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So what do I get? The bank's view of lending relationships ☆

Sreedhar Bharath[a], Sandeep Dahiya[b], Anthony Saunders[c,*], Anand Srinivasan[d]

[a]University of Michigan, Ann Arbor, MI 48109, USA
[b]Georgetown University, Washington, DC 20057, USA
[c]New York University, New York, NY 10012, USA
[d]NUS Business School, 117952, Singapore

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Abstract

While many empirical studies document borrower benefits of lending relationships, less is known about lender benefits. A relationship lender's informational advantage over a non-relationship lender may generate a higher probability of selling information-sensitive products to its borrowers. Our results show that the probability of a relationship lender providing a future loan is 42%, while for a non-relationship lender, this probability is 3%. Consistent with theory, we find that borrowers with greater information asymmetries are significantly likely to obtain future loans from their relationship

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*Corresponding author. Tel.: +1 212 998 0711; fax: +1 212 995 4232.
E-mail address: asaunder@stern.nyu.edu (A. Saunders).

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lenders. Relationship lenders are likely to be chosen to provide debt/equity underwriting services, but this effect is economically small.

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1. Introduction

The special nature of lending relationships has been the subject of extensive theoretical and empirical research in finance.[1] While there is no precise definition of "relationship banking," scholars broadly agree that if a financial intermediary's decision to supply various services to a firm is based on borrower-specific information that the intermediary collects over multiple interactions (over time as well as across multiple products), and further, if this information is proprietary (available only to the borrower and the intermediary), the intermediary is engaged in relationship banking (for a detailed discussion, see Berger, 1999; Boot, 2000). Existing theories predict that the establishment of strong lender-borrower relationships can generate significant benefits for the lender.[2]

Empirical evidence on the benefits of banking relationships has largely focused on documenting these benefits to the *borrower*. This literature can be broadly classified into two distinct approaches. The first approach uses indirect tests to establish the value of banking relationships. Specifically, James (1987) and Lummer and McConnell (1989) find a positive stock market reaction to the renewal of lending relationships and thereby establish the value-enhancement role of relationships to borrowers.[3] The second approach attempts to estimate the effects of relationships on borrowers directly by examining the impact that such relationships have on the cost and availability of credit. This approach is best characterized by Petersen and Rajan (1994) and Berger and Udell (1995), who find, among other things, that the stronger (i.e., the longer the duration of) the relationship, the greater the credit availability and the lower the collateral requirements.

In contrast, the focus of our paper is on establishing the existence and the nature of the benefits of relationship banking from the perspective of the *lender*, a subject that has attracted far less attention in the literature. Indeed, relationship studies do not provide any guidance with respect to the sources of these benefits to lenders and how the value created by establishing such relationships is shared between lenders and borrowers.[4] Thus, an

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[1]See Boot (2000) and Ongena and Smith (1998) for an extensive survey of this literature.

[2]The benefits could come from multiple sources such as the ability to share sensitive information (Bhattacharya and Chiesa, 1995), more flexible contracts compared to public debt (Berlin and Mester, 1992; Boot et al., 1993), the ability to monitor collateral (Rajan and Winton, 1995), and the ability to smooth out loan pricing over multiple loans (Berlin and Mester, 1999). A relationship lender can also benefit from potential monopoly (holdup) power of the lender (e.g., Sharpe, 1990; Rajan, 1992), which allows the lender to charge its captive borrowers excessive rates for loans. Berlin (1996) provides a good overview of these issues of relationship lending.

[3]Further evidence is provided by Slovin et al. (1993) and Dahiya et al. (2003a), who document a *negative* impact of the potential *termination* of lending relationships on the borrower's market value. Ongena et al. (2003) report similar results for capital-constrained Norwegian borrowers when banks of such borrowers face distress.

[4]One study that attempts to indirectly measure the relationship benefits to the lenders is Dahiya et al. (2003b). They find that a bank's share price drops when its borrower announces default. The stock price decrease is much

important question is: what is the value of establishing a lending relationship to a lender (rather than a borrower)?

Existing theories of financial intermediation (see, e.g., Leland and Pyle, 1977; Diamond, 1984; Ramakrishnan and Thakor, 1984) emphasize the role of banks in generating information, for instance, through screening (Diamond, 1991) and monitoring (Rajan and Winton, 1995). Because relationship lending typically involves repeated interaction between a lender and a borrower over time, such interactions may generate "inside information" for the lender and reduce its cost of providing further loans and other services.[5] To the extent that relationship lending produces reusable and proprietary information about the borrower, a possible benefit for the relationship lender is that it would be better placed to win future loan business and other fee-generating services from its relationship borrower.[6] While the association between past lending relationships and future investment banking business has been examined recently by Drucker and Puri (2005) (for seasoned equity offerings), Yasuda (2005), and Burch et al. (2005) (for public debt underwriting), as far as we are aware, no study has examined the impact of lending relationships on the ability to win future loan business. Our paper provides tests that examine whether establishing a lending relationship translates into a higher probability of winning future lending as well as non lending business for a lender.

The central result of this paper is that strong past lending relationships significantly increase the probability of securing future lending and investment banking business. Holding all else constant, a bank with a prior lending relationship has more than a 40% probability of winning subsequent loan business from its borrower while a bank lacking such a relationship has only a 3% probability of being chosen to provide future loans. Consistent with theory, borrowers that suffer from greater information asymmetry (e.g., small, non rated firms) are more likely to use their relationship lender for future loans. Moreover, on average, a prior lender is almost twice as likely to be retained as the lead debt underwriter by its (loan) borrowers. While the impact of a prior lending relationship has a limited effect on the choice of a seasoned equity offering (SEO) underwriter, the existence of a past lending relationship is associated with almost a four-fold increase in the probability of being retained as a lead initial public offering (IPO) underwriter by a relationship borrower. To the extent that an increase in future lending and underwriting business is profitable, a greater likelihood of winning future business is a significant benefit to a relationship lender.

A number of recent studies examine the effect of past lending relationships on the choice of underwriter. Yasuda (2005) examines the impact of prior lending relationships on the choice of debt underwriter and finds that past lending relationships are associated with

(*footnote continued*)
greater when the borrower has had an ongoing relationship with the bank, signalling that potential termination of the relationship also results in a loss of value to the *bank*.

[5]Petersen and Rajan (1994) provide a succinct description of this argument: "... if scale economies exist in information production, and information is durable and not easily transferable, these theories suggest that a firm with close ties to financial institutions should have a lower cost of capital ... Implicit, therefore, in our analysis is the assumption that reductions in lender's cost are passed on to the borrower in a lower rate."

[6]Petersen and Rajan (1994) discuss reasons as to why a relationship lender would incur lower information production costs. They argue that over time a relationship lender acquires information about its borrower that would be costly for a new lender to acquire, thus giving the relationship lender a cost advantage. Also, if fixed costs of producing information can be spread over multiple products, the marginal cost of providing any individual product would be lower for a relationship lender.

a significantly higher probability of securing the debt underwriting business. Ljungqvist et al. (2006) examine how analyst coverage affects a bank's ability to win both debt and equity underwriting business. While not the focus of their paper, they report that prior lending relationships are associated with a significantly higher probability of winning future investment banking business, especially for debt underwriting. Drucker and Puri (2005) focus exclusively on SEOs and report that "concurrent lending" (a loan six months before or six months after the issue) is associated with a higher likelihood of winning the underwriting business. Our results for underwriter selection are broadly similar to the results of these studies. Similar to Yasuda (2005) and Ljungqvist et al. (2006), we find that prior lending relationships are significantly associated with a higher probability of winning debt underwriting business. While we find that prior lending relationships are associated with a significantly higher probability of winning IPO business, our results for SEOs are not as significant as those reported by Drucker and Puri (2005). This difference in significance could arise in part due to our different methodologies in constructing the relationship measures, as their paper focuses on concurrent lending and underwriting. Also unlike Drucker and Puri, we explicitly control for market shares of potential underwriters in both the lending as well as the underwriting markets. Overall, our results are consistent with the findings of these recent studies, which show that prior lending relationships are associated with a significantly higher likelihood of winning underwriting business.

The remainder of the paper is organized as follows. We describe our main hypotheses in Section 2. Section 3 describes the data and sample selection process. We present the methodology and major results in Section 4. We conclude in Section 5.

2. Theoretical predictions and hypotheses

In this section we discuss testable predictions of existing theories of relationship lending and the main hypotheses that we test in this paper. The hypotheses that we test examine the benefits of relationship lending that accrue from the efficiencies in information production that a relationship lender enjoys. These hypotheses predict that a relationship lender is more likely to secure future business than is a non-relationship lender. We refer to these benefits collectively as *higher business volume benefit*.

As we discuss in the introduction, theoretical models view the economies of scale in information production as the key source of the benefits that arise from strong relationships. If there are fixed costs of information production and if this information is proprietary and reusable, theory suggests that strong relationships would be associated with a lower cost of information production for subsequent lending and service provision decisions (see Greenbaum and Thakor, 1995). A testable implication therefore is that a relationship lender is more likely to capture the future lending business of its borrower.[7] We formalize this implication in Hypothesis 1:

Hypothesis 1 (*H1*). *The stronger the bank-borrower relationship, the greater the probability that a lender attracts future lending business from that borrower.*

[7] A tendency to repeat past relationships is well documented in areas other than the lender-borrower context. For instance, Levinthal and Fichman (1988) report that relationships between auditors and clients are more likely to be renewed as the duration of these relationships increased, and Carlton (1986) reports that the average duration of buyer-supplier relationships in the manufacturing industry typically exceeds five years.

The choice between bank debt and direct public debt has been the focus of a number of studies. Rajan (1992) defines bank financing as ''inside'' debt due to a bank's enhanced ability to collect information about its borrower. Conceptually, relationship lending can be thought of as repeated extensions of such ''informed'' debt by the same lender, whereas public debt can be regarded as ''arms-length'' financing or ''outside'' debt, as in this case lenders do not engage in proprietary information production. Diamond (1991) argues that the borrowers that suffer from the most severe information asymmetries (e.g., small firms with less established repayment histories and/or borrowers with poor credit ratings) have the most to gain from the monitoring services that banks provide. Such firms would choose bank financing over public debt financing. Also, Berlin and Mester (1992) suggest that borrowers with poor credit would choose bank loans with stringent covenants (because renegotiation of these covenants is easier than that of public debt covenants). In sum, these models predict that informationally opaque borrowers would use relationship loans more frequently than borrowers for whom a substantial amount of information is available publicly. We capture this conjecture in Hypothesis 2:

Hypothesis 2 (*H2*). *The more informationally opaque a borrower, the greater the likelihood it will borrow from its relationship lender.*

Kanatas and Qi (2003) focus on the benefits of ''scope economies'' that arise when a single institution offers both lending and underwriting services. These scope economies arise in their model, when information costs of learning about their customers in the process of supplying one product, need not be fully incurred again when supplying other products to them.[8] Petersen and Rajan (1994) also discuss the potential benefits to a relationship lender in generating enhanced sales of other non lending products (e.g., investment banking, deposit-related products, etc.). Such future sales may be a source of value creation since cross-selling multiple products gives the bank the ability to spread the fixed costs of information production over multiple products as well as to generate additional revenues.[9] This motivates our Hypothesis 3:

Hypothesis 3 (*H3*). *The stronger the bank-borrower relationship, the greater the probability a lender will attract future investment banking business from that borrower.*

3. Data and sample selection

To gain insights into these hypotheses we construct a unique database using three primary data sources, namely, the Loan Pricing Corporation Dealscan (henceforth, LPC) database,[10] a merged CRSP and COMPUSTAT database, and the Securities Data Corporation (SDC) new securities issues database. As we describe later in the paper, the large number of mergers and acquisitions in the U.S. banking sector over our sample period poses special challenges. To deal with mergers and acquisitions, we manually match

[8] Additionally, these benefits can also arise from ''purchasing economies of scope'' as outlined in Klemperer and Padilla (1997), who argue that borrowers prefer a single source of multiple products to lower their transaction costs.

[9] That is, the potential for cost and revenue economies of scale.

[10] We discuss the details of data obtained from LPC database in the following sections.

data from the SDC mergers and acquisition database, Lexis-Nexis, and the Hoover's corporate histories database to construct a chronology of banking mergers. Since our hypotheses seek to establish directly measurable benefits of relationships to lenders, the estimation of these benefits requires data on the following four different dimensions: data to construct meaningful relationship variables; characteristics of lenders; characteristics of each loan facility; and, characteristics of the borrowers. We discuss each of these four characteristics next in Sections 3.1–3.4.

3.1. Construction of relationship measures

One of the primary goals of this paper is to examine the existence and extent of the benefits of relationships to lenders. Thus, it is critical to construct meaningful and measurable proxies for bank relationships as well as their associated benefits. There is no uniformly accepted methodology for measuring the presence and strength of banking relationships. In cases in which the precise point of the start of a banking relationship is available, researchers often use the length of a relationship as a proxy for its strength (see, for example, Petersen and Rajan, 1994; Berger and Udell, 1995). In cases in which this information is not available, the existence of a prior lending relationship is used as a proxy (see, for example, Dahiya et al., 2003b; Schenone, 2004). All these relationship measures have a potential drawback, however. If an unobservable characteristic (e.g., physical proximity) causes a borrower and a lender to match up in the first place, and if this factor continues to be present when the borrower seeks subsequent loans or other banking services, our relationship measure would include the effect of this factor. This limitation characterizes all relationship measures that are based on the existence and/or intensity of prior interactions between a borrower and its lender. We try to mitigate this drawback by including a physical proximity measure, LOCATION (described later), that controls for the locational distance between a borrower and its potential lenders.

To construct the relationship measures, we employ the LPC database. This database contains data on loans made to large publicly traded companies.[11] Our sample period extends from 1986 to March 31, 2001. Since coverage of our sample data starts in 1986, our sample period is truncated in the left tail. Thus, a length of relationship measure would be biased because we lack a definitive starting date for any such relationship. Nevertheless, our data set still allows us to construct several other measures that capture the evolution of the bank-borrower relationship over time. We focus on three distinct markets in which a relationship lender can benefit from its close ties with its borrower, specifically, the market for bank loans, the market for public debt underwriting services, and the market for public equity underwriting services. Since we need to take into account the historical relationship at the point in time of a particular transaction, we construct these relationship measures for each of the three markets separately. We describe next our methodology for constructing the measures for each of these markets (Appendix A provides a summary of all the relationship variables and how they are constructed).

[11]Researchers examining bank loans are increasingly employing the LPC database. See, for example, Carey et al. (1998), Strahan (2000), Dahiya et al. (2003b), and Drucker and Puri (2005).

3.1.1. Market for bank loans

For every loan facility, we construct three alternative measures of relationship strength by looking back and searching the past borrowing record of the borrower.[12] Thus, for each loan by borrower *i*, we look back over a period of five years for any previous loans taken by *i*.[13] Based on the banks retained for these past loans, we construct various relationship measures as discussed below. For each bank *m*, we construct the lending relationship measure $\text{LOANREL(M)}_m^{\text{BankLoans}}$, where M indicates one of the three alternative measures.

The process is best illustrated by an example: In May 1997, Texas Instruments Inc. borrowed \$600 million from a syndicate led by ABN-AMRO, Citicorp, and NationsBank. To calculate the strength of ABN-AMRO's relationship at the time of this loan we *look back* at the borrowing history of Texas Instruments over the five years preceding this May 1997 loan. In this window, the following records of borrowing activity by Texas Instruments appear in the LPC database. In May 1994, Texas Instruments borrowed \$300 million from a syndicate led by JP Morgan. It borrowed another \$440 million from ABN-AMRO, Citicorp, Fuji Bank, and NationsBank in May 1995. Then in May 1996, it borrowed \$600 million from ABN-AMRO, Citicorp, Fuji Bank, and NationsBank. Thus, looking back from the point of the May 1997 loan, Texas Instruments contracted loans of \$1340 million (300 + 440 + 600) prior to the May 1997 loan of \$600 Million. Of the \$1340, ABN-AMRO provided \$1040 (440 + 600). Thus, in this measure we give full relationship attribution to ABN-AMRO although the loans are syndicated (in constructing the relationship measure for Citicorp or NationsBank, the other lead banks on this loan, we follow the same process). That is, the relationship is established by the granting of the loan rather than the fraction lent by an individual lead bank. Note that in most cases, LPC does not provide details on the shares of individual banks in a syndicated loan. We use this example to illustrate the methodology for constructing various relationship measures.

The first relationship strength variable, $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$, is a binary measure designed to pick up the *existence* of prior lending by the same lender in the past. In this case, for ABN-AMRO, $\text{LOANREL(Dummy)}_{\text{ABN-AMRO}}^{\text{BankLoans}}$ would equal one, denoting the existence of prior lending to Texas Instruments by ABN-AMRO.

The other two measures of relationship strength are continuous. The first continuous measure of relationship strength, $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$, captures the *size* of past lending by bank *m* to borrower *i*. We calculate this variable as

$$\text{LOANREL(Amount)}_m^{\text{BankLoans}} = \frac{\text{\$ Amount of loans to borrower } i \text{ by bank } m \text{ in last 5 years}}{\text{Total \$ amount of loans by borrower } i \text{ in last 5 years}}. \quad (1)$$

[12]We focus on the lead bank(s) of a particular loan facility, as the information-intensive role that we test in our hypotheses is most appropriate for the lead bank, which typically holds the largest share of a syndicated loan (see Kroszner and Strahan, 2001), and is frequently the administrative agent that has the fiduciary duty to other syndicate members to provide timely information about the borrower. Dennis and Mullineux (2000) and Madan et al. (1999) list the functions performed exclusively by the administrative agent; these include monitoring the performance of covenants; relationship management; administration of collateral; and, loan workouts in the case of default. Thus, the responsibilities of a lead bank best fit the description of a relationship lender.

[13]We choose the five year window as approximately 75% of the loan facilities in our sample have maturities of less than or equal to five years. Thus, most of the borrowers in our sample would need to refinance their debt within five years.

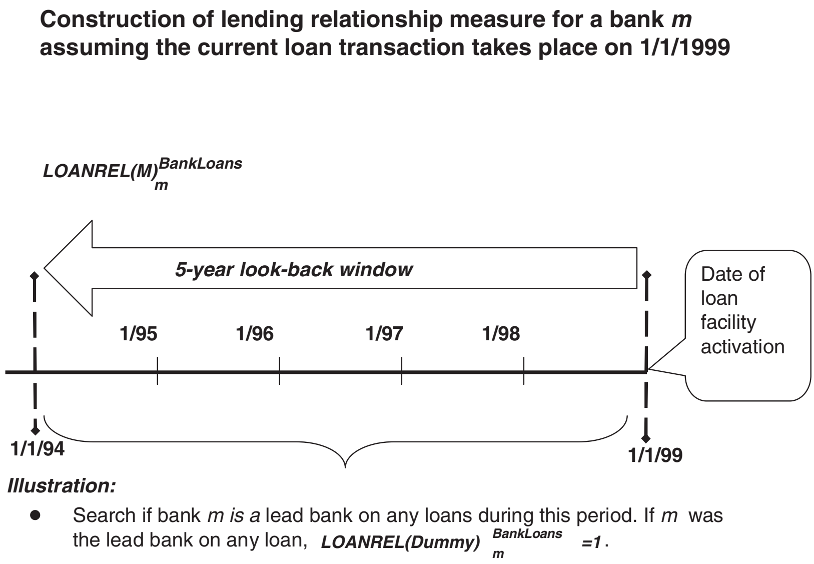

Fig. 1. Construction of relationship measures in bank loan market.

Thus, in the case of the May 1997 loan to Texas Instruments, LOANREL $(\text{Amount})^{\text{BankLoans}}_{\text{ABN-AMRO}}$ for ABN-AMRO is 0.776 (= \$1,040/\$1,340).[14]

The second continuous measure of relationship strength, $\text{LOANREL}(\text{Number})_m^{\text{BankLoans}}$, captures the *frequency* of past lending by a bank m to a borrower i. We calculate this variable as

$$\text{LOANREL}(\text{Number})_m^{\text{BankLoans}} = \frac{\text{Number of loans to borrower } i \text{ by bank } m \text{ in last 5 years}}{\text{Total Number of loans by borrower } i \text{ in last 5 years}}. \tag{2}$$

Thus, in the case of the May 1997 loan to Texas Instruments, LOANREL $(\text{Number})^{\text{BankLoans}}$ for ABN-AMRO is 0.67 (= 2/3).[15] We depict the construction of $\text{LOANREL}(\text{M})_m^{\text{BankLoans}}$ in Fig. 1.

3.1.2. Market for underwriting public debt

To test H3, we focus on two investment banking products that a bank can offer to its relationship borrowers, that is, underwriting services for public debt and for public equity issues. To examine the impact of a prior lending relationship on winning a public debt underwriting mandate for any bank m, we construct a new lending relationship variable, $\text{LOANREL}(\text{M})_m^{\text{PublicDebt}}$, in exactly the same way as $\text{LOANREL}(\text{M})_m^{\text{BankLoans}}$, the only difference being that for $\text{LOANREL}(\text{M})_m^{\text{PublicDebt}}$ the date of the look-back period is the

[14]Because we want to capture relationship strength and because of limited data on syndicate shares, we give full attribution to all lending banks.

[15]For this example $\text{LOANREL}(\text{M})^{\text{BankLoans}}_{\text{Citicorp}}$ and $\text{LOANREL}(\text{M})^{\text{BankLoans}}_{\text{NationsBank}}$ would be the same as those calculated for ABN-AMRO as both these banks were also lead banks on the two past loans on which ABN-AMRO was the lead bank.

date of a public issue of debt while that for $\text{LOANREL(M)}_m^{\text{BankLoans}}$ is the loan facility activation date.

Eccles and Crane (1988) argue that prior *investment banking* relationships have a significant impact on winning new investment banking business. Thus, we need to control for the existence of such prior investment banking relationships in identifying the independent effect of lending relationships. To better illustrate how we construct prior investment banking relationships, we use the example of a firm i that issues public debt and for which we wish to calculate the strength of prior investment banking relationships (as we describe in the next section, the process is the same for an equity issuer). There are two types of investment banking relationship that a bank m can have with issuer i. The first type is a *same-market relationship*, i.e., for any bank m and a debt issuer i, we look for previous debt underwriting relationships that m has had with i. The second type is a *cross-market relationship*, i.e., for a debt issuer i, we look to see if i has had a prior *equity* underwriting relationship with bank m. We describe the same-market relationship measures first. For any debt issuer i, we construct $\text{Lead-DEBTREL(M)}_m^{\text{PublicDebt}}$ for a bank m in the following way. We take the date of the public issue of debt as the starting point and look back over the preceding five years to determine whether bank m was the "lead underwriter" to any other public issues of debt by this issuer. The variable, $\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicDebt}}$, equals one if m was a lead underwriter on any previous debt issue. The variable, $\text{Lead-DEBTREL(Amount)}_m^{\text{PublicDebt}}$ for bank m reflects the ratio of public issues of debt underwritten by m (as a lead underwriter) relative to the total number of debt issues of issuer i over the last five years and, is calculated as

$$\text{Lead-DEBTREL(Amount)}_m^{\text{PublicDebt}} = \frac{\text{\$ Amount of } i\text{' s public debt underwritten by bank } m \text{ in last 5 years}}{\text{Total \$ amount of public debt issued by } i \text{ in last 5 years}}. \tag{3}$$

Similarly, we calculate $\text{Lead-DEBTREL(Number)}_m^{\text{PublicDebt}}$ for underwriter m and debt issuer i as

$$\text{Lead-DEBTREL(Number)}_m^{\text{PublicDebt}} = \frac{\text{Number of } i\text{' s public debt issues underwritten by bank } m \text{ in last 5 years}}{\text{Total number of public debt issued by } i \text{ in last 5 years}}. \tag{4}$$

While we focus on lead underwriters, we also construct expanded versions of the $\text{Lead-DEBTREL(M)}_m^{\text{PublicDebt}}$ variables, denoted by $\text{DEBTREL(M)}_m^{\text{PublicDebt}}$, in which we include both lead underwriting and co-manager roles on prior debt issues.

Next, we describe the cross-market relationship measures for a debt issuer i. We take the date of the public issue of debt as the starting point and look back over the preceding five years to determine whether bank m was the lead underwriter to any public issues of *equity* by this issuer. The variable $\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicDebt}}$ equals one if m was a lead underwriter on any previous *equity* issue. The calculations of $\text{Lead-EQUITYREL(Amount)}_m^{\text{PublicDebt}}$ and $\text{Lead-EQUITYREL(Number)}_m^{\text{PublicDebt}}$ are done in the same way. Again, we construct expanded versions of these cross-market relationship measures (denoted by $\text{EQUITYREL(M)}_m^{\text{PublicDebt}}$) by including both the lead underwriting and co-manager roles on previous equity issues. Fig. 2. illustrates the methodology for creating various relationship measures for the public debt underwriting market.

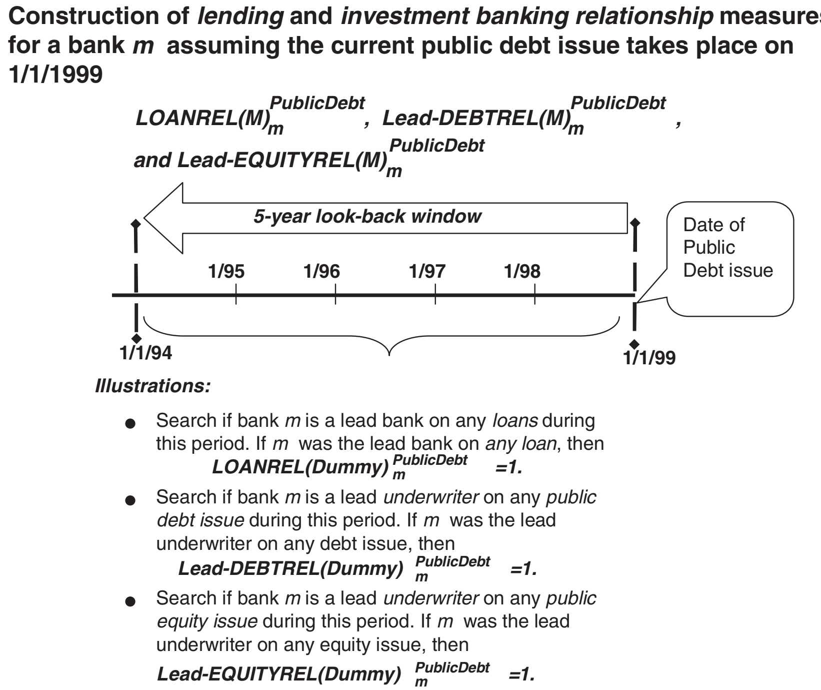

Fig. 2. Construction of relationship measures in public debt underwriting market.

3.1.3. Market for underwriting public equity

The process for constructing relationship measures for the public equity underwriting market is very similar to the one we describe in Section 3.1.2. We separate our equity issuers into IPO and SEO subsamples as the prior investment banking relationships are not meaningful for the IPO sample since the issuer is conducting its first sale of securities in the public market.[16] However, both IPO and SEO issuers can have prior *lending* relationships. We therefore estimate $\text{LOANREL(M)}_m^{\text{PublicEquity}}$ using the date of public issue of equity as the anchor point for the five year look-back window. For SEOs the measure for a same-market investment banking relationship (denoted by $\text{Lead-EQUITYREL(M)}_m^{\text{PublicEquity}}$) and a cross-market relationship (denoted by $\text{Lead-DEBTREL(M)}_m^{\text{PublicEquity}}$) are constructed in a similar fashion. Again we construct expanded versions of $\text{Lead-EQUITYREL(M)}_m^{\text{PublicEquity}}$ and $\text{Lead-DEBTREL(M)}_m^{\text{PublicEquity}}$ variables, denoted by $\text{EQUITYREL(M)}_m^{\text{PublicEquity}}$ and $\text{DEBTREL(M)}_m^{\text{PublicEquity}}$, in which we include both lead underwriting and co-manager roles on the prior equity and debt issues, respectively. Fig. 3 illustrates the construction methodology for all of these relationship measures.

Appendix B provides the correlations among the various relationship measures. Within each market our three relationship measures (Dummy, Number, and Amount)

[16]While an IPO firm cannot have prior equity underwriting relationships, it may still have prior debt underwriting relationships. However, our data show that firms rarely access the debt market if they do not already have publicly traded equity. We therefore assume that prior investment banking relationships are not well defined for IPO issuers.

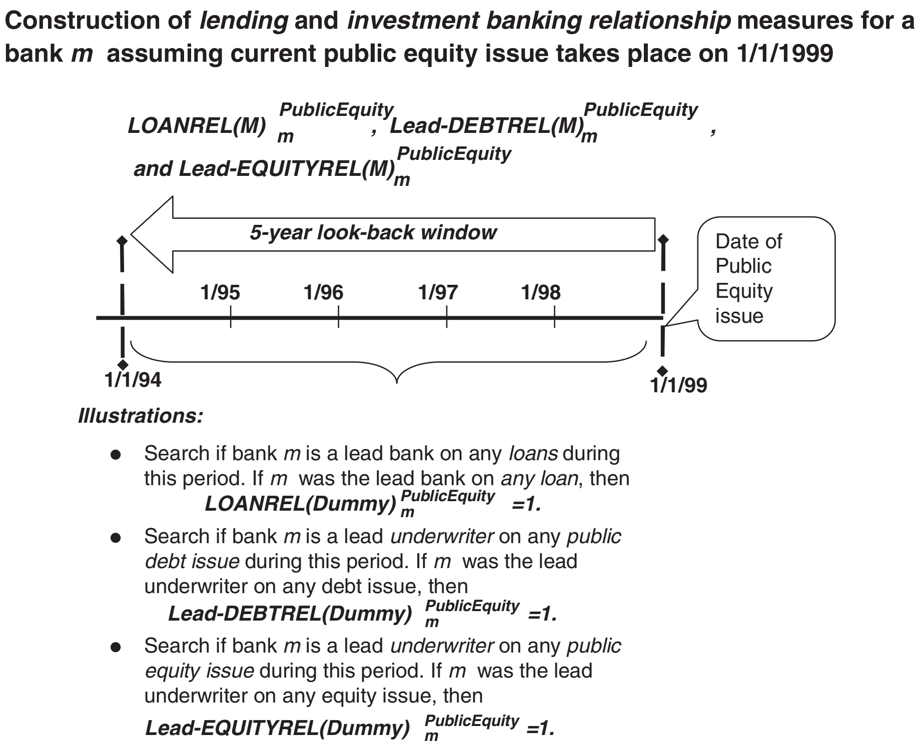

Fig. 3. Construction of relationship measures in public equity underwriting market.

demonstrate a strong positive correlation. Across different markets, however, the relationship measure in one market does not appear to be strongly correlated with relationship measures in other markets.

Table 1 provides descriptive statistics for our data and segregates relationship and non-relationship loans (i.e., loans from a bank that did not have a past relationship with the borrower in the previous five years). Panel A provides the calendar-time distribution of the loan sample. The low number of observations in the early years is driven by two factors. First, LPC database coverage is better in more recent years. Second, our methodology for constructing relationship measures ensures that the very first loan reported for any borrower is excluded, otherwise we would not have a historical starting point with which to classify a loan as either a relationship or a non-relationship loan. To control for this time trend in the sample we include a calendar-year dummy variable in our tests.

We also segregate the samples of public debt issuers and public equity issuers on the basis of prior lending relationships. Panels B and C of Table 1 provide the calendar-time distribution for these issuers.

3.2. Data on lender (bank) characteristics

H1, H2, and H3 hypothesize that the higher volume benefits to lenders manifest as the ability to supply future loans and investment banking services to borrowers. We measure

Table 1

Calendar-time distribution of loan facilities, public debt issues and public equity issues

Panel A below provides the calendar-time distribution for the sample of loan facilities, broken in to loans for which none of the lead banks on the current facility had a prior lead lending relationship in the past five years (LOANREL(Dummy)$^{\text{BankLoans}} = 0$) and those for which at least one of the lead banks on the current facility was also the lead lender in the past five years (LOANREL(Dummy)$^{\text{BankLoans}} = 1$). Panel B provides similar data for public debt issues segregated by LOANREL(Dummy)$^{\text{PublicDebt}}$ (i.e., if one of the lead underwriters had a lead lending relationship in the five years prior to the current debt issue). Panel C provides similar data for public equity issues segregated by LOANREL(Dummy)$^{\text{PublicEquity}}$ (i.e., if one of the lead underwriters had a lead lending relationship in the five years prior to the current equity issue).

Year of loan sanction	No relationship LOANREL(Dummy)$^{\text{BankLoans}} = 0$	Relationship LOANREL(Dummy)$^{\text{BankLoans}} = 1$	Total
Panel A: Calendar time distribution of loans			
1986	1	2	3
1987	67	33	100
1988	222	174	396
1989	237	240	477
1990	212	329	541
1991	222	366	588
1992	373	491	864
1993	404	714	1,118
1994	398	961	1,359
1995	311	1,070	1,381
1996	488	1,207	1,695
1997	543	1,551	2,094
1998	523	1,384	1,907
1999	434	1,293	1,727
2000	348	1,530	1,878
2001Q1	106	464	570
Total	4,889	11,809	16,698

Year of public debt issue	No relationship LOANREL(Dummy)$^{\text{PublicDebt}} = 0$	Relationship LOANREL(Dummy)$^{\text{PublicDebt}} = 1$	Total
Panel B: Calendar-time distribution of public debt issues			
1989	48	1	49
1990	71	1	72
1991	98	14	112
1992	197	44	241
1993	187	72	259
1994	119	64	183
1995	182	109	291
1996	240	171	411
1997	349	191	540
1998	341	283	624
1999	139	248	387
2000	129	178	307
2001	92	259	351
Total	2,192	1,635	3,827

Table 1 (*continued*)

Year of public equity issue	No relationship $\text{LOANREL(Dummy)}^{\text{PublicEquity}} = 0$	Relationship $\text{LOANREL(Dummy)}^{\text{PublicEquity}} = 1$	Total
Panel C: Calendar-time distribution of public equity issues			
1989	1	0	1
1990	1	0	1
1991	24	0	24
1992	45	2	47
1993	70	13	83
1994	43	10	53
1995	58	10	68
1996	147	30	177
1997	154	31	185
1998	125	47	172
1999	128	80	208
2000	94	68	162
2001	85	64	149
Total	975	355	1,330

relationship benefits to the lender in three complementary ways. In particular, a strong relationship implies a higher likelihood of providing future loans to relationship borrowers, a higher probability of winning future debt underwriting from relationship borrowers, and a higher probability of winning future equity underwriting business from relationship borrowers.

However, the choice of lender (see H1) is also be affected by the potential lender's market share or reputation (all else being equal, a top-ranked lender is more likely to be chosen compared to a lower-ranked lender) and the loan's characteristics. Similarly, the probability of winning investment banking business (see H3) would also depend on the lender's reputation in the relevant investment banking product markets.[17] Thus, we need data on lender characteristics. We use the LPC and SDC databases to gather these data.

For the loan market, a key issue is the identification of the "lead" bank (or banks) for a particular loan facility. While the LPC database contains a field that describes the lender's role, it does not have a uniform and consistent methodology to classify which bank is the lead bank. Rather, it includes a number of descriptions such as "arranger," " administrative agent," "agent," or "lead manager" that roughly correspond to the lead bank status of the lender. To ensure that we do not mislabel a lead bank we follow a simple rule. Any bank(s) that is (are) *not* described as a "participant" is (are) treated as a lead bank.[18] This approach ensures that we do not include banks that play a limited information production role. Indeed, Madan et al. (1999) define participant as "the lowest

[17]Krigman et al. (2001), show that issuers often switch underwriters to graduate to a more reputable underwriter.

[18]For example, Walt Disney Co. contracted a $ 1 billion facility on December 19, 1997. Citicorp and Bank of America with the largest share are listed as Administrative Agents, while all others are listed as Participants. We classify Citicorp and Bank of America as the lead banks on this facility.

title given to a bank in a syndication" and describe its role as little more than taking the allocated share of the loan.

Because the borrower's choice of lender bank should also depend on the reputation of the lender, we also need to control for this effect. We measure the reputation of a lender by calculating the market share of that lender, defined as the share of a bank in the loans reported by LPC database in a particular year (market share is a commonly used proxy for reputation; see, e.g., Megginson and Weiss, 1991). Specifically, we calculate market share in the following way: if a bank is a sole lead lender, it gets 100% credit for the loan, and if there are M lead banks, each gets $(1/M)$th share of the loan. As we note earlier the LPC database rarely gives the precise shares of lead and other banks in a loan syndication. To illustrate by an example, if bank m is the sole lead bank on a loan of \$100 Million, the entire loan amount would be used in calculating its market share, whereas if bank m was one of four lead banks, only \$25 Million ((1/4)th of \$100 Million) would be included in its market share calculation.[19] We calculate the market share of bank m in any year t as denoted by $(\text{LOAN MKT SHARE})_{mt}$ as

$$(\text{LOAN MKT SHARE})_{mt} = \frac{(\text{Loan Amount})_{mt}}{\sum_{i=1}^{N} (\text{Loan Amount})_{it}}, \tag{5}$$

where $(\text{Loan Amount})_{mt}$ is the dollar amount of loans in year t for which the bank m was the lead bank and N is the total number of borrowers in the LPC database. Thus, while the numerator captures the lending volume of bank m in year t, the denominator is the "total amount of loans" raised (by all borrowers) in year t. Panel A of Table 2 provides a list of the top 20 lenders over our entire sample period, ranked by their market share. This table shows that while no single bank dominates the sample, the top 20 banks still account for nearly 70% of all loans.

To test H3, we focus on the underwriting business in two distinct markets: issues of public debt and issues of public equity. While debt underwriting is related to commercial banks' historical corporate lending business, e.g., because loan and bond pay-off structures are similar, equity underwriting is a relatively new market for U.S. commercial banks. We use the SDC new issues database to obtain all the public issues of debt and public issues of equity by our sample borrowers. This results in 5,203 distinct issues of debt by 945 firms and 5,219 issues of equity by 3,129 firms. Next we verify whether relationship lenders of these issuers were eligible to underwrite debt (equity) issues at the date of debt (equity) issue.[20] If, at the date of issue, none of the relationship lenders are eligible to underwrite that issue, we exclude that issue from our sample. Our final sample consists of 3,923 distinct issues of debt by 721 firms and 1,358 issues of equity by 895 firms. For this sample we collect data on the amount raised from the debt (equity) issue, the identity of the lead underwriter(s), and the identity of the co-manager(s) of the issue from the SDC database.

[19]For example, Bank of Boston was the sole lender on a June 1997, \$11.9 million facility to GenRad Inc. and thus gets 100% credit for this deal. In contrast, it extended a \$350 million line of credit to Boston Scientific Corp on June 10, 1996 along with Chase Manhattan Bank and Lehman Brothers; for this loan, it gets 1/3rd of the credit in computing market share.

[20]At any given date t, a commercial bank is assumed to be eligible to underwrite a particular class of security if it has underwritten (either as lead or as co-manager) at least one issue of that class of securities in any of the years before t. We could have also used the regulatory approval date as the start of eligibility but in some cases this date is not available. The requirement of having underwritten at least one deal is thus more conservative and ensures that only active participants are included.

Table 2
Market share ranking of major lenders, debt underwriters, and equity underwriters

Panel A describes the top 20 lenders for sample period based on data from the LPC dealscan database. Panel B and Panel C describe the top 20 debt and equity underwriters as reported by the SDC new issues database.

Rank	Bank	Number of Deals	Market share	Amount ($ Million)
Panel A: *Top* 20 *lenders*				
1	CITICORP	2,622	9.72%	429,162
2	BANK-AMERICA	4,257	9.44%	416,913
3	CHASE	3,102	7.84%	346,470
4	J-P-MORGAN	1,347	5.76%	254,320
5	CHEMICAL	1,457	5.09%	224,738
6	NATIONS-BANK	2,660	4.54%	200,338
7	FIRST-CHICAGO	1,298	3.04%	134,310
8	BANKERS-TRUST	1,217	2.72%	120,261
9	BANK-NOVA-SCOTIA	1,594	2.58%	113,954
10	BANK-ONE	1,477	2.31%	101,901
11	BANK-NEW-YORK	1,300	2.14%	94,328
12	FIRST-UNION	1,556	2.06%	90,885
13	ABN-AMRO	1,054	1.85%	81,868
14	DEUTSCHE-BANK	767	1.75%	77,314
15	TORONTO-DOMINION-BANK	886	1.66%	73,362
16	CIBC	1,059	1.59%	70,022
17	BANK-BOSTON	1,296	1.44%	63,541
18	CREDIT-LYONNAIS	989	1.38%	60,857
19	SOC-GEN	665	1.20%	53,208
20	WACHOVIA	671	1.20%	53,207
	Overall	24,174	69.29%	4,417,304
Panel B: *Top* 20 *debt underwriters*				
1	GOLDMAN-SACHS	640	16.03%	119,331
2	MERRILL	634	14.56%	108,386
3	MORGAN-STANLEY	498	11.38%	84,737
4	CITICORP	319	9.95%	74,119
5	CSFB	371	9.49%	70,660
6	LEHMAN	339	8.81%	65,588
7	SALOMON	310	5.63%	41,895
8	J-P-MORGAN	303	5.28%	39,341
9	BANK-AMERICA	159	4.06%	30,236
10	BEAR-STERNS	109	3.00%	22,309
11	CHASE	132	2.44%	18,167
12	DLJ	89	2.09%	15,544
13	DEUTSCHE-BANK	45	1.04%	7,732
14	UNION-BANK-SWITZERLAND	81	0.97%	7,257
15	SMITH-BARNEY	80	0.89%	6,629
16	BANKERS-TRUST	20	0.46%	3,427
17	NATIONS-BANK	51	0.38%	2,820
18	BANK-ONE	28	0.38%	2,803
19	DILLON-READ	19	0.34%	2,507
20	PAINE-WEBBER	24	0.32%	2,354
	Overall		97.48%	744,643
Panel C: *Top* 20 *equity underwriters*				
1	GOLDMAN-SACHS	200	17.05%	47,033
2	MERRILL	236	15.61%	43,082

Table 2 (*continued*)

Rank	Bank	Number of Deals	Market share	Amount ($ Million)
3	MORGAN-STANLEY	180	15.29%	42,195
4	CSFB	131	9.11%	25,129
5	DLJ	98	5.89%	16,247
6	CITICORP	74	5.86%	16,167
7	J-P-MORGAN	40	5.58%	15,397
8	LEHMAN	88	5.09%	14,051
9	SALOMON	76	4.82%	13,301
10	BEAR-STERNS	57	2.95%	8,148
11	BANK-AMERICA	24	1.43%	3,948
12	SMITH-BARNEY	42	1.41%	3,882
13	BANKERS-TRUST	34	1.32%	3,636
14	ALEX-BROWN	21	1.10%	3,044
15	DEUTSCHE-BANK	26	0.97%	2,665
16	UNION-BANK-SWITZERLAND	22	0.65%	1,802
17	MONTGOMERY	19	0.64%	1,773
18	PAINE-WEBBER	26	0.52%	1,438
19	PRUDENTIAL	19	0.42%	1,169
20	ROBERTSON-STEPHENS	9	0.28%	770
	Overall		95.99%	275,927

The sample construction methodology we employ to test H3 ensures that only those debt (equity) issuers who *could* have chosen their relationship lender as an underwriter are included. For example, if an issuer had borrowed exclusively from banks that did not have regulatory approval to underwrite securities then it would not be in our sample. This allows us to test the association between lending relationship and investment banking more precisely. However, this also implies that in the early part of our sample period when fewer issuers meet this criteria (since only a limited number of lenders were eligible to underwrite debt and/or equity issues) our sample size is relatively smaller. By the mid-1990s, a larger number of lenders had received regulatory approval to do such investment banking business and our sample size is relatively larger (Table 1, Panels B and C). We control for this trend by including individual year dummy variables in our tests.

The probability of winning underwriting business in any particular market depends also on the reputation of various players in that market. Again, we use the market share of major underwriters as the proxy for reputation. While we estimate the loan market share for each bank as in Eq. (5), we use the SDC database's league tables to obtain data on the market share for major underwriters. Panel B and Panel C of Table 2 provide the list of top 20 underwriters in debt underwriting and equity underwriting, respectively, and their relative market share. The debt and equity underwriting markets appear to be fairly concentrated, as the top 20 institutions account for over 95% of the market.

Finally, in order to control for physical proximity between a bank and a lender (see discussion in Section 3.1), we construct LOCATION, which is a dummy variable that equals one if both the bank and the borrower have their respective head offices in the same state and zero otherwise. For lenders the head office location is identified by searching Hoover's online company history database and for borrowers the head office state is identified by searching COMPUSTAT. For non-U.S. banks we search for the U.S. headquarters. For a few Japanese banks we are not able to ascertain the exact location of U.S. headquarters; for these, we assume that New York is the U.S. head office (we confirm that all of these banks do have a New York office). For banks that underwent mergers we use the historical head office for the pre-merger period and the head office of the new merged entity in the post-merger period.

3.3. Data on characteristics of loan facilities, debt issues and equity issues

We also need to control for various loan characteristics such as maturity, security, and type of facility. To generate data on loan terms we employ the LPC database. LPC provides data on a facility-level as well as deal-level basis. A given deal may correspond to multiple facilities (i.e., multiple loan contracts) of different types of loans to the same firm by one or more banks. Examples of different types of facilities include term loans, lines of credit, revolvers, etc. In this study, we use each facility as the unit of observation. Panel A of Table 3 provides summary statistics on key loan facility terms.

The key characteristics for the debt and the equity issues are proceeds raised from the issue, date of issuance and identity of lead underwriters and co-managers. Our primary source for these data items, is the SDC new issues database. Panel B of Table 3 reports the summary statistics for debt issues. We segregate the public equity issues into IPOs and SEOs as the fee structure across these two issue classes is different. Panel C of Table 3 provides the summary statistics for equity issues.

3.4. Data on borrower characteristics

Existing theories argue that informational asymmetries between a borrower and potential debt providers are addressed more effectively by relationship lending than by arms-length financing. Because borrowers that suffer from greater information asymmetries should gain more from relationship lending, such borrowers are expected to borrow from their relationship lender more frequently (see H2). We use different proxies for information opacity of a borrower such as borrower size, the loan's credit rating, and the tangibility of borrower's assets. COMPUSTAT is our primary data source for borrower-related variables, since the LPC database does not provide a borrower Cusip that can be used as an identifier to match the borrower to other data sets such as COMPUSTAT or CRSP. We therefore manually match the LPC companies with the merged CRSP/COMPUSTAT database using the name of the company in the LPC database. The matching procedure is conservative in that we assign a match only when we are sure that the company is the same in the two databases. Using this procedure, we obtain a set of 6,322 borrowers in the LPC database for which we can obtain the Cusip of the company from the COMPUSTAT database. Since a number of borrowers merged or were acquired by other borrowers over our sample period, we take this M&A activity into account in constructing our relationship measures. If the post-merger/post-acquisition company retains the Cusip of one of the predecessor firms, we assume that the relationships of the Cusip-retaining firm are inherited by the post-merger/post-acquisition entity while the relationships of the other firm are assumed to be not inherited. Thus, to the extent a post-merger entity also retains the relationships of the target, we underestimate the strength of the relationship variable. If the merger creates an entity with a new Cusip we follow

Table 3
Summary statistics for key loan, debt issue, and equity issue characteristics

The table below provides summary statistics of various loan and borrower characteristics. Panel A reports these for the loan facilities sample. Panel B and Panel C report these for debt issue and equity issue samples respectively. AISD is the "All In Spread-Drawn," which is the all-inclusive cost of a drawn loan to the borrower. This equals the coupon spread over LIBOR on the drawn amount plus the annual fee and is reported in basis points. Loans per borrower is the number of loan facilities for any particular borrower that are included in the LPC Dealscan database. Number of lead banks per loan facility is also from LPC Dealscan database. Number of relationship lead banks are those lead banks that have extended at least one loan to a particular borrower in the five-year period immediately preceding the current loan facility. Loan Facility Size is the dollar amount of the loan facility in millions. Maturity is length in months between facility activation date and maturity date. Syndicate, Secured, and Investment Grade are percent of facility that have the stated attribute. To be classified as Investment Grade the loan has to be rated BBB or above by S&P. Proceeds is the amount of proceeds in USD millions from the debt or the equity issue. Underwriting fee (i.e., gross spread) is the fee charged divided by the proceeds and is reported in basis points. All data are winsorized at the 1st and 99th percentiles.

Variable	*N*	Mean	Std. Dev.	Min	25th Pctile	Median	75th Pctile	Max
Panel A: Loan facilities sample								
AISD	21,843	211.07	129.64	17.5	100.00	200.00	300.00	580.00
Number of loans per borrower	5,687	4.4	4.0	1.0	2.0	3.0	6.0	21.0
Number of lead banks per loan	24,174	2.2	2.8	1.0	1.0	1.0	2.0	18.0
Number of relationship lead banks per loan	15,937	1.4	2.0	0.0	0.0	1.0	1.0	12.0
Loan facility size	25,476	161.51	312.26	0.50	10.78	50.00	151.70	2000.00
Maturity	22,667	44.42	27.51	3.00	18.00	37.00	60.00	120.00
Secured	16,016	0.82	0.38	0.0	1.0	1.0	1.0	1.0
Investment grade	8,484	0.48	0.50	0.0	0.0	0.0	1.0	1.0
Syndicate	25,470	0.77	0.42	0.0	1.0	1.0	1.0	1.0
Panel B: Debt issues sample								
Proceeds	3,923	189.81	249.11	0.20	33.0	124.8	249.3	3237.3
Fee (gross spread)	3,070	88.80	72.33	0.10	55.00	65.00	87.50	465.00
Panel C: Equity issues sample								
Initial public offerings (IPOs):								
Proceeds	283	200.12	536.04	10.80	51.00	96.00	149.80	7322.40
Fee (gross spread)	283	650.96	73.96	250.00	600.00	700.00	700.00	750.00
Seasoned equity offerings (SEOs):								
Proceeds	1,074	204.13	277.05	1.50	63.00	116.50	220.00	2733.70
Fee (gross spread)	1,012	426.73	114.80	24.80	347.55	448.80	500.75	812.50

a conservative approach and consider such an entity as having had no prior relationships. For subsidiaries we follow a similar methodology—if subsidiaries have the same Cusip as the parent company, we assume that subsidiaries have the same relationships as that of the parent company.

We use COMPUSTAT to extract data on accounting variables for the given company. We also extract the primary SIC code for the borrowers from COMPUSTAT and exclude all financial services firms (SIC codes between 6000 and 6999). To ensure that we only use accounting information that is publicly available at the time of a loan, we employ the following procedure: for a loan made in calender year t, we use fiscal year t data only if the loan activation month is at least six months after the fiscal year-ending month. Otherwise, we use fiscal year $t-1$ data.[21] The six-month minimum gap between fiscal year-end and the loan activation date is conservative given the SEC requirement that accounting data be made available within 90 days of the fiscal year-end. However, compliance with this requirement is patchy. Fama and French (1992) state that "on average 19.8% do not comply (with this requirement)."[22]

4. Methodology and empirical results

In this section we describe the tests we employ to estimate the hypothesized (higher volume) benefits of relationships to lenders (Hypotheses H1, H2 and H3).

4.1. Tests of Hypothesis 1

As we discuss in Section 2, existing theories of relationship lending predict that strong relationships should be associated with a lower cost of information production over time, provided this information is proprietary and reusable. A testable implication of these theories is that a relationship lender is more likely to secure the future lending business of its borrower. We formalize this implication in our Hypothesis 1. To test this, for each loan facility we focus on any bank *m's* likelihood of winning the loan business of borrower i at time t.

While the number of lenders that appear in our sample is quite large (see Table 2), a handful of banks account for the bulk of lending. To economize on the size of the data set but still retain most of the large transactions, we choose the following approach. In each year, we keep only those transactions for which one of the lead banks was ranked in the top 40 banks by market share in the prior year. That is, we reduce our sample to those transactions for which the lead bank(s) was among the top 40 in the previous year. This allows us to retain 73% of our original sample as the top 40 banks provide the bulk of all loans.[23] For each loan we create a choice set of 40 potential lenders, thereby creating 40 loan-bank pairs.[24] Since each loan facility generates a cluster of up to 40 loan-bank pair observations, our data set consists of over 400,000 loan-bank pairs, which is the unit of

[21]The following examples illustrate this methodology. Walmart contracted a $1.1 billion loan on October 1, 1999. Walmart's fiscal year ends on January 31 and thus the October loan is more than six months after the month of the fiscal year-end closing. In this case we use the accounting data for fiscal year ending January 31, 1999. On the other hand, Walmart took a $1.25 billion loan on May 29, 1995. Since the May loan was less than six months after the fiscal year-end closing, we use accounting data for the previous fiscal year, i.e., for the year ending January 31, 1994.

[22]Even for those firms that do comply, a large proportion file on the last allowed day. Alford et al. (1992) report that more than 40% of firms with a December fiscal year-end file on March 31, thus, the data becomes available only in April.

[23]Even for the 27% of the original sample that we do not use, a large fraction (20% of the original) is unusable regardless of this requirement because these loans were made in the early years of our sample period and we do not have a long enough history to allow codification of their relationship variables. Thus, we only lose 7% of our sample to the requirement that it must be led by a top 40 bank.

[24]Drucker and Puri (2005) and Ljungqvist et al. (2006) use a similar approach to implement their underwriter selection models.

observation in the following logit model:[25]

$$(\text{CHOSEN})_m = \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m + \beta_3(\text{LOCATION})_m + \sum \beta_k(\text{CONTROL})_k. \quad (6)$$

The variables are

- $(\text{CHOSEN})_m$: For each loan facility i, we create a dummy variable $(\text{CHOSEN})_m$, which takes the value of one if a bank m was retained as the lead bank for that loan transaction and zero otherwise.[26]
- $\text{LOANREL(M)}_m^{\text{BankLoans}}$: This is the measure of relationship strength constructed by looking back over five years from the date of the loan facility activation and searching whether the bank had a prior lending relationship with this borrower. As we discuss in Section 3.1.1 and Appendix A, we construct three different specifications for this variable to measure the strength of relationship for each of the 40 banks in each loan-bank pair.
- $(\text{LOAN MKT SHARE})_m$: To estimate the probability of winning the loan business by a particular bank, we need to control for the reputation of that bank in the loan market. We use its market share as a proxy for reputation. If the loan facility was activated in the year t, $(\text{LOAN MKT SHARE})_m$ is the market share of bank m in the prior year, $t-1$, calculated as in Eq. (5).
- $(\text{LOCATION})_m$: This variable is a dummy variable that equals one if bank m and the borrower in a loan-bank pair both have their head offices in the same state and zero otherwise. We include this variable to control for the fact that a borrower may be more likely to give repeat business to a particular bank due to its physical proximity. Since our relationship measure is based on existence and intensity of past interactions, it may be biased by a non-relationship factor such as the proximity of a borrower to a particular lender. Including the LOCATION variable controls for the effect of physical proximity between a borrower and a lender and partially mitigates this possible bias in our relationship measures.
- $(\text{CONTROL})_k$: We control for borrower industry (one-digit SIC codes), the stated purpose of the loan facility, and the year of the loan facility activation with dummy variables.

A large number of banking mergers and acquisitions took place during our sample period. We assume that in the case of acquisitions the customer relationships of a bank being acquired are inherited by the acquiring bank.[27] For mergers, the relationships of the merger partners are assumed to be inherited by the new post-merger entity. We also adjust the market shares to reflect the M&A activity. Appendix C describes these issues in more detail and also provides an illustrative example.

[25] Since observations within each cluster may not be independent, we estimate cluster-corrected standard errors using the approach suggested by Williams (2000).

[26] Thus, if a bank was the sole lead bank, only the loan-bank pair for this bank would have CHOSEN equal to one and for the other 39, CHOSEN would be zero. If the loan facility was led by multiple banks, than all the loan-bank pairs corresponding to these banks would have CHOSEN equal one while it would be zero for the rest.

[27] This is one of the objectives of bank mergers and acquisitions.

Table 4

Impact of lending relationships on probability of getting future lending business

Panel A of this table provides the logit regression estimates of the following equation:

$$(\text{CHOSEN})_m = \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m + \beta_3(\text{LOCATION})_m + \sum \beta_k(\text{CONTROL}_k).$$

For each loan facility i we create a choice set of 40 potential lenders, which creates 40 loan-bank pairs. The top 40 commercial banks in the previous year form the consideration set for each firm in the current year. The dependent variable, $(\text{CHOSEN})_m$, takes a value of one if a bank m was retained as the lead bank for that loan transaction and zero otherwise. We use three proxies for relationship: $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$ (equals one if there is a relationship with the bank m in the last five years before the current loan and zero otherwise), $\text{LOANREL(Number)}_m^{\text{BankLoans}}$ (ratio of the number of loans with bank m to the total number of loans of the firm in the last five years before the current loan), $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$ (ratio of the dollar value of loans with bank m to the total dollar value of loans of the firm in the last five years before the current loan). $(\text{LOAN MKT SHARE})_m$ is the share of total lending by bank m in the year prior to the year of loan facility i. $(\text{LOCATION})_m$ is a dummy variable that equals one if both bank m and the borrower have their respective head offices in the same state and zero otherwise. In the panel at the bottom we illustrate the economic impact that various variables have on the probability of a bank being chosen as the lead lender. We use the specification estimated in column 1 to estimate the probability of a bank being chosen as the lead lender if all variables except the variable being examined are held equal to their mean. We then estimate the predicted probability as the variable being examined goes from zero to one (except for LOAN MKT SHARE, which is varied from 1% market share (approximately lowest market share of a top 20 lender) to 10% market share (approximately highest market share of a top 20 lender)). For example, the first row reports the predicted probability of a bank being chosen as a lead lender if it did not have a past lending relationship with a borrower ($\text{LOANREL(Dummy)}^{\text{BankLoans}} = 0$) and if all other variables are assumed equal to their means. The next row reports the predicted probability of being chosen if the bank did have a past lending relationship ($\text{LOANREL(Dummy)}^{\text{BankLoans}} = 1$), again holding all else constant at their means. The third row reports the increase in the predicted probability of being chosen as the lead lender for a relationship lender compared to a lender with no prior relationship. Panel B reports the results for a number of alternative specifications of the model estimated in Panel A. Column 1 repeats the analysis in Panel A but uses individual loan deals as the unit of analysis instead of loan facilities. Column 2 provides a control for loan facilities that are renewals of existing facilities-RENEWAL equals one if LPC classifies a facility as a refinancing and zero otherwise. Column 3 uses an alternative measure of lending relationship, MOST RECENT LENDER, which equals one if a bank m was the lead bank on the most recent loan facility preceding the current facility and zero otherwise. Column 4 uses the market share of banks in the borrower's industry, INDUSTRY LOAN MKT SHARE_m, which is the share of loans made to that borrower's industry by bank m in the year preceding the current loan. Finally in Column 5 we control for any pricing effects that could affect the lender selection by imputing the loan spreads that banks that were not chosen may have charged had they been selected. This is denoted by IMPUTED LOAN SPREAD and is estimated using the Expectation-Maximization (EM) algorithm. Numbers in parentheses are standard errors corrected for heteroskedasticity and clustering (*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level).

	(1)	(2)	(3)
Panel A			
Const.	−3.53***	−2.94***	−3.32***
	(.41)	(0.4)	(0.42)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	3.27***		
	(0.03)		
$\text{LOANREL(Number)}_m^{\text{BankLoans}}$		4.59***	
		(0.04)	
$\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			4.23***
			(0.04)
$(\text{LOAN MKT SHARE})_m$	12.23***	11.37***	11.32***
	(0.21)	(0.21)	(0.22)
$(\text{LOCATION})_m$	0.38***	0.44***	0.39***
	(0.05)	(0.05)	(0.05)

Table 4 (*continued*)

	(1)	(2)	(3)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes
Number of observations	416,239	416,239	416,239
Pseudo R^2	0.32	0.31	0.32

Impact of past lending relationships on the probability of being chosen as the lead lender using the column 1 *specification*

	Probability of being chosen (%)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$	2.73
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$	42.46
Increase in probability	39.73
$\text{(LOAN MKT SHARE)}_m = 1\%$	3.16
$\text{(LOAN MKT SHARE)}_m = 10\%$	8.93
Increase in probability	5.77
$\text{(LOCATION)}_m = 0$	3.54
$\text{(LOCATION)}_m = 1$	5.08
Increase in probability	1.54

	(1)	(2)	(3)	(4)	(5)
Panel B					
Const.	−4.36***	−3.52***	−3.40***	−3.28***	−2.49***
	(0.39)	(0.41)	(0.43)	(0.65)	(0.41)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	3.27***	3.23***		3.16***	3.05***
	(0.03)	(0.03)		(0.03)	(0.03)
RENEWAL		−0.10*			
		(0.06)			
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} \times \text{RENEWAL}$		0.31***			
		(.08)			
$\text{(MOST RECENT LENDER)}_m$			3.41***		
			(0.03)		
$\text{(LOAN MKT SHARE)}_m$	12.56***	12.25***	13.03***		12.92***
	(0.25)	(0.21)	(0.21)		(0.25)
$\text{(INDUSTRY LOAN MKT SHARE)}_m$				5.93***	
				(0.14)	
(LOCATION)_m	0.37***	0.38***	0.52***	0.31***	0.39***
	(.06)	(0.05)	(0.05)	(0.05)	(0.06)
$\text{(IMPUTED LOAN SPREAD)}_m$					−0.001***
					(.0003)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	288,500	416,239	413,300	230,088	249,440
PseudoR^2	0.32	0.32	0.30	0.31	0.30

Impact of past lending relationships on the probability of being chosen as the lead lender using the column 1 *specification* (*Deal basis*)

	Probability of being chosen (%)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$	2.51
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$	40.52
Increase in probability	38.01

Panel A of Table 4 reports the results for logit tests of H1. The three columns report the results for different proxies of lending relationship. The coefficient for all specifications of past lending relationships is positive and significant at the 1% level. The panel at the bottom of the table illustrates the economic significance of past lending relationships on the probability of being chosen to provide future loans. We use the model estimated in column (1), where the past lending relationship is captured simply by the existence or lack of prior lending by the same bank in the last five years to calculate these probabilities.[28] The predicted probability of a bank being chosen as the lender for a loan facility if it did not have a past lending relationship (i.e., $\text{LOANREL(Dummy)}^{\text{BankLoans}} = 0$), holding all other variables constant at their respective means, is 2.73% (bottom panel, first row). When we recalculate the predicted probability keeping all else the same but changing $\text{LOANREL(Dummy)}^{\text{BankLoans}} = 1$, the predicted probability of being chosen for a relationship lender rises to 42.46%.[29] Thus, holding all else equal, a bank's probability of being chosen to provide a loan is increased by 39.73% if it had a past lending relationship in the prior five years. These results are equally strong if we use continuous measures (specifications in columns 2 and 3) that take into account both the existence and intensity of past lending relationships. For example, changing the $\text{LOANREL(Number)}^{\text{BankLoans}}$ measure from its minimum value of zero to its maximum value of one increases the probability of being chosen from 3% to 77%, while for $\text{LOANREL(Amount)}^{\text{BankLoans}}$ this probability is predicted to increase from 3% to 69%.[30]

It is important to highlight that other variables have a predicted and significant impact on the probability of a bank being retained to provide future loans but their economic impact is smaller compared to the existence of prior lending relationships. As expected, past market share is strongly associated with the ability to win a particular loan mandate. The coefficients for LOAN MKT SHARE and LOCATION are positive and significant at the 1% level across all specifications. The bottom panel reports the economic interpretation of these results. As reported in Table 2, the top-ranked lender (Citicorp) had approximately a 10% share of the loan market over our sample period, while the 20th-ranked bank (Wachovia) had approximately a 1% market share. To illustrate the impact of a lender's reputation on its probability of being retained, we calculate predicted probability by first keeping LOAN MKT SHARE equal to 1% and then changing it to 10%, while all other variables are kept constant at their respective means. The effect of this is to increase the probability of being chosen from 3% to 9%. Similar calculations show that the probability of being chosen for a lender that does not have its head office in the same state as the borrower's head office (LOCATION = 0) is 3.54% and increases to 5.08% if both lender and borrower are located in the same state (LOCATION = 1).

[28]To test the power of our specification, we estimate the predicted probabilities for each loan-bank pair observation by fitting our model to the data. If this predicted probability is greater than 0.5, we assign the bank to the chosen group and if it is less than 0.5 we assign it to the not-chosen group. Our model predicts the correct outcome for 93.80% of the observations.

[29]An alternative approach is to interpret the coefficients in terms of an increase in odds ratio. The logit model for a binary dependent variable Y can be written in terms of the odds that Y would equal 1 as $\frac{Prob(Y=1)}{1-Prob(Y=1)} = e^{(\beta' x)}$. Thus, the odds of being chosen as a lender as a function of prior lending relationship is $\frac{Prob((CHOSEN)_m=1)}{1-Prob((CHOSEN)_m=1)} = e^{(\beta_0+\beta_1(\text{LOANREL(Dummy)}^{\text{BankLoans}})+\sum \beta_{\text{other}}(\text{other variables}))}$. The coefficient of 3.27 for $\text{LOANREL(Dummy)}^{\text{BankLoans}}$ implies that the odds of being chosen as the lender is $e^{3.27}$, or approximately 26 times higher if a lender had a prior relationship compared to if it did not have a prior relationship.

[30]These results are available from the authors on request.

Again, while significant, this is a much smaller economic effect compared to the one associated with having (or not having) a past lending relationship. These results suggest that establishing a lending relationship with a borrower confers significant economic benefits upon a lender in terms of a higher probability of securing the future lending business of that borrower.

4.2. *Robustness checks of Hypothesis 1 and other issues*

4.2.1. *Facilities vs. deals*

In Panel B of Table 4 we report results for alternative specifications of lender choice model in Eq. (6) so as to verify the robustness of the results reported above to an alternative definition of "loan business."[31] Specifically, we conduct our analysis on an individual loan facility basis, i.e., we treat each loan facility, including those that are part of the same deal, as new loan business. While this treatment is likely to have a limited effect, since over 70% of the deals in our sample are single loan facility deals, it can still inflate our relationship results since a lender gets multiple "credits" for winning the mandate for a deal that consists of multiple facilities. To examine this issue, we hand-match each loan facility to the original deal and re estimate our relationship measures on a deal-by-deal basis. We report the results in column 1 of Panel B, Table 4. The coefficient for the LOANREL(Dummy)$^{\text{BankLoans}}$ is essentially unchanged at 3.27 compared to the original facility-basis specification and is significant at the 1% level. The economic significance continues to be high as well: on a deal-by-deal basis, a bank with a prior lending relationship has a 40.52% probability of getting a future loan deal compared to 2.51% for a bank that lacks such past relationships. The results for LOANREL(Number)$^{\text{BankLoans}}$ and LOANREL(Amount)$^{\text{BankLoans}}$ are very similar and are omitted to conserve space.

4.2.2. *Renewals vs. non-renewals*

Another potential issue is whether a loan facility is a new loan or a renewal of an existing facility. For example, a borrower may simply be renewing a revolving line of credit that was part of a deal with a long-maturity loan. In such a case our tests would treat such a renewal as equivalent to winning new loan business. Thus, our test would attribute winning such renewals to a past relationship although it is simply a continuation of a prior loan. To address this concern we check the LPC database to determine whether a particular facility was a renewal. We create the variable RENEWAL, which equals one for a particular facility if the LPC recorded that facility as refinancing, and zero otherwise, and include both RENEWAL and the interaction RENEWAL $\times$ LOANREL(Dummy)$^{\text{BankLoans}}$ in our logit model. As expected, the results which we report in column 2, Panel B, show that conditional on a loan being a renewal, past relationships significantly increase the likelihood of winning such a renewal facility (coefficient for the interaction term is positive and significant at the 1% level). Moreover, even after controlling for renewals, the coefficient for LOANREL(Dummy)$^{\text{BankLoans}}$ remains essentially unchanged and continues to be positive and significant at the 1% level.

[31]We thank the referee for pointing out the issues discussed below and for suggesting the tests to address them.

4.2.3. Syndication among few dominant banks

Given that a limited number of banks dominate the syndicated loan market (a significant proportion of the LPC loans are syndicated loans), it is possible that borrowers are simply rotating their lending business among relatively few banks. If this is the case, these dominant banks would be classified as relationship banks for most borrowers according to our methodology. The association between past lending and a high probability of winning future business that we report in Panel A of Table 4 would then simply be due to syndicate rotation among banks. To address this issue we construct an alternative measure of lending relationships, MOST RECENT LENDER, which equals one if a particular bank was the lead bank on the most recent loan (prior to the current loan), and zero otherwise. This definition implies that if borrowers are simply rotating their loan business rather than rewarding relationships, MOST RECENT LENDER should have a negative coefficient (since rotation implies switching lenders after each loan). However, if future loan business is associated with strong lending relationships then the MOST RECENT LENDER variable should have a positive coefficient. As we report in column 3, this variable has a coefficient of 3.41 (significant at the 1% level), which is of similar magnitude to the LOANREL(Dummy)$^{\mathrm{BankLoans}}$ variable in Panel A. This result is consistent with the argument that lending relationships are associated with a higher likelihood of winning future lending opportunities.

4.2.4. Lender characteristics

A further issue pertains to individual lender characteristics. While we control for the physical proximity and lender reputation of each bank, it is possible that a bank may acquire a very strong reputation for expertise in lending to a certain industry, e.g., chemical industry. In such a case, borrowers in that industry would prefer to borrow from that bank independent of past relationships. To control for "industry lending expertise," we construct lending market shares of each bank for all the major industry sectors of borrowers in our sample (these market shares are constructed for each year for every two-digit industry group for which LPC reports at least 10 loans made in that year). For any bank m this is denoted by INDUSTRY LOAN MKT SHARE$_m$. We reestimate our logit model by using each bank's lagged industry loan market share for that borrower's industry. The results in column 4 show that the coefficient for lagged industry market share is 5.93 and is significant at the 1% level. Thus, having large lending market share to a particular borrower's industry increases the likelihood of winning future loan business. Even after controlling for such industry expertise the coefficient for the LOANREL(Dummy)$^{\mathrm{BankLoans}}$ is 3.16 (significant at the 1% level), which is similar to the coefficient we estimate in the original specification.

4.2.5. Loan pricing effects

Finally, we address the issue of controlling for loan pricing effects when a borrower chooses its lender. If the relationship lender also offers the lowest interest rate (measured by all-in-spread drawn or (AISD)), it is even more likely to win lending business.[32] Thus, part of the effect we attribute to relationships may be due in part to a lower price of the relationship loan. However, we cannot directly control for the price charged for a loan in

[32] AISD measures the interest rate spread on a loan (over LIBOR) plus any associated fees in originating the loan.

our logit model since we only observe the actual AISD charged by the bank that was *chosen*, i.e., data are missing for the other "potential" lenders in the choice set that were *not chosen*. We address this issue by imputing the loan price for other banks in the choice set that were *not chosen* using the expectation–maximization (EM) algorithm as suggested by Yasuda (2005).[33]

The EM algorithm is a general technique for finding the maximum-likelihood estimates for parametric models when data are not fully observed. In our context, the principal missing variable of interest is the rate charged (AISD) by the banks that are *not* retained in a given loan facility. We use the observed data on AISD and other borrower- and loan-specific characteristics to construct the following model:

$$\begin{aligned}(\mathrm{AISD})_{im} = \beta_0 &+ \beta_1 \mathrm{LOANREL(Dummy)}_m + \beta_2(\mathrm{LOAN\ MKT\ SHARE})_m \\ &+ \sum \beta_i(\mathrm{LOAN\_CHARACTERSTICS})_i \\ &+ \sum \beta_j(\mathrm{BORROWER\_CHARACTERSTICS})_j \\ &+ \sum \beta_k(\mathrm{CONTROL}_k).\end{aligned}$$

Thus, for a loan i by borrower j, if bank m was chosen the AISD_m is the actual observed price charged for the loan, and if bank m was not chosen the value for AISD_m is set to missing.

The loan characteristics we use are:

- LN(LOAN SIZE): natural log of loan facility amount.
- MATURITY: maturity of loan facility in months.
- SYNDICATE: equals one if the loan facility was syndicated, and zero otherwise.
- SECURED: equals one if the loan facility was secured, and zero otherwise.

The borrower specific characteristics are:

- LN(ASSET): natural log of the book value of the assets of the borrower.
- LEVERAGE: ratio of the book value of total debt to the book value of assets.
- COVERAGE: natural log of the ratio $\left(1+\frac{\mathrm{EBITDA}}{\mathrm{Interest\ Expenses}}\right)$.
- PROFITABILITY: ratio of EBITDA to Sales.
- TANGIBILITY: ratio of net property, plant, and equipment (NPPE) to the book value of assets.
- CURRENT RATIO: ratio of current assets to current liabilities.
- MARKET TO BOOK: ratio of (book value of assets $-$book value of equity $+$ market value of equity) to the book value of assets.
- R&D TO SALES: ratio of research and development expenses to sales.

The other control variables include dummy variables for the year and reported purpose and type of the loan facility, the credit rating of the borrower, and the industry of the borrower (two-digit SIC codes).

Each iteration of the algorithm consists of two steps, an expectation step (E step) and a maximization step (M step). The E step involves finding the conditional expectation of the missing data given the observed data and current estimated parameters (or initial estimated

[33]See Dempster et al. (1977) and McLachlan and Krishan (1997) for good surveys of EM methods.

parameters). Thus, the E step can be thought of as filling in the missing data. The parameter estimates for the complete data set are then computed in the M Step by using maximum likelihood estimation. This process is repeated iteratively until convergence obtains.

This procedure allows us to estimate loan prices that a given bank would have charged if it had been chosen. We call this variable IMPUTED LOAN SPREAD. We then reestimate our original logit model in Eq. (6) including the IMPUTED LOAN SPREAD for each potential lending bank. We present the results of this analysis in the last column of Table 4, Panel B. As expected, the coefficient for IMPUTED LOAN SPREAD is negative and significant, implying higher spreads charged make it less likely that the bank would be chosen to provide the loan. The relationship variable, however, continues to be significant and is essentially unchanged.[34]

4.2.6. Modeling the lender selection process

In our lender choice model we allow up to 40 banks as possible choices to a borrower. This borrower choice set may include a number of banks that potentially did not bid for the business and thus our results may overstate the importance of relationships. To address this concern we carry out a number of robustness checks.[35]

First we model the selection of a particular bank as a two-stage decision. In the first stage the borrower decides whether to use a relationship borrower or not and in the second stage it chooses a *specific* bank conditional on its propensity to choose relationship banks. We construct a binary variable REL for each loan facility; REL equals one if at least one of the lenders chosen had been a lender in the previous five years. We model the choice between a relationship and non-relationship loan as a function of various loan and borrower characteristics. These include loan size, credit rating, borrower size, profitability, leverage, and a specific measure that captures the intensity of using relationship lenders in the past. We estimate this past usage of relationship banks by calculating the fraction of all prior loans in which relationship lenders were used. This model allows us to estimate the predicted probability of using relationship lenders for each loan, which we denote by $\widehat{PROBREL}$. In the second stage we focus on specific *lender* characteristics that determine the choice of a *particular* lender after controlling for the borrower's propensity to choose relationship lenders. Specifically, we estimate a modified version Eq. (6) in which we include $\widehat{PROBREL}$ as another explanatory variable. This second-stage estimation allows us to measure the impact of prior relationships that a *specific* bank *m* has after controlling for that borrower's propensity to use relationship lenders in general. The coefficient for LOANREL(Dummy) in the second-stage regression is 3.09, which is significant at the 1% level and similar to the coefficient of 3.27 as reported in the original specification (column 1 of Panel A, Table 4). Thus, even after controlling for a particular borrower's propensity to use relationship lenders, the prior relationship that a specific lender has is significantly associated with that lender's ability to win future lending business.

[34]We also use an alternative method suggested by Schafer (1997) whereby we simulate 100 random data sets for loan spreads based on the observed distributions of spreads and other independent variables. For each of these samples, we estimate the effect of bank's market share and relationships on loan prices. We use the average estimates from these 100 simulations to calculate imputed fees for a given transaction for each bank-transaction pair. The results from using imputed loan spreads obtained from this simulation- based approach are similar to those estimated by using the EM algorithm.

[35]The results for these tests are not reported but are available from authors on request.

We also reestimate our model with smaller choice set of potential lenders for each loan facility. First we reduce the potential choice of lenders for each loan facility to top 20 banks (as ranked by market share in the previous year). This smaller choice set makes it more likely that all the lenders were potential bidders for the loan. This choice set size is also similar to that used by Drucker and Puri (2005), who use a choice set of 20, and Yasuda (2005), who uses a choice set of 16. The coefficient for LOANREL(Dummy) is 3.17 (significant at the 1% level), which is very similar to that for the original specification. We also rerun our model by restricting the choice set to the top 10 lenders. The coefficient of LOANREL(Dummy) remains essentially unchanged at 3.15, significant at the 1% level. Finally, we restrict the choice set of lenders for each borrower to top 10 lenders in the *borrower's industry* (defined at the two-digit SIC code level). The coefficient for LOANREL(Dummy) is 3.14 and significant at the 1% level. These results imply that our findings of a prior lending relationship having a significant impact on the ability to win future lending business is not driven by the size of the choice set used.

Finally, we construct a subset of borrowers for which key requirements for implementing the nested logit model hold.[36] We construct a subsample of borrowers, which, when faced with a lender selection decision, could have either chosen one of its two relationship borrowers or one of the 37 non-relationship borrowers. These restrictions yield a subsample of 13,416 observations. At the upper level a borrower chooses between the relationship and non-relationship nest. At the lower level it chooses a specific lender. We model the first-stage decision as largely determined by borrower characteristics and the lower-level decision to be based on specific lender characteristics such as market share, location, and whether it was the lead bank for the most recent loan (denoted by MOST RECENT LENDER). We find that the coefficient for MOST RECENT LENDER is positive and significant at the 1% level. Thus, even after conditioning for a borrower choosing a relationship lender, the lender that provided that most recent loan has a significantly higher probability of winning the next loan.

Overall, the robustness tests we employ above suggest that past lending relationships are significantly and positively associated with future lending opportunities.

4.3. *Tests for Hypothesis 2*

Theoretical models (e.g., Diamond, 1991) predict that relationships are more beneficial for firms that suffer from greater informational asymmetries. This motivates our Hypothesis 2, which conjectures that informationally opaque firms use relationship lenders more frequently. To test this we use different proxies for information "opaqueness," specifically, the borrower's size and the borrower's credit rating (see Sections 4.3.1 and 4.3.2 below). We also report results for alternative proxies for borrower's information opaqueness in Section 4.3.3.

4.3.1. *The effect of borrower size and Hypothesis 2*

A priori, it is reasonable to argue that smaller-sized firms are less likely to be widely followed by either capital market investors (or credit rating agencies). Stein (2002) argues that small-business lending "relies heavily on information that is *soft*—that is, information

[36]These requirements entail that all borrowers face exactly the same number of choices in both the relationship nest and the non-relationship nests, and that each borrower chooses exactly one lender.

that cannot be verified by anyone other than the agent who produces it." This characterization suggests that smaller borrowers should find strong relationships with their lenders particularly beneficial. Smaller firms are also likely to be relatively more informationally opaque; for example, Petersen and Rajan (1994) state that "... there may be large information asymmetries between these [*small*] firms and potential public investors."[37] Thus, small firms offer the most potential for proprietary information generation by a relationship lender. To the extent that relationships do mitigate the information problems that smaller firms face, we should expect to find a strong association between the size of a borrower and its use of a relationship bank for future loans.

To examine if relationship lending varies across different borrower sizes, we divide our sample into three size terciles based on borrower's book value of assets. Specifically, we add the two dummy variables MIDDLE and BIG to Eq. (6). These variables equal one if the borrower falls in the stated size tercile and zero otherwise. We also add two interaction terms, multiplying the relationship variable with MIDDLE and BIG. The modified logit model is then

$$\begin{aligned}(\text{CHOSEN})_m = \beta_0 &+ \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m \\ &+ \beta_3(\text{LOCATION})_m + \beta_4(\text{MIDDLE}) + \beta_5(\text{BIG}) \\ &+ \beta_6(\text{MIDDLE} * \text{LOANREL(M)}_m^{\text{BankLoans}}) \\ &+ \beta_7(\text{BIG} * \text{LOANREL(M)}_m^{\text{BankLoans}}) + \sum \beta_k(\text{CONTROL}_k). \qquad (7)\end{aligned}$$

The results, in Table 5, Panel A, describe how past lending relationships affect the probability of winning future lending business across different-sized borrowers. Since larger borrowers are likely to be informationally more transparent, holding everything else constant the effect of past relationships on the probability of being chosen as a lender should be the weakest for the large borrowers and the strongest for small borrowers. The coefficient of $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$ is 5.01 if the borrower is in the smallest size tercile, 4.13 for the middle tercile and 3.71 for the largest tercile, even as it continues to be statistically significant across all borrower size terciles (Table 5, column 1). Thus, the effect of past relationships, while significant, declines as one goes from the smallest borrowers to the largest borrowers. This is also captured in the negative coefficient of the size and relationship interaction terms, which are negative and significant at the 1% level across all specifications. In the panel at the bottom of Table 5 we use the specification estimated in column 1 to illustrate the economic significance of past lending relationship benefits across different borrower size terciles. Specifically, we estimate the probability of a bank being chosen as the lead lender if all variables except the relationship variables and the size variables are held equal to their means. The impact of a past relationship on the probability of being chosen as lead lender is measured by setting each specific size variable equal to one while keeping the other size variables equal to zero. The first row reports the predicted probabilities (for borrowers in small, medium, and large terciles) of a bank being chosen as a lead lender if it did not have a past lending relationship with a borrower ($\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$) and if all other variables are assumed to be equal to their means. The next row reports the predicted probability of being chosen if the bank did have a past lending relationship ($\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$). We find that having

[37] A number of empirical studies use smaller borrower size as proxy for higher information asymmetries. See, for example, Blackwell and Kidwell (1988) and Houston and Christopher (1996).

Table 5
Borrower information asymmetries, lending relationships and probability of getting future lending business

Panel A of this table provides the logit regression estimates of the following equation:

$$\begin{aligned}(\text{CHOSEN})_m = {} & \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m + \beta_3(\text{LOCATION})_m \\ & + \beta_4(\text{MIDDLE}) + \beta_5(\text{BIG}) + \beta_6(\text{MIDDLE} * \text{LOANREL(M)}_m^{\text{BankLoans}}) \\ & + \beta_7(\text{BIG} * \text{LOANREL(M)}_m^{\text{BankLoans}}) + \sum \beta_k(\text{CONTROL}_k).\end{aligned}$$

The model is the same as one we estimate in Table 4 with except here we include, two dummy variables, MIDDLE and BIG, which take the value one if the borrower falls in the stated size tercile (as measured by the book value of assets) and zero otherwise. We also add two interaction terms, multiplying the relationship variables with MIDDLE and BIG.

Panel B reports the estimates of the following logit regression:

$$\begin{aligned}(\text{CHOSEN})_m = {} & \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m + \beta_3(\text{LOCATION})_m \\ & + \beta_4(\text{NOT RATED}) + \beta_5(\text{NOT RATED} * \text{LOANREL(M)}_m^{\text{BankLoans}}) \\ & + \sum \beta_k(\text{CONTROL}_k).\end{aligned}$$

Again, the model is the same as the one we estimate in Table 4 except we add an additional variable NOT RATED (and the interaction with relationship measures), which equals one if the loan is not rated and zero otherwise.

Panel C provides estimates the following logit regression:

$$\begin{aligned}(\text{CHOSEN})_m = {} & \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m + \beta_3(\text{LOCATION})_m \\ & + \beta_4(\text{INVESTMENT GRADE}) + \beta_5(\text{INVESTMENT GRADE*(LOANREL(M)}_m^{\text{BankLoans}}) \\ & + \sum \beta_k(\text{CONTROL}_k).\end{aligned}$$

The model is the same as the one we estimate in Table 4 except we add an additional variable INVESTMENT GRADE (and the interaction with relationship measures), which equals one if the loan is rated BBB or above by S&P and zero otherwise.

At the bottom of each panel we illustrate the economic impact of past lending relationships on the probability of being chosen as the lead lender (across borrowers with different levels of information opacity) using the specification estimated in column 1. Specifically, we estimate the probability of a bank being chosen as the lead lender if all variables except the relationship variables and the information opacity measure (size, credit rating, etc.) are held equal to their means. Then the impact of a past relationship on the probability of being chosen is measured across different information opacity measures for each size tercile (e.g., by setting each size variable equal to one while keeping the other size variables equal to zero). Numbers in parentheses are standard errors corrected for heteroskedasticity and clustering (*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level).

	(1)	(2)	(3)
Panel A: Borrower size and relationship lending			
Const.	−4.45***	−4.01***	−4.30***
	(0.39)	(0.38)	(0.40)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	5.01***		
	(0.09)		
$\text{LOANREL(Number)}_m^{\text{BankLoans}}$		5.88***	
		(0.13)	
$\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			5.70***
			(0.12)
$(\text{LOAN MKT SHARE})_m$	12.7***	11.97***	11.90***
	(0.21)	(0.22)	(0.22)
$(\text{LOCATION})_m$	0.36***	0.44***	0.38***
	(0.05)	(0.05)	(0.05)
MIDDLE	0.37***	0.41***	0.39***
	(0.05)	(0.05)	(0.05)
BIG	1.26***	1.34***	1.31***
	(0.05)	(0.05)	(0.05)

Table 5 (*continued*)

	(1)	(2)	(3)
MIDDLE × $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	-0.88^{***} (0.1)		
BIG × $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	-2.30^{***} (0.10)		
MIDDLE × $\text{LOANREL(Number)}_m^{\text{BankLoans}}$		-0.56^{***} (0.15)	
BIG × $\text{LOANREL(Number)}_m^{\text{BankLoans}}$		-1.89^{***} (0.14)	
MIDDLE × $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			-0.59^{***} (0.13)
BIG × $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			-2.07^{***} (0.13)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes
Number of observations	401,699	401,699	401,699
Pseudo R^2	0.33	0.32	0.33

Impact of past lending relationships on the probability of being chosen as the lead lender using the column 1 specification

	Probability of being chosen		
	Small (%)	*Medium* (%)	*Big* (%)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$	1.21	1.74	4.14
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$	64.87	52.24	39.28
Increase in probability	63.66	50.50	35.14

Panel B: *Availability of borrower credit rating and relationship lending*

	(1)	(2)	(3)
Const.	-3.20^{***} (0.39)	-2.57^{***} (0.38)	-2.97^{***} (0.41)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	2.87^{***} (0.03)		
$\text{LOANREL(Number)}_m^{\text{BankLoans}}$		4.19^{***} (0.06)	
$\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			3.82^{***} (0.05)
$\text{(LOAN MKT SHARE)}_m$	12.41^{***} (.21)	11.65^{***} (0.22)	11.58^{***} (0.22)
(LOCATION)_m	0.37^{***} (0.05)	0.45^{***} (0.05)	0.39^{***} (0.05)
NOT RATED	-0.70^{***} (0.04)	-0.70^{***} (0.03)	-0.69^{***} (0.04)
NOT RATED × $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	1.12^{***} (0.06)		
NOT RATED × $\text{LOANREL(Number)}_m^{\text{BankLoans}}$		0.97^{***} (0.09)	
NOT RATED × $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			1.06^{***} (0.08)
Industry dummies	Yes	Yes	Yes

Table 5 (*continued*)

	(1)	(2)	(3)
Year dummies	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes
Number of observations	416,239	416,239	416,239
Pseudo R^2	0.32	0.32	0.33

Impact of past lending relationships on the probability of being chosen as the lead lender using the column 1 specification

	Probability of being chosen	
	Not rated (%)	*Rated* (%)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$	1.84	3.66
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$	50.31	40.06
Increase in probability	48.47	36.40

Panel C: Borrower credit rating and relationship lending

Const.	−2.98***	−2.34***	−2.70***
	(0.55)	(0.53)	(0.55)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	3.18***		
	(0.05)		
$\text{LOANREL(Number)}_m^{\text{BankLoans}}$		4.61***	
		(0.08)	
$\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			4.24***
			(0.07)
$\text{(LOAN MKT SHARE)}_m$	13.82***	12.55***	12.58***
	(0.27)	(0.29)	(0.29)
(LOCATION)_m	0.39***	0.45***	0.39***
	(0.06)	(0.07)	(0.07)
INVESTMENT GRADE	0.52***	0.49***	0.51***
	(.06)	(0.05)	(0.05)
INVESTMENT GRADE × $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$	−0.59***		
	(0.07)		
INVESTMENT GRADE × $\text{LOANREL(Number)}_m^{\text{BankLoans}}$		−0.75***	
		(0.11)	
INVESTMENT GRADE × $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$			−0.76***
			(0.10)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes
Number of observations	213,420	213,420	213,420
Pseudo R^2	0.30	0.29	0.30

Impact of past lending relationships on the probability of being chosen as the lead lender using the column 1 specification

	Probability of being chosen	
	Non investment grade (%)	*Investment grade* (%)
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 0$	2.80	4.64
$\text{LOANREL(Dummy)}_m^{\text{BankLoans}} = 1$	40.99	39.08
Increase in probability	38.19	34.44

a past lending relationship increases the probability of being chosen by 63.7% (from 1.2% to 64.9%) for the borrowers in the smallest tercile. The predicted probability increase for borrowers in the middle and the largest size terciles is 50.5% (1.7% to 52.2%) and 35.2% (from 4.1% to 39.3%), respectively. Thus, the probability of a bank being chosen to provide future loans gets smaller as borrower size increases.

4.3.2. The effects of credit rating and Hypothesis 2

An alternative proxy for informational asymmetries is the availability of a credit rating for the borrower. If the borrower is not rated, a debt-holder needs to generate and process a relatively larger amount of information to make its lending decision. Thus, nonrated borrowers are more likely to turn to their relationship lender for their financing needs than to public debt markets. For example, Diamond (1991) argues that a borrower's past repayment reputation would drive its choice of borrowing source. A key prediction of his model is that firms with good reputations (i.e., with high credit ratings) would be able to issue (cheaper) public debt, while firms with lower reputations (as evidenced by lower credit ratings) would use bank financing. It is also frequently argued that the information advantages of an insider lender (scale economies in information production, better ability to renegotiate covenants, etc.) would allow it to adopt a more flexible approach towards debt renegotiations. Thus, a relationship bank is expected to "lean against the wind" when its borrowers face financial difficulties.[38] Consequently, a borrower with a poor credit rating is more likely to use its relationship bank for its borrowing needs.[39] Below, we employ the existence and level a of credit rating for a borrower as a proxy for the information asymmetries that the borrower faces.

To do this we first partition our sample into firms that have a credit rating and those that do not. We use the credit rating of the loan facility being examined (as reported by LPC) as the most timely measure of the borrower's credit worthiness. It is reasonable to assume that, on average, the firms whose loans are not publicly rated, are likely to be less informationally transparent relative to those that have a rating. Thus, we estimate the model

$$\begin{aligned}(\text{CHOSEN})_m = \beta_0 &+ \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m \\ &+ \beta_3(\text{LOCATION})_m + \beta_4(\text{NOT RATED}) \\ &+ \beta_5(\text{NOT RATED} * \text{LOANREL(M)}_m^{\text{BankLoans}}) \\ &+ \sum \beta_k(\text{CONTROL}_k). \end{aligned} \tag{8}$$

The model in Eq. (8) includes a dummy variable (NOT RATED), which equals one if the loan is not rated and zero otherwise. We also add an interaction term that interacts the relationship variable with NOT RATED to better isolate the effect of the availability of a credit rating on the use of a relationship banker for future borrowing.

[38] Hoshi et al. (1990) provide evidence in support of this view. They report that among the financially distressed Japanese firms, those with strong banking relationships are better able to maintain their investment programs compared to firms that lacked such banking relationships.

[39] Anecdotal evidence of the limited benefits of relationship lending to the best quality borrowers is highlighted in an Economist article dated February 12, 1998, which states: "... Part of [JP] Morgan's problem is that its customers are simply too good. The trouble with serving only the best firms is that they typically like to maintain relationships with at least three banks and play them off against each other to get prices down."

For the subsample in which the credit rating of the borrower is available, we estimate the model

$$\begin{aligned}(\text{CHOSEN})_m = {} & \beta_0 + \beta_1(\text{LOANREL(M)}_m^{\text{BankLoans}}) + \beta_2(\text{LOAN MKT SHARE})_m \\ & + \beta_3(\text{LOCATION})_m + \beta_4(\text{INVESTMENT GRADE}) \\ & + \beta_5(\text{INVESTMENT GRADE} * \text{LOANREL(M)}_m^{\text{BankLoans}}) \\ & + \sum \beta_k(\text{CONTROL}_k), \end{aligned} \tag{9}$$

where INVESTMENT GRADE is a dummy variable that equals one if the loan is rated BBB or above by S&P, and zero otherwise. We also add an interaction term that multiplies the relationship variable with INVESTMENT GRADE to better isolate the effect of credit rating on the use of a relationship banker for future borrowing.

Panel B of Table 5 reports the results of Eq. (8). Consistent with our earlier finding, while the existence of a past relationship increases the probability of winning future loans for all borrowers, this increase is significantly higher for borrowers whose loans have not been rated. Specifically, the coefficient of 3.19 for $\text{LOANREL(Amount)}^{\text{BankLoans}}$ if a borrower's loan does not have a rating is higher compared to the coefficient of 2.87 for the borrowers with a rated loan (Table 5, column 1). The impact of credit ratings is also captured by the positive and significant (t-value $= 18.7$) coefficient of the interaction term (multiplying past relationship by the availability of a borrower's credit rating). The bottom panel provides the economic interpretation of these results. For a nonrated borrower, a relationship lender has a 48% higher probability (50% vs. 2%) of winning future lending business, while for a rated borrower, the existence of past relationships increases the predicted probability of being chosen for future loans by 36% (40% vs. 4%). As a result, while the likelihood of being retained for future loans is fairly low for non-relationship lenders to both nonrated (2%) and rated borrowers (4%), the probability of a relationship lender being retained by a nonrated borrower is 10% higher compared to a rated borrower (50% vs. 40%).

Next, we employ the quality of credit rating as a measure of the informational transparency of a borrower as in Eq. (9). Borrowers with an investment grade rating (BBB or above) are classified as INVESTMENT GRADE. As we discuss earlier, theoretical models predict that high quality borrowers gain relatively less from borrowing from their relationship lender. Thus, we expect the effect of relationships to be weaker for borrowers with a high credit rating. The results we report in Table 5, Panel C provide some weak support for these predictions. The coefficient on the relationship and investment grade rating interaction term is negative and significant at the 1% level across all specifications (t-value range of -6.82 to -8.43). Holding all other variables constant at their means, the existence of a past lending relationship is associated with a 38% increase (3% to 41%) in the probability of being retained for borrowers with loans rated below investment grade. For BBB or above borrowers, past relationships increase the probability of being retained by 34% (5–39%).

4.3.3. Alternative proxies for borrower opaqueness

We also employ some alternative proxies for borrower information transparency to test H2.[40] In particular, we focus on proxies that measure the tangibility of assets owned by

[40] To conserve space these results are not reported but are available from the authors upon request.

a firm so as to capture the information asymmetry faced by its lenders. Firms that have a relatively lower fraction of their asset base in tangible assets, such as plant and machinery, face higher information asymmetries and are more likely to use an informed "insider" lender for their financing needs. For example, Houston and Christopher (1996) note "... smaller firms and firms with higher proportion of intangible assets (and presumably more difficult to value assets) are expected to rely primarily on bank financing."

The first proxy we use is the market-to-book ratio of the borrower, which equals the ratio of the market value of assets to the book value of assets. The market value is calculated as the book value of the assets minus the book value of equity plus the market value of equity. Smith and Watts (1992) and Barclay and Smith (1995a, b) use the market-to-book ratio to proxy for the growth options in a firm's investment opportunity set. Since a firm's balance sheet does not include intangible assets such as growth options but its market value reflects such intangible assets, a high market-to-book ratio can be considered as a firm having a larger fraction of their assets as intangible assets.[41] We also employ the ratio of Research and Development expenses to Sales as another measure of growth options, since a relatively high R&D expenditure could be interpreted as investment in assets that would yield higher future growth. Finally, we also use a "tangibility ratio," calculated as the ratio of net plant, property, and equipment (NPPE) to total assets. A higher fraction of total assets in the form of easier-to-value NPPE implies that such firms face a lower level of informational asymmetry when it comes to raising nonbank debt. This, in turn, implies a lower propensity to use a relationship bank for future financing.

For each of these ratios we partition our sample into three "tangibility" terciles and estimate the impact of lending relationships on these alternative measures of information opacity. We expect firms with a higher market-to-book ratio, a lower NPPE-to-total asset ratio and a higher R&D-to-sales ratio to be more likely to borrow from their relationship lenders. The results for the market-to-book ratio measure are as predicted. Specifically, the coefficient for $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$ is largest (3.27) for the highest tercile (market-to-book) borrowers and smallest (3.13) for the lowest tercile. When we use the R&D-to-sales ratio as a proxy for the borrower's asset intangibility, we obtain mixed results. The borrowers in the middle tercile have the highest coefficient (3.72) for $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$, with no statistical difference between the lowest and the highest terciles (3.25 and 3.21, respectively). Using the NPPE-to-total assets ratio as a proxy for the borrower's asset tangibility, we obtain results in the expected direction, i.e., borrowers in the highest tercile (borrower's for which the bulk of their assets are in NPPE), had the lowest coefficient for $\text{LOANREL(Dummy)}_m^{\text{BankLoans}}$ (3.09) while borrowers in the lowest tercile have the highest coefficient (3.39).

Taken together our findings in Section 4.3 provide support for the theoretical predictions underlying H2. That is, informationally opaque firms are more likely to find relationship borrowing beneficial, than are informationally transparent firms.

4.4. Tests for Hypothesis 3

In Hypothesis 3 we conjecture that if there are scope economies in information production, a relationship lender would have a higher probability of supplying future

[41] Houston and Christopher (1996) find that for borrowers with multiple banking relationships, those that have higher market-to-book ratios are more likely to use bank financing.

investment banking and/or underwriting services (i.e., this is the cross-product marketing motivation behind lending relationships—see, for example, Kanatas and Qi, 2003).

4.4.1. Tests of Hypothesis 3 and debt underwriting

For our empirical tests, we concentrate on two specific investment banking products that a relationship lender can potentially sell to its existing borrower. The first is the underwriting of public debt issues and the second is the underwriting of public equity issues (IPOs and SEOs).

From the SDC database we obtain details related to all the debt and equity issues completed by our sample borrowers, that had at least one relationship lender eligible to provide the underwriting service (see Section 3.2 for our sample selection methodology). For each issue of public debt in year t (in what follows, the process for equity markets is exactly the same) we construct a choice set of top 20 financial institutions (ranked by market share of debt underwriting in the year $t-1$). To this set of 20, we add all the commercial banks that are not in the top 20 list that were eligible to underwrite public issues of debt at the date of the debt issue.[42] To test whether prior lending relationships are associated with a higher probability of winning an underwriting mandate for issues of public debt, we estimate the following logit model:

$$\begin{aligned}(\text{RETAIN})_m^{\text{lead-debt}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicDebt}}) \\ & + \beta_3(\text{Lead-DEBTREL(M)}_m^{\text{PublicDebt}}) \\ & + \beta_4(\text{Lead-EQUITYREL(M)}_m^{\text{PublicDebt}}) \\ & + \beta_5(\text{LOAN MKT SHARE})_m + \beta_6(\text{TOP TIER-DEBT})_m \\ & + \beta_7(\text{MID TIER-DEBT})_m + \beta_8(\text{TOP TIER-EQUITY})_m \\ & + \beta_9(\text{MID TIER-EQUITY})_m + \sum \beta_k(\text{CONTROL}_k). \end{aligned} \tag{10}$$

The variables are:

- $(\text{RETAIN})_m^{\text{lead}}$-debt: For each debt issue, we create a dummy variable $(\text{RETAIN})_m^{\text{lead-debt}}$ that takes a value of one if a bank m was retained as the "*Lead Underwriter*" for that debt issue transaction, and zero otherwise.[43]
- PROCEEDS: The dollar amount of proceeds from the debt issue in USD millions.
- $\text{LOANREL(M)}_m^{\text{PublicDebt}}$: The measure of the lending relationship that m has with the issuer, constructed in exactly the same way as $\text{LOANREL(M)}_m^{\text{BankLoans}}$ except that for $\text{LOANREL(M)}_m^{\text{PublicDebt}}$, the date of the look-back period is the date of a public issue of debt, while for $\text{LOANREL(M)}_m^{\text{BankLoans}}$, the loan facility activation date is used.
- $\text{Lead-DEBTREL(M)}_m^{\text{PublicDebt}}$ and Lead-EQUITYREL $(\text{M})_m^{\text{PublicDebt}}$: The relationship strength measures for debt issue and equity issue markets, respectively. These measure the intensity of past investment banking relationships of a bank m in debt underwriting

[42]That is, if it had underwritten (either as lead or as co-manager) at least one debt issue in the years prior to year t.

[43]Thus, if a bank was the sole underwriter, only the issue-bank pair for this bank would have RETAIN equal to one and for the other members of the choice set RETAIN would be zero. If the issue were led by multiple banks, than all the issue-bank pairs corresponding to these banks would have RETAIN equal one while it would equal zero for the rest.

and equity underwriting markets. The construction of these variables is described in Section 3.1 and Appendix A.

- $(\text{LOAN MKT SHARE})_m$: for each bank m, is calculated for the year prior to the year of the debt issue and is calculated as in Eq. (5).
- $(\text{TOP TIER-DEBT})_m$: a dummy variable equal to one if the bank m is ranked in the top 5 debt underwriters in the previous year, and zero otherwise.
- $(\text{MID TIER-DEBT})_m$: a dummy variable equal to one if the bank m is ranked from 6th to 15th in debt underwriting in the previous year, and zero otherwise.
- $(\text{TOP TIER-EQUITY})_m$: a dummy variable equal to one if the bank m is ranked in the top 5 equity underwriters in the previous year, and zero otherwise.
- $(\text{MID TIER-EQUITY})_m$: a dummy variable equal to one if the bank m is ranked from 6th to 15th in equity underwriting in the previous year, and zero otherwise.

We do not include the LOCATION variable for underwriter selection models as most of the institutions in the choice set of potential underwriters have a New York City head office.

The results, reported in Table 6, provide strong support for H3 in the debt issue underwriting business. In columns 1–3 we report the results for all three alternative measures of prior lending and prior investment banking relationship variables and the controls for underwriter reputation both in the debt and the equity markets (as we describe in Eq. (10)). The coefficient for $\text{LOANREL(M)}^{\text{PublicDebt}}$ is positive and significant at the 1% level for all specifications.[44] Not surprisingly, a prior investment banking relationship in the same market ($\text{Lead-DEBTREL(M)}^{\text{PublicDebt}}$) is a strong determinant of future debt underwriter selection. The bottom panel, in which we use the model specification described in column 1 of Table 6 to explore the impact of prior lending and investment banking relationships, illustrates the economic significance of prior lending relationships and prior debt underwriting relationships. If all variables are held constant at their means and a bank did not have a past lending relationship ($\text{LOANREL(Dummy)}^{\text{PublicDebt}} = 0$) with a debt issuer, its probability of being retained as the lead underwriter of that debt issue is 0.29%. This probability increases to 0.55% if the bank had a prior lending relationship ($\text{LOANREL(Dummy)}^{\text{PublicDebt}} = 1$) with the issuer. While a past lending relationship has a statistically significant impact on the probability of being chosen as the future debt underwriter, the economic significance (0.55% probability) is, nevertheless, relatively small. The economic significance of having a past record of providing (underwriting) the same product is larger but still economically small, as illustrated by the change in probability for a bank with and without a prior debt underwriting with the customer relationship holding all variables constant at their respective means. The existence of a prior debt underwriting relationship increases the probability of winning the lead underwriter role (from 0.28% for banks with no prior debt underwriting relationship to 2.61% for banks with prior debt underwriting relationships). Finally, the existence of a past cross-market investment banking relationship ($\text{Lead-EQUITYREL}^{\text{PublicDebt}} = 1$) is associated with an increase in the probability of being retained as lead debt underwriter (0.31% to 0.79%). A prior investment-banking relationship, even in a different product market (equity underwriting), has a positive relationship with thelikelihood of winning

[44] These results are similar to those reported by Yasuda (2005), who also finds that past lending relationships have a significant impact on winning future debt underwriting mandates.

Table 6
Impact of lending relationships on probability of getting future debt underwriting business

This table provides the logit regression estimates of the following equation:

$$\begin{aligned}(\text{RETAIN})_m^{\text{Lead-debt}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicDebt}}) \\ & + \beta_3(\text{Lead-DEBTREL(M)}_m^{\text{PublicDebt}}) \\ & + \beta_4(\text{Lead-EQUITYREL(M)}_m^{\text{PublicDebt}}) + \beta_5(\text{LOAN MKT SHARE})_m \\ & + \beta_6(\text{TOP TIER-DEBT})_m + \beta_7(\text{MID TIER-DEBT})_m \\ & + \beta_8(\text{TOP TIER-EQUITY})_m + \beta_9(\text{MID TIER-EQUITY})_m + \sum \beta_k(\text{CONTROL}_k).\end{aligned}$$

For each debt issue, we create the dummy variable $\text{RETAIN}_m^{\text{Lead-debt}}$, which takes a value of zero if a bank m was retained as the lead underwriter for that debt issue transaction and zero otherwise. For each debt underwriting deal i we create a choice set of at least 20 potential underwriters, creating at least 20 deal-underwriter pairs. The top 20 debt underwriters (based on market share) from the previous year and all commercial banks eligible to do debt underwriting in the previous year form the consideration set for each issuer in the current year. For each institution in a transaction-bank pair we estimate relationships across three markets: the bank loan market, the debt underwriting market, and the equity underwriting market. Within each market we use three different proxies of relationship strength for any bank m: $\text{LOANREL(Dummy)}_m^{\text{PublicDebt}}$ (one if there is a loan relationship with bank m in the last five years before the present debt underwriting transaction and zero otherwise), $\text{LOANREL(Number)}_m^{\text{PublicDebt}}$ (ratio of the number of loan deals with bank m to the total number of loan deals of the firm in the last five years before the current debt underwriting transaction), and $\text{LOANREL(Amount)}_m^{\text{PublicDebt}}$ (ratio of the dollar value of loan deals with bank m to the total dollar value of loan deals of the firm in the last five years before the current debt underwriting transaction). $\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicDebt}}$ (one if there is a debt underwriting relationship in the lead underwriter capacity with bank m in the last five years before the present debt underwriting transaction and zero otherwise), $\text{Lead-DEBTREL(Number)}_m^{\text{PublicDebt}}$ (ratio of the number of debt underwriting deals in the lead underwriter capacity with bank m to the total number of debt underwriting deals of the firm in the last five years before the current debt underwriting transaction), and $\text{Lead-DEBTREL(Amount)}_m^{\text{PublicDebt}}$ (ratio of the dollar value of debt underwriting deals in the lead underwriter capacity with bank m to the total dollar value of debt underwriting deals of the firm in the last five years before the current debt underwriting transaction). $\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicDebt}}$ (one if there is an equity underwriting relationship in the lead underwriter capacity with bank m in the last five years before the present debt underwriting transaction and zero otherwise), $\text{Lead-EQUITYREL(Number)}_m^{\text{PublicDebt}}$ (ratio of number of the equity underwriting deals in the lead underwriter capacity with bank m to the total number of equity underwriting deals of the firm in the last five years before the current debt underwriting transaction), and $\text{Lead-EQUITYREL(Amount)}_m^{\text{PublicDebt}}$ (ratio of the dollar value of equity underwriting deals in the lead underwriter capacity with bank m to the total dollar value of equity underwriting deals of the firm in the last five years before the current debt underwriting transaction). PROCEEDS is the amount raised in USD millions for the debt underwriting transaction (reported coefficient has been divided by 1,000). $(\text{LOAN MKT SHARE})_m$ is the market share of bank m in the loan market in the year before the current debt underwriting transaction. Similar calculations estimate market shares for the debt underwriting and the equity underwriting markets. $(\text{TOP TIER-DEBT})_m$ and $(\text{TOP TIER-EQUITY})_m$ are dummy variables that equals one if the bank m is ranked in the top five debt and equity underwriters, respectively, and zero otherwise. $(\text{MID TIER-DEBT})_m$ and $(\text{MID TIER-EQUITY})_m$ are dummy variables that equals one if the bank m is ranked from 6th to 15th in debt and equity underwriting, respectively, and zero otherwise. $(\text{COMMERCIAL BANK})_m$ is a dummy variable that equals one if bank m had a Section 20 and/or investment banking subsidiary that was eligible to underwrite debt securities on the date of issuance and zero otherwise.

At the bottom of each panel we illustrate the economic impact of past lending, debt underwriting, and equity underwriting relationships on the probability of being chosen as the debt underwriter using the specification estimated in column 1. The first row reports the probability of a non-relationship bank ($\text{LOANREL(Number)}^{\text{PublicDebt}} = 0$) being chosen as the debt underwriter if all other variables are held equal to their mean. The second row reports the probability for a relationship bank ($\text{LOANREL(Number)}^{\text{PublicDebt}} = 1$) in the same way. Numbers in parentheses are standard errors corrected for heteroskedasticity and clustering (*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level).

	(1)	(2)	(3)	(4)	(5)
Const.	-6.27^{***}	-7.06^{***}	-6.98^{***}	-5.96^{***}	-6.27^{***}
	(.20)	(.18)	(.17)	(.35)	(.20)
PROCEEDS	0.34^{***}	0.19^{***}	0.29^{***}	1.22^{***}	0.34^{***}
	(0.11)	(0.06)	(0.06)	(0.24)	(0.11)
LOANREL(Dummy)$_m^{\text{PublicDebt}}$	0.66^{***}				0.68^{***}
	(0.09)				(0.11)
LOANREL(Number)$_m^{\text{PublicDebt}}$		1.22^{***}			
		(0.12)			
LOANREL(Amount)$_m^{\text{PublicDebt}}$			0.86^{***}		
			(0.18)		
(LOAN MKT SHARE)$_m$	4.51^{***}	3.82^{***}	5.5^{***}	3.11^{***}	4.59^{***}
	(1.02)	(1.08)	(1.19)	(0.80)	(1.01)
Lead-DEBTREL(Dummy)$_m^{\text{PublicDebt}}$	2.27^{***}			1.93^{***}	2.29^{***}
	(.09)			(0.07)	(0.10)
Lead-DEBTREL(Number)$_m^{\text{PublicDebt}}$		3.71^{***}			
		(0.16)			
Lead-DEBTREL(Amount)$_m^{\text{PublicDebt}}$			3.08^{***}		
			(0.13)		
(TOP TIER-DEBT)$_m$	2.30^{***}	2.65^{***}	2.75^{***}	1.80^{***}	2.30^{***}
	(0.18)	(0.17)	(0.17)	(0.10)	(0.18)
(MIDDLE TIER-DEBT)$_m$	2.09^{***}	2.26^{***}	2.30^{***}	1.52^{***}	2.09^{***}
	(0.16)	(0.15)	(0.15)	(0.08)	(0.16)
Lead-EQUITYREL(Dummy)$_m^{\text{PublicDebt}}$	0.94^{***}			0.79^{***}	0.94^{***}
	0.08			0.07	0.08
Lead-EQUTYREL(Number)$_m^{\text{PublicDebt}}$		0.79^{***}			
		(0.11)			
Lead-EQUTYREL(Amount)$_m^{\text{PublicDebt}}$			0.88^{***}		
			(0.11)		
(TOP TIER-EQUITY)$_m$	0.96^{***}	1.29^{***}	1.24^{***}	1.17^{***}	0.96^{***}
	(0.14)	(0.13)	(0.13)	(0.09)	(0.14)
(MIDDLE TIER-EQUITY)$_m$	0.66^{***}	0.91^{***}	0.93^{***}	0.99^{***}	0.67^{***}
	(0.12)	(0.12)	(0.12)	(0.07)	(0.12)
LOANREL(Dummy)$_m$ × Lead-DEBTREL(Dummy)$_m$				0.29^{***}	
				(0.11)	
LOANREL(Dummy)$_m$ × (1-Lead-DEBTREL(Dummy)$_m$)				1.83^{***}	
				(0.07)	
Lead-DEBTREL(Dummy)$_m$ × (COMMERCIAL BANK)$_m$					-0.04
					(0.13)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	77,350	77,350	77,350	77,350	77,350
Pseudo R^2	0.40	0.40	0.38	0.34	0.40

Impact of past relationships on the probability of being chosen as the lead debt underwriter using the column 1 specification

	Probability of being chosen (%)
LOANREL(Dummy)$_m^{\text{PublicDebt}} = 0$	0.29
LOANREL(Dummy)$_m^{\text{PublicDebt}} = 1$	0.55
Increase in probability	0.26
Lead-DEBTREL(Dummy)$_m^{\text{PublicDebt}} = 0$	0.28
Lead-DEBTREL(Dummy)$_m^{\text{PublicDebt}} = 1$	2.61
Increase in probability	2.33
Lead-EQUITYREL(Dummy)$_m^{\text{PublicDebt}} = 0$	0.31
Lead-EQUITYREL(Dummy)$_m^{\text{PublicDebt}} = 1$	0.79
Increase in probability	0.48

future debt underwriting mandates. Nevertheless, the economic impact of such cross-market relationships is also small.

We also explore the cumulative impact of having a lending relationship in conjunction with a prior underwriting relationship. Thus, we replace the LOANREL(Dummy)$^{\text{PublicDebt}}$ variable in Eq. (10) by the two interaction terms LOANREL(Dummy)$^{\text{PublicDebt}}$ $\times$ Lead-DEBTREL(M)$^{\text{PublicDebt}}$ and LOANREL(Dummy)$^{\text{PublicDebt}}$ $\times$ (1-Lead-DEBTREL (M)$^{\text{PublicDebt}}$). These interaction terms allow us to estimate the *incremental* impact that prior lending relationships have if a bank already has a prior debt underwriting relationship. As column 4 reports, LOANREL(Dummy)$^{\text{PublicDebt}}$ $\times$ Lead-DEBTREL (M)$^{\text{PublicDebt}}$ has a positive and significant (at the 1% level) coefficient (0.29), which implies that a past lending relationship provides an extra benefit in terms of increasing the likelihood of winning future debt underwriting mandates over and above what a prior underwriting relationship provides.

Finally, in column 5 we test whether the identity of an underwriter is a significant factor in an issuer's choice. We segregate our choice set of potential underwriters between commercial banks and investment banks. Based on information from the Board of Governors of the Federal Reserve System, we create the dummy variable COMMERCIAL BANK, which equals one if the bank had a Section 20 and/or an investment banking subsidiary that was eligible to underwrite the debt security on the date when it was issued. To test if underwriter identity affects its selection, we include the interaction term Lead-DEBTREL(M)$^{\text{PublicDebt}}$ $\times$ COMMERCIAL BANK in our underwriter selection model. The coefficient for this interaction term is insignificant, implying that commercial banks do not have a significant advantage in winning debt underwriting mandates over and above the effect that past lending and underwriting relationships provide. Overall, compared to the impact of relationships in the market for loans, their impact in the debt underwriting market is economically weaker.[45]

4.4.2. *Tests of Hypothesis 3 and equity underwriting*

The second investment banking product we examine is the lead underwriting mandate for issues of public equity. We segregate our sample of public equity issues into SEOs and IPOs. This partitioning also allows us to conduct tests of another aspect of the information production role of relationship lenders. Typically, IPO issuers suffer from a high degree of information asymmetry. Schenone (2004) notes, "... when firms go public, the market and the firm are asymmetrically informed about true value of the firm." Thus, an underwriter with a strong past lending relationship can provide credible certification about the true value of an IPO-issuing firm. Holding all else constant, we therefore expect that an IPO issuer is more likely to use its relationship lender as its equity underwriter than is an SEO issuer. We examine this in more detail below.

[45] We also use an alternative underwriting strength variable, $\text{RETAIN}_m^{\text{PublicDebt}}$, which takes the value of one if a bank m was retained as either the "Lead Underwriter" or as "Co-Manager" for that debt issue transaction, and zero otherwise. This more inclusive definition addresses the fact that even a second-tier underwriting role offers the bank incremental revenues. While the overall results (available upon request from the authors) are similar to those in Table 6, the coefficient for LOANREL(M)$^{\text{PublicDebt}}$ is almost twice as large across all specifications. That is, the prior lending relationship variable now has a much stronger association with the probability of winning a lead underwriter or a co-manager role.

For SEOs we estimate the logit model

$$
\begin{aligned}
(\text{RETAIN})_m^{\text{lead-SEO}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicEquity}}) \\
& + \beta_3(\text{Lead-EQUITYREL(M)}_m^{\text{PublicEquity}}) \\
& + \beta_4(\text{Lead-DEBTREL(M)}_m^{\text{PublicEquity}}) \\
& + \beta_5(\text{LOAN MKT SHARE})_m + \beta_6(\text{TOP TIER-DEBT})_m \\
& + \beta_7(\text{MID TIER-DEBT})_m + \beta_8(\text{TOP TIER-EQUITY})_m \\
& + \beta_9(\text{MID TIER-EQUITY})_m + \sum \beta_k(\text{CONTROL}_k). \qquad (11)
\end{aligned}
$$

Since an IPO is the first equity issue by a firm, prior *equity* underwriting relationships are not meaningful for IPO issuers. Also, since few IPO firms issue public debt prior to their IPO, debt underwriting relationships are not common. Thus, for IPOs we estimate the modified logit model

$$
\begin{aligned}
(\text{RETAIN})_m^{\text{Lead-IPO}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicEquity}}) \\
& + \beta_4(\text{LOAN MKT SHARE})_m + \beta_5(\text{TOP TIER-EQUITY})_m \\
& + \beta_6(\text{MIDDLE TIER-EQUITY})_m \\
& + \sum \beta_k(\text{CONTROL}_k). \qquad (12)
\end{aligned}
$$

In both models, $(\text{RETAIN})_m$ is a dummy variable that takes a value of one if a bank m was retained as the "Lead Underwriter" for that transaction, and zero otherwise. Table 7 reports the results. In the first three columns we report the results for three alternative measures of prior lending and underwriting relationships. The coefficient for LOANREL, while positive, has a lower statistical significance (it is significant in two out of three specifications). The predicted probability of being retained as a lead SEO underwriter for a bank that did not have a prior lending relationship is 0.30% (holding all other variables constant at their respective means). This probability essentially remains unchanged at 0.31% if a bank did have a prior lending relationship (the results are somewhat stronger if continuous measures of relationship are used with the probability going up from 0.3% to 0.5%). These results suggest that a bank's past lending relationship with a borrower is not strongly associated with that bank's probability of being retained as a lead SEO underwriter by its relationship borrower.[46]

Similar to our test for debt underwriting, we explore the cumulative impact of having a lending relationship in conjunction with a prior equity underwriting relationship by replacing the $\text{LOANREL(Dummy)}^{\text{PublicEquity}}$ variable by the two interaction terms $\text{LOANREL(Dummy)}^{\text{PublicEquity}} \times \text{Lead-EQUITYREL(M)}^{\text{PublicEquity}}$ and $\text{LOANREL(Dummy)}^{\text{PublicEquity}} \times (\text{1-Lead-EQUITYREL(M)}^{\text{PublicEquity}})$, which isolate the

[46]A possible explanation for these results is that since equity underwriting is somewhat removed from traditional commercial banking business, a borrower may feel uncomfortable about rewarding the *lead* role in SEO underwriting to its relationship lender. However, it can still provide its relationship lender with incremental revenues by including it as a second-tier underwriter by awarding it a co-manager role. To test this, we use a broader measure of underwriting business, $\text{RETAIN}_m^{\text{SEO}}$, which equals one if bank m gets either the lead underwriter or a co-manager's role. Our results (not reported) show that past lending relationships are significantly associated with the ability to win some sort of underwriting role in SEOs (the probability of being retained as either lead or co-manager is 1.7% for a bank lacking past lending relationships and 2.9% for a relationship lender). However, the economic impact is still small.

Table 7
Impact of lending relationships on probability of getting future equity underwriting business-seasoned equity offerings (SEOs)

This table provides the logit regression estimates of the following equation:

$$\begin{aligned}(\text{RETAIN})_m^{\text{Lead-SEO}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicEquity}}) \\ & + \beta_3(\text{Lead-EQUITYREL(M)}_m^{\text{PublicEquity}}) \\ & + \beta_4(\text{Lead-DEBTREL(M)}_m^{\text{PublicEquity}}) + \beta_5(\text{LOAN MKT SHARE})_m \\ & + \beta_6(\text{TOP TIER-DEBT})_m + \beta_7(\text{MIDDLE TIER-DEBT})_m \\ & + \beta_8(\text{TOP TIER-EQUITY})_m + \beta_9(\text{MIDDLE TIER-EQUITY})_m \\ & + \sum \beta_k(\text{CONTROL}_k).\end{aligned}$$

For each equity issue, we create the dummy variable $\text{RETAIN}_m^{\text{Lead-SEO}}$, which takes a value of one if a bank m was retained as the lead underwriter for that equity issue transaction and zero otherwise. For each equity underwriting deal i we create a choice set of at least 20 potential underwriters, creating at least 20 deal-underwriter pairs. The top 20 equity underwriters (based on market share) from the previous year and all commercial banks eligible to do equity underwriting in the previous year form the consideration set for each issuer in the current year. For each institution in a transaction-bank pair we estimate relationships across three markets: the bank loan market, the debt underwriting market, and the equity underwriting market. Within each market we use three different proxies of relationship strength for any bank m: $\text{LOANREL(Dummy)}_m^{\text{PublicEquity}}$ (one if there is a loan relationship with bank m in the last five years before the current equity underwriting transaction and zero otherwise), $\text{LOANREL(Number)}_m^{\text{PublicEquity}}$ (ratio of the number of loan deals with bank m to the total number of loan deals of the firm in the last five years before the current equity underwriting transaction), and $\text{LOANREL(Amount)}_m^{\text{PublicEquity}}$ (ratio of the dollar value of loan deals with bank m to the total dollar value of loan deals of the firm in the last five years before the current equity underwriting transaction). $\text{Lead-DEBTREL(Dummy)}^{\text{PublicEquity}}$ (one if there is a debt underwriting relationship in the lead underwriter capacity with bank m in the last five years before the present equity underwriting transaction and zero otherwise), $\text{Lead-DEBTREL(Number)}^{\text{PublicEquity}}$ (ratio of the number of debt underwriting deals in the lead underwriter capacity with bank m to the total number of debt underwriting deals of the firm in the last five years before the current equity underwriting transaction), and $\text{Lead-DEBTREL(Amount)}^{\text{PublicEquity}}$ (ratio of the dollar value of debt underwriting deals in the lead underwriter capacity with bank $m$to the total dollar value of debt underwriting deals of the firm in the last five years before the current equity underwriting transaction). $\text{Lead-EQUITYREL(Dummy)}^{\text{PublicEquity}}$ (one if there is an equity underwriting relationship in the lead underwriter capacity with bank m in the last five years before the present equity underwriting transaction and zero otherwise), $\text{Lead-EQUITYREL(Number)}^{\text{PublicEquity}}$ (ratio of the number of equity underwriting deals in the lead underwriter capacity with bank m to the total number of equity underwriting deals of the firm in the last five years before the current equity underwriting transaction), and $\text{Lead-EQUITYREL(Amount)}^{\text{PublicEquity}}$ (ratio of the dollar value of equity underwriting deals in the lead underwriter capacity with bank m to total dollar value of equity underwriting deals of the firm in the last five years before the current equity underwriting transaction). PROCEEDS is the amount raised in USD millions for the equity underwriting transaction (reported coefficient has been divided by 1,000). $(\text{LOAN MKT SHARE})_m$ is the market share of bank m in the loan market in the year before the current equity underwriting transaction. $(\text{TOP TIER-DEBT})_m$ and $(\text{TOP TIER-EQUITY})_m$ are dummy variables that equals one if bank m is ranked in the top five debt and equity underwriters, respectively, and zero otherwise. $(\text{MID TIER-DEBT})_m$ and $(\text{MID TIER-EQUITY})_m$ are dummy variables that equals one if bank m is ranked from 6th to 15th in debt and equity underwriting, respectively, and zero otherwise. $(\text{COMMERCIAL BANK})_m$ is a dummy variable that equals one if bank m had a Section 20 and/or investment banking subsidiary that was eligible to underwrite equity securities on the date of issuance and zero otherwise.

At the bottom of each panel we illustrate the economic impact of past lending, debt underwriting, and equity underwriting relationships on the probability of being chosen as the debt underwriter using the specification estimated in column 1. The first row reports the probability of a non-relationship bank ($\text{LOANREL(Number)}^{\text{PublicEquity}} = 0$) being chosen as the debt underwriter if all other variables are held equal to their mean. The second row reports the probability for a relationship bank ($\text{LOANREL(Number)}^{\text{PublicEquity}} = 1$) in the same way. Numbers in parentheses are standard errors corrected for heteroskedasticity and clustering (*** significant at the 1% level, ** significant at the 5% level,* significant at the 10% level).

	(1)	(2)	(3)	(4)	(5)
Const.	-6.78^{***}	-6.79^{***}	-6.76^{***}	-6.83^{***}	-6.77^{***}
	(0.38)	(0.35)	(0.35)	(0.40)	(0.40)
PROCEEDS	0.16	0.31	0.33	0.16	0.16
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}}$	0.02				-0.01
	(0.36)				(0.38)
$\text{LOANREL(Number)}_m^{\text{PublicEquity}}$		0.65^{*}			
		(0.38)			
$\text{LOANREL(Amount)}_m^{\text{PublicEquity}}$			0.39^{**}		
			(0.18)		
$\text{(LOAN MKT SHARE)}_m$	-20.13^{***}	-21.98^{***}	-19.46^{***}	-19.78^{***}	-23.14^{***}
	(6.90)	(6.24)	(6.07)	(6.87)	(8.81)
$\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicEquity}}$	1.34^{***}			1.34^{***}	1.33^{***}
	(0.21)			(0.21)	(0.21)
$\text{Lead-DEBTREL(Number)}_m^{\text{PublicEquity}}$		1.89^{***}			
		(0.28)			
$\text{Lead-DEBTREL(Amount)}_m^{\text{PublicEquity}}$			1.92^{***}		
			(0.29)		
TOP TIER-DEBT	1.53^{***}	1.65^{***}	1.62^{***}	1.53^{***}	1.56^{***}
	(0.34)	(0.33)	(0.33)	(0.33)	(0.34)
MIDDLE TIER-DEBT	0.92^{***}	0.96^{***}	0.93^{***}	0.92^{***}	0.91^{***}
	(0.30)	(0.31)	(0.30)	(0.30)	(0.31)
$\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicEquity}}$	2.38^{***}			2.42^{***}	2.32^{***}
	(0.22)			(0.23)	(0.24)
$\text{Lead-EQUITYREL(Number)}_m^{\text{PublicEquity}}$		2.97^{***}			
		(0.27)			
$\text{Lead-EQUITYREL(Amount)}_m^{\text{PublicEquity}}$			2.97^{***}		
			(0.26)		
TOP TIER-EQUITY	2.36^{***}	2.54^{***}	2.52^{***}	2.39^{***}	2.34^{***}
	(0.43)	(0.43)	(0.43)	(0.44)	(0.43)
MIDDLE TIER-EQUITY	2.09^{***}	2.14^{***}	2.15^{***}	2.12^{***}	2.07^{***}
	(0.37)	(0.37)	(0.37)	(0.38)	(0.37)
$\text{LOANREL(Dummy)}_m \times \text{Lead-EQUITYREL(Dummy)}_m$				-0.19	
				(0.50)	
$\text{LOANREL(Dummy)}_m \times \text{(1-Lead-EQUITYREL(Dummy)}_m)$				0.26	
				(0.38)	
$\text{Lead-EQUITYREL(Dummy)}_m \times \text{(COMMERCIAL BANK)}_m$					0.29
					(0.45)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	12,310	12,310	12,310	12,310	12,310
Pseudo R^2	0.47	0.48	0.49	0.48	0.48

Impact of past relationships on the probability of being chosen as the lead SEO underwriter using the column 1 *specification*

	Probability of being chosen (%)
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}} = 0$	0.30
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}} = 1$	0.31
Increase in probability	0.01
$\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicEquity}} = 0$	0.29
$\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicEquity}} = 1$	1.09
Increase in probability	0.80
$\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicEquity}} = 0$	0.28
$\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicEquity}} = 1$	2.95
Increase in probability	2.67

incremental impact that prior lending relationships have if a bank already has a prior equity underwriting relationship with that issuer. As column 4 reports, $\text{LOANREL(Dummy)}^{\text{PublicEquity}} \times \text{Lead-EQUITYREL(M)}^{\text{PublicEquity}}$ has an insignificant coefficient (−0.19), implying that a past lending relationship provides no significant extra benefit in terms of increasing the likelihood of winning future equity underwriting mandates over and above what a prior underwriting relationship provides. The coefficient for $\text{LOANREL(Dummy)}^{\text{PublicEquity}} \times (\text{1-Lead-EQUITYREL(M)}^{\text{PublicEquity}})$ is also insignificant, thus, even when prior equity underwriting relationships is absent, a past lending relationship does not increase the likelihood of winning the SEO mandate significantly. In column 5 we test whether the identity of an underwriter is a significant factor in an issuer's choice. We segregate our choice set between commercial banks and investment banks. We create the dummy variable COMMERCIAL BANK, which equals one if the bank had a Section 20 and/or an investment banking subsidiary that was eligible to underwrite the equity security on the date when it was issued, and we include the interaction term $\text{Lead-EQUITYREL(M)}^{\text{PublicEquity}} \times \text{COMMERCIAL BANK}$ in our underwriter selection model. The coefficient for this interaction term is insignificant, implying that commercial banks do not have a significant advantage in winning equity underwriting mandates over and above that conferred by past lending and investment banking relationships.

As expected, the results for choice of lead IPO underwriter are different from SEOs. As Table 8 reports, prior lending relationships are associated with a significantly higher probability of winning the lead IPO underwriting role. As one can see at the bottom of Table 8, a bank that had been a lender in the past had a three-times higher probability of winning the future IPO underwriting business (increasing from 0.48% to 1.81%). However, as with the debt underwriting, the economic impact is much smaller compared to the impact of such relationships on the probability of winning future lending business.[47]

With respect to the other variables in the logit equation, equity underwriting reputation (TOP TIER-EQUITY) translates into a higher probability of being chosen for the equity underwriting role for both SEOs and IPOs.[48] While the effect of a prior equity underwriting relationship is relevant only for SEOs, similar to the results for debt underwriter selection (Table 6), we find that a prior equity underwriting relationship increases the probability of being retained as lead underwriter of an SEO from 0.3% to almost 3%.

Although lending relationships do have a positive (but economically small) impact on the probability of generating future investment banking business, overall, the impact of relationships seems to be considerably stronger in the loan market compared to the public debt or equity underwriting markets.

[47]When we use a broader measure of underwriting business, that is, $\text{RETAIN}_m^{\text{IPO}}$, which equals one if bank m gets either the lead underwriter or a co-manager's role, we find (results not reported) a significantly higher association between prior lending relationships and probability of winning an underwriter role in the IPOs. For IPOs, a relationship lender has a 13.46% probability of winning some sort of underwriting role in the IPO equity issue compared to a 2.03% probability for a bank lacking such a relationship.

[48]This is similar to the results of Krigman et al. (2001), who find that issuers often switch underwriters to graduate to more reputable underwriters

Table 8
Impact of lending relationships on probability of getting future equity underwriting business-initial public offerings (IPOs)

This table provides the logit regression estimates of the following equation:

$$
\begin{aligned}
(\text{RETAIN})_m^{\text{Lead-IPO}} = {} & \beta_0 + \beta_1(\text{PROCEEDS}) + \beta_2(\text{LOANREL(M)}_m^{\text{PublicEquity}}) + \beta_4(\text{LOAN MKT SHARE})_m \\
& + \beta_5(\text{TOP TIER-EQUITY})_m + \beta_6(\text{MIDDLE TIER-EQUITY})_m \\
& + \sum \beta_k(\text{CONTROL}_k).
\end{aligned}
$$

For each equity issue, we create the dummy variable $\text{RETAIN}_m^{\text{Lead-IPO}}$, which takes a value of one if a bank m was retained as the lead underwriter for that IPO equity issue transaction and zero otherwise. The model is a reduced version of the one estimated for SEOs in Table 7. We drop the investment banking relationship variables as these are not meaningful for firms conducting an IPO. At the bottom of each panel we illustrate the economic impact of past lending relationships on the probability of being chosen as the equity underwriter using the specification estimated in column 1. The first row reports the probability of a non-relationship bank ($\text{LOANREL(Number)}^{\text{PublicEquity}} = 0$) being chosen as the debt underwriter if all other variables are held equal to their mean. The second row reports the probability for a relationship bank ($\text{LOANREL(Number)}^{\text{PublicEquity}} = 1$) in the same way. Numbers in parentheses are standard errors corrected for heteroskedasticity and clustering (*** significant at the 1% level, ** significant at the 5% percent level, * significant at the 10% level).

	(1)	(2)	(3)
Const.	−6.25***	−6.23***	−6.23***
	(0.22)	(0.22)	(0.22)
PROCEEDS	0.27***	0.30***	0.29***
	(0.09)	(0.08)	(0.08)
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}}$	1.34***		
	(0.34)		
$\text{LOANREL(Number)}_m^{\text{PublicEquity}}$		1.52***	
		(0.39)	
$\text{LOANREL(Amount)}_m^{\text{PublicEquity}}$			1.44***
			(0.38)
$(\text{LOAN MKT SHARE})_m$	−11.2**	−10.39*	−10.27*
	(5.41)	(5.41)	(5.37)
TOP TIER-EQUITY	4.21***	4.18***	4.19***
	(0.24)	(0.24)	(0.24)
MIDDLE TIER-EQUITY	2.99***	2.97***	2.98***
	(0.24)	(0.24)	(0.24)
Year dummies	Yes	Yes	Yes
Number of observations	15,112	15,112	15,112
Pseudo R^2	0.24	0.24	0.23

Impact of past relationships on the probability of being chosen as the lead IPO underwriter using the column 1 *specification*

	Probability of being chosen (%)
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}} = 0$	0.48
$\text{LOANREL(Dummy)}_m^{\text{PublicEquity}} = 1$	1.81
Increase in probability	1.33

5. Conclusion

Our paper seeks to measure the direct benefits that a bank-borrower relationship generates for a lender. For lenders, the establishment of a relationship with a borrower allows for more efficient information production and processing in offering future loans and other information sensitive products. Consequently, a relationship lender should be more likely to secure the future business of its borrowers. We find that indeed, establishing a relationship with a borrower significantly increases the likelihood of winning this borrower's future loan business both statistically and economically. As predicted by theory, we find that the increased likelihood of winning future business is most powerful for those borrowers that suffer from the greatest degree of informational asymmetry. We also find a statistically strong, though economically weak, association between lending relationships and the probability of winning future debt and equity underwriting business from the same borrower. Again, consistent with theory, we find that firms conducting IPOs (in contrast to firms conducting SEOs) are significantly more likely to use their prior lenders as their equity underwriters.

Appendix A

A.1. Methodology for construction of relationship variables

The table below describes how various relationship measures are constructed. Panel A describes the methodology for constructing measures that capture the existence and extent of prior lending relationship. Panels B and C describe the methodology for constructing prior investment banking relationship measures

Relationship variable	Methodology
Panel A: Lending relationships-bank loan and investment banking markets	
Binary measures	
$\mathrm{LOANREL(Dummy)}_m^{\mathrm{BankLoans}}$	Equals one if a bank *m* had a prior lending relationship with the firm in at least one loan during the five-year window preceding the date of activation of the current loan
$\mathrm{LOANREL(Dummy)}_m^{\mathrm{PublicDebt}}$	Same as $\mathrm{LOANREL(Dummy)}_m^{\mathrm{BankLoans}}$, except the look-back window is from the date of debt issue
$\mathrm{LOANREL(Dummy)}_m^{\mathrm{PublicEquity}}$	Same as $\mathrm{LOANREL(Dummy)}_m^{\mathrm{BankLoans}}$, except the look-back window is from the date of equity issue
Continuous measures	
$\mathrm{LOANREL(Amount)}_m^{\mathrm{BankLoans}}$	Ratio of the dollar value of loans contracted by a firm with the lending bank *m* to the total dollar value of loans contracted by the firm during the five-year

	window preceding the date of activation of current loan
$\text{LOANREL(Amount)}_m^{\text{PublicDebt}}$	Same as $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$, except the look-back window is from the date of debt issue for examining the impact of a lending relationship on the ability to attract underwriting of debt issues
$\text{LOANREL(Amount)}_m^{\text{PublicEquity}}$	Same as $\text{LOANREL(Amount)}_m^{\text{BankLoans}}$, except the look-back window is from the date of equity issue for examining the impact of a lending relationship on the ability to attract underwriting of equity issues
$\text{LOANREL(Number)}_m^{\text{BankLoans}}$	Ratio of the number of loans contracted by a firm with the lending bank m to the total number of loans contracted by the firm during the five-year window preceding the date of activation of current loan
$\text{LOANREL(Number)}_m^{\text{PublicDebt}}$	Same as $\text{LOANREL(Number)}_m^{\text{BankLoans}}$, except the look-back window is from the date of debt issue for examining the impact of a lending relationship on the ability to attract underwriting of debt issues
$\text{LOANREL(Number)}_m^{\text{PublicEquity}}$	Same as $\text{LOANREL(Number)}_m^{\text{BankLoans}}$, except the look-back window is from the date of equity issue for examining the impact of a lending relationship on the ability to attract underwriting of equity issues
Panel B: Investment banking relationships-debt underwriting market	
Binary measures	
$\text{Lead-DEBTREL(Dummy)}_m^{\text{PublicDebt}}$	Equals one if the bank m had underwritten at least one public debt issue (as the Lead underwriter) during the five-year window preceding the current debt issue
$\text{Lead-EQUITYREL(Dummy)}_m^{\text{PublicDebt}}$	Equals one if the bank m had underwritten at least one public equity issue (as the Lead underwriter) during the five-year window preceding the current debt issue
Continuous measures	
$\text{Lead-DEBTREL(Amount)}_m^{\text{PublicDebt}}$	Ratio of the dollar value of public debt issues of a firm underwritten by the bank m (as the Lead underwriter) to the total dollar value of public debt issues by the

	firm during the five-year window preceding the date of the current debt issue
Lead-DEBTREL(Number)$_m^{\text{PublicDebt}}$	Ratio of number of public debt issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total Number of public debt issues by the firm during the five-year window preceding the date of the current debt issue
Lead-EQUITYREL(Amount)$_m^{\text{PublicDebt}}$	Ratio of the dollar value of public equity issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total dollar value of public equity issues by the firm during the five-year window preceding the date of the current debt issue
Lead-EQUITYREL(Number)$_m^{\text{PublicDebt}}$	Ratio of number of public equity issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total Number of public equity issues by the firm during the five-year window preceding the date of the current debt issue
Panel C: Investment banking relationships-equity underwriting market	
Binary measures	
Lead-EQUITYREL(Dummy)$_m^{\text{PublicEquity}}$	Equals one if the bank *m* had underwritten at least one public equity issue (as the Lead underwriter) during the five-year window preceding the current equity issue
Lead-DEBTREL(Dummy)$_m^{\text{PublicEquity}}$	Equals one if the bank *m* had underwritten at least one public debt issue (as the Lead underwriter) during thefive-year window preceding the current equity issue
Continuous measures	
Lead-EQUITYREL(Amount)$_m^{\text{PublicEquity}}$	Ratio of the dollar value of public equity issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total dollar value of public equity issues by the firm during the five-year window preceding the date of the current equity issue
Lead-EQUITYREL(Number)$_m^{\text{PublicEquity}}$	Ratio of number of public equity issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total Number of public equity issues by the firm during the five-year window preceding the date of the current equity issue
Lead-DEBTREL(Amount)$_m^{\text{PublicEquity}}$	Ratio of the dollar value of public debt issues of a firm underwritten by the bank *m* (as the Lead underwriter) to the total

	dollar value of public debt issues by the firm during the five-year window preceding the date of the current equity issue
Lead-DEBTREL(Number)$_m^{\text{PublicEquity}}$	Ratio of number of public debt issues of a firm underwritten by the bank m (as the Lead underwriter) to the total Number of public debt issues by the firm during the five-year window preceding the date of the current equity issue

Appendix B

B.1. Descriptive statistics, relationship variables

The relationship measures are reported on an individual loan facility, debt issue transaction, and equity issue transaction basis. The bank loan market relationship measure on a particular loan facility is estimated by identifying the lead bank(s) on that facility and then searching over the prior five years to determine whether any of the lead bank(s) had been lead banks on any loans during this period. Thus, LOANREL(M)$^{\text{BankLoans}}$ is estimated for all the lead banks on the current facility and the highest value across these is assigned as LOANREL(M)$^{\text{BankLoans}}$ for that loan facility. A similar procedure is followed to estimate the relationship variables for debt and equity issue transactions.

	(1)	(2)	(3)
Panel A: Bank loan market-correlations across different relationship measures			
(1) LOANREL(Dummy)$^{\text{BankLoans}}$	1.00		
(2) LOANREL(Number)$^{\text{BankLoans}}$	0.89	1.00	
(3) LOANREL(Amount)$^{\text{BankLoans}}$	0.87	0.97	1.00

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Public debt underwriting market-correlations across different relationship measures									
(1) Lead-DEBTREL(Dummy)$^{\text{PublicDebt}}$	1.00								
(2) Lead-DEBTREL(Number)$^{\text{PublicDebt}}$	0.60	1.00							
(3) Lead-DEBTREL(Amount)$^{\text{PublicDebt}}$	0.56	0.94	1.00						
(4) Lead-EQUITYREL(Dummy)$^{\text{PublicDebt}}$	0.23	0.41	0.46	1.00					
(5) Lead-EQUITYREL(Number)$^{\text{PublicDebt}}$	0.25	0.44	0.49	0.94	1.00				
(6) Lead-EQUITYREL(Amount)$^{\text{PublicDebt}}$	0.24	0.44	0.49	0.94	0.99	1.00			
(7) LOANREL(Dummy)$^{\text{PublicDebt}}$	−0.06	0.08	0.08	0.03	0.01	0.00	1.00		
(8) LOANREL(Number)$^{\text{PublicDebt}}$	−0.07	0.10	0.10	0.07	0.05	0.05	0.88	1.00	
(9) LOANREL(Amount)$^{\text{PublicDebt}}$	−0.07	0.09	0.10	0.06	0.04	0.03	0.91	0.98	1.00

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel C: Public equity underwriting market-correlations across different relationship measures									
(1) Lead-EQUITYREL(Dummy)^{PublicEquity}	1.00								
(2) Lead-EQUITYREL(Number)^{PublicEquity}	0.87	1.00							
(3) Lead-EQUITYREL(Amount)^{PublicEquity}	0.89	0.98	1.00						
(4) Lead-DEBTREL(Dummy)^{PublicEquity}	0.32	0.33	0.31	1.00					
(5) Lead-DEBTREL(Number)^{PublicEquity}	0.27	0.37	0.35	0.83	1.00				
(6) Lead-DEBTREL(Amount)^{PublicEquity}	0.29	0.37	0.35	0.86	0.99	1.00			
(7) LOANREL(Dummy)^{PublicEquity}	0.16	0.19	0.18	0.13	0.11	0.10	1.00		
(8) LOANREL(Number)^{PublicEquity}	0.15	0.20	0.18	0.09	0.06	0.04	0.89	1.00	
(9) LOANREL(Amount)^{PublicEquity}	0.15	0.20	0.18	0.10	0.08	0.06	0.94	0.97	1.00

Appendix C

C.1. Issues related to bank M&A activity

The high level of M&A activity in the U.S. banking industry during our sample period poses two issues that need to be addressed. The first issue is how to account for the relationships of banks that are acquired or merged. We assume that in the case of acquisitions, all the customer relationships of the bank being acquired are inherited by the acquiring bank. For mergers, the relationships of the merger partners are assumed to be inherited by the new post-merger entity. The second issue also arises from the significant consolidation of banking industry over our sample period. This affects the identity of the top 40 banks, the calculation of bank market share, as well as bank relationships. Several banks that existed in the earlier part of the sample ceased to exist later (due to mergers) or become relatively unimportant in terms of total loan market share in later years. For example, Manufacturers Hanover, which was one of the largest commercial banks in the late 1980s, merged with Chemical Bank in 1991. Clearly, for loan transactions on or before 1991, Manufacturers Hanover was an important bank that had a chance of securing the lending business. Post 1991, it no longer existed. Thus, it is clear that we need to account for the changing identities of potential lead banks for a given loan over time.

We use the Chemical-Manufacturers Hanover merger discussed above to illustrate how we address these methodological issues. As we mention before, all borrowers that had a lending relationship with either the old Chemical or the old Manufacturers Hanover are assumed to be relationship borrowers of the new Chemical Bank. The next issue is to determine the historical market share of a new bank resulting from a merger or acquisition if it is the first year of operation for this new entity. We address this in the following way: the historical market share of the new bank is simply imputed from the historical market share of the individual banks that merged (or the shares of the target and the acquiror in case of acquisition). Thus, 1992 was the first full operating year for the new Chemical Bank resulting from the merger between the old Chemical and the old Manufacturers Hanover. Since there is no history for this new bank, the historical market share is calculated by summing the 1991 market shares of the old Chemical and the old Manufacturer's Hanover. A related issue concerns the choice set of potential lenders in 1992. For illustrative purposes, assume no other mergers or acquisitions took place in 1991 and that both old Chemical and old Manufacturers Hanover were in the top 40 banks in 1991. Using the methodology we discuss earlier, both these banks would be in the choice set of potential lenders. However, neither of these two banks exist in 1992 due to the merger, while the new Chemical is very much a potential provider of loans in 1992. We address this issue by assuming in our calculations *as if* the new Chemical Bank existed in 1991. This imputed bank would have a market share equal to the sum of its two constituents as discussed above and the choice set in 1992 would consist of 39 banks instead of 40 as the two merger partners (in this example-the old Chemical and Manufacturers Hanover) are replaced by a single merged entity (in this example-the new Chemical Bank). If the merger was between a top 40 bank and a nontop 40 bank no adjustment is made; only the market share needs to be updated and the choice set would still consist of 40 banks.

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