(.160)*	(.176)	(.423)	(.240)
Working Capital	-.335	.172	.080	-.279	.077
	(.019)***	(.138)	(.152)	(.370)	(.223)
Long Term Loans	.246	-.175	-.174	-.460	.139
	(.016)***	(.109)	(.132)	(.342)	(.172)
Short Term Loans	-.492	-.215	-.176	-.495	-.171
	(.021)***	(.093)**	(.101)*	(.198)**	(.129)
Syndicate	-.284	-.527	-.431		-.344
	(.016)***	(.085)***	(.100)***		(.139)**
Obs.	16459	5075	4184	716	2562
Pseudo R^2 or R^2	.248	.052	.068	.08	.064

Table VI: New Relationship and Deal Terms

Panel A reports the results of a panel regression relating the amount and yield on a loan deal to the firm's decision to switch to a new bank. Specifically we estimate the panel regressions

$$y_{it} = \beta_0 + \beta_1 * \text{New Relationship}_d + \beta_2 * X_i + \beta_3 * X_d + \mu_t + \mu_i$$

on our entire sample of loan deals, where y is *Log(Amount)* in Columns 1-4 and *Log(Yield)* in Columns 4-7. In Columns 3 and 7, we confine the sample to the deals till the borrower switches banks for the first time. In Column 4, we estimate the first-differences procedure as an alternative to firm fixed effects. *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. X_i is *Non Compustat*, a dummy variable that identifies borrowing firms for which financial data is not available in Compustat. The deal controls (X_d) include *Short Term*, *Long Term*, *Repayment*, *Takeover*, *Working Capital* and *Syndicate*. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial information on banks is obtained from the Call Reports Data.

Panel A: Deal Amount, Deal Pricing and New Relationships (All Firms)

	Log(Amount)				Log(Yield)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
New Relationship	-.295	.006	.293	.079	.194	.00005	.078
	(.031)***	(.040)	(.084)***	(.038)**	(.031)***	(.027)	(.064)
Non Compustat	-.244	-.004	.126	-.066	.313	-.018	.079
	(.039)***	(.066)	(.110)	(.042)	(.029)***	(.043)	(.060)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes	No	No	Yes	Yes
Obs.	8782	8782	6678	6847	6908	6908	5150
R^2	.337	.935	.955	.159	.261	.924	.947

Panel B reports the results of a panel regression relating the terms of a deal to the firm's decision to switch to a new bank. Specifically we estimate the panel regressions

$$y_{it} = \beta_0 + \beta_1 * \text{New Relationship}_d + \beta_2 * X_i + \beta_3 * X_d + \mu_t + \mu_i$$

on our entire sample of loan deals, where y is *Secured* in Columns 1-3 and *Financial Covenants* in Columns 4-6. *Secured* is a dummy variable that takes a value 1 for those deals which are secured. *Financial Covenants* is a dummy variable that takes a value 1 for those deals that include financial covenants. The controls and sample are similar to that in Panel A.

Panel B: Security, Financial Covenants and New Relationships (All Firms)

	Secured			Financial Covenants		
	(1)	(2)	(3)	(4)	(5)	(6)
New Relationship	.025	.006	.029	.010	.028	.013
	(.013)**	(.028)	(.065)	(.014)	(.021)	(.047)
Non Compustat	.137	.040	.020	-.016	.023	.0006
	(.016)***	(.042)	(.056)	(.015)	(.043)	(.057)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	Yes	No	Yes	Yes
Obs.	4501	4501	3267	3649	3649	2537
R^2	.146	.892	.929	.341	.848	.891

Table VII: Firm Performance and New Relationships

This table reports the results of a panel regression relating firm investment and leverage to the firm forming new banking relationships. Specifically, we estimate the panel OLS regressions

$$y_{it} = \beta_0 + \beta_1 * \text{New Relationship}_d + \beta_2 * X_i + \mu_t + \mu_i,$$

where y is *Log(Capex)* in Columns 1 & 2, and *Leverage* in Column 3. The sample is limited to the period 1990-2005 and to firms with at least one deal reported in Dealscan, and for which we have financial data in Compustat. *Log(Capex)* is the log of the total capital expenditure of the firm, and *Leverage* is the book value of total debt normalized by the book value of total assets in the previous year. *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. Among the firm characteristics (X_i) that we control for, *Size* is the log of the book value of assets of the borrower; *Leverage* is the ratio of the book value of total debt to the book value of total assets; *Market to Book* is the ratio of the market value of total assets to the book value of total assets of the borrower; *Sales Growth* is the year or year sales growth for the borrower; *Profitability* is the ratio of Earnings Before Interest, Depreciation and Taxes to book value of total assets (the subscript 't-1' denotes lagged values, i.e., values corresponding to the previous year). In all the specifications, the standard errors are robust and clustered at the individual borrower level. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial data on borrowers is from Compustat.

Firm Investment and New Relationships

	Log(Capex)		Leverage	
	(1)	(2)	(3)	(4)
New Relationship$_t$	-.001	.00006	.004	.007
	(.002)	(.002)	(.003)	(.004)**
Log(Amount)	-.0002	-.0002	.001	.002
	(.0005)	(.0005)	(.0005)***	(.0005)***
New Relationship$_t$*Size$_{t-1}$		-.003		-.006
		(.001)**		(.002)***
Leverage$_{t-1}$	.035	.035		
	(.007)***	(.007)***		
Size$_{t-1}$	.019	.020	.028	.028
	(.002)***	(.002)***	(.003)***	(.003)***
Sales Growth$_{t-1}$	.001	.001	.0002	.0002
	(.001)	(.001)	(.002)	(.002)
Profitability$_{t-1}$	.030	.030	-.006	-.006
	(.004)***	(.004)***	(.007)	(.007)
Market to Book$_{t-1}$	.004	.004	-.006	-.006
	(.0005)***	(.0005)***	(.0009)***	(.0009)***
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Obs.	30582	30582	30930	30930
R^2	.611	.611	.575	.575

Table VIII: New Relationships and Competition in the Bank Market

This table reports the results of a logit regression relating the probability of a new bank-borrower relationship to the level of competition in bank market. Specifically we estimate the logit regression

$$y_{it} = F(\beta_0 + \beta_1 * X_b + \beta_2 * X_i + \beta_3 * X_d),$$

where y is *New Relationship*, X_b represents various bank and bank market characteristics, X_i represents borrower characteristics, and X_d represents deal characteristics. *New Relationship* is a dummy variable that takes a value 1 when the borrower borrows from a non-relationship bank, and 0 otherwise. We estimate the regression on the 2^{nd} to 4^{th} deals of all the borrowers in our sample. Among the bank and bank market characteristics (X_b) that we examine, *Deposits Herfindahl* is the sum of the squares of the deposit market shares of all the banks in the lead bank's local market; *Prev Deposits Herfindahl* is the minimum of *Deposits Herfindahl* over all of the borrower's previous deals; *Prev. Bank Merger* is a dummy variable that takes a value 1 if any of the previous lead banks of a borrower has been acquired and 0 otherwise; *Prev. Large Bank Merger* is a dummy variable that takes a value 1 if any of the previous lead banks of a borrower that was also a large bank (as defined by *Large Bank*) has been acquired, and 0 otherwise; *Deposit Growth* is the quarterly growth in deposits of the lead lender. X_i represents *Non Compustat*, a dummy variable that identifies borrowing firms for which financial data is not available in Compustat. Among the deal characteristics (X_d) that we control for, *Short Term* and *Long Term* are dummy variables that identify deals with average maturity less than 1 year and greater than 5 years, respectively; *Repayment*, *Takeover* and *Working Capital* are dummy variables that identify whether the main purpose of the deal is to repay previous debt, finance a takeover, or finance working capital, respectively; *Long Time Bet. Deals* is a dummy variable that takes the value 1 if the time between the current deal and the most recent deal of the borrower is greater than the sample median. In all the specifications, the standard errors are robust and clustered at the individual borrower level. The data on loan deals is from Dealscan and covers deals originated during 1990-2005. Financial information on banks is obtained from the Call Reports Data.

	Pr(New Relationship)			
	(1)	(2)	(3)	(4)
Deposits Herfindahl	-.025	.345		
	(.187)	(.289)		
Prev. Deposits Herfindahl	-1.256	-.654		
	(.222)***	(.349)*		
Deposits Herfindahl* Non Compustat		-.552		
		(.377)		
Prev. Deposits Herfindahl* Non Compustat		-.895		
		(.455)**		
Prev. Bank Merger			.324	
			(.098)***	
Prev. Bank Merger*Non Compustat			-.135	
			(.120)	
Deposit Growth				.555
				(.146)***
Deposit Growth*Non Compustat				-.483
				(.195)**
Non Compustat	-.175	-.201	-.119	-.152
	(.058)***	(.057)***	(.046)***	(.053)***
Obs.	7510	7510	12264	8209
Pseudo R^2	.047	.048	.044	.047