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Why Do Firms Form New Banking Relationships?

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Abstract

Using a large loan sample from 1990 to 2006, we examine why firms form new banking relationships. Small public firms that do not have existing relationships with large banks are more likely to form new banking relationships. On average, firms obtain higher loan amounts when they form new banking relationships, while small firms also experience an increase in sales growth, capital expenditure, leverage, analyst coverage, and public debt issuance subsequently. Our findings suggest that firms form new banking relationships to expand their access to credit and capital market services, and highlight an important cost of exclusive banking relationships.

I. Introduction

Information and agency problems can limit the ability of firms to access external finance and result in financial constraints. While a large literature in finance argues that strong banking relationships can mitigate information and agency problems,[1] the literature is ambiguous about the effect of such banking relationships on firm financial constraints: The relationship bank can use its private information to make more informed credit decisions but may also exploit its informational advantage to hold up the borrower, thus worsening the borrower's financial constraints (Sharpe (1990), Rajan (1992)). The empirical evidence on

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[1]See, for example, Diamond (1984), Boyd and Prescott (1986), and Ramakrishnan and Thakor (1984). Highlighting the role of banks in mitigating informational problems, James (1987), Lummer and McConnell (1989), Shockley and Thakor (1992), and Billett, Flannery, and Garfinkel (1995) document positive stock price reactions following announcement of bank loan commitments.

this important question is also mixed. While a large literature documents that banking relationships ease financial constraints for small firms (e.g., Petersen and Rajan (1994), Berger and Udell (1995), and Cole (1998)), other studies that examine larger borrowers highlight that strong banking relationships may actually worsen financial constraints for high-growth firms (Houston and James (1996)) and during periods when observable borrower risk increases (Santos and Winton (2008)).

In this paper we use a large loan-level panel data set of more than 12,000 loans from Loan Pricing Corporation's (LPC) Dealscan database, spanning the time period 1990–2006, to analyze why firms form new banking relationships for their repeat credit needs. We study how firm-, bank-, and loan-level characteristics affect a firm's propensity to form new banking relationships, as well as the effect of new banking relationships on the availability of credit and future firm performance. Dealscan covers a wide spectrum of firms, both private and public, ranging in revenue size from $15 million at the 5th percentile level to around $12 billion at the 95th percentile.[2] We augment these data with data from bank Call Reports and Compustat. The presence of both small and large firms in our sample enables us to separately estimate the costs and benefits of banking relationships for both sets of firms. The panel structure of the data also allows us to characterize the effect of new banking relationships on loan outcomes and firm outcomes, after controlling for firm fixed effects and year fixed effects.

The key idea underlying our analysis is that the impact of banking relationships on firm financial constraints varies across a firm's life cycle. As per theory, relationship building through accumulation of soft information is likely to be more valuable for informationally opaque private firms than for the more transparent public firms (Rajan (1992), Boot and Thakor (2000)). As a firm grows in size and becomes more transparent, the benefits of an exclusive banking relationship are likely to be offset by its costs. While the literature has largely focused on hold-up costs, another cost of an exclusive banking relationship could be that the relationship bank is unable to meet the growing credit needs of the borrower. The latter cost is likely to arise because of the specialization and segmentation in the U.S. banking industry (Stein (2002), Berger et al. (2005)), where small banks specialize in relationship lending to small and opaque firms, whereas large banks specialize in providing syndication and capital market services to large firms. Therefore, over its life cycle, a firm may switch to a nonrelationship bank in order to improve its access to credit and capital market services.[3]

We conduct our analysis at the level of a loan "deal" that may comprise multiple loans contracted simultaneously by a borrower with the same lead arranger. We define a firm's banking relationship as the pairing between the firm and the lead arranger providing the firm with financing, because prior research has shown

[2]Therefore, we can overcome a key limitation in the existing literature where researchers have typically focused on either exclusively small firms (e.g., Petersen and Rajan (1994), Berger and Udell (1995), and Berger, Miller, Petersen, Rajan, and Stein (2005)) or exclusively large firms (e.g., Hadlock and James (2002), Drucker and Puri (2005), and Yasuda (2005)). A notable exception is Bharath, Dahiya, Saunders, and Srinivasan (2011) which we discuss presently.

[3]Existing literature highlights the benefits to firms of obtaining banking and capital market services from the same institution (Puri (1996), Schenone (2004), and Drucker and Puri (2005)).

that the lead arranger is typically responsible for screening and monitoring the firm (Sufi (2007)). We examine a firm's repeat deals, and our main variable of interest is whether the deal involves a new banking relationship for the firm (i.e., as per our definition, a new relationship is when a firm borrows from a lead arranger that it has not borrowed from in the past in our data set). In further analysis, we distinguish a new banking relationship into instances when the firm appears to switch to a new bank and instances when the firm appears to form multiple banking relationships, and evaluate the determinants of both. Our preliminary analysis indicates that new relationships are quite common: *46% of the repeat borrowings in our sample involve a firm borrowing from a nonrelationship bank.* This in itself is striking in light of the large literature that documents the benefits of banking relationships.

Our analysis indicates a nonmonotonic relationship between firms' informational transparency and their propensity to form new banking relationships. Consistent with opaque firms benefiting from banking relationships, we find that our most opaque firms, those not covered in the Compustat database ("non-Compustat" firms), are less likely to borrow from nonrelationship banks than are Compustat firms.[4] However, among the subsample of Compustat firms (ranging from moderately opaque to transparent), we find that firms that are relatively more opaque (mid-sized firms, firms without a credit rating, and firms tracked by fewer security analysts) are more likely to borrow from nonrelationship banks. Examining bank characteristics, we find that firms that have existing relationships with large banks and banks that are active in underwriting and merger and acquisition (M&A) advisory services are less likely to form new banking relationships.

Consistent with firms forming new banking relationships to overcome borrowing constraints, we find that, after controlling for firm and year fixed effects, firms on average obtain 9% higher loan amounts when they borrow from a nonrelationship bank. This result is robust to controlling for the endogeneity of the new banking relationship, and holds both when firms form multiple banking relationships and when they switch to new banks. Examining the subsample of Compustat firms for which we have detailed financial information, we find that smaller Compustat firms, which are more likely to experience borrowing constraints at their relationship banks, undertake higher capital expenditures (i.e., invest more in new property, plant, and equipment (PPE)), and experience an increase in sales growth, leverage, and analyst coverage in the year when they form a new banking relationship. Moreover, small Compustat firms that switch to a new bank also experience an increase in public debt issuance in the subsequent year. Overall, these results are strongly consistent with the life cycle hypothesis that firms form new banking relationships in order to improve their access to credit and capital market services.

The main contribution of our paper is to highlight the effect of banking relationships on firm financial constraints across a wide spectrum of firms. A novel

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[4]As an alternative test, we repeat our analysis using a dummy variable that identifies the public status of a firm, and obtain similar results. We report our results using NON_COMPUSTAT because availability of financial information in Compustat is likely to be a better proxy for a firm's information transparency, as even private firms that have public debt outstanding file periodic reports with the Securities and Exchange Commission (SEC) and are covered by the Compustat database.

result in the paper is that a strong banking relationship may exacerbate firm financial constraints if the relationship bank is small and unable to meet the growing credit needs of the firm. This cost of banking relationships that we uncover is unlikely to be important for the small firms surveyed in the Survey of Small Business Finances (SSBF) that most of the studies on banking relationships have focused on. However, it is an important consideration for the mid-sized public firms with growing credit needs. We show that such firms can broaden their access to credit and capital market services by forming new banking relationships.

Our paper complements the large and growing literature on the benefits of strong banking relationships, particularly for small firms. The documented benefits include increased credit availability (e.g., Petersen and Rajan (1994), Cole (1998)), lower collateral requirements (e.g., Berger and Udell (1995)), and insurance against interest rate shocks (e.g., Berlin and Mester (1998)).[5] Using a sample of loans similar to ours, Bharath et al. (2011) document that strong banking relationships translate into lower interest rates of about 5 basis points (bp) to 15 bp, higher loan amounts, and lower collateral requirements. Puri (1996) shows that firms obtain better pricing in bond issues underwritten by their relationship bank, while Schenone (2004) documents lower underpricing in initial public offerings (IPOs) underwritten by firms' relationship bank.

There are, however, crucial differences between our paper and those cited above. Unlike many of these papers, which employ cross-sectional data from the SSBF on loans made to small firms that employ less than 500 people, we employ data on loans made to medium- and large-size U.S. firms over the period 1990–2006. The long time span of the data provides us with a dynamic view of firms' banking relationships, and also allows us to employ better controls for firm characteristics such as firm fixed effects. Second, unlike, say, Bharath et al. (2011), we treat a firm's banking relationships as endogenous and examine why firms form new banking relationships. Highlighting this difference, unlike Bharath et al., we find that firms obtain higher loan amounts when they form new banking relationships.

Our paper is also related to Ongena and Smith (2000), (2001), who highlight the transient nature of bank-borrower relationships. Similar to our finding that small firms are more likely to form new banking relationships, Ongena and Smith (2001) find that small, highly leveraged, Norwegian growth firms are more likely to end a banking relationship. Apart from the different banking market examined, our paper complements theirs by examining how bank and loan characteristics affect firms' propensity to form new banking relationships, and how these affect subsequent firm performance and access to capital market services.

Two related papers that examine the question of why firms borrow from nonrelationship banks are Farinha and Santos (2002) and Ioannidou and Ongena (2010). Using the monthly credit reports filed by Portuguese banks with their central bank, Farinha and Santos find that firms with more growth opportunities

[5]International evidence on the benefits of close banking relationships is provided by Hoshi, Kashyap, and Scharfstein (1990), Elsas and Krahnen (1998), Harhoff and Körting (1998), La Porta, Lopez-de-Silanes, and Zamarripa (2003), Charumilind, Kali, and Wiwattanakantang (2006), and Park, Shin, and Udell (2006).

and poorly performing firms are more likely to prefer multiple bank relationships. Using a detailed data set of Bolivian loans, Ioannidou and Ongena show that borrowers switch to new banks mainly to obtain a lower rate on their loans; however, once the borrower is informationally locked in with the new bank, the new bank charges a higher interest rate. Our paper differs from these papers on several dimensions. Both the previous papers examine small firms that are similar to the firms in the SSBF data, whereas we focus on medium- and large-size U.S. firms. Interestingly, the different focus also leads to different results. While Ioannidou and Ongena find that firms obtain lower interest rates when they switch banks, we do not find any such evidence in our sample. Our paper also complements these papers by examining how bank-level heterogeneities affect firms' decisions to switch banks. Given the differences in the structures of the banking markets, we also examine how new banking relationships enable firms to obtain better access to capital market services.

Our paper is also related to Berger et al. (2005), who highlight the heterogeneity and specialization in the U.S. banking industry. Using a sample of small firms surveyed in the SSBF, Berger et al. show that small banks specialize in lending to small firms and that such firms are hurt when they are forced to borrow from large banks. Our paper shows that bank-level heterogeneities in terms of both size and the scope of services offered affect the duration of banking relationships for the medium to large firms in the United States. Our paper also extends their analysis to a dynamic setting by examining how firms form new banking relationships in order to achieve a better match between their current needs and the bank's capabilities.

The remainder of our paper is organized as follows. We describe our data and summary statistics in Section II. Our main results are presented in Section III. Section IV concludes the paper.

II. Data, Key Variables, and Summary Statistics

A. Data Description

We obtain data on individual loan contracts from the 2006 extract of the LPC's Dealscan database. Dealscan provides information on loans made to medium- and large-size U.S. and foreign firms. According to LPC, 70% of the data is gathered from SEC filings (13-Ds, 14-Ds, 13-Es, 10-Ks, 10-Qs, 8-Ks, and Registration statements), and the remaining portion is collected through direct queries to lenders and borrowers.[6] We extract information on all syndicated and nonsyndicated dollar-denominated loans made by U.S. lenders to U.S. borrowers during the 1990–2005 period. We exclude borrowers that are in the financial

[6]Public companies and private companies that have public debt securities traded are required to file with the SEC. Because LPC has established a reputation for tracking loans and publishing league tables that rate lenders, and because these ratings are very important in the syndicated loan market, lenders have an incentive to voluntarily report their loans. The loan data obtained from lenders are confirmed by appropriate officials and are run through stringent editing tests before they are entered into the database.

services sector (i.e., borrowers with Standard Industrial Classification (SIC) codes between 6000 and 6900).

Dealscan provides information on deals or loan packages obtained by borrowers. For the purpose of our study, the unit of observation is a deal. Each deal may consist of multiple loan facilities contracted simultaneously between borrowers and lenders and is financed either by a single lender or by a syndicate of lenders. Our sample includes both single lender deals and syndicated deals. When the deal is financed by a syndicate, Dealscan allows us to identify the lead arranger for the deal. Specifically, we use the variable LEAD_ARRANGER_CREDIT to identify if a lender is also a lead arranger. We also obtain the loan contract terms, such as the total loan amount, yield spread,[7] maturity, loan type, loan purpose, and presence of security, and syndicate structure details, such as the fraction of the loan retained by the lead arranger from Dealscan. Since our analysis is conducted at the level of a deal, we aggregate these loan terms at the deal level. We discuss the aggregation methodology when we describe the variables we use in our analysis.

We use the Compustat database to obtain detailed financial information on the borrowers at the beginning of the financial year in which the loan is originated. We use the Compustat-Dealscan link made publicly available by Michael Roberts (see Chava and Roberts (2008)) to match the databases. We obtain data on security analyst coverage and public debt issuances from the Institutional Brokers' Estimate System (IBES) and Securities Data Company (SDC) databases, respectively, after manually matching the firm names in IBES and SDC with the borrower names in Dealscan.

B. Key Dependent Variables

We want to understand why firms borrow from nonrelationship banks for their repeat credit needs, and how this choice affects the availability of credit and future performance. Therefore, our key variable of interest is NEW_RELATIONSHIP, a dummy variable that identifies if the deal involves a new banking relationship for the borrowing firm. We define a bank-borrower relationship as a pairing between a lead arranger and a borrower, because past literature (e.g., Sufi (2007)) and anecdotal evidence suggest that it is the lead arranger, and not participant lenders, that generally possesses soft information about the borrower. To construct NEW_RELATIONSHIP, we examine all the previous deals of the borrowing firm reported in Dealscan. We then code NEW_RELATIONSHIP equal to 1 if the firm has *never before borrowed from any of the lead arrangers* (after adjusting for M&As among lead arrangers) of the current deal, and 0 otherwise.[8] Since we look at a firm's past deals to code NEW_RELATIONSHIP, we construct this variable only from a firm's 2nd deal onward.

[7]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 Offered Rate (LIBOR).

[8]Note that, as per our definition, a syndicated deal with multiple lead arrangers will be classified as a new relationship only if all the lead arrangers are new to the borrower.

A firm may form a new banking relationship either because it wants to maintain multiple banking relationships or because it wants to switch to a new bank entirely by severing its relationship with its existing bank. While there is no clear-cut ex ante method to identify if a new relationship represents a switch or not, in our empirical analysis we make this distinction based on whether at the time of a new deal, the past deal with the relationship bank is outstanding or not. Specifically, we define the dummy variable MULTIPLE_RELATIONSHIPS (SWITCH) to identify instances when the firm forms a new relationship when a past deal with its relationship bank is outstanding (not outstanding), or when it borrows from a syndicate with multiple lead arrangers. We use the stated maturity of past loan deals to identify if they are outstanding.[9]

A few comments on Dealscan's data coverage are in order at this point because they have implications for the definition of NEW_RELATIONSHIP. First, firms may have deals that are not reported in Dealscan because Dealscan is not a comprehensive listing of all U.S. private debt deals.[10] Since we identify new relationships based on a firm's past deals in Dealscan, absence of deal information will result in misclassification of repeat relationships as new relationships. To partly control for this misclassification, we repeat most of our analysis on subsamples of deals originated during the time period 1995–2006, when Dealscan significantly improved its coverage. Second, in the case of firms that have multiple banking relationships, left-censoring of the data may result in misclassification of repeat relationships as new relationships. To control for this, we repeat our regressions using the first 2 deals of every firm to identify its relationship banks. Third, Dealscan is sometimes known to report renegotiated deals as new deals (Roberts and Sufi (2009)). Given that a renegotiated deal is most likely to be financed by the existing bank, we are likely to classify most renegotiated deals as repeat relationships. However, as we mention in Section II.C, 46% of the deals in our sample involve new banking relationships. This high percentage indicates that renegotiated deals may not be a large fraction of the deals in our sample.

We do not impose any time restriction in defining NEW_RELATIONSHIP, but we control our regressions for the time elapsed since the firm's previous deal. Also, we classify a deal as involving a repeat relationship (i.e., NEW_RELATIONSHIP = 0) even if the lead arranger in the current deal was a syndicate participant in any of the firm's previous deals. There are only 175 such instances in our data.

[9]We thank the referee for this suggestion. Given that we rely on the stated maturity of past loans to identify whether they are outstanding, our classification of NEW_RELATIONSHIP into MULTIPLE_RELATIONSHIPS or SWITCH is likely to be noisy if the actual maturity is different from the stated maturity. However, we believe that our classification is reasonably accurate. For instance, out of the 1,825 deals that we identify as involving a SWITCH, borrowers of only 82 deals switch back to their relationship bank in the future.

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

C. Summary Statistics

We provide the descriptive statistics for our sample of deals in Table 1. Our sample includes all deals made during the period 1990–2005 in which the borrower is a nonfinancial U.S. firm, the lead arranger is identified as a U.S. bank, and they are among the 2nd, 3rd, or 4th deals of the borrower; 12,806 deals meet these conditions.[11] The average deal amount is about $256 million, while the median amount is $100 million. The average deal yield is about 165 bp over the LIBOR. Of the deals in our sample, 31% involve a single lender, whereas the remaining 69% are financed by a syndicate of lenders. Of the deals for which we have information on collateral, 75% are secured. On average, deals in our sample have a maturity of about 43 months and involve 4 lenders.

TABLE 1

Summary Statistics

Table 1 reports the summary statistics for key variables in our sample. All variables are defined in the Appendix. The data on deals are from Dealscan and cover deals originated during 1990–2006. Financial data on firms are from Compustat, and data on analyst following are from the IBES database.

Variable	*N*	Mean	Median	SD
Panel A. Deal Characteristics				
AMT (in $ million)	12,806	255.739	100	617.071
YIELD (bp over LIBOR)	9,836	164.569	150	104.211
SYNDICATE	12,806	0.692	1	0.462
SECURED	6,911	0.752	1	0.432
DEAL_MATURITY (months)	12,806	43.411	36	301.506
NO_OF_LENDERS	12,806	4.228	3	5.209
TIME_BTW_DEALS (years)	12,806	1.998	1.389	1.934
NEW_RELATIONSHIP	12,806	0.463	0	0.499
MULTIPLE_RELATIONSHIPS	12,806	0.380	0	0.485
SWITCH	12,806	0.143	0	0.350
REVOLVER	12,806	0.767	1	0.423
TERM_LOAN	12,806	0.225	0	0.418
WORKING_CAPITAL	12,806	0.580	1	0.494
REPAYMENT	12,806	0.214	0	0.410
TAKEOVER	12,806	0.129	0	0.335
SHORT_TERM	12,806	0.231	0	0.422
LONG_TERM	12,806	0.137	0	0.344
Panel B. Firm Characteristics				
NON_COMPUSTAT	12,806	0.452	0	0.498
MARKET_CAPITALIZATION (in $ million)	6,211	2,338.612	270.017	24,600
RATED	7,363	0.327	0	0.469
ANALYST	3,907	8.309	6	7.696
MARKET_TO_BOOK	6,210	1.846	1.415	2.933
PROFITS	6,817	0.126	0.131	0.120
LEVERAGE	6,984	0.315	0.289	0.248
Panel C. Bank Characteristics				
LARGE_BANK	12,806	0.571	1	0.495

[11] We drop the 1st deal of each firm from our analysis because we use it to define NEW_RELATIONSHIP for the firm's subsequent deals. Also, since the probability of borrowing from a relationship bank is likely to mechanically increase with the number of past deals of the firm and because large firms are likely to have more deals reported in Dealscan, we drop all deals beyond a firm's 4th deal, as their inclusion may bias our results. Our qualitative results are unchanged when we include all deals of all firms (other than the 1st), and control for the deal number.

On average, firms in our sample borrow every 2 years. As can be seen from the summary statistics of NEW_RELATIONSHIP, 46.3% of the repeat deals in our sample involve a new bank-borrower relationship. To understand the bias introduced by left-censoring of data, we redefine NEW_RELATIONSHIP for the 3rd and 4th deals of each borrower after using the borrower's first 2 deals to identify its relationship banks. Even then, we find that new relationships constitute 42% of the sample, which suggests that left-censoring is not a serious concern in our sample.

We also distinguish between multiple bank relationships and bank switches. We classify a deal as involving a multiple banking relationship (switch) if the firm forms a new relationship when a past deal with its relationship bank is outstanding (not outstanding), or when it borrows from a syndicate with multiple lead arrangers. We find that of the deals in our sample, 38% involve multiple banking relationships, whereas 14.3% represent a switch to a new bank.[12]

We use dummy variables to identify the nature and purpose of the deal. Approximately 77% of the deals in our sample involve at least 1 revolving line of credit (mean value of REVOLVER), while 23% involve at least 1 term loan (mean value of TERM_LOAN). Of the deals in our sample, 58% identify financing working capital, 21% identify repayment of previous debt, and 13% identify financing a takeover as their main purpose. We compute deal maturity as the weighted average maturity of all the loans in the deal, using loan amounts as weights. We code 2 dummy variables, SHORT_TERM and LONG_TERM, to represent deals with maturity less than 1 year and greater than 5 years, respectively. While 23% of the deals in our sample have a maturity of less than 1 year, 14% have a maturity of greater than 5 years.

Deals involving firms without Compustat data constitute about 45% of our sample. The median market capitalization of the Compustat firms in our sample is \$270 million. Among the deals to Compustat firms, only 33% involve firms that have debt ratings. The average number of analysts following the Compustat firms in our sample is 8.3, while the average market-to-book ratio and profitability (measured as the ratio of earnings before depreciation, interest, and taxes over total assets) of those firms is 1.85 and 12.6%, respectively. This indicates that the Compustat firms in our sample have growth opportunities and are also profitable. The average leverage ratio of the Compustat firms, which we calculate as the ratio of book value of total debt to book value of total assets, is 31.5% in our sample.

Of the deals in our sample, 57% are originated by LARGE_BANKS, which are in the top 5th percentile in terms of the number of deals originated in the previous year.

We now proceed to formal multivariate tests.

[12]Note that the total percentage of deals involving either a multiple banking relationship or a switch exceeds the percentage of deals classified as new relationship deals. This is because when a firm borrows from a syndicate with multiple lead arrangers, we classify the deal as involving a multiple banking relationship even if the firm has a relationship with one of the lead arrangers.

III. Empirical Results

A. Informational Transparency and the Propensity to Form New Banking Relationships

We begin our analysis by estimating the relationship between a firm's informational transparency and its propensity to form a new banking relationship. To analyze this choice, we estimate panel logit regressions that are variants of the following form:

$$\text{(1)} \qquad \text{NEW\_RELATIONSHIP}_d = F(\beta_0 + \beta_1 X_i + \beta_2 X_b + \beta_3 X_d + \varepsilon_{i,d}),$$

where the subscript i indicates the borrowing firm, subscript b indicates the bank, and subscript d indicates the deal. Recall that NEW_RELATIONSHIP is a dummy variable that identifies whether the deal involves a new bank-borrower relationship. The results of our estimation are presented in Table 2. In all specifications that we estimate, the standard errors are robust to heteroskedasticity and are clustered at the individual borrower level. Detailed definitions of all the variables we use are provided in the Appendix.

TABLE 2

Firm Characteristics and New Banking Relationships

Table 2 reports the results of a panel regression investigating the impact of firm characteristics on a firm's propensity to form new banking relationships. In Panel A, we estimate the following logit regression on the 2nd–4th deals of all firms in our sample:

$$\text{NEW\_RELATIONSHIP}_d = F(\beta_0 + \beta_1 X_i + \beta_2 X_b + \beta_3 X_d + \varepsilon_{i,d}).$$

In column (2), the sample is confined to the 3rd and 4th deals of all firms, while in columns (3)–(5), the sample is confined to loan deals made to Compustat firms. In column (6), we estimate an OLS model with borrower fixed effects (FE). In Panel B, we estimate the following multinomial-logit regression on the 2nd–4th deals of all firms in our sample:

$$y_{id} = F(\beta_0 + \beta_1 X_i + \beta_2 X_b + \beta_3 X_d + \varepsilon_{i,d}),$$

where y is an ordered variable that takes a value 0 for deals from relationship banks, a value 1 for deals from nonrelationship banks that we classify as multiple bank relationships, and a value 2 for deals from nonrelationship banks that we classify as bank switches. The results in the odd-numbered columns compare the choice between having multiple bank relationships and borrowing from the relationship bank, while the results in the even-numbered columns compare the choice between switching banks and borrowing from the relationship bank. The deal-level control variables are similar to those employed in Panel A. We suppress their coefficients to conserve space. All variable definitions are provided in the Appendix. In columns (3)–(8), the sample is confined to loan deals made to Compustat firms. In all the specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level. Here, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Firm Transparency and New Banking Relationships

	Pr(NEW_RELATIONSHIP)					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
NON_COMPUSTAT	–0.151 (0.040)***	–0.157 (0.055)***				–0.100 (0.026)***
log(MARKET_CAPITALIZATION)			–0.071 (0.027)***			
RATED				–0.150 (0.089)*		
ANALYST					–0.012 (0.006)**	
INTENSE_{t-1}		–0.469 (0.053)***				
LARGE						–0.048 (0.022)**

(continued on next page)

TABLE 2 (continued)

Firm Characteristics and New Banking Relationships

Panel A. Firm Transparency and New Banking Relationships (continued)

	Pr(NEW_RELATIONSHIP)					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
MARKET_TO_BOOK			–0.021 (0.032)	–0.050 (0.031)	–0.052 (0.034)	
LEVERAGE			–0.006 (0.204)	0.094 (0.215)	–0.175 (0.240)	
PROFITS			0.716 (0.374)*	0.567 (0.373)	0.844 (0.424)**	
log(AGE)			–0.035 (0.039)	–0.050 (0.039)	–0.061 (0.045)	
DEFAULT_LIKELIHOOD			–0.399 (0.338)	–0.230 (0.328)	0.282 (0.379)	
log(AMT)	–0.111 (0.014)***	–0.118 (0.019)***				
OUTSTANDING	–0.326 (0.047)***	–0.335 (0.068)***	–0.293 (0.084)***	–0.309 (0.084)***	–0.397 (0.096)***	–0.065 (0.014)***
TERM_LOAN	–0.098 (0.082)	–0.152 (0.120)	–0.230 (0.160)	–0.227 (0.160)	–0.335 (0.188)*	–0.060 (0.025)**
REVOLVER	–0.056 (0.078)	–0.116 (0.114)	–0.191 (0.151)	–0.196 (0.151)	–0.211 (0.179)	–0.058 (0.024)**
IPO/SEO			–0.169 (0.166)	–0.199 (0.167)	–0.214 (0.184)	
ACQUISITION			0.048 (0.155)	0.016 (0.155)	–0.015 (0.173)	
REPAYMENT	–0.236 (0.081)***	–0.177 (0.120)	–0.289 (0.192)	–0.292 (0.193)	–0.213 (0.237)	–0.077 (0.024)***
WORKING_CAPITAL	–0.097 (0.072)	–0.057 (0.109)	–0.109 (0.186)	–0.120 (0.186)	–0.012 (0.232)	–0.021 (0.022)
TAKEOVER	0.252 (0.086)***	0.184 (0.127)	0.041 (0.206)	0.041 (0.206)	0.157 (0.252)	–0.005 (0.025)
LONG_TERM	0.070 (0.061)	0.066 (0.089)	0.135 (0.126)	0.137 (0.126)	0.184 (0.148)	0.041 (0.021)**
SHORT_TERM	–0.310 (0.050)***	–0.325 (0.068)***	–0.267 (0.095)***	–0.290 (0.094)***	–0.287 (0.108)***	–0.047 (0.013)***
SYNDICATE	–0.264 (0.050)***	–0.237 (0.071)***	–0.235 (0.092)**	–0.298 (0.087)***	–0.274 (0.101)***	–0.072 (0.017)***
LONG_TIME_BTW_DEALS	0.625 (0.041)***	0.723 (0.057)***	0.694 (0.078)***	0.709 (0.077)***	0.648 (0.088)***	0.102 (0.011)***
No. of obs. Pseudo R^2 or R^2	12,806 0.058	6,668 0.073	3,679 0.055	3,679 0.054	2,847 0.058	13,164 0.45
Specification	Logit	Logit	Logit	Logit	Logit	OLS with FE

(continued on next page)

In column (1) of Panel A in Table 2, we estimate the regression on all the deals in our sample using NON_COMPUSTAT, a dummy variable that identifies firms not covered in the Compustat database, as our key measure of a firm's opacity. Since we do not have financial information on the borrowing firm for 45% of the deals, we partially control for firm size using $\log(\text{AMT})_{d-1}$, the logarithm

TABLE 2 (continued)

Firm Characteristics and New Banking Relationships

Panel B. Firm Transparency, Multiple Banking Relationships, and Bank Switches

	MR	SWITCH	MR	SWITCH	MR	SWITCH	MR	SWITCH	MR	SWITCH
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NON_COMPUSTAT	–0.142 (0.045)***	–0.257 (0.064)***							–0.144 (0.053)***	–0.430 (0.071)***
log(MARKET_CAPITALIZATION)			0.018 (0.031)	–0.212 (0.039)***						
RATED					0.004 (0.100)	–0.367 (0.142)***				
ANALYST							0.010 (0.007)	–0.016 (0.009)*		
LARGE									–0.014 (0.061)	–0.273 (0.081)***
MARKET_TO_BOOK			–0.122 (0.044)***	0.086 (0.042)**	–0.101 (0.038)***	0.014 (0.036)	–0.109 (0.040)***	0.0006 (0.039)		
LEVERAGE			0.805 (0.253)***	–1.064 (0.355)***	0.808 (0.264)***	–0.849 (0.370)**	0.745 (0.290)**	–1.730 (0.453)***		
PROFITS			0.846 (0.444)*	1.206 (0.475)**	0.795 (0.431)*	0.755 (0.459)*	0.962 (0.493)*	0.671 (0.527)		
DEFAULT_LIKELIHOOD			–0.746 (0.404)*	0.445 (0.468)	–0.820 (0.394)**	0.976 (0.456)**	0.0004 (0.490)	2.112 (0.592)***		
log(AGE)			–0.070 (0.044)	0.123 (0.058)**	–0.063 (0.043)	0.076 (0.057)	–0.040 (0.051)	0.065 (0.068)		
TERM_LOAN	0.157 (0.098)	–0.033 (0.138)	0.265 (0.209)	–0.066 (0.277)	0.260 (0.209)	–0.013 (0.274)	0.094 (0.268)	–0.414 (0.357)	0.136 (0.098)	0.036 (0.140)
REVOLVER	–0.718 (0.095)***	–0.352 (0.132)***	–0.883 (0.205)***	–0.967 (0.266)***	–0.883 (0.205)***	–0.963 (0.263)***	–1.131 (0.270)***	–1.202 (0.352)***	–0.720 (0.095)***	–0.376 (0.134)***
SYNDICATE	0.021 (0.055)	–0.194 (0.077)**	0.265 (0.102)***	–0.325 (0.129)**	0.288 (0.096)***	–0.556 (0.121)***	0.229 (0.112)**	–0.517 (0.142)***	0.131 (0.051)**	–0.652 (0.067)***
No. of obs.	12,806		3,679		3,679		2,845		12,806	
Pseudo R^2	0.064		0.072		0.067		0.070		0.050	

of the deal amount on the firm's most recent deal, and SYNDICATE, a dummy variable that identifies syndicated deals, which typically involve larger firms. We control for whether an earlier loan of the firm is outstanding at the time the current deal is contracted, using the dummy variable OUTSTANDING. We also control for the frequency with which the firm borrows, using the dummy variable LONG_TIME_BTW_DEALS, which takes a value of 1 if the time since the firm's most recent deal is greater than the sample median across all firms. We control in the regression for deal maturity (SHORT_TERM and LONG_TERM), deal purpose (REPAYMENT, TAKEOVER, and WORKING_CAPITAL), and deal type (TERM_LOAN and REVOLVER).

The negative and significant coefficient on NON_COMPUSTAT indicates that firms not covered in Compustat are less likely to form new banking relationships, which is consistent with the idea that informationally opaque firms benefit from strong and exclusive banking relationships. In terms of coefficients on the control variables, the negative coefficients on $\log(\text{AMT})_{d-1}$ and SYNDICATE suggest that deals involving new banking relationships involve smaller loan amounts and are less likely to be syndicated. As we show presently, this result is driven by the fact that smaller firms, which are more likely to borrow smaller amounts in the nonsyndicated loan market, are more likely to form new banking relationships. We also find that firms are more likely to form new banking relationships if a previous deal is not outstanding (negative coefficient on OUTSTANDING), and if a long time has passed since its previous deal (positive coefficient on LONG_TIME_BTW_DEALS). Firms are more likely to form new banking relationships to finance takeovers and are more likely to borrow from their relationship bank when the purpose is to repay existing debt.

In column (2) of Panel A in Table 2, we test if firms with strong banking relationships are less likely to form new banking relationships. To do this we create a dummy variable INTENSE that identifies instances when firms borrow 2 or more successive loans from the same bank. We then repeat our estimation of the regression after including lagged values of INTENSE. Since we need 2 loan deals to construct INTENSE, we estimate this regression only on the 3rd and 4th loan deals of a borrower. The significant negative coefficient on INTENSE_{d-1} indicates that firms with strong banking relationships are less likely to form new banking relationships.

In columns (3)–(5) of Panel A in Table 2, we repeat regression (1) on the subsample of deals involving firms that are covered in the Compustat database (i.e., firms that are at the more transparent end of the information spectrum). Following prior literature, we measure informational transparency using, alternatively, firm size ($\log(\text{MARKET\_CAPITALIZATION})$), an indicator for whether the firm has a long-term credit rating (RATED), and the number of security analysts following the firm's stock (ANALYSTS). The other firm-level controls (X_i) we employ are: log(AGE) to proxy for age; MARKET_TO_BOOK to proxy for growth opportunities; PROFITS to proxy for profitability; and LEVERAGE and DEFAULT_LIKELIHOOD to control for firm risk, where DEFAULT_LIKELIHOOD is the modified version of the Merton-KMV expected default probability estimated using the procedure outlined in Bharath and Shumway (2008). We measure all the firm financial variables at the beginning of the financial year in which the deal is originated. Because past literature has highlighted that firms benefit from having lending relationships with their merger advisors or equity underwriters (Drucker and Puri (2005), Schenone (2004)), we also include the dummy variables ACQUISITION and IPO/SEO, which identify firms that undertook an acquisition or an equity issue, respectively, in the previous year as additional controls.

In column (3) of Panel A in Table 2, we use log(MARKET_CAPITALIZATION) as the proxy for the firm's informational transparency. As can be seen, the coefficient on log(MARKET_CAPITALIZATION) is negative and statistically significant, which is surprising because it indicates that, among Compustat firms, the less transparent firms are more likely to approach nonrelationship banks for their repeat credit needs. However, this result is consistent with the life cycle hypothesis, because smaller firms are more likely to face borrowing constraints at their relationship banks. In terms of economic significance, a 1-standard-deviation increase in log(MARKET_CAPITALIZATION) reduces the probability of forming new banking relationships by about 4%; as against this, the average likelihood of a deal involving a new banking relationship in our sample is 46%. We obtain similar results when we repeat this regression with RATED (column (4)) and ANALYSTS (column (5)) as alternative measures of information quality (i.e., less transparent firms are more likely to form new banking relationships). Interestingly, we also find that more profitable firms are more likely to form new banking relationships, which indicates that these are not poorly performing firms that were rejected by their relationship banks.

Our results so far indicate that the most opaque firms in our sample (the non-Compustat firms) and the most transparent firms (the large Compustat firms) are more likely to borrow from their relationship bank compared to firms in the middle of the information spectrum (i.e., the small Compustat firms). One concern with this conclusion is that it is based on tests run on 2 separate samples. To see if this pattern is evident in the full sample, in column (6) of Panel A in Table 2, we estimate the regression on the full sample with NON_COMPUSTAT and LARGE as the key explanatory variables, where LARGE is a dummy variable that identifies Compustat firms with above-median market capitalization. Note that the omitted category in this regression consists of the Compustat firms with below-median market capitalization. Since we include all deals in this regression, we drop all the financial variables because these are only available for Compustat firms. We include firm fixed effects to examine if a firm's tendency to form new banking relationships changes with its inclusion in the Compustat database or with a change in its size category. Since a logistic specification with fixed effects is subject to the incidental parameters problem (Wooldridge (2002)), we employ an ordinary least squares (OLS) specification in column (6) of Table 2. Furthermore, to ensure sufficient within-firm variation, we also include all loan deals in our sample.

The negative and significant coefficients on both NON_COMPUSTAT and LARGE in column (6) of Panel A in Table 2 are consistent with our earlier results. Since this is an OLS model, the coefficient is the same as the marginal effect. Therefore, the coefficient of −0.100 on NON_COMPUSTAT indicates that when a firm without Compustat data changes status, its probability of forming a new banking relationship increases by 10%. Similarly, the coefficient of −0.048 on LARGE indicates that when a firm grows to become a large Compustat firm, its probability of forming a new banking relationship decreases by 4.8%. Thus, these results are highly economically significant.

In unreported tests, we show that our results are robust to controlling for incomplete data coverage in Dealscan and left-censoring of the data. We repeat our regression after confining the sample to deals originated during 1995–2006, when Dealscan significantly improved its coverage. To control for left-censoring of the data, especially in cases where firms have multiple banking relationships, we repeat our estimation after using the first 2 deals of a borrower to identify its relationship banks, which we then use to define NEW_RELATIONSHIP for the borrower's 3rd and 4th deals. To ensure that our results are not driven by firms with more repeat deals, we repeat the regression on a balanced panel of firms; that is, we limit the sample to firms that have a minimum of 4 deals reported in Dealscan and estimate the regression on the 2nd–4th deals of each firm. We obtain consistent results in all specifications; that is, the coefficients on NON_COMPUSTAT and LARGE are negative and significant, indicating that non-Compustat firms and large Compustat firms are less likely to form new banking relationships.

1. Multiple Banking Relationships versus Switches

A firm may form a new banking relationship either to maintain multiple banking relationships or to switch to a new bank and entirely sever its relationship with its existing bank. While both of these represent a dilution of the firm's existing banking relationship, it is interesting to examine how firms differ in their propensity to form multiple relationships and to switch to new banks. We investigate this question using a multinomial logit model, the results of which are presented in Panel B of Table 2. The dependent variable in this regression is an ordered variable that takes a value of 0 for deals from relationship banks, a value of 1 for deals from nonrelationship banks that we classify as multiple banking relationships, and a value of 2 for deals from nonrelationship banks that we classify as bank switches. As mentioned before, we classify a deal as involving a multiple banking relationship (switch) if the firm forms a new relationship when a past deal with its relationship bank is outstanding (not outstanding), or when it borrows from a syndicate with multiple lead arrangers.

The results of our estimation are presented in 2 columns. Column (1) of Panel B in Table 2 represents the choice between borrowing from a relationship bank (the base case) and forming multiple banking relationships, while column (2) represents the choice between borrowing from a relationship bank and switching to a new bank. We employ the same set of deal-level control variables as in Panel A, but we do not report their coefficients to conserve space. The negative and significant coefficients on NON_COMPUSTAT in columns (1) and (2) indicate that opaque non-Compustat firms are less likely to both form multiple banking relationships and to switch banks as compared to Compustat firms. In terms of economic significance, the estimates indicate that a NON_COMPUSTAT firm is about 1.8% less likely to both form multiple banking relationships and switch banks. In comparison, the likelihood of a firm forming multiple banking relationships (switching banks) in our sample is 38% (14.3%). Similarly, the negative and significant coefficient on log(MARKET_CAPITALIZATION) in column (4) indicates that, among Compustat firms, larger Compustat firms are less likely to switch banks. Interestingly we do not find large Compustat firms to be less likely to form multiple banking relationships. We believe this is because large firms are more likely to borrow through syndicates with multiple lead arrangers, which we classify as a multiple banking relationship. Examining columns (5) and (6), we find that while rated firms are less likely to switch to a new bank compared to unrated firms, there is no statistically significant difference in their propensity to form multiple banking relationships. The findings with respect to analyst coverage (columns (7) and (8)) are also similar to those with respect to rating status. Our results using the full sample in columns (9) and (10) confirm the nonlinear relationship between a firm's information environment and its propensity to switch to a new bank. However, we do not detect a similar nonlinear pattern in terms of firms' propensity to form multiple banking relationships.

To summarize the results in Table 2, we find that the opaque non-Compustat firms are more likely to continue borrowing from their relationship bank, which is consistent with the theory that informationally opaque firms benefit from strong banking relationships. However, among the subsample of Compustat firms, the more opaque firms (small firms, firms without a credit rating, and firms tracked by fewer analysts) are more likely to borrow from nonrelationship banks. This latter finding suggests that the informational benefit of borrowing from a relationship bank is not equally valuable to all firms, and that there may be costs to continuing to borrow from the relationship bank.

B. Bank Characteristics and the Propensity to Form New Banking Relationships

In this section, we examine how a firm's propensity to form a new banking relationship is affected by the characteristics of its existing relationship bank. We do this by estimating the logit regression (1) after including the characteristics of the firm's relationship bank as additional regressors. We control for all of the variables that we employed in Table 2, although we do not report all of the coefficients to conserve space. The results of our estimation are presented in Panel A of Table 3.

In column (1) of Panel A in Table 3, we estimate regression (1) after including PREV_LARGE_ BANK, a dummy variable that identifies if the firm ever borrowed from a large bank in the past, as an additional regressor. We define a bank as large if it is in the top 5th percentile in terms of the number of loans syndicated the previous year. The negative coefficient on PREV_LARGE_BANK in column (1) indicates that a firm is more likely to form a new banking relationship if it does not have an existing relationship with a large bank (i.e., if PREV_LARGE_BANK = 0). This result is also economically significant. The coefficient on PREV_LARGE_BANK indicates that a firm that does not have an existing relationship with a large bank is 18% more likely to form a new banking relationship.

Apart from size, another important bank characteristic of interest is whether the relationship bank is active in a full array of capital market activities, such as

TABLE 3

Bank Characteristics and New Banking Relationships

Table 3 reports the results of a panel logit regression investigating the effect of the characteristics of a firm's relationship bank on the firm's propensity to form new banking relationships. Specifically we estimate the following logit regression on the 2nd–4th deals of all the firms in our sample:

$$\text{NEW\_RELATIONSHIP}_d = F(\beta_0 + \beta_1 X_i + \beta_2 X_b + \beta_3 X_d + \varepsilon_{i,d}),$$

where X_b represents various bank characteristics, X_i represents firm characteristics, and X_d represents deal characteristics. We control the regressions for all the variables employed in Table 2, but we suppress the coefficients to conserve space. Panel B reports the results of a regression investigating the characteristics of banks that borrowers form new relationships with. Specifically we estimate the following multinomial-logit regression on the 2nd–4th deals of all the firms in our sample:

$$y_{id} = F(\beta_0 + \beta_1 X_i + \beta_2 X_b + \beta_3 X_d + \varepsilon_{i,d}),$$

where y is an ordered variable that takes a value 0 for loan deals from a relationship bank, a value 1 for loan deals from a small nonrelationship bank, and a value 2 for loans from a large nonrelationship bank. We control the regressions for all the variables employed in Panel A, but we suppress the coefficients to conserve space. All variables are described in the Appendix. In all the specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level. Here, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Previous Bank Characteristics and New Banking Relationships

	Pr(NEW_RELATIONSHIP)		MR	SWITCH	MR	SWITCH
Variable	(1)	(2)	(3)	(4)	(5)	(6)
PREV_LARGE_BANK	–0.950 (0.302)***		–0.185 (0.223)	–0.881 (0.337)***		
PREV_SECTION_20_BANK		–0.456 (0.389)			–0.007 (0.318)	–0.594 (0.430)
NON_COMPUSTAT	–0.124 (0.072)*	–0.154 (0.068)**	–0.135 (0.089)	–0.131 (0.116)	–0.132 (0.079)*	–0.146 (0.112)
SMALL	–0.093 (0.072)	0.013 (0.098)	–0.044 (0.074)	0.385 (0.122)***	–0.034 (0.081)	0.380 (0.113)***
OUTSTANDING	–0.313 (0.051)***	–0.374 (0.074)***				
TERM_LOAN	–0.120 (0.083)	–0.121 (0.076)	0.108 (0.132)	–0.040 (0.163)	0.111 (0.126)	–0.029 (0.153)
REVOLVER	–0.133 (0.087)	–0.138 (0.084)	–0.728 (0.129)***	–0.341 (0.141)**	–0.727 (0.128)***	–0.331 (0.138)**
No. of obs.	12,806	12,806	12,806		12,806	
Pseudo R^2	0.084	0.062	0.059		0.056	

Panel B. Characteristics of the Current Bank

	NR Small Bank	NR Large Bank
Variable	(1)	(2)
PREV_LARGE_BANK	–1.146 (0.312)***	–0.784 (0.353)**
NON_COMPUSTAT	–0.191 (0.080)**	0.224 (0.084)***
OUTSTANDING	–0.290 (0.065)***	–0.278 (0.061)***
REVOLVER	–0.125 (0.111)	–0.051 (0.107)
TERM_LOAN	–0.126 (0.105)	–0.048 (0.111)
No. of obs.	12,806	
Pseudo R^2	0.090	

underwriting and M&A advisory services. Banks were active in these areas via Section 20 subsidiaries prior to 2000, and via financial holding companies after the Graham-Leach-Bliley Act of 1999. To examine how this affects firms' propensity to form new banking relationships, we repeat our estimation after replacing PREV_LARGE_BANK with PREV_SECTION_20_BANK, a dummy variable that identifies if any of the firm's relationship banks has a Section 20 subsidiary.[13] Although the coefficient on PREV_SECTION_20_BANK is negative, indicating that firms without existing relationships with banks that are active in underwriting and M&A advisory services are more likely to form new banking relationships, it is not significant at conventional levels.

In columns (3) and (4) of Panel A in Table 3, we examine how the size of the relationship bank affects a firm's choice among the following 3 options: continuing to borrow from the relationship bank, forming multiple banking relationships, and switching to a new bank. We do this using the multinomial logit specification that we outlined in Section I. Our results indicate that an existing relationship with a large bank makes it less likely that the firm will switch to a new bank (negative and significant coefficient on PREV_LARGE _BANK in column (4)), but there is no corresponding effect on the firm's propensity to form multiple banking relationships (insignificant coefficient on PREV_LARGE_BANK in column (3)).

In columns (5) and (6) of Panel A in Table 3, we examine how the presence of a Section 20 subsidiary at the firm's relationship bank affects a firm's choice between continuing to borrow from the relationship bank, forming multiple banking relationships, and switching to a new bank. While the coefficient on PREV_SECTION_20_BANK is negative in both columns, indicating that firms with existing relationship with a Section 20 bank are less likely to either form multiple banking relationships or switch banks, the coefficients are not significant at conventional levels.[14]

Our next set of tests is aimed at understanding the types of banks firms form new relationships with. Since the characteristic of the bank in the current loan deal is endogenous, we do not use it as a right-hand side variable. Instead, we estimate multinomial logit regressions with an ordered variable that distinguishes across banks that firms form new relationships with. We control in these regressions for all of the deal-level variables employed in Table 2 but do not report the coefficients to conserve space. The results of our estimation are presented in Panel B of Table 3.

In columns (1) and (2) of Panel B in Table 3, we distinguish between banks based on size, and we estimate the determinants of a firm's propensity to form a new banking relationship with small and large banks. Thus, the dependent variable takes a value of 0 if the deal is from a relationship bank, a value of 1 if the deal involves a new relationship with a small bank, and a value of 2 if the deal involves a new relationship with a large bank. Note that we do not differentiate between forming multiple banking relationships and switching banks. The negative and significant coefficients on PREV_LARGE_BANK in both columns (1) and (2) indicate that firms that have an existing relationship with a large bank are less likely to form new relationships with both small and large banks. Consistent with

[13]We obtain the list of banks with Section 20 subsidiaries from Table 1 in Gande, Puri, and Saunders (1999).

[14]In unreported tests, we estimate the effect of other bank and bank market characteristics on a firm's propensity to form new banking relationships. We find that firms are more likely to form a new banking relationship if their relationship bank is in a more competitive banking market (as measured by deposit Herfindahl), when their relationship bank has experienced a merger or lower deposit growth rate.

the evidence in Berger et al. (2005), we find that small firms are more likely to form new relationships with small banks. Interestingly, in contrast with our earlier finding that non-Compustat firms are, on average, less likely to form new relationships (see Table 2), we find that non-Compustat firms are more likely to form new relationships with large banks and less likely to form new relationships with small banks. We believe that this contrast is likely driven by the large private firms in our sample, which are able to form new relationships with large banks.

Overall, our findings in Table 3 are broadly consistent with the life cycle hypothesis. A firm is more likely to form new banking relationships when it does not have an existing relationship with a large bank and when its relationship bank does not have a Section 20 subsidiary.

C. New Banking Relationships and Deal Terms

So far, our analysis has focused on examining how firm and bank characteristics affect a firm's propensity to form new banking relationships. To better understand firms' motives for forming new banking relationships, we now examine how new banking relationships affect deal terms and subsequent firm performance. We estimate panel OLS regressions that are variants of following form:

$$(2)\ y_{it} \quad = \quad \beta_0 + \beta_1 \times \text{NEW\_RELATIONSHIP}_d + \beta_2 X_i + \beta_3 X_d + \beta_4 X_b + \mu_i + \mu_t,$$

where the dependent variable y is either a deal or a firm characteristic, and NEW_RELATIONSHIP is the key independent variable of interest. We discuss issues arising from the endogeneity of NEW_RELATIONSHIP in Section I.

We focus on deal terms in this section, and examine firm performance in Section III.D. The deal terms that we model are $\Delta\log(\text{AMT})$ and $\Delta\log(\text{YIELD})$, which represent changes in $\log(\text{AMT})$ and $\log(\text{YIELD})$, respectively, between the current deal and the firm's most recent deal. We model changes in loan amounts and yields because they capture benefits to firms from forming new banking relationships. We estimate these regressions on all of the deals in our sample. We control in these regressions for all of the firm, deal, and bank characteristics employed in Tables 2 and 3, but to conserve space, we only report the coefficients on a few control variables. Because deal amounts and yields can depend on unobserved firm characteristics, we also include firm fixed effects (μ_i) in addition to year fixed effects (μ_t). The results of our estimation are presented in Panel A of Table 4. The dependent variable y is $\Delta\log(\text{AMT})$ in columns (1)–(4), and $\Delta\log(\text{YIELD})$ in columns (5)–(8). In all specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level.

The positive coefficient on NEW_RELATIONSHIP in column (1) of Panel A in Table 4 indicates that the deal amount obtained by a firm increases by 9.0% when it forms a new banking relationship, which is consistent with the key prediction of the life cycle hypothesis. In column (2), we examine whether the increase in loan amount varies with the intensity of the firm's relationship with its bank. To do this, we repeat the regression in column (1) after including 2 additional terms, INTENSE and NEW_RELATIONSHIP × INTENSE, where INTENSE is a dummy variable that identifies if the firm has obtained at least 2 loan deals from its relationship bank in the past. The insignificant coefficients on the new terms in column (2) indicate that the increase in loan amount from forming a new banking relationship does not vary with the intensity of the firm's relationship with its bank. In column (3), we include firm fixed effects to control for unobserved time-invariant firm characteristics. The coefficient on NEW_RELATIONSHIP continues to be positive and significant, and its magnitude is also similar to that in column (1). In column (4), we differentiate new relationships into those involving multiple bank relationships and those involving bank switches. As mentioned before, we classify a deal as involving a multiple banking relationship (switch) if the firm forms a new relationship when a past deal with its relationship bank is outstanding (not outstanding), or when it borrows from a syndicate with multiple

TABLE 4

Impact of New Banking Relationships on Deal Terms

Table 4 reports the results of regressions relating the amount and yield on a deal to the firm's decision to form a new banking relationship. In Panel A, we estimate the panel OLS regressions

$$y_{it} = \beta_0 + \beta_1 \text{NEW\_RELATIONSHIP}_d + \beta_2 X_i + \beta_3 X_d + \beta_4 X_b + \mu_i + \mu_t$$

on our entire sample of deals, where y is $\Delta\log(\text{AMT})$ in columns (1)–(4) and $\Delta\log(\text{YIELD})$ in columns (5)–(8). Here, $\Delta\log(\text{AMT})$ ($\Delta\log(\text{YIELD})$) is the difference between the logarithm of the amount (yield) of the current deal and the logarithm of the amount (yield) on the most recent past deal. Panels B and C report the results of a switching regression model aimed at understanding the impact of NEW_RELATIONSHIP on log(AMT), after controlling for the endogeneity of NEW_RELATIONSHIP. The model consists of a selection equation (Probit) to estimate the probability of a firm forming a new banking relationship (column (1)), and 2 outcome equations that examine $\Delta\log(\text{AMT})$ separately on deals involving existing relationships (column (2)) and those involving new banking relationships (column (3)). The INVERSE_MILLS_RATIO and the MILLS_RATIO estimated from the coefficient estimates in column (1) are used as additional controls in columns (2) and (3), respectively. Panel C presents the results of a t-test for the difference between the actual $\Delta\log(\text{AMT})$ on loans involving new banking relationships and the counterfactual $\Delta\log(\text{AMT})$ (estimated using coefficient estimates in column (2)) if the same loan had involved a repeat relationship. All variables are described in the Appendix. In all the specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level. Here, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Deal Amount, Pricing, and New Banking Relationships

	$\Delta\log(\text{AMT})$				$\Delta\log(\text{YIELD})$			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NEW_RELATIONSHIP	0.090 (0.018)***	0.093 (0.020)***	0.083 (0.030)***		0.021 (0.012)*	0.015 (0.014)	0.030 (0.021)	
INTENSE_{d-1}		–0.017 (0.024)				–0.009 (0.015)		
NEW_RELATIONSHIP × INTENSE_{d-1}		–0.026 (0.044)				0.024 (0.027)		
SWITCH				0.175 (0.038)***				0.011 (0.029)
MULTIPLE_RELATIONSHIPS				0.085 (0.019)***				0.012 (0.012)
LARGE	–0.032 (0.023)	–0.031 (0.023)	0.089 (0.066)	–0.033 (0.023)	–0.053 (0.016)***	–0.053 (0.016)***	–0.114 (0.051)**	–0.053 (0.016)***
NON_COMPUSTAT	–0.081 (0.020)***	–0.081 (0.020)***	0.071 (0.080)	–0.080 (0.020)***	–0.030 (0.014)**	–0.030 (0.014)**	0.048 (0.062)	–0.031 (0.014)**
OUTSTANDING	–0.406 (0.024)***	–0.407 (0.024)***	–0.381 (0.040)***	–0.353 (0.030)***	–0.015 (0.017)	–0.015 (0.017)	–0.013 (0.031)	–0.017 (0.021)
REVOLVER	0.205 (0.039)***	0.206 (0.039)***	0.250 (0.071)***	0.206 (0.039)***	–0.084 (0.023)***	–0.084 (0.023)***	–0.176 (0.047)***	–0.084 (0.023)***
TERM_LOAN	0.051 (0.040)	0.051 (0.040)	0.039 (0.072)	0.052 (0.040)	0.025 (0.024)	0.025 (0.024)	–0.008 (0.049)	0.025 (0.024)
No. of obs.	12,806	12,806	12,806	12,806	7,806	7,806	7,806	7,806
R^2	0.117	0.117	0.524	0.118	0.107	0.107	0.576	0.107
Firm fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(continued on next page)

TABLE 4 (continued)

Impact of New Banking Relationships on Deal Terms

Panel B. Switching Regression Model

		Δ log(AMT)	
	Pr(NEW_RELATIONSHIP)	EXISTING_RELATIONSHIPS	NEW_RELATIONSHIPS
Variable	(1)	(2)	(3)
MILLS_RATIO		–1.645 (0.675)**	
INVERSE_MILLS_RATIO			2.372 (1.001)**
REPAYMENT	–0.137 (0.050)***	0.329 (0.073)***	0.082 (0.108)
OUTSTANDING	–0.240 (0.029)***	–0.061 (0.107)	–0.825 (0.147)***
LARGE	–0.014 (0.034)	–0.018 (0.030)	–0.036 (0.038)
NON_COMPUSTAT	–0.096 (0.029)***	0.042 (0.047)	–0.257 (0.067)***
WORKING_CAPITAL	–0.052 (0.045)	0.140 (0.049)***	0.011 (0.071)
TAKEOVER	0.162 (0.053)***	0.384 (0.090)***	0.834 (0.121)***
TERM_LOAN	–0.049 (0.050)	0.056 (0.053)	0.032 (0.072)
REVOLVER	–0.065 (0.048)	0.227 (0.054)***	0.164 (0.076)**
LONG_TERM	0.003 (0.038)	0.072 (0.036)**	0.171 (0.049)***
SHORT_TERM	–0.223 (0.030)***	–0.083 (0.094)	–0.605 (0.145)***
SYNDICATE	–0.266 (0.029)***	0.410 (0.113)***	0.066 (0.167)
LONG_TIME_BTW_DEALS	0.388 (0.025)***	–0.379 (0.154)**	0.605 (0.259)**
No. of obs.	12,806	6,874	5,932
Pseudo R^2 or R^2	0.054	0.094	0.145

Panel C. Difference between Actual and Counterfactual Δlog(AMT)

	Actual	Counterfactual	Difference
Δ log(AMT) for new relationship deals	0.274	0.191	0.083 (0.014)***

lead arrangers. Our results indicate that firms obtain higher loan amounts both when they form multiple banking relationships and when they switch banks, although the increase is much larger when firms switch to new banks.

Overall, these results indicate that a key benefit of forming new banking relationships is that firms obtain larger loan amounts.[15] These results offer strong support for the hypothesis that firms form new banking relationships in order to overcome credit constraints at their relationship bank and to borrow more.

[15]In unreported tests, we examine if the effect of new banking relationships on deal amount varies among the 3 categories of firms in our sample: non-Compustat firms, small Compustat firms, and large Compustat firms. We find that firms in all 3 categories experience increases in loan amounts when they form new banking relationships.

In columns (5)–(8) of Panel A in Table 4, we repeat our analysis with $\Delta \log(\text{YIELD})$ as the dependent variable. The positive coefficient on NEW_RELATIONSHIP in column (5) indicates that firms pay a slightly higher yield when they borrow from a nonrelationship bank.[16] This may reflect the greater uncertainty faced by the nonrelationship bank in assessing firm quality. However, after we control for unobserved firm characteristics using firm fixed effects, we do not detect any effect of new relationships on the yield of the loan deal (column (7)). In column (8), we differentiate between forming multiple bank relationships and switching banks, and we find that neither of these choices has a significant effect on loan yields.

1. Controlling for the Endogeneity of New Banking Relationships

An important concern with regression model 2 is that it treats NEW_RELATIONSHIP as an exogenous variable, conditional on all the firm-, bank-, and deal-level controls and the inclusion of firm fixed effects and year effects. However, there could be unobserved time-varying omitted variables that affect both loan amounts and firms' propensity to form new relationships, which would bias our estimates in Panel A of Table 4.

In this section, we estimate a switching regression model (see Fang (2005), Li and Prabhala (2007)) to control for both observable and unobservable characteristics that may affect a firm's propensity to form new banking relationships. We estimate this model only with $\Delta \log(\text{AMT})$ as the dependent variable, because we did not find any effect of new banking relationships on yields in Panel A of Table 4. The model consists of estimating 3 regressions: a probit selection model with NEW_RELATIONSHIP as the dependent variable, and 2 separate OLS models with $\Delta \log(\text{AMT})$ as the dependent variable, which are estimated for deals with NEW_RELATIONSHIP = 1 and NEW_RELATIONSHIP = 0, respectively.[17] We augment the 2 OLS models with the inverse Mills ratio and the Mills ratio, respectively, estimated from the selection model, to control for any unobserved characteristics (e.g., private information) that may affect firms' propensity to form new banking relationships.[18]

The results of our estimation are presented in Panel B of Table 4. Column (1) presents the results of the selection model. Since we lack an exogenous instrument for the matching between firms and banks, we model selection using all the firm-, deal-, and bank-level controls employed in Tables 2 and 3. In columns (2) and (3), we present the results of the OLS regressions with $\Delta \log(\text{AMT})$ as the dependent

[16] In contrast, Ioannidou and Ongena (2010) find that Bolivian firms that switch banks initially obtain lower interest rates, but these rates increase thereafter.

[17] The switching regression model, while similar to a Heckman selection model, is more general because it estimates two 2nd-stage equations and thus allows for different coefficients on covariates for the "selected" and the "not selected" samples. Similar to the Heckman model, the identification comes from the nonlinearity of the model, which arises from the assumption of joint normality for the error terms.

[18] The Mills ratio and the inverse Mills ratio are given by the formulas $(\phi(\hat{\gamma}Z'))/(\Phi(\hat{\gamma}Z'))$ and $(-1 \times \phi(\hat{\gamma}Z'))/([1-\Phi(\hat{\gamma}Z')])$, where ϕ and Φ denote the probability density function and cumulative density function, respectively, of the standard normal distribution; Z is the vector of regressors used in the selection model; and $\hat{\gamma}$ denotes the vector of coefficient estimates from the selection model.

variable for deals that involve new relationships (column (2)) and those that do not (column (3)). A comparison of the coefficients in columns (2) and (3) reveals that the effects of firm and deal characteristics on the deal amount are very different for deals involving new relationships as compared to those involving repeat relationships, which justifies the estimation of 2 separate OLS regressions. The significant coefficients on the MILLS_RATIO and the INVERSE_MILLS_RATIO indicate that unobserved characteristics that affect a firm's propensity to form a new banking relationship also affect loan amounts.

To test whether firms obtain larger deal amounts when they form new banking relationships, we compare the actual $\Delta \log(\text{AMT})$ on new relationship deals with the counterfactual increase in deal amount, denoted $\Delta \log(\widehat{\text{AMT}})$, if the same deal had been arranged by a relationship bank. We estimate $\Delta \log(\widehat{\text{AMT}})$ by applying the coefficient estimates in column (3) of Panel B to the firm-, bank-, and deal-characteristics of a new relationship deal. In Panel C of Table 4, we report the result of a *t*-test for the statistical significance of the difference between $\Delta \log(\text{AMT})$ and $\Delta \log(\widehat{\text{AMT}})$. As can be seen, the difference is positive and statistically significant, which indicates that, even after controlling for the endogeneity of new banking relationships, borrowers obtain larger deal amounts when they form new banking relationships. Moreover, the magnitude of the difference is comparable to the coefficient in column (1) of Panel A. In unreported tests, we employ the propensity score matching model to control for the endogeneity of new relationships and obtain results similar to the results reported.

D. New Banking Relationships and Firm Performance

We showed in Table 4 that firms obtain larger deal amounts when they form new banking relationships. The ability to borrow more should also translate into an increase in firms' subsequent capital expenditures, growth rates, and leverage ratios. To examine if firms experience such positive outcomes after they form new banking relationships, we estimate the panel OLS regression (2) with various firm-level outcomes as dependent variables and NEW_RELATIONSHIP as the main independent variable. The firm characteristics that we model are CAPEX, SALES_GROWTH, and LEVERAGE (see the Appendix for detailed definitions). We estimate this regression on a panel of Compustat firms that spans the time period 1990–2005, has 1 observation for each firm-year, and includes all Compustat firms that have at least 1 loan deal reported in Dealscan. We code NEW_RELATIONSHIP to take a value of 1 in the year in which the firm forms a new banking relationship. To control for unobserved firm characteristics that might affect firm outcomes, we include firm fixed effects (μ_i) in addition to year fixed effects (μ_t) in all specifications. In all specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level.

Table 5 reports the results of regressions relating firm capital expenditure, sales growth rate, and leverage to NEW_RELATIONSHIP. In these regressions we control for lagged values of firm size (log(TOTAL_ASSETS)), profitability (PROFITS), investment opportunities (MARKET_TO_BOOK), and TANGIBILITY of assets. To ensure that we are not just identifying a mechanical increase in

TABLE 5

Impact of New Banking Relationships on Firm Performance

Table 5 reports the results of a panel OLS regression relating firm investment, sales growth rate, leverage, and analyst coverage to new banking relationships. Specifically, we estimate the panel OLS regressions, $y_{it} = \beta_0 + \beta_1 \text{NEW\_RELATIONSHIP}_t + \beta_2 X_i + \mu_t + \mu_i$, where y is CAPEX in columns (1)–(3), SALES_GROWTH in columns (4)–(6), and LEVERAGE in columns (7)–(9). The panel spans the period 1990–2005, has 1 observation for each firm-year combination, and includes all the borrowing firms in our sample for which we have financial data in Compustat. All variables are as described in the Appendix. We control the regression for firm and year fixed effects (FE). In all the specifications, the standard errors are robust to heteroskedasticity and are clustered at the individual firm level. Here, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAPEX			SALES_GROWTH			LEVERAGE		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEW_RELATIONSHIP	–0.004	–0.008		–0.022	–0.041		0.003	–0.016	
	(0.001)***	(0.002)***		(0.008)***	(0.009)***		(0.004)	(0.005)***	
NEW_RELATIONSHIP × SMALL		0.010			0.045			0.046	
		(0.003)***			(0.015)***			(0.008)***	
SWITCH			–0.012			–0.049			–0.031
			(0.002)***			(0.012)***			(0.008)***
MULTIPLE_RELATIONSHIPS			–0.007			–0.030			–0.025
			(0.002)***			(0.009)***			(0.005)***
SWITCH × SMALL			0.006			0.054			0.065
			(0.004)			(0.021)***			(0.012)***
MULTIPLE_RELATIONSHIPS × SMALL			0.011			0.077			0.079
			(0.004)***			(0.019)***			(0.010)***
SMALL		0.002	0.002		–0.002	–0.009		–0.035	–0.038
		(0.002)	(0.002)		(0.012)	(0.011)		(0.006)***	(0.006)***
log(AMT)	0.003	0.003	0.002	0.019	0.019	0.022	0.014	0.015	0.028
	(0.0002)***	(0.0002)***	(0.0006)***	(0.001)***	(0.001)***	(0.004)***	(0.0007)***	(0.0007)***	(0.002)***
$\log(\text{TOTAL\_ASSETS})_{t-1}$	–0.026	–0.025	–0.025	–0.111	–0.112	–0.110	–0.021	–0.027	–0.029
	(0.001)***	(0.001)***	(0.001)***	(0.007)***	(0.007)***	(0.007)***	(0.003)***	(0.004)***	(0.004)***
PROFITS_{t-1}	–0.002	–0.002		–0.239	–0.237		–0.002	–0.002	
	(0.001)*	(0.001)		(0.013)***	(0.013)***		(0.003)	(0.003)	
TANGIBILITY							0.124	0.118	0.112
							(0.022)***	(0.022)***	(0.021)***
MARKET_TO_BOOK	0.009	0.009	0.009	0.059	0.059	0.054	–0.013	–0.013	–0.013
	(0.0006)***	(0.0006)***	(0.0006)***	(0.004)***	(0.004)***	(0.004)***	(0.001)***	(0.001)***	(0.001)***
No. of obs.	46,487	45,868	46,261	47,094	46,467	44,090	46,982	46,356	46,728
R^2	0.589	0.588	0.586	0.398	0.396	0.337	0.586	0.583	0.582
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

capital expenditure, sales growth, and leverage after the firm obtains a large loan deal, and to identify the incremental impact of NEW_RELATIONSHIP on these variables, in our regressions we control for the aggregate loan amount that the firm borrows during the year using log(AMT).

Our results in column (1) of Table 5 indicate that while a firm's capital expenditure does increase in the amount it borrows during the year (positive coefficient on log(AMT)), on average, there is a decline in capital expenditure when a firm forms a new banking relationship. Although the latter result might seem inconsistent with the predictions of the life cycle hypothesis, we emphasize that this test does not distinguish the effect of new relationships by how financially constrained the firm is. A sharper test of the life cycle hypothesis, which predicts that financially constrained firms benefit from new banking relationships, would be to interact NEW_RELATIONSHIP with a measure of financial constraints, such as firm size (see Almeida, Campello, and Weisbach (2004)). Accordingly, in column (2), we repeat our estimation after including SMALL and an interaction term NEW_RELATIONSHIP×SMALL, where SMALL is a dummy variable that identifies Compustat firms with below-median book value of total assets. Consistent with small firms experiencing an increase in capital expenditure when they form new banking relationships, we find that the coefficient on the interaction term is positive and significant. Our results are also economically significant. The coefficient on the interaction term in column (2) indicates that a small firm experiences a 10% increase in capital expenditure in the year when it forms a new banking relationship. In column (3), we differentiate between multiple banking relationships and bank switches and find that small firms experience an increase in capital expenditure when they form multiple banking relationships.

When we examine the effect of new banking relationships on sales growth and leverage, we obtain results similar to those with regard to capital expenditure. While the average firm experiences a decrease in sales growth and no change in leverage in the year when it forms a new banking relationship (columns (4) and (7)), small firms do experience a significant increase in both sales growth and leverage in the year when they form new banking relationships (positive coefficient on NEW_RELATIONSHIP × SMALL in columns (5) and (8)). We also find that small firms experience an increase in sales growth (column (6)) and leverage (column (9)) both when they form multiple banking relationships and when they switch banks.

In unreported tests, we estimate the switching regression model that we outlined in Section I as well as the propensity score matching model to examine the effect of new banking relationships on CAPEX, SALES_GROWTH, and LEVERAGE, after controlling for the endogeneity of new banking relationships. We obtain results qualitatively similar to those in Table 5. While the increase in capital expenditure and leverage is significant for small firms, the increase in sales growth rate is not statistically significant at conventional levels. To conserve space, we do not report these results in the paper. They are available from the authors.

Firms may also form new relationships in order to improve their access to capital market services such as analyst coverage and underwriter services, which can further ease their financial constraints by making it easier to tap public capital markets. To test whether there is any evidence of improved access to capital market services when firms form new banking relationships, we estimate regression (2) with ANALYSTS and ISSUE as the dependent variables, where ISSUE is a dummy variable that identifies if the firm issued any public bonds during the year. To construct ISSUE, we obtain data on firms' bond issuances from the SDC Database, and we match this information with our panel using firm names.

The results of our estimation are presented in Table 6. The panel and empirical specification are similar to those in Table 5, except for 2 differences. First, we use a lagged measure of NEW_RELATIONSHIP as the independent variable because it might take a while for the firm to start obtaining capital market services from its new bank. Second, we include industry fixed effects (at the 4-digit SIC level) instead of firm fixed effects, and we cluster standard errors at the industry level.

TABLE 6

Impact of New Banking Relationships on Analyst Coverage and Debt Issuance

Table 6 reports the results of a regression relating the extent of analyst coverage and a firm's public debt issuance decision to new banking relationships. Specifically, we estimate the panel OLS regressions

$$y_{it} = \beta_0 + \beta_1 \text{NEW\_RELATIONSHIP}_t + \beta_2 X_i + \mu_t,$$

where y is ANALYSTS in columns (1)–(2) and ISSUE in columns (3)–(5). The panel spans the period 1990–2005, has 1 observation for each firm-year combination, and includes all firms in our sample with financial data in Compustat. All variables are described in the Appendix. We control the regression for industry fixed effects (FE) (at the 4-digit SIC level) and year FE. In all the specifications, the standard errors are robust to heteroskedasticity and clustered at the industry level. Analyst coverage data are from IBES and bond issue data are from SDC. Here, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ANALYSTS		ISSUE		
Variable	(1)	(2)	(3)	(4)	(5)
NEW_RELATIONSHIP	–0.171	–0.310	–0.003	–0.007	
	(0.182)	(0.216)	(0.007)	(0.009)	
SMALL		0.660		0.023	0.023
		(0.231)***		(0.006)***	(0.006)***
NEW_RELATIONSHIP × SMALL		0.420		0.013	
		(0.219)*		(0.008)	
MULTIPLE_RELATIONSHIPS					–0.0007
					(0.010)
SWITCH					–0.020
					(0.013)
MULTIPLE_RELATIONSHIPS × SMALL					0.005
					(0.010)
SWITCH × SMALL					0.026
					(0.013)**
BORROW	0.281	0.275	–0.003	–0.003	–0.003
	(0.151)*	(0.151)*	(0.006)	(0.006)	(0.006)
MARKET_TO_BOOK	0.861	0.947	–0.0001	0.003	0.003
	(0.083)***	(0.094)***	(0.002)	(0.002)	(0.002)
log(TOTAL_ASSETS)	3.389	3.523	0.052	0.056	0.056
	(0.110)***	(0.138)***	(0.003)***	(0.004)***	(0.004)***
PROFITS_{t-1}	6.331	6.689	0.043	0.055	0.055
	(0.820)***	(0.842)***	(0.016)***	(0.016)***	(0.016)***
No. of obs.	23,247	23,247	23,247	23,247	23,247
R^2	0.494	0.494	0.164	0.166	0.166
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

In columns (1) and (2) of Table 6, the dependent variable is ANALYSTS. Similar to our findings with regard to LEVERAGE in Table 5, we find that while the average firm does not experience an increase in analyst coverage after forming a new banking relationship, small firms do experience a significant increase in analyst coverage in the year after they form a new banking relationship (positive coefficient on NEW_RELATIONSHIP$_{t-1}$ $\times$ SMALL$_{t-1}$ in column (2)).

In columns (3)–(5) of Table 6, we examine if firms are more likely to issue public debt after they form new banking relationships. Our results in column (3) indicate that the average firm is not more likely to issue public bonds in the year after it forms a new banking relationship. When we distinguish between small and large firms forming new banking relationships in column (4), we find that while the coefficient on NEW_RELATIONSHIP $\times$ SMALL is positive, indicating that small firms are more likely to issue public debt in the year after they form a new banking relationship, the coefficient is not statistically significant at the conventional levels of significance. To explore this further, in column (5) we distinguish between new relationships that involve multiple banking relationships and those that involve switches. Our results indicate that small firms are more likely to issue public bonds following new banking relationships only if these involve switching to a new bank, and not otherwise (positive and significant coefficient on SWITCH $\times$ SMALL, and insignificant coefficients on other interaction terms).

In unreported tests, we use the switching regression model and the propensity score matching model to control for the endogeneity of new relationships and obtain results similar to the results reported here.

The results in Table 6 are broadly consistent with the idea that firms form new banking relationships in order to obtain access to capital market services. It is reasonable that these benefits are limited to small Compustat firms, because large Compustat firms may already have access to these capital market services at their relationship banks. Interestingly, when we examine the underwriters of bond issues, we find that in 33% of the instances when a small Compustat firm issues bonds in the year after it forms a new banking relationship, it uses the new bank as the lead underwriter. Thus, consistent with earlier literature (Puri (1996), Schenone (2004)), our results also offer a rationale for the universal banking model by highlighting how banks can attract clients by offering a broader scope of services.[19]

IV. Concluding Remarks

In this paper, we examine a large database of loan deals contracted over the period 1990–2006 to understand why firms form new banking relationships for their repeat credit needs. Consistent with theories that argue that strong banking relationships are more useful for informationally opaque firms, we find that firms without financial data in Compustat (the non-Compustat firms), which may be thought of as highly opaque, are significantly less likely to form new banking relationships than Compustat firms. However, among the subsample of Compustat

[19]In other unreported tests, we test if firms are more likely to form a new banking relationship with their bond underwriters or M&A advisors and do not find any supportive evidence.

firms, the more opaque firms (small firms, firms without a credit rating, and firms tracked by fewer analysts) are more likely to form new banking relationships. Examining bank characteristics, we find that firms that have existing relationships with large banks and banks that are active in underwriting and M&A advisory services are less likely to form new banking relationships.

Consistent with firms forming new banking relationships to overcome borrowing constraints, we find that firms that form new banking relationships obtain large loan amounts, on average. This result is robust to controlling for the endogeneity of the new banking relationship and holds both when firms form multiple banking relationships and when they switch to new banks. Examining the subsample of Compustat firms for which we have detailed financial information, we find that smaller Compustat firms, which are more likely to face borrowing constraints at their relationship banks, experience an increase in capital expenditures, sales growth, and leverage in the year when they form a new banking relationship. Moreover, small Compustat firms that switch to a new bank also experience an increase in analyst coverage and public debt issuance in the subsequent year. Overall, these results are strongly consistent with the life cycle hypothesis that firms form new banking relationships in order to improve their access to credit and capital market services.

To summarize, our analysis shows that while strong banking relationships can benefit a firm by lowering adverse selection costs of private debt, there are attendant costs too, especially if the relationship bank is small and unable to meet the firm's growing needs for credit and capital market services. The cost of banking relationships that we uncover is an important consideration for small but relatively transparent public firms, and it affects their propensity to form new banking relationships. Our results on how firms switch banks to combine banking and capital market services from the same institution highlight an important benefit of the universal banking model. Overall, our analysis highlights how the impact of banking relationships on firm financial constraints varies across a firm's life cycle.

Appendix. Definitions of Variables

AMT: The size of the deal in $ million.

ANALYSTS: The number of security analysts following the firm's stock.

BORROW: A dummy variable that takes a value 1 in the years in which the firm borrows through a bank loan.

CAPEX: The ratio of the total investment in PPE to lagged book value of total assets.

DEAL_MATURITY: The weighted-average maturity (in months) of all the loans within the deal.

LARGE_BANK: A dummy variable that identifies lead arrangers that are in the top 5th percentile in terms of number of deals originated the previous year.

LEVERAGE: The ratio of the book value of total debt to the book value of total assets.

LONG_TERM: A dummy variable that identifies deals with DEAL_MATURITY greater than 5 years.

LONG_TIME_BTW_DEALS: A dummy variable that identifies if the time between the borrower's current deal and its most recent past deal is above the sample median across all firms.

MARKET_CAPITALIZATION: The market capitalization of the firm (in $ million).

MARKET_TO_BOOK: The ratio of the sum of the market value of equity and book value of debt to the book value of total assets of the firm.

MULTIPLE_RELATIONSHIPS: A dummy variable that takes a value 1 if the firm forms a new banking relationship when a past loan from its relationship bank is still outstanding (based on stated maturity of past loan), or if it borrows from a syndicate with multiple lead arrangers.

NEW_RELATIONSHIP: A dummy variable that takes a value 1 when the firm borrows from a nonrelationship bank, and 0 otherwise.

NO_OF_LENDERS: The number of lenders in the syndicate.

NON_COMPUSTAT: A dummy variable that identifies borrowing firms for which financial data are not available in Compustat.

PREV_LARGE_BANK: A dummy variable that identifies if any of the borrower's relationship banks is a LARGE_BANK.

PREV_SECTION_20_BANK: A dummy variable that identifies if any of the borrower's relationship banks is a SECTION_20 bank.

SECTION_20: A dummy variable that identifies banks that have a Section 20 subsidiary involved in securities business. We obtain data on bank's Section 20 subsidiaries from Gande et al. (1999).

PROFITS: The ratio of the firm's earnings before interest, tax, depreciation, and amortization to the book value of total assets.

RATED: A dummy variable that identifies firms that have a long-term credit rating.

REPAYMENT: A dummy variable that identifies deals whose stated purpose is to repay debt.

REVOLVER: A dummy variable that identifies deals with revolving lines of credit.

SALES_GROWTH: The growth rate in total firm sales.

SECURED: A dummy variable that identifies if any of the loans within the deal is secured.

SHORT_TERM: A dummy variable that identifies deals with DEAL_MATURITY less than 1 year.

SMALL: A dummy variable that identifies Compustat firms with below-median value of lagged market capitalization.

SWITCH: A dummy variable that takes a value 1 if the firm borrows from a nonrelationship bank when loan deals with its relationship bank are not outstanding (based on stated maturity of past deals), and 0 otherwise.

SYNDICATE: A dummy variable that identifies syndicated deals.

TAKEOVER: A dummy variable that identifies deals whose stated purpose is to finance a takeover.

TANGIBILITY: The ratio of the book value of fixed assets to the book value of total assets.

TERM_LOAN: A dummy variable that identifies deals with a term loan.

TIME_BTW_DEALS: The time in years between the borrower's current deal and its most recent past deal.

WORKING_CAPITAL: A dummy variable that identifies deals whose stated purpose is to finance working capital.

YIELD: The weighted-average basis-point spread over LIBOR for all the loans within the deal.

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