The "Dominant Bank Effect:" How High Lender Reputation Affects the Information Content and Terms of Bank Loans

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Three large banks control over half of the U.S. commercial loan market by volume through the syndication process. Using attributes of a borrower's location to instrument for lender–borrower matching, I show that the borrower stock price response to a loan announcement is more favorable if one of these dominant banks is the lender, especially if the borrower is "opaque." I then show that these banks charge lower interest rates and are more likely to lend without the protection of a borrowing base. The results suggest that the dominant banks have a particularly high reputation for screening and monitoring borrowers. (*JEL* G21, L14)

In financial economics, it has long been recognized that commercial banks play a special certification role through inside lending (Fama 1985) and delegated monitoring (Diamond 1984). It therefore follows that bank loan announcements should convey a positive signal or certification to the market that the borrower is "good."[1] In that regard, Mikkelson and Partch (1986) and James (1987) document that bank loan announcements elicit positive abnormal returns in borrower stocks, whereas announcements of public securities issues give rise to neutral or negative abnormal returns.[2]

However, existing work on the role of banks as inside lenders has generally not accounted for the fact that the U.S. commercial loan market has come to be dominated by three large banks, J.P. Morgan Chase, Bank of America, and

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[1] See Boot (2000) and Saunders and Cornett (2004) for comprehensive reviews of the special role of banks and relationship banking.

[2] More recent papers on loan announcements study moderating effects such as whether the announcement concerns a new loan or revision (Lummer and McConnell 1989), the size of the borrower (Slovin, Johnson, and Glascock 1992), stock analyst forecast errors (Best and Zhang 1993), the lender's credit rating (Billett, Flannery, and Garfinkel 1995), and the year the loan was made (Fields et al. 2006). See James and Smith (2000) for a review of recent empirical evidence that banks play a special role in financial intermediation.

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Citigroup. Through loan syndication, whereby one bank (the "lead arranger") negotiates the loan with the borrower and then assembles a group of other lenders to account for most of the loan's principal, these "dominant banks" collectively account for over half of U.S. lending volume on a lead-arranged basis and have substantially larger individual market shares than their nearest competitors. Even in 2008, with loan volumes down by over half year-on-year and many large financial institutions facing financial distress due to the subprime crisis, the dominant banks account for over 55% of the market. (See table 1.)

As an excessively risky or cut-price loan would not meet with a successful syndication, it seems unlikely that the dominant banks have obtained their market shares by offering loans on more favorable terms or to less creditworthy borrowers than sound business practice would dictate. Moreover, since the dominant banks frequently distribute a majority of the principal of the loans they syndicate, any advantage these banks may have in raising money from depositors or public investors is unlikely to help them undercut competitors. What, then, accounts for the banks' dominant position, and how are the certification value and terms of lending affected if one of these banks is the lender?

One possibility is that the dominant banks benefit from a structural barrier to entry that allows them to exploit borrowers and, perhaps, other lenders. If so, it would be better, where possible, for borrowers to seek alternative sources of funding. Alternatively, the dominant banks may have a particularly high reputation for screening and monitoring borrowers. Loans from the dominant banks would then provide a more credible signal of borrower quality than loans from less reputable lenders.

To test these competing hypotheses, I perform an event study using data on 1,064 loan announcements from 2000 to 2003. The results show that the borrower stock price response to a loan announcement is more favorable when the loan is from one of the dominant banks and that this "dominant bank effect" is markedly larger when the borrower is "opaque," suggesting that the dominant banks provide a higher level of certification than other lenders.

I then conduct a follow-on analysis of loan terms and conditions, finding that, vis-à-vis other lenders, the dominant banks charge lower interest rates and are less likely to be protected by a borrowing base, which limits the outstanding principal on a loan over the course of its term to a fraction of the borrower's readily saleable assets.[3] Taken together, these results provide additional evidence that the dominant banks have a particularly good reputation for evaluating a borrower's underlying business and true risk for default, both initially (screening) and while the loan is outstanding (monitoring), and thus

[3] To my knowledge, this is the first large-sample empirical study of the borrowing base. Other papers that consider how lender identify influences loan terms include Carey, Post, and Sharpe (1998), who find that finance companies are more likely to lend to observably riskier borrowers, as well as Coleman, Esho, and Sharpe (2002) and Hao (2004), who link various lender characteristics like size and expense ratios to loan interest rates and other terms.

can offer borrowers more attractive terms while still inducing syndicate banks to participate in the transaction. The interest rate discount from the dominant banks is also materially larger when the loan is used as a source of capital and not to back up a commercial paper program. As borrower screening may be less relevant on commercial paper backup facilities, one can interpret the discount on such loans as the part of the dominant banks' pricing advantage that is attributable purely to distribution capability.

Billett, Flannery, and Garfinkel (1995) were the first to study lender reputation in the context of loan announcements, finding that lenders with better credit ratings generate a more positive borrower stock price response. This article builds on their results in a number of ways. First, a lender's credit rating is arguably most closely linked with a lender's "safety and soundness," an increase in which should not harm other market participants; by contrast, the market share proxy used herein is a measure of market dominance, the public policy implications of which may not be benign. In fact, controlling for lender credit ratings has no material impact on this article's estimates of the dominant banks' ability to provide an enhanced level of borrower certification. Second, this article also studies how lender reputation affects loan terms and conditions, whereas Billett, Flannery, and Garfinkel (1995) confine their analysis to loan announcements.

Another significant difference is methodological. Billett, Flannery, and Garfinkel (1995) rely on ordinary least squares (OLS) and similar techniques. As discussed at length below, there are strong theoretical and practical reasons to believe that the matching process between borrowers and lenders is influenced by their relative reputations, that is, that the lender's reputation is endogenous. If so, estimates of the importance of intermediary reputation from OLS may be significantly biased and lead to erroneous conclusions.

To remedy this, the analysis herein uses instruments based on the location of the borrower and embeds these instruments in a maximum likelihood specification that simultaneously determines the probability that one of the dominant banks is the lender on a given loan and measures the impact of lender reputation. The results not only suggest that endogeneity is a material concern in the context of lender reputation but also validate the instruments for use in other studies of lender identity.

The remainder of the article is organized as follows. Section 1 discusses why lender reputation as represented by market share might matter. Section 2 presents the event study. Section 3 provides an analysis of loan terms and conditions. Section 4 concludes.

1. Background

Contrary to the traditional conception of corporate lending as a bilateral relationship between a borrower and a lender, the U.S. commercial loan market makes much use of syndication, whereby a bank acting as "lead arranger" is responsible for due diligence, allocation of loan principal to other lenders (which may be numerous and provide most of the capital[4]), monitoring after the loan is made, and renegotiation of terms over the life of the loan. In effect, the banks in the syndicate rely on the reputation of the lead arranger in making lending decisions.[5]

By 2000, the syndication process had allowed three large commercial banks to capture a commanding position in the U.S. commercial loan market. As shown in table 1, the top three banks' collective share of market volume on a lead-arranged basis ranges from 57.0% to 66.2% over the sample period of 2000–2003, with J.P. Morgan Chase,[6] Bank of America, and Citigroup ranked 1, 2, and 3, respectively, throughout. The lowest individual market share of the top three banks in any year is 10.4%, and only once does a bank from outside the top three achieve a market share over 6%.

Since the dominant banks syndicate most of their loans, the dominant banks could not plausibly offer terms unattractive to other lenders or pass on any advantage in raising money at favorable rates. What, then, accounts for the dominant banks' commanding market share?

One possibility is that the dominant banks have achieved oligopolistic market power through some structural barrier that prevents other institutions from competing effectively for many loans. The dominant banks should then be able to extract rents from borrowers, perhaps in the form of higher interest rates. If so, loans from the dominant banks would generate a lower borrower stock price response and be made at less favorable terms than loans from other lenders.

And yet, given the absence of an obvious structural barrier to entry in the corporate loan market, it is perhaps more likely that these banks have achieved a high market share due to a unique reputation for reducing information asymmetry between corporations that raise capital and the investors who ultimately provide it.

Since the lead arranger retains less than the entire principal on a syndicated loan (by definition), the marginal benefit to the lead arranger of screening and monitoring the borrower is less than the total benefit to the lenders in aggregate. Sufi (2007) provides evidence that the resulting moral hazard problem has a material impact on the syndication market. Yet, an intermediary's reputation may act as a bonding device (Booth and Smith 1986), prompting the intermediary to incur the cost to screen corporations raising capital (Chemmanur and Fulghieri 1994a) and to monitor loans (Chemmanur and Fulghieri 1994b) in order to maintain the intermediary's reputation. The large market share of the

[4] Specifically, Sufi (2007) finds that on approximately 10% of syndicated loans, the lead arranger retains less than 8% of the principal, and on half of syndicated loans, the lead arranger retains less than 23.5%.

[5] Sufi (2007) and Carey and Nini (2007) provide further discussion of the syndicated lending market and its history.

[6] Prior to the J.P. Morgan/Chase Manhattan merger at the end of 2000, J.P. Morgan Chase herein refers to Chase Manhattan.

Table 1
Top ten lead arrangers of U.S. loans by year

2000		2001	
J.P. Morgan Chase	32.4%	**J.P. Morgan Chase**	33.6%
Bank of America	20.5%	*Bank of America*	16.8%
Citigroup	10.4%	*Citigroup*	15.8%
Bank One	4.7%	Bank One	4.5%
Credit Suisse First Boston	4.4%	FleetBoston	2.8%
FleetBoston	3.0%	Wachovia	2.5%
Deutsche Bank	2.7%	Credit Suisse First Boston	2.2%
First Union	2.2%	Deutsche Bank	2.0%
Bank of New York	1.3%	Bank of New York	1.2%
Wells Fargo	1.0%	Goldman Sachs	1.1%
2002		**2003**	
J.P. Morgan Chase	31.3%	**J.P. Morgan Chase**	24.8%
Bank of America	17.9%	*Bank of America*	18.1%
Citigroup	14.2%	*Citigroup*	14.1%
Bank One	5.6%	Bank One	6.2%
Deutsche Bank	3.2%	FleetBoston	3.7%
FleetBoston	2.7%	Wachovia	3.5%
Wachovia	2.6%	Deutsche Bank	3.5%
Credit Suisse First Boston	2.0%	Credit Suisse First Boston	3.0%
Lehman Brothers	1.6%	Wells Fargo	1.8%
Wells Fargo	1.4%	Barclays	1.7%
2008			
J.P. Morgan Chase	24.5%		
Bank of America	18.1%		
Citigroup	13.1%		
Wells Fargo	7.4%		
Deutsche Bank	5.1%		
Royal Bank of Scotland	2.9%		
BNP Paribas	2.3%		
Goldman Sachs	1.9%		
PNC Bank	1.7%		
General Electric	1.6%		

Market share of total lending volume is attributed on a lead-arranged and historical basis, reflecting ownership at the time. Bank mergers are pro forma for the end of the year in which they occur. In 2008, Wells Fargo's market share was only 2.9% if Wachovia (acquired on December 31, 2008) is not included, and Bank of America's market share was 19.0% if Merrill Lynch (acquired on January 1, 2009) is included.

dominant banks may thus give them a greater incentive to screen and monitor than other lenders have, making reputation and market share self-reinforcing.

Likewise, by seeing and participating in more deals, the dominant banks may have a better feel for pricing conditions and better information on the business prospects of potential borrowers than competing banks. Such economies of scale may form the basis for a self-perpetuating competitive advantage.

The dominant banks may also have a particular competence at screening and monitoring. It has been argued in the strategic management literature that many such competencies are difficult for competitors to acquire, even in the presence of employee mobility, because the proper implementation of the relevant practices is embedded in a firm's culture (Barney 1986) or routines (Nelson and Winter 1982), which are a product of unique historical experience.

These arguments suggest that the dominant banks would do a better job screening and monitoring than other lenders. Loans from the dominant banks would then provide a particularly high level of certification and generate a particularly positive borrower stock price response, what I call the "dominant bank effect."[7] Moreover, in line with Chemmanur and Fulghieri's (1994a) results in an underwriting context, the higher level of certification provided by the dominant banks—and any competitive advantage in cost efficiency and distribution they enjoy—should allow them to offer loans at more favorable terms to borrowers than can other lenders.[8]

Lastly, Chemmanur and Fulghieri (1994a) show that a firm will raise capital from the most reputable intermediary that agrees to provide certification, so that the most reputable intermediaries tend to do business with the most reputable corporate clients à la the matching literature in economics (e.g., Roth and Sotomayor 1990). I make use of this reasoning in my empirical identification strategy.

2. Event Study

2.1 Loan announcements data

To construct the sample of loan announcements, I searched Factiva[9] for news stories with the key words "credit," "loan," "borrow," or relevant cognates. The search is restricted to 2000–2003 to avoid confounding effects from changes in the laws separating commercial and investment banking with the passage of the Gramm–Leach–Bliley Act of 1999. Several criteria are then used to produce a clean sample. The time stamp on the earliest news story concerning the loan is used to date the announcements, with announcements after 4:00 p.m. moved to the subsequent trading day. I include only straight loan contracts, so, for example, any loan contract where the lender receives warrants or conversion rights is excluded. To create the most comparable sample, I also exclude announcements concerning loans guaranteed by third parties, loans from affiliated companies, or where an existing facility is merely extended for a few days or weeks to permit the closing of a new financing. Non-U.S. borrowers are also

7 Similar results have been obtained in the literature on underwriting. Megginson and Weiss (1991) find that underwriter market share is associated with a smaller initial return on initial public offerings (IPOs), and Carter, Dark, and Singh (1998) find that underwriter market share is negatively associated with short-term price performance. Safieddine and Wilhelm (1996) obtain similar results for seasoned equity offerings. Fang (2005) finds that bond underwriters with a high market share obtain lower yields for their clients.

8 Chemmanur and Fulghieri (1994a) also argue that more reputable intermediaries should receive higher fees than other intermediaries, although the empirical evidence for this is mixed. (See Fang 2005 and the references therein.) Regrettably, the information on upfront fees in the loan-pricing data used herein is too sparse and imprecise to test this hypothesis.

9 Factiva includes major news services such as Dow Jones News Service, PR Newswire, AP Newswire, and many others, including Loan Market Week and Bank Loan Report, which are of particular relevance.

excluded. To "clean the event window," I checked a $[-2, 0]$ trading day window around the announcement date for confounding news such as dividend declarations, acquisitions or divestitures, litigation, earnings announcements, or other forms of capital raising. Where such stories are found, the announcements are dropped. Lastly, I require that the borrower's stock actually trade on the announcement date.

To check and enrich the data, the entire sample is then hand matched against DealScan, a database of commercial loans provided by Reuters' Loan Pricing Corporation, using such information as the name of the borrower or parent, announcement or amendment date, principal amount, and names of lenders. Between DealScan and the news stories, I tabulate a number of data, subject to availability; these include principal amount, term, the names of the lenders, whether there is collateral, the type of loan contract, whether the loan is a revision to an existing facility, and if so, the nature of the revision, etc. Where a discrepancy exists between DealScan and the news stories, the DealScan information is used; however, the controlling date of the announcement is determined by the earliest news story.

Following the practice in the literature, I classify loans according to their renewal status. Loans are designated as new where the news story indicates the lender does not have a previous relationship with the borrower. Amended or revised loans are where the announcement indicates a renewal of or change to an existing facility. Following Best and Zhang (1993), revised loans are further classified according to whether they are, from the borrower's perspective, (i) favorable or (ii) mixed according to changes in maturity, principal, interest rates, and covenants. (Entirely unfavorable revisions are included with the mixed, as there are only four of the former in the sample.)

Financial information on borrowers is from Compustat. Borrower credit ratings are from Compustat and DealScan. Securities prices are from the Center for Research in Security Prices (CRSP), so only borrowers trading on the NYSE, AMEX, or NASDAQ exchanges are included. To perform the event study, I also need the borrower to have a sufficient stock price history (see below). All told, the sample has 1,064 useable loan announcements, although data availability reduces this figure for the multivariate regressions, which are the focus of the analysis.

For loans with multiple lenders, which constitute the bulk of the sample, the lender of interest is considered to be the "lead arranger," since that institution is responsible for due diligence, negotiation of terms, and monitoring. Some loans have multiple lead arrangers, in which case all are considered the lenders of interest.

2.2 Empirical specifications

I use the EVENTUS (Cowan 2003a) interface at Wharton Research Data Services to implement the same basic event study methodology used in the literature on loan announcements. Like Billett, Flannery, and Garfinkel (1995), I use a one-day window, because the time stamps on the news stories allow me to identify which announcements occurred during the trading day and which did not. As expected, the statistical significance of day 0 returns is higher than that for other days in the event period.[10] For each loan announcement, a market model regression is computed over the period $[-200, -51]$, where the dependent variable is the daily return of the borrower's stock, and the independent variables are a constant and the return on CRSP's equally weighted index.[11] The coefficients from this regression are then used to calculate predicted changes in the borrower's stock price on the event day. The residual from this predicted value is the abnormal return (or prediction error), which is denoted A_j for borrower j.

2.2.1 Univariate analysis. To demonstrate that the data in this study are consistent with those of prior work, I perform two univariate analyses, although these methods do not account for the endogeneity of lender–borrower matching or the many factors that may influence the borrower stock price response to a loan announcement. The first procedure is a binomial sign test on the A_j's, which assumes that positive and negative values are equally likely. The second procedure involves standardizing and then aggregating the A_j's such that the mean of N thereof is distributed $N\left(0, N^{-1}\right)$. For details, see Cowan (2003b).

2.2.2 Multivariate analysis. While OLS could account for other influences on borrower abnormal returns, OLS does not account for the endogeneity of lender–borrower matching. The problem becomes salient if, as is surely the case, there are *unobserved* characteristics of the borrower and lender that influence the magnitude of the borrower stock price response as well as the propensity of certain borrowers to borrow from certain lenders. Then, if certain unobserved borrower characteristics both make it more likely that the borrower receives a loan from a high-reputation bank and make the borrower more (less) susceptible to the loan certification effect, the effect of the lender's reputation on the borrower stock price response will be overestimated (underestimated) by OLS.

Since the focus of the study is on the effect of having a dominant top three bank as the lender, I operationalize high lender reputation using a dummy variable (see Section 2.3.1). In the finance literature, authors have resolved the problem of endogenous dummy variables using two-step "treatment effects" procedures (e.g., Campa and Kedia 2002; Fang 2005), which are based on

[10] The results are qualitatively unchanged using $[-2, 0]$ and $[-1, 0]$ windows.

[11] This index measures the return from investing a fixed amount in every security on the NYSE, AMEX, and NASDAQ exchanges.

Heckman's (1979) work on sample selection. Such procedures use a first-stage equation to determine the probability that the endogenous dummy variable equals 1 and then adjust the sample moments of the second-stage multivariate regression to produce unbiased estimates.

However, a difficulty arises here in that the abnormal returns are systematically heteroskedastic. More volatile stocks respond with greater volatility to a loan announcement.[12] To produce "best linear unbiased estimates," we must apply a weight to each observation proportional to $s^2_{A_j}$, the estimated variance of A_j (Cowan 2003b). This cannot be done in a two-step procedure. Therefore, I use a maximum likelihood procedure proposed by Maddala (1983), which estimates the lender–borrower matching probit equation and the second-stage regression on the borrower stock price response simultaneously. This specification is essentially the treatment effects model of Campa and Kedia (2002) but with simultaneous estimation of the two equations.

When using the two-step treatment effects procedure, it is common to test the impact of endogeneity by examining the coefficient on the parameter λ, the extra term added to the second-stage multivariate regression to adjust its sample moments. Although we can recover an estimate of this coefficient, it is more convenient here to examine the sign and significance of ρ, the correlation between the error terms in the lender–borrower matching equation and the second-stage regression of interest.

2.3 Variables

2.3.1 Lender reputation and quality. I follow Fang (2005) and use a dummy variable to test the proposition that loans from the three dominant banks provide a particularly valuable signal of borrower quality. Specifically, I set BIG3 equal to 1 for the 329 loans in the sample that have J.P. Morgan Chase, Bank of America, or Citigroup as lead arranger.[13] The binary classification of lender reputation reflects the qualitative distinction between the dominant banks and the rest that is apparent from table 1. Moreover, if we view lead arrangers and syndicate banks as playing a dynamic game, the lead arranger will "cheat" by not properly screening the borrower whenever the benefits to so doing outweigh the damage to the lead arranger's reputation and consequent loss of future syndication opportunities. This implies that for low (high) levels of reputation, the lead arranger will always (never) cheat, suggesting that reputation has a *threshold* rather than continuous effect.

[12] This is evident from the maximum likelihood estimate of the variance of each abnormal return: $s^2_{A_j} = \bar{s}^2_{A_j}\left[1 + \frac{1}{150} + \frac{(R_m - \bar{R}_m)^2}{\sum_{k=1}^{150}(R_{mk} - \bar{R}_m)^2}\right]$, where $\bar{s}^2_{A_j} = \frac{\sum_{k=1}^{150} A^2_{jk}}{148}$, A^2_{jk} denotes the square of the residual from the market model regression on day $k \in [-200, -51]$, R_m is the market return on the event day, R_{mk} is the market return on day k, and $\bar{R}_m$ is the mean market return over the estimation period.

[13] Chase Manhattan acquired J.P. Morgan on December 31, 2000. Chase Manhattan was the number 1 lead arranger of U.S. loans in 2000, even with J.P. Morgan loans excluded, and I exclude J.P. Morgan loans for the purpose of defining BIG3.

2.3.2 Other variables. In line with prior work, I control for technical influences on abnormal returns with STANDVN, the market model root mean square error; RUNUP, the cumulative abnormal return over $[-10, -1]$; and BETA, the estimated coefficient on the CRSP equally weighted index in the market model regression. Borrower characteristics are LNMVEQ, a log transformation of market equity;[14] OIBD, the ratio of EBITDA to book assets; LNTOBQ, a log transformation of the ratio of market assets to book assets; LNLOANSCALE, a log transformation of the ratio of the size of the loan to market assets; LEVERAGE, market leverage; and HASRATING, which equals 1 if the borrower either has a rating reported in Compustat in respect of the fiscal year-end prior to the year when the loan was made or has a rating reported in DealScan concurrent with the loan. I control for renewal status with NONFAVREV, a dummy variable taking the value 1 whenever the loan announcement concerns an existing loan that is being revised in an unfavorable or partially unfavorable way from the borrower's perspective. Other authors have found that unfavorable and mixed revisions are associated with larger abnormal returns, perhaps because borrowers likely to receive an unfavorable revision are facing financial difficulty and are thus particularly susceptible to the loan certification effect.

2.3.3 Matching equation. My estimation procedure requires that I identify variables that predict the likelihood that BIG3 equals 1 in a probit regression. At least some of these should be valid instruments in the sense that they are not only meaningful predictors of this likelihood but also independent of the borrower stock price response and thus properly excludable from the second-stage regression.

I argue that geography can serve as the basis for constructing such instruments. It is highly unlikely that either a lender or a borrower would change the location of its headquarters solely for the purpose of consummating a loan. Moreover, it is not obvious why two otherwise observationally equivalent borrowers should differ in their susceptibility to the loan certification effect, merely because the borrowers' headquarters are located in different regions of the United States. By contrast, location likely plays a large role in determining the propensity of lenders and borrowers to do business with each other.[15]

Figure 1 shows a scatter diagram of the locations of borrowers from the sample of loan announcements. Most borrowers are located in major urban

14 Slovin, Johnson, and Glascock (1992) find that borrower size is negatively associated with abnormal returns, perhaps because larger borrowers are already well known to the financial markets.

15 Note that I am not arguing that the distance between the borrower and the lender does not affect loan terms, although the evidence that it may is related to small business loans (Degryse and Ongena 2005), and distance may have become less important over time (Petersen and Rajan 2002). Rather, I am arguing that the borrower's location, in and of itself and controlling for other factors, is not a determinant of credit quality or susceptibility to the loan certification effect.

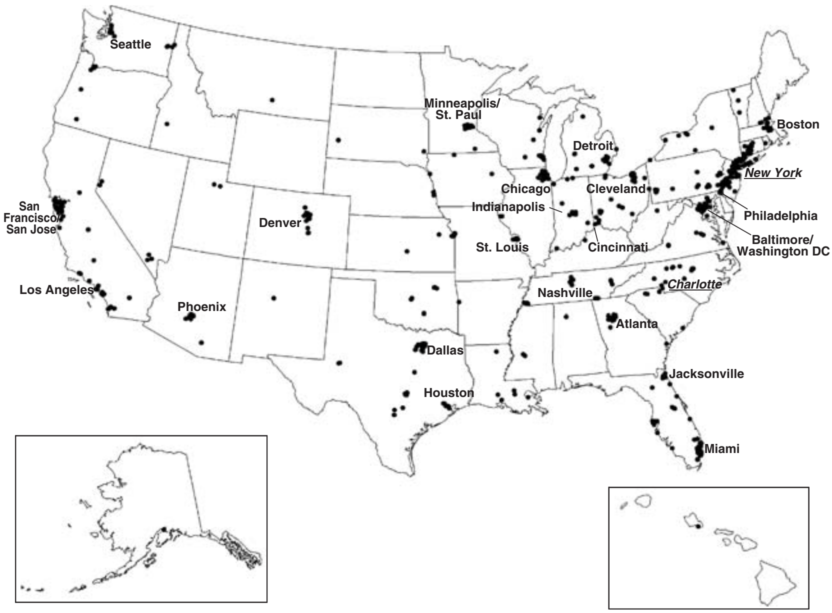

Figure 1
Distribution of borrowers–loan announcements data
Scatter diagram showing the 644 unique zip codes of borrowers from the sample of loan announcements. The concentration of borrowers in large urban areas is higher than it may appear in the diagram, because overlapping dots from neighboring zip codes and the 383 duplicate zip codes are primarily from those areas. The headquarters cities of J.P. Morgan Chase, Bank of America, and Citigroup are in italics and underlined. Other urban areas with a relatively high number of borrowers are also labeled. Alaska and Hawaii are not drawn to scale.

centers like the Northeast Corridor (from Washington, DC, to Boston), the San Francisco Bay area, and "Chicagoland." In fact, the degree of concentration is higher than is apparent from fig. 1, since many of the dots near the urban centers overlap. (For example, it is not necessarily obvious from fig. 1 that 12% of the loans are to borrowers in Texas, mostly near Dallas and Houston; only California has more.) By contrast, sparsely populated states without major cities never account for more than three observations and some account for none (e.g., Wyoming).

Such urban centers are also where major national and regional banks are headquartered and where most of their relationship bankers work. For the dominant banks, the relevant urban centers are New York City, where J.P. Morgan Chase and Citigroup are headquartered and Bank of America has a large office, and Charlotte, NC, where Bank of America is headquartered.[16] (The names of these two cities are italicized and underlined in fig. 1.) It seems intuitive that a borrower is more likely to borrow from the dominant banks if its own

16 The dominant banks have satellite offices in many regions of the country, but these offices are the primary place of work for only a minority of the corporate bankers who maintain relationships with the large, public borrowers that are the focus of this study.

headquarters is within easy driving distance of either location, because transactions costs are minimized for both parties, especially the travel time of executives. I therefore define the variable NEARBIG3, which equals 1 if the borrower's headquarters is within 60 km of any of the dominant banks' headquarters.[17]

In contrast, one would expect that away from the dominant banks' headquarters, the greater the level of local intermediation activity, the less likely would be a borrower to borrow from a dominant bank, given the presence of credible local alternative lenders in nearby metropolitan areas. As state banking markets tend to be distinct, I measure the intensity of financial intermediation activity at the state level. Specifically, I define FININTEN as the ratio of statewide financial sector revenue to estimated population, with both sets of figures coming from the 2002 Economic Census from the U.S. Census Bureau.[18] As an alternative, I also try dummy variables denoting the proximity of a major regional bank, and the results are qualitatively the same.[19]

I also use instruments that reflect, *inter alia*, the theoretical prediction that more reputable and creditworthy borrowers are more likely to borrow from the dominant banks. As these instruments may be correlated with the borrower's susceptibility to the loan certification effect, they are all included in the second-stage regression on the borrower stock price response. The variables, which are defined above, are LNMVEQ, since a large market capitalization may be a proxy for reputation; OIBD, as higher cash flow makes a borrower more creditworthy; LNTOBQ, which may be a proxy for firm quality, suggesting a positive relationship, or a proxy for risk-shifting opportunities, suggesting a negative relationship; and LNLOANSCALE, as larger loans in relation to the borrower's size may require more screening or distribution capability.[20] A summary of the variable definitions can be found in table 2.

2.4 Results

2.4.1 Univariate analysis. Table 3 presents the results of the univariate tests. The results for the whole sample show a positive mean abnormal return of 1.03%, which is significant at the 1% level, indicating that the "specialness" of

[17] Headquarters addresses are from Compustat, and distances are calculated using zip code latitudes and longitudes from the U.S. Census Bureau and the great circle formula.

[18] Note that FININTEN is not a measure of local banking competition. The measure is intentionally constructed so as not to vary systematically with the number of banks in a given area or the nature of their rivalry.

[19] For example, I define a dummy that equals 1 if the borrower is located in a state (other than NY or NC) where at least one bank is lead arranger on 100 or more loans in DealScan in at least one year in the sample period. This instrument, as well as others using a different threshold number of loans, performs very similarly in both the lender–borrower matching equations and second-stage regressions.

[20] Since the dependent variable in the regression is BIG3, which denotes a class of lenders, using lender characteristics as independent variables in the lender–borrower matching equation (e.g., lender size) would result in a "circular" specification. In a sense, the lender–borrowing matching equation is designed to "predict" the lender's characteristics on a given loan.

Table 2
Variable definitions

Name	Definition
BETA	Coefficient on equity index in market model regression
BIG3	Dummy variable indicating that lead arranger is J.P. Morgan Chase, Bank of America, or Citigroup
BIG3-TRANSPARENT	Interaction of BIG3 and HASRATING
BIG3-OPAQUE	Interaction of BIG3 and ∼HASRATING
BIG3-CP	Interaction of BIG3 and dummy indicating loan to be used as commercial paper backup
BIG3-NOTCP	Interaction of BIG3 and dummy indicating loan not to be used as commercial paper backup
COSTOFFUNDS	Interest rate on six-month Eurodollar deposits
CREDITSPREAD	Difference in annual yield between corporate bonds rated Aaa and Baa by Moody's
FININTEN	Ratio of financial sector revenue in the borrower's state to the state's population
HASRATING	Dummy variable indicating that borrower has debt rating
LEVERAGE	Market leverage
LNLOANSCALE	Log transformation of ratio of loan principal to market assets
LNMVEQ	Log transformation of market equity
LNSIZE	Log transformation of loan principal
LNTOBQ	Log transformation of the ratio of market assets to book assets
NEARBIG3	Dummy variable indicating borrower is located within 60 kilometers of the headquarters of J.P. Morgan Chase, Bank of America, or Citigroup
NONFAVREV	Dummy variable indicating that loan announcement concerns unfavorable or mixed revision
OIBD	Ratio of EBITDA to book assets
RUNUP	Cumulative abnormal return over $[-10, -1]$
STANDVN	Market model root mean square error
SYNDUMMY	Dummy variable indicating that loan is syndicated
TANGIBILITY	Ratio of net property, plant, and equipment to assets
TERM	Term of loan in months

These variable definitions are abridged to conserve space. See the text for complete definitions. Also see the text for the definitions of variables with untabulated coefficients.

private lending is preserved in these data.[21] In line with the results of Lummer and McConnell (1989), mixed revisions have the highest mean abnormal return at 4.39%, which is significantly higher than all of the other categories on a pair-wise basis. None of the other pair-wise comparisons are significant.[22]

2.4.2 Matching equation. Table 4 (column 1) shows the underlying lender–borrower matching equation for the loan announcements data.[23] NEARBIG3 and FININTEN are highly statistically significant and have, respectively, the

[21] Fields et al. (2006) do not find that loan announcements over 2000–2003 generate statistically significant positive returns. The difference may be that they use Lexis/Nexis to search for *press releases* and find 224 clean announcements, whereas I use Factiva to search for *all* news stories on loans and find 1,064 clean announcements. This not only results in more statistical power but may also mean that event days herein more closely correspond to the day the stock market first learned of the loans.

[22] Like Lummer and McConnell (1989), I also find that new loans do not produce statistically significant positive abnormal returns, although there are only seventy-four such loans in the sample. Lummer and McConnell (1989) extensively researched annual reports to determine renewal status. James and Smith (2000) point out that news stories often do not allow for a refined classification on this dimension.

[23] Table 4 (column 1) is jointly estimated with table 5 (column 2). The coefficient estimates in the underlying matching equations for table 5 (columns 3 and 4) are not materially different.

Table 3
Univariate analysis

	Number of loans	Mean abnormal return	Mean standardized abnormal return	z-statistic	Percent positive
Panel A: Full sample					
Total	1,064	1.03%	0.19	6.20***	0.56***
Panel B: Renewal status					
New loans	74	0.72%	0.16	1.40	0.53
Favorable revisions	274	0.74%	0.12	2.00**	0.59***
Mixed revisions	44	4.39%	0.77	5.09***	0.70***
Unknown	672	0.97%	0.18	4.76***	0.54**

Sample of 1,064 loan announcements from 2000 to 2003 not contaminated by confounding news stories. New loans are where the lender did not have a loan extended to the borrower at the time the loan was made. Favorable revisions are renewals or amendments where all the terms of the loan are weakly better than those of the loan replaced. Mixed (and unfavorable) revisions are where the terms of the new facility are worse on at least some dimensions. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4
Lender–borrower matching equations

	Loan announcements (1)		Loan terms and conditions (2)	
NEARBIG3	0.6689***	(3.68)	0.2559***	(3.71)
FININTEN	−0.0283***	(−2.79)	−0.0053**	(−2.15)
LNMVEQ	0.5295***	(13.05)	0.3551***	(22.08)
LNTOBQ	−0.4313***	(−2.86)	−0.3787***	(−7.87)
OIBD	1.0149	(1.61)	0.4429*	(1.73)
LNLOANSCALE	0.3160***	(6.21)	0.1848***	(9.40)
CONSTANT	−4.4412***	(−12.17)	−2.6524***	(−18.44)
Observations	1,027		6,975	
Pr(Wald X^2)	0.00		0.00	

Underlying probit matching equations for probability that J.P. Morgan Chase, Bank of America, or Citigroup acts as lead arranger on a given loan from 2000 to 2003. Variables are defined in the text and table 2. Column 1 uses the loan announcements data and is simultaneously estimated with table 5 (column 2). Column 2 uses the DealScan data on a loan facility basis, clusters standard errors by deal where a deal has more than one loan facility, and is simultaneously estimated with table 6 (column 2). t-statistics appear to the right of each coefficient in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

expected positive and negative coefficients, implying that proximity plays an important role in lender–borrower matching. LNMVEQ is positive and highly significant, suggesting that larger, more reputable borrowers tend to use the larger, more reputable banks. LNTOBQ is significant and negative, implying that it is a proxy for risk-shifting opportunities. OIBD is positive but not quite significant. LNLOANSCALE is positive and highly significant, indicating that borrowers tend to use a dominant bank for the more significant loans in their capital structures.

2.4.3 Multivariate analysis. Table 5 presents a multivariate analysis of the effect of lender reputation on the borrower stock price response to a loan announcement. Column 1 is a weighted least squares regression of the stock price response on the control variables. Column 2 uses the maximum likelihood estimation procedure described in Section 2.2.2 and includes the variable BIG3, the coefficient of which is positive and significant at the 1% level. In fact, a loan with one of the dominant banks as lead arranger will, *ceteris paribus*, generate an average abnormal return approximately 2.8% higher than a loan from another lender.

Among the controls, STANDVN is positive and highly significant, indicating that more volatile stocks respond more to a loan announcement. RUNUP is significant and negative, possibly suggesting information leakage in respect of the loan. LNMVEQ is significant and negative, in line with Slovin, Johnson, and Glascock (1992). LNLOANSCALE is marginally significant and negative, perhaps a sign that loans that are large in relation to the borrower's capital structure may carry some of the adverse selection effects associated with public securities issues. NONFAVREV is significant and positive, as expected. None of the other controls are significant. ρ, the correlation coefficient between the

Table 5
Regression analysis of borrower abnormal returns

	(1)		(2)		(3)		(4)		(5)	
BIG3			0.0278***	(7.60)	0.0276***	(7.55)			−0.0022	(−1.08)
BIG3-TRANSPARENT							0.0264***	(7.46)		
BIG3-OPAQUE							0.0359***	(7.18)		
SYNDUMMY					0.0023	(0.87)				
STANDVN	0.3811***	(4.23)	0.3240***	(3.54)	0.3233***	(3.53)	0.3173***	(3.47)	0.3929***	(4.33)
RUNUP	−0.0186*	(−1.75)	−0.0212**	(−2.00)	−0.0214**	(−2.02)	−0.0214**	(−2.02)	−0.0191*	(−1.80)
BETA	−0.0012	(−0.66)	−0.0004	(−0.22)	−0.0005	(−0.27)	−0.0003	(−0.16)	−0.0012	(−0.66)
LNMVEQ	0.0008	(0.87)	−0.0038***	(−3.30)	−0.0041***	(−3.41)	−0.0041***	(−3.53)	0.0012	(1.18)
OIBD	−0.0091	(−0.86)	−0.0099	(−0.85)	−0.0107	(−0.92)	−0.0116	(−0.99)	−0.0089	(−0.84)
LNTOBQ	−0.0011	(−0.33)	0.0012	(0.35)	0.0013	(0.39)	0.0013	(0.36)	−0.0014	(−0.42)
LNLOANSCALE	0.0009	(0.90)	−0.0019*	(−1.73)	−0.0024*	(−1.93)	−0.0021*	(−1.87)	0.0011	(1.09)
HASRATING	−0.0026	(−1.06)	−0.0030	(−1.25)	−0.0035	(−1.41)	−0.0004	(−0.17)	−0.0025	(−1.03)
LEVERAGE	0.0093	(1.60)	0.0080	(1.38)	0.0083	(1.43)	0.0085	(1.46)	0.0092	(1.58)
NONFAVREV	0.0139**	(2.15)	0.0139**	(2.20)	0.0136**	(2.14)	0.0142**	(2.25)	0.0140**	(2.16)
CONSTANT	−0.0120	(−1.49)	0.0157*	(1.72)	0.0173*	(1.86)	0.0162*	(1.77)	−0.0143*	(−1.72)
ρ			−0.6205***	(−8.72)	−0.6221***	(−8.79)	−0.6400***	(−9.44)		
Observations	1,041		1,027		1,027		1,027		1,041	
Pr(F-statistic/Wald X^2)	0.00		0.00		0.00		0.00		0.00	

Regressions of one-day abnormal returns for the sample of loan announcements from 2000 to 2003. Columns 1 and 5 use weighted least squares. Columns 2–4 use the maximum likelihood procedure described in the text. Variables are defined in the text and table 2. ρ is the correlation between the error terms in the lender–borrower matching and abnormal returns equations. t-statistics appear to the right of each coefficient in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

error terms in the lender–borrower matching and abnormal returns equations, is negative and highly significant.

2.4.4 Potential explanations. One explanation for the positive coefficient on BIG3 is that the dominant banks may be more likely than other lenders to make use of syndication, a process which may diffuse information about the borrower more widely than bilateral lending, resulting in a larger borrower stock price response. Column 3 tests this possibility by including SYNDUMMY, a dummy indicating that the loan is syndicated, that is, that the loan has more lenders than lead arrangers, but the variable has no explanatory power. I also try controls for the total number of lenders (untabulated). The results are similar.

The dominant banks are all universal banks with fully fledged securities underwriting operations. The certification value of a loan from the dominant banks may be larger, because these banks have acquired more knowledge of the borrower by previously acting as an underwriter for the borrower's securities. Alternatively, the certification effect from the dominant banks may be understated if it is confounded with a negative effect arising from a tendency by the dominant banks to lower lending standards to win investment banking mandates.

I test these contrasting hypotheses using variables constructed from data from the Securities Data Company, including the amount of annual revenue the lender earns from underwriting fees, the ratio of the loan's principal to the volume of securities issued by the borrower for which the lender acts as underwriter soon before or after the loan announcement, and measures of the total volume of securities issued by the borrower, in each case separately for debt and equity. In untabulated results, these various controls are not significant and do not materially change the other coefficients in the regression.

Another possibility is that BIG3 is capturing the lender's credit rating as per Billett, Flannery, and Garfinkel (1995). I therefore collect Standard & Poor's (S&P) senior unsecured debt rating for each lender and follow these authors in assigning the value 20 to the rating AAA, 19 to AA+, and so forth, using this value, a natural log transformation thereof, and a dummy variable indicating an AAA rating as alternative measures of a lender's credit rating.[24] In untabulated results, I find that the coefficient on BIG3 is materially unchanged regardless of which credit rating measure is included in the regression.

I also try dropping loans with more than one lead arranger (to verify that BIG3 is not spuriously capturing the additional certification that multiple leads may provide); loans by J.P. Morgan Chase, Bank of America, and Citigroup in turn (to ensure that the results are not being driven by one bank); and all loan announcements where the borrower's stock price was under a dollar on

[24] Billett, Flannery, and Garfinkel (1995) use Moody's ratings. As I have access through my institutional affiliation to S&P's historical debt ratings, I use those instead. Moody's and S&P's ratings are highly correlated.

the announcement date. The coefficient on BIG3 remains positive and highly statistically significant.

This article advances the hypothesis that the dominant banks generate a larger borrower stock price response, because these banks have a reputation for better screening and monitoring of borrowers. If so, the certification bestowed by the dominant banks should have more information content where the borrower is relatively "opaque." To test this, I partition BIG3 into BIG3-TRANSPARENT, which equals BIG3 if the borrower has a debt rating and is otherwise 0, and BIG3-OPAQUE, which equals BIG3 if the borrower does not have a debt rating and is otherwise 0. I then rerun the specification from column 2 in column 4 with the partitioned variables and compare their magnitude and statistical significance using a Chow test (Greene 2003). Consistent with this article's hypothesis, the coefficient on BIG3-OPAQUE is roughly one-third larger than that on BIG3-TRANSPARENT, and the two coefficients are statistically different with a p-value of 0.026.

Finally, column 5 adds BIG3 to the OLS regression of column 1. Not only is BIG3 no longer significant but also, contrary to intuition, LNMVEQ is not significant, and RUNUP is estimated less precisely. The contrast between this result and that obtained with the full model demonstrates the importance of controlling for the endogeneity of lender–borrower matching.

3. Loan Terms and Conditions

3.1 Background

3.1.1 Loan pricing. The enhanced certification provided by the dominant banks begs the question of whether there is a corresponding cost to borrowers of obtaining this certification or rather, as per Chemmanur and Fulghieri (1994a), the dominant banks' reputation for screening borrowers more effectively allows the banks to offer borrowers lower rates. The dominant banks may also have an advantage in distribution, leading to a better match between borrowers and syndicate lenders. If the dominant banks and borrowers share the benefits so derived, the resulting interest rate should lie between the (lower) best possible offer from a dominant bank and the (higher) best offer from another bank.

Note, however, that the lead arranger receives a substantially larger portion of the upfront fees than other lenders (Altunabas, Gadanecz, and Kara 2006).[25] This suggests that a loan led by a dominant bank may represent a "win–win–win," whereby the borrower gets a cheaper cost of funds, the syndicate banks accept a lower interest rate as a *quid pro quo* for benefiting from the dominant bank's reputation for screening, and the dominant bank enjoys high profits

[25] Fees earned solely by the lead arranger include arrangement fees for putting the transaction together, agency fees for administering the loan, and underwriting fees if the lead arranger first makes the loan to the borrower and only subsequently syndicates the principal. See Altunabas, Gadanecz, and Kara (2006).

either by capturing a disproportionate share of the upfront and ongoing fees or through a larger market share.

I investigate this using the All-In Drawn Spread, which is the borrower's total ongoing cost of borrowing in basis points (hundredths of 1%) assuming that the loan is fully drawn and fully incorporating ongoing and commitment fees. The All-In Drawn Spread is thus the most complete measure of the cost of borrowing associated with a loan offered by DealScan and has been widely used as a measure of borrowing cost in recent studies (e.g., Dennis, Nandy, and Sharpe 2000; Hao 2004; Yu 2007).[26]

Use of the All-In Drawn Spread restricts the sample to floating rate loans, which are more common than fixed rate loans in the corporate lending market. To maintain comparability across the sample, I restrict the analysis to U.S. dollar loans based on the most commonly used index for U.S. corporate loans, the London Interbank Offered Rate (LIBOR). I also drop the small number of loans DealScan flags as being of junior status.

3.1.2 Borrowing base. The lead arranger would normally be expected to monitor the borrower's financial condition and business prospects on an ongoing basis. However, many loans contain a provision called a "borrowing base," which significantly eases this burden by restricting the amount outstanding on the loan at any point to a fraction of an appraised value of specified assets of the borrower (often, inventories and accounts receivable) regardless of the loan's nominal principal, which could be substantially higher.[27] Frequently, the lenders will also have a security interest in these assets, but a borrowing base is distinct from a security interest, which would not necessarily limit the amount outstanding on the loan over the course of the loan's term. In addition, the borrowing base tends to be a standardized provision, unlike security interests per se, which, using DealScan's definitions, apply whenever lenders have a lien on an asset of the borrower.

Clearly, a borrowing base reduces the utility of the loan to the borrower. If loans from the dominant banks are more likely to have such provisions, it could explain any discount in the All-In Drawn Spread on such loans. By contrast, if loans from the dominant banks are less likely to have such provisions, it would suggest that the dominant banks have a particularly high reputation for the ongoing monitoring of borrowers in the sense of Chemmanur and Fulghieri (1994b) and are trusted to make good decisions regarding default and renegotiation of covenants.

[26] According to DealScan, the All-In Drawn Spread does not include fees associated with syndication, which are usually paid "up front," that is, upon loan closing. Moreover, upfront fees are rarely included in the DealScan data and even when present are not provided in sufficient detail to be allocated among the lenders. The share of loan principal allotted to each lender is also missing for most loans. Thus, I cannot test the hypothesis that the dominant banks receive more in upfront fees than other lenders.

[27] For example, if the borrowing base is 90% of accounts receivable, and the balance thereof stands at $100 million at a given month-end, the borrower can have no more than $90 million outstanding on the loan even if the nominal principal is much larger.

The DealScan database includes a field indicating whether a loan has a borrowing base. However, details regarding the formula underlying the borrowing base are often missing. For this reason, I operationalize this characteristic as a dummy variable. I again restrict the estimation sample to U.S. dollar LIBOR-based loans not of junior status.

3.2 Empirical specifications

The endogeneity of lender–borrower matching is equally at issue in the analysis of loan terms and conditions. In addition, loan announcements relate to loan "deals," which may include more than one loan "facility" or individual loan contract. For example, a borrower may simultaneously take out a three- and a five-year loan, each with different pricing and other terms. As only one of these loans might have a borrowing base, it is appropriate to analyze loan terms and conditions on an individual loan facility level and then cluster standard errors on a deal basis to account for the interdependent nature of different facilities within the same deal. This cannot be done using the two-step treatment effects procedure. Therefore, for the loan-pricing regressions, I apply the same econometric model described in Section 2.2.2 but without weighting the observations.

The analysis of the borrowing base provision has a dichotomous dependent variable and thus requires a different estimation technique. I use the bivariate probit model, a maximum likelihood specification proposed by Maddala (1983), which is essentially the econometric model used for the loan-pricing regressions but with a probit equation in the second stage instead of a linear regression. I analyze loan terms and conditions for the years 2000–2003 to coincide with the event study.

3.2.1 Variables. The variable of interest is BIG3. I also include a range of control variables that are similar to those used in prior work on loan pricing,[28] and, as above, include all the determinants of lender–borrower matching except the instruments based on the borrower's location. Borrower characteristics are LNMVEQ, LNTOBQ, OIBD, LNLOANSCALE, TANGIBILITY (the ratio of net property, plant, and equipment to assets), LEVERAGE, HASRATING, LNRATING (a log transformation of the numerical code associated with the borrower's S&P long-term rating at the closing of the loan),[29] and dummies for one-digit Standard Industrial Classification codes (not reported to economize on space).[30]

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[28] See, for example, Dennis, Nandy, and Sharpe (2000), Coleman, Esho, and Sharpe (2002), Hao (2004), and Carey and Nini (2007).

[29] The codes are from Compustat, that is, AAA = 2, AA+ = 4, and so on up to D = 27.

[30] Where a variable's name coincides with one from the event study, the variable has the same definition.

To account for conditions in the loan market, I define CREDITSPREAD, the difference in annual yield between corporate bonds rated Aaa and Baa by Moody's, and COSTOFFUNDS, the interest rate on six-month Eurodollar deposits. Loan terms are TERM, the time to maturity in months; LNSIZE, a log transformation of the loan's principal; dummies indicating, respectively, whether the loan is for refinancing, merger and acquisition activity, corporate purposes, or commercial paper backup; and dummies indicating whether there are, respectively, financial covenants, nonfinancial covenants like limitations on dividends or asset sales, and performance pricing.[31] (The coefficients on these dummy variables are not reported, to conserve space.)

Data for the foregoing variables are from the following sources: DealScan, for loan terms and conditions as well as borrower credit ratings; Compustat, for borrower financial information; CRSP, to compute borrower market values; and the Federal Reserve Bank Reports for credit market conditions.[32] I use the same variables in the matching equation as in the regression analysis of abnormal returns. Table 2 summarizes the variable definitions.

3.3 Results

3.3.1 Matching equation. Table 4 (column 2) shows the underlying lender–borrower matching equation, this time using the DealScan data.[33] The signs and significance levels are similar to those in column 1, but the coefficient on OIBD is now marginally significant. The magnitude of the coefficients is somewhat lower in column 2 than in column 1. This may reflect the fact that larger loan deals tend to have more facilities, not just a larger principal amount per facility, affecting the predictive power of, for example, LNLOANSCALE.

3.3.2 Loan pricing. Table 6 presents regressions for loan pricing. Column 1 uses OLS on the control variables. Column 2 uses the maximum likelihood procedure described above. In column 2, the coefficient on BIG3 is negative and highly statistically significant. In fact, using a dominant bank as the lender results in an average reduction in the All-In Drawn Spread of about 0.30%, implying annual savings on a $100 million loan of $300,000. This is a meaningful amount but, perhaps, smaller than the increase in firm value implied by

[31] Demiroglu and James (2007) provide evidence that covenants convey private information about the borrower's business prospects, while Bradley and Roberts (2004) present results suggesting covenants are a means of mitigating borrower agency costs. Covenant indicators often assume positive coefficients and thus may proxy for unobservable borrower risk factors (e.g., Carey and Nini 2007).

[32] The loan announcements and DealScan samples differ. First, for many loans in the DealScan data, no announcement or no clean announcement was found. Second, a minority of announcements concern loans that DealScan appears to have missed. Third, many loan announcements concern revisions, which usually do not give rise to a new loan entry in the DealScan data.

[33] Table 4 (column 2) is simultaneously estimated with table 6 (column 2). The coefficient estimates in the underlying matching equations for table 6 (columns 3 and 4) and table 7 (column 2) are not materially different. In the DealScan data, there are a small number of loans to borrowers located in U.S. territories and other possessions; for these, I use census reports specifically on those regions to calculate FININTEN.

Table 6
Regression analysis of loan pricing

	(1)		(2)		(3)		(4)		(5)	
BIG3			−30.1291***	(−2.89)					−0.3773	(−0.13)
BIG3-TRANSPARENT					−29.5557***	(−2.82)				
BIG3-OPAQUE					−31.3179***	(−2.76)				
BIG3-CP							−19.6031*	(−1.75)		
BIG3-NOTCP							−31.6959***	(−3.02)		
LNMVEQ	−28.2430***	(−7.00)	−28.2717***	(−5.83)	−28.2424***	(−5.82)	−28.3010***	(−5.82)	−28.2472***	(−6.99)
LNTOBQ	22.6902***	(5.87)	18.7499***	(4.41)	18.7027***	(4.39)	18.7794***	(4.42)	22.6723***	(5.85)
OIBD	−128.9255***	(−6.23)	−119.7952***	(−5.70)	−119.4253***	(−5.66)	−119.0871***	(−5.66)	−128.8716***	(−6.22)
LNLOANSCALE	−18.1383***	(−4.64)	−20.1142***	(−4.50)	−20.0984***	(−4.50)	−20.1558***	(−4.50)	−18.1562***	(−4.64)
TANGIBILITY	−16.1706**	(−2.52)	−15.8301**	(−2.46)	−15.8706**	(−2.47)	−15.7311**	(−2.45)	−16.2115**	(−2.52)
LEVERAGE	100.3228***	(8.98)	93.6089***	(7.88)	93.6739***	(7.88)	93.6382***	(7.88)	100.2926***	(8.97)
HASRATING	−259.4459***	(−15.20)	−259.1151***	(−15.10)	−260.2871***	(−14.46)	−259.7324***	(−15.22)	−259.4203***	(−15.20)
LNRATING	138.2445***	(15.64)	138.1294***	(15.58)	138.3365***	(15.46)	138.5767***	(15.71)	138.2519***	(15.64)
CREDITSPREAD	10.2820	(1.26)	10.5339	(1.28)	10.5421	(1.28)	10.5583	(1.28)	10.2684	(1.25)
COSTOFFUNDS	−3.8174***	(−4.36)	−3.8357***	(−4.35)	−3.8275***	(−4.34)	−3.8165***	(−4.33)	−3.8151***	(−4.35)
TERM	0.7813***	(11.79)	0.7762***	(11.64)	0.7763***	(11.64)	0.7729***	(11.59)	0.7813***	(11.79)
LNSIZE	7.5072*	(1.84)	11.3105**	(2.51)	11.3019**	(2.51)	11.3286**	(2.51)	7.5519*	(1.84)
CONSTANT	200.3731***	(8.81)	202.6866***	(8.17)	202.7003***	(8.17)	203.1868***	(8.18)	200.2872***	(8.79)
ρ			0.2116***	(2.66)	0.2125***	(2.67)	0.2103***	(2.63)		
Observations	7,093		6,975		6,975		6,975		7,093	
Pr(F-statistic/Wald X^2)	0.00		0.00		0.00		0.00		0.00	

Regressions of All-In Drawn Spread over LIBOR on senior U.S. dollar loans from 2000 to 2003. Columns 1 and 5 use OLS. Columns 2–4 use the estimation procedure described in the text. Variables are defined in the text and in table 2. Regressions include unreported dummy variables for industry, loan purpose, the presence of financial and nonfinancial covenants, and performance pricing. Errors are clustered by deal, where a deal has more than one loan facility. ρ is the correlation between the error terms in the lender–borrower matching and loan-pricing equations. t-statistics appear to the right of each coefficient in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.

the event study. That reinforces the notion that the dominant bank effect reflects not only a cheap source of funds but also a certification of the borrower. The interest savings also suggest that the dominant banks' superior screening allows them to maintain a high market share without a structural barrier to competition.

As noted, the fact that the lead arranger receives a disproportionate share of the upfront fees means that the lead arranger's implied yield on the loan may be much higher than the borrower's cost of funds. Unfortunately, the limitations of the fee information in DealScan do not permit me to verify this. All the same, in the sample of loans used in table 6, the average upfront fee, where disclosed, is approximately 0.47% versus an average term of almost three years, for an annual cost of roughly 0.16%. Therefore, it seems unlikely that any premium in upfront fees would change the conclusion that the dominant banks offer a lower all-in cost of funds to borrowers.

Most of the control variables have the expected sign and are significant. LNMVEQ is negative and significant, perhaps reflecting greater access by larger borrowers to other sources of funding. LNTOBQ is positively associated with the cost of borrowing, suggesting again that Tobin's Q is a proxy for risk-shifting opportunities, not quality, in the loan market. Cash flow (OIBD) is strongly associated with a lower cost of borrowing. LNLOANSCALE is negative and significant; a bank may have to offer a particularly compelling interest rate to prompt a borrower to overweight the bank as a source of capital. TANGIBILITY is negative and significant, reflecting the liquidation value of hard assets. LEVERAGE is strongly associated with a higher cost of borrowing. As expected, rated borrowers enjoy a lower cost of funds, and the better the rating, the lower the cost. CREDITSPREAD is not significant. COSTOFFUNDS is negative and significant, suggesting that banks must share some of the burden of tight monetary conditions with borrowers. TERM is significant and positive, as long-term lending is riskier than short-term lending. LNSIZE is positive and significant, suggesting a modest diseconomy of scale in borrowing, once borrower size is accounted for; this may reflect an upward sloping supply curve for loans to a given borrower. Finally, the parameter ρ is highly statistically significant.

In accordance with the event study, I try dropping loans with multiple lead arrangers and loans by each of J.P. Morgan Chase, Bank of America, and Citigroup in turn, and the results are consistent. I also split BIG3 into transparent and opaque versions, with the results in table 6 (column 3). There is no meaningful difference between the two versions of BIG3. Syndicate banks are given detailed memoranda describing prospective borrowers' financial condition and business prospects. Such information may largely supersede the information content of a credit rating.

From the standpoint of a syndicate bank, loans may more usefully be classified according to whether the loan is intended as a source of capital or to support a commercial paper program, in which case the loan would be drawn only under duress. Loans of the latter type are to borrowers that have already demonstrated their creditworthiness to the credit markets, in which case any discount in pricing from using the dominant banks may be more reflective of the banks' distribution capability. Column 4 depicts the results of splitting BIG3 into two versions: where the loan is for commercial paper backup (BIG3-CP) and where the loan is for another purpose (BIG3-NOTCP). The coefficient on BIG3-NOTCP is positive and significant at the 1% level and reflects interest savings of almost thirty-two basis points vis-à-vis loans from other lenders. In contrast, the coefficient on BIG3-CP is significant at only the 10% level and is twelve basis points smaller in absolute value. The two coefficients are also statistically different at the 1% level. These results can be interpreted as showing that roughly 60% of the loan-pricing discount provided by the dominant banks arises from their superior distribution capability and the remainder from their higher reputation for screening.

In table 6 (column 5), I rerun the OLS specification with BIG3, which is not close to significant. The contrast of this result with that in column 2 again illustrates the importance of controlling for the endogeneity of lender–borrower matching.

3.3.3 Borrowing base. Table 7 analyzes the propensity of loans to have a borrowing base. Column 1 uses a univariate probit model with the controls.

Table 7
Probability loan has borrowing base

	(1)		(2)		(3)	
BIG3			−1.1455***	(−5.24)	−0.2048***	(−3.23)
LNMVEQ	−0.3067***	(−5.68)	−0.1686***	(−2.67)	−0.3060***	(−5.69)
LNTOBQ	0.1286	(1.63)	0.0024	(0.03)	0.1146	(1.47)
OIBD	−1.1955***	(−3.74)	−0.9736***	(−3.08)	−1.1649***	(−3.67)
LNLOANSCALE	0.1623***	(2.89)	0.1896***	(3.66)	0.1518***	(2.72)
TANGIBILITY	−0.9934***	(−7.03)	−0.9128***	(−6.69)	−1.0143***	(−7.06)
LEVERAGE	−0.6203***	(−3.03)	−0.5760***	(−3.05)	−0.6313***	(3.08)
HASRATING	−2.8858***	(−6.00)	−2.4580***	(−5.34)	−2.8972***	(−6.06)
LNRATING	1.4490***	(6.23)	1.2528***	(5.58)	1.4650***	(6.32)
CREDITSPREAD	0.1796	(1.05)	0.1399	(0.91)	0.1832	(1.07)
COSTOFFUNDS	−0.0205	(−1.01)	−0.0181	(−0.99)	−0.0185	(−0.90)
TERM	−0.0120***	(−8.64)	−0.0107***	(−7.47)	−0.0121***	(−8.66)
LNSIZE	0.0120	(0.22)	0.0314	(0.63)	0.0307	(0.57)
CONSTANT	−1.6081***	(−3.24)	−1.6839	(−3.82)	−1.6606***	(−3.37)
ρ			0.5853***	(3.27)		
Observations	7,155		7,037		7,155	
Pr(F-statistic/Wald X^2)	0.00		0.00		0.00	

Probit regressions for probability that U.S. dollar LIBOR-based loan facility has a borrowing base from 2000 to 2003. Columns 1 and 3 are univariate probit regressions. Column 2 uses the bivariate probit estimation procedure described in the text. Variables are defined in the text and in table 2. Regressions include unreported dummy variables for industry, loan purpose, the presence of financial and nonfinancial covenants, and performance pricing. Errors are clustered by deal, where a deal has more than one loan facility. ρ is the correlation between the error terms in the lender–borrower matching and borrowing base equations. t-statistics appear to the right of each coefficient in parentheses. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level. The number of observations for some specifications includes observations perfectly determined by the dummy variables; these observations are not used to calculate the other coefficients.

Column 2 uses the bivariate procedure described above. The coefficient on BIG3 is negative and highly statistically significant, which result is consistent with the dominant banks having a reputation for superior monitoring.[34]

With regard to the controls, loans to larger firms (LNMVEQ) and high cash flow firms (OIBD) are less likely to have a borrowing base. The coefficient on LNLOANSCALE is positive and significant, indicating that loans occupying a larger share of a borrower's capital structure are more likely to carry the provision, perhaps as a *quid pro quo* for the lower interest rates associated with this variable. TANGIBILITY has a strong negative association with the probability that a loan has a borrowing base; banks may not demand a borrowing base when a borrower has a large quantity of hard assets, which can be resold in the event of default. LEVERAGE is negatively associated with the presence of the provision; this is somewhat counterintuitive, but may indicate that highly levered borrowers cannot afford the restricted access to liquid funds that a borrowing base imposes. Loans to rated borrowers are less likely to have a borrowing base, and the effect is stronger the better the rating. TERM has a highly significant negative association with the presence of a borrowing base, reflecting the fact that borrowing base formulas typically emphasize short-term assets. None of the other coefficients are significant, while the parameter ρ is positive and highly statistically significant.

Again, the results are qualitatively similar if loans with multiple leads or from any one of the dominant banks are excluded. In table 7 (column 3), I run a probit specification. The coefficient on BIG3 is highly significant and negative but not as large in magnitude as with the correction for the endogeneity of lender–borrower matching.

4. Conclusion

Overall, the results of this study are consistent with theory. More reputable borrowers tend to borrow from more reputable banks, which provide a higher level of certification—particularly when the borrower is opaque—and lend on more favorable terms. The dominant banks, it would seem, have a commanding market share because they have a particularly high—and possibly self-reinforcing—reputation for screening and monitoring. The results also suggest that the dominant banks have an advantage in distribution, allowing them to offer loans at a lower all-in cost, even to borrowers with an established reputation in the credit markets.

The results also raise numerous questions. Is there a downside to borrowing from a dominant bank that was not captured in this study? Does the market "punish" reputable borrowers that choose not to borrow from a dominant bank, even if there is a good reason not to do so? What are the costs and benefits to

[34] It is not possible to split BIG3 into CP and NOTCP versions in this regression, as using a loan as a commercial paper backup is (almost) a sufficient statistic for the loan not having a borrowing base.

a lender of joining a syndicate led by a dominant bank? For example, do the syndicate banks sometimes accept lower yields out of fear that not participating will leave them shut out of future syndicates? These questions suggest the need for further research on the determinants and effects of lender identity.

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