J Financ Serv Res (2009) 35:189–224
DOI 10.1007/s10693-009-0058-7

Relationship Banking and the Pricing of Financial Services

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Received: 17 February 2009 / Revised: 30 March 2009 / Accepted: 14 April 2009 /
Published online: 16 May 2009

Abstract We investigate pricing effects of the joint production of loans and security underwritings. We control for firm and borrower characteristics, including differences in sequencing, which are important for pricing. Contrary to previous studies, when banks combine lending and underwriting within the same customer relationship they charge premiums for both loans and underwriting services. Abstracting from effects of joint production within relationships, depository banks engaged in underwriting price lending and underwriting more cheaply than stand alone investment banks. One advantage borrowers enjoy from bundling products within a banking relationship is a form of liquidity risk insurance, which is manifested in a reduced demand for lines of credit. We also find evidence of a "road show" effect; firms enjoy loan pricing discounts on loans that are negotiated at times close to the debt underwritings, whether or not the same bank provides both services. Relationship effects are only visible when lending and underwriting both occur, and are stronger for equity-loan relationships than for debt-loan relationships.

Keywords Universal banking · Relationship banking · Underwriting · Lending

1 Introduction

This study analyzes the consequences of bundling different financing transactions (specifically, lending and underwriting) within the same banking relationship (which we will call "relationship bundling"). We address three main questions:

First, how does relationship bundling affect pricing by lenders and underwriters? Does bundling of lending and underwriting create net benefits from joint production, and if so,

Electronic supplementary material The online version of this article (doi:10.1007/s10693-009-0058-7) contains supplementary material, which is available to authorized users.

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how have those benefits been shared between banks and their clients? Some scholars (Drucker and Puri 2005) have argued that information and transaction cost economies of scope produce savings from relationship bundling that are passed on to customers in the form of lower costs. Others (Rajan 1992) have argued that stronger relationships may provide opportunities for quasi rent extraction (hence higher costs).

Second, do universal (depository) banks enjoy a comparative advantage in providing lending and underwriting services in comparison to stand-alone investment banks? Universal banks have gained enormous market share in underwriting. Is there a fundamental cost advantage of universal banking that shows itself in the pricing of lending and underwriting services? Do universal banks involved in relationship bundling price transactions differently from stand-alone investment banks, both in the context of relationship bundling and when providing a non-bundled loan or underwriting services?

Third, how does relationship bundling affect borrowers' financing needs? Previous work suggests that relationships provide real options to customers (e.g., faster or greater access to credit when needed). We investigate whether the existence of a bundling relationship, and the implied real option of future access to credit associated with that relationship, allows borrowers to reduce the size of their maintained lines of credit.

To address these questions, we construct a database of 7,315 firms, comprising information about their loans, debt issues, and equity issues for 1992–2002. When measuring the pricing effects of relationship bundling, we find that it is important to control for borrowers' and lenders' characteristics, as well as the sequencing of financial transactions, which we find has important effects on pricing. In order to investigate the value of relationship bundling for reducing borrowers' funding needs, we model loan supply and loan demand simultaneously (ours is the first study of which we are aware that identifies loan supply and loan demand when measuring the effects of relationship bundling).

Our methodological innovations have important implications. With respect to pricing effects of bundling, when one controls for borrowers' attributes and for transaction sequencing, relationship bundling (by either depository banks or stand alone investment banks) tends to be associated with higher pricing of underwriting services irrespective of whether underwriting precedes or follows lending. Relationship bundling is associated with higher pricing of loans only when loans precede an equity offering.

With respect to differences in the behavior among financial institutions, we find some important differences between depository banks and stand-alone investment banks. In general, abstracting from the effects of relationship bundling, stand-alone investment banks charge more than depository banks for lending and for underwriting of both debt and equity. In the context of relationship bundling, when loans are made after an equity underwriting, stand-alone investment banks offer a pricing discount on the loan, but depository banks do not. That discount is a form of "rebate" that compensates for the fact that depository banks generally price loans lower than investment banks; in other words, investment banks generally charge more for loans, but reduce that charge when combining lending and underwriting in the same banking relationship, but only if the loan follows an equity underwriting.

With respect to real-option benefits from bundling, we find that the demand for loans is lower in the presence of relationship bundling. Thus, although relationship bundling provides financial institutions with opportunities for quasi rent extraction, it also creates real-option advantages for customers.

We find that transaction sequencing matters for pricing irrespective of relationship bundling. Firms that issue public debt before negotiating a loan experience a "road show" effect—the loan is priced cheaper in the wake of a public offering of debt.

Section 2 reviews the literature on relationship bundling. Section 3 discusses our data sources and research methodology. Section 4 describes our regression modeling and presents our results for loan transactions. Section 5 presents our regression modeling and empirical results for equity and debt underwriting transactions. Section 6 concludes.

2 Literature review

Over the past two decades, research has substantially altered the view of the likely costs and benefits of universal banking (see Calomiris 2000 for a review). Prior to the mid-1980s, combining lending and underwriting was seen by many as undesirable from the standpoints of systemic stability and the quality of intermediation. But this point of view, which was based largely on anecdotal interpretations of the U.S. historical experience, has been largely overturned by academic research, which was motivated in part by the policy debate in the 1980s and 1990s over the deregulation of bank powers.

Joint production of multiple banking products can create efficiency gains associated with better portfolio diversification, scale-related economies of scope in product delivery, lower operating costs, and relationship economies of scope due to information reusability, although, as pointed out by Rajan (1992) and others, it can be difficult to detect scope economies in bank cost functions (Berger and Humphrey 1991; Pulley and Humphrey 1993). The current literature on combining lending and underwriting has increasingly focused on the potential costs and benefits for bank customers of combining lending and underwriting within the same banking relationship.

From the standpoint of measuring customer gains from relationship bundling, three categories of effects have been identified: (1) it can alter firm investment and financing behavior by providing real options for contingent access to external finance, which reduce financing costs and the cash flow sensitivity of investment; (2) it can either reduce or increase the costs of borrowing and underwriting, depending on whether relationship bundling leads to quasi rent extraction or, alternatively, to a sharing of production cost savings between banks and clients; and (3) it can improve the pricing of securities underwritten by banks engaged in relationship bundling.

One approach to measuring the effects of relationship bundling investigates how deeper bank relationships affect the behavior of clients. De Long (1991) examines how the presence of universal bankers on boards of directors affected corporate valuation. He finds that a Morgan partner on the board increased stock values by 30% ceteris paribus. Ramirez (1995) connects Morgan involvement with increases in the elasticity of credit supply in responding to firms' needs. He shows that the presence of a Morgan partner substantially reduced the cash flow sensitivity of a firm's investment. In other words, firms with access to a deeper banking relationship received a form of liquidity risk insurance—a real option to access external finance as needed. Below, we will return to this "real-option" effect when considering how the presence of strong banking relationships affect firms' demands for lines of credit. Lines of credit are an alternative source of liquidity risk insurance. To the extent that stronger banking relationships provide liquidity insurance, they should reduce the demand for lines of credit. Other recent studies of banking relationships have found evidence that the presence of stronger relationships increases access to credit or improves the terms of access (Chakravarty and Yilmazer 2007; Brick and Palia 2007; Jiangli et al. 2008)

A second approach to capturing the effects of relationship bundling measures effects on the pricing of underwritten securities. Relationship bundling can benefit client firms through the superior signaling ability of underwriters. Puri (1996) investigates bond yield spreads over Treasuries for the pre-Glass Steagall era and documents that universal banks obtain better prices for their customers than investment banks do. This provides some evidence of net benefits from the joint production of loans and debt underwriting. For the more recent period, Gande et al. (1997) compare the yield spreads of bonds underwritten by investment banks with the spreads of bonds underwritten by subsidiaries of commercial banks from 1993 to 1995. They find evidence that firms obtain better pricing for their bonds when they have an existing relationship with the underwriting bank. Roten and Mullineaux (2002) investigate the same question for bonds underwritten from 1995 to 1998 but find that an existing relationship with the underwriting bank has no impact on bond pricing.[1]

Schenone (2004) focuses on the possible effect of an existing lending relationship in reducing IPO underpricing, and documents a substantial reduction in IPO underpricing for firms that have existing lending relationship with banks with underwriting capability (i.e., universal banks, as opposed to non-universal banks). However, whether the firms go public with their relationship banks (or, alternatively, choose to use another underwriter) has no incremental impact on IPO underpricing. One interpretation of these findings, which we take into account in our own results reported below, is that they reflect selectivity bias related to client firm or transaction characteristics unrelated to relationship bundling. That is, there may be characteristics associated with the decision of a firm to employ a universal bank that are also associated with reduced IPO underpricing. The omitted variables of interest here may be related to a firm's financing strategy. For example, a firm with exceptional business opportunities and a foreseeable need for a future IPO may be more likely to use a universal bank. It might be the case that the firm's exceptional business opportunities explain the lower IPO underpricing found in the study; relationship bundling, per se, may have no effect on underpricing.

A third approach measures the effects of relationship bundling on the pricing of financial services. If the joint production of lending and underwriting gives rise to stronger banking relationships, that may allow bank quasi rent creation and extraction (e.g., Greenbaum et al. 1989; Sharpe 1990; Rajan 1992). If it is costly for a firm to credibly communicate its prospects to the public or to other banks, an informed relationship banker can gain market power that can potentially be translated into charging higher prices for some loans and other services. As Rajan (1992) shows, in a competitive environment with asymmetric information, relationships predictably give rise to quasi rents for banks, which they reap in later phases of their relationships by virtue of their information advantage relative to other banks.

Drucker and Puri (2005) investigate the pricing of financial services (loan interest rates and underwriting fees) for 2,301 seasoned equity underwritings during the period 1996 to 2001. Of the 2,301 seasoned equity underwritings in their sample, 201 issues are bundled with 358 loans (that is, loans and underwriting services are provided by the same institution). They estimate a gross underwriting spread equation and find that investment banks offer a discount on their underwriting fees when an equity underwriting is bundled with a loan.[2] The discount only applies to non-investment grade issuers, where the authors argue the gains from scope economies are relatively large. They find no underwriting fee discount for bundled issues underwritten by universal banks. In addition, they perform a

[1] In their study, commercial banks also charge lower underwriting fees, regardless of relationships.

[2] Bharath et al. (2008) similarly report lower interest rates and underwriting fees when the services are provided by the same bank, and they find a relationship advantage to the bank in the form of a higher probability of future business with the firm.

matched sample analysis of bundled and non-bundled loans, comparing their all-in-spreads, and find that universal banks give a pricing discount to loans that are bundled with underwriting deals. They find no loan pricing discount on bundled loans from investment banks. Their results are consistent with the existence of economies of scope in lending and underwriting, although the authors find that universal banks and investment banks pass on the associated cost savings to firms through different channels, depending of the skills in which they have a comparative advantage.

Two other studies, which differ from Drucker and Puri (2005) in their methodologies, report somewhat contrary results. Fraser et al. (2007) examine relationship bundling for loans and debt issues. They find that non-investment grade firms that use a universal bank as their debt underwriter concurrently with the extension of a line of credit receive better terms on the line than similarly situated firms that do not use the bank as a debt underwriter. But they find that the sequencing of the transactions matters importantly for their result. If the underwriting relationship precedes the lending relationship, then the borrower pays more, not less, for the line of credit. They argue that these results are consistent with the Rajan (1992) view that lenders make concessions to borrowers in the early phase of relationship formation, but extract rents from the relationships in the later phases. It should be noted, however, that Fraser et al. (2007) categorize a loan as matched with a debt underwriting if the same bank acts as both a lender and an underwriter at any time during a five-year period, which is much longer than the period used to define matching in Drucker and Puri (2005).

Sufi (2004) studies the underwriting fees and yield spreads of bonds underwritten by universal banks and investment banks from 1990 to 2003. The analysis includes firm fixed effects to control for time-constant unobserved heterogeneity among firms. The main finding is that universal banks provide a 10 to 15% discount in underwriting fees for joint transactions of loans and debt underwriting. However, there is no evidence of lower yields on bonds underwritten jointly with bank loans. Sufi (2004) demonstrates that OLS estimates of the bond spread equation are biased and can lead to an incorrect inference when firm fixed effects or controls are excluded from the regression.

Our paper contributes primarily to this third literature that measures the effects of relationship bundling on the pricing of financial services. We employ a comprehensive dataset on loans and both equity and debt underwritings and a research methodology designed to isolate the effects of relationship bundling on the pricing of lending and underwriting. We also contribute to the first literature, on real-option effects of relationship bundling, by investigating how relationships affect the demand for credit.

We incorporate two important insights from Fraser et al. (2007) and Sufi (2004), namely the need to take into account the sequencing of transactions within relationships, and the need to control for a variety of factors other than relationship bundling when measuring the effects of relationships on pricing, which Drucker and Puri (2005) do not do. Our study is more comprehensive than others in its treatment of firms' financing decisions. Previous studies focus on a pair of transaction types (i.e., loans and debts, or loans and equities) and usually investigate the pricing or fees of one type of transaction, ignoring the other type of transaction (with the exception of Drucker and Puri 2005). By examining all three types of transactions together we can trace whether a discount or premium charged for fees on bundled underwritings is offset or magnified by a premium or discount charged for interest on bundled loans.

Our results for the effects of relationships on the pricing of loans and underwriting fees differ dramatically from those of Drucker and Puri (2005). The primary reason for the differences in results is that Drucker and Puri (2005) use risk differences to instrument for relationship intensity (bundling), but do not allow risk to affect pricing directly.[3] We do not believe that firm risk can be used as a valid instrument for relationship formation; in contrast, we control for firm risk characteristics in pricing loans, and we do not attempt to instrument for relationship formation, as we are unable to identify a priori plausible relationship instruments (that is, variables that predict relationship formation, but are unrelated to risk or other variables that should affect pricing).

We construct a rich financing history of 7,315 firms (comprising available loan, debt, and equity transactions)[4] for the period 1992 to 2002, which spans a decade in which commercial banks increased their role in the underwriting business and eventually were allowed to compete without limit (after 1999). We investigate the effects of relationships on underwriting fees (for both bonds and equities) and on loan prices.

We identify and take into account three potential sources of model misspecification: (1) insufficient inclusion of balance sheet and income statement characteristics of borrowers and issuers in the list of explanatory variables that control for differences in firms' riskiness; (2) insufficient controls for possible heterogeneity in the cost functions of lenders and underwriters; and (3) insufficient controls for heterogeneity in the financing strategies (that is, the combinations and sequencing of funding sources) employed by borrowers and issuers, which could capture additional aspects of risk.

We employ more control variables than previous studies. A novel aspect of our methodology is that we include variables that capture patterns of firm financing strategies (in particular, the specific combinations of financings in which firms engage within defined windows of time). We find that the *combination*s of transactions and the *sequencing* of transactions that firms engage in matters importantly for pricing, both when those transactions are bundled within a relationship and when they are not. The details of our regression specifications, and our dataset construction methods, are presented in Section 3.

Finally, our analysis of the loan market uses a structural modeling approach of the price and quantity of the loan. Several recent studies recognize the importance of the joint determination of loan terms (Berger et al. 2005; Brick and Palia 2007; Chakravarty and Yilmazer 2007; Jiangli et al. 2008). In the same spirit as those studies, and unlike previous studies of relationship bundling, we explicitly model the joint determination of the price and quantity of loans in our analysis. While this structural approach does not materially affect our key results relating to the pricing of financial services by banks, it

[3] Drucker and Puri (2005) use a numerical ratings scale, loan size, loan type, loan maturity, and year and industry dummies to forecast matching (relationship bundling of loans and equity underwriting) using a probit model. They then group each matched observation with a set of non-matched neighbors that have the closest forecasted matching score from the probit, and then calculate the average spread differences between matched loans and their non-matched neighbors. This approach ignores the effects of risk and other firm factors on loan pricing. We believe that the forecasting variables they employ are not proper instruments for forecasting matching, since those variables are related to loan pricing irrespective of matching. We have several other methodological differences with Drucker and Puri (2005), including the way bank relationships are defined, the way ratings are measured, and several other less important differences. These differences and their consequences for explaining differences in our findings relative to Drucker and Puri (2005) are reviewed in a "Appendix A2-Comparison Appendix (ESM)," available upon request from the authors. With respect to underwriting fees, the choice of control variables are important in explaining why our results differ from Drucker and Puri (2005), but differences in the method for identifying relationships are a more important source of difference in our findings (they assume that loan participation is sufficient to create a lending relationship, while we assume that loan origination is necessary to relationship formation).

[4] The exclusion of private placements and commercial paper is discussed in the Data Appendix below.

improves the accuracy of our results, and more importantly, it allows us to capture an important real-option benefit of relationships, namely the reduced demand for credit that coincides with relationship bundling.

3 Data sources and construction

An ideal dataset would contain a complete history of firm financing transactions, including bank loans and all public and private placements of securities. To the extent that this can be approximated, one must construct firm financing histories by combining multiple data sources. The Data Appendix explains our approach to combining loan data from Loan Pricing Corporation's *DealScan* with underwriting data from Securities Data Corporation (SDC). We have 7,315 firms with "complete" histories of financing transactions (i.e., all bank loans and securities offerings reported in *DealScan* and SDC) in our final dataset. Once firms are matched, accounting information from *Compustat* and the market equity price from *CRSP* are added to the final dataset.

Table 1 provides a summary of loan observations used in the study broken down by lender types, loan classifications, and loan distribution method. Table 2 provides a summary of underwriting deals in our sample broken down by type of financial institutions. Table 2 shows that investment banks have lost significant market share in underwriting. This trend represents a combination of greenfield investments and acquisitions of investment banks by commercial banks. Our period begins in 1992 (when commercial banks were able to underwrite securities to a limited extent as the result of Federal Reserve actions). Underwriting limits for commercial banks and "firewall" regulations were relaxed over time, and all limits on the amount of underwriting that universal banks could do were eliminated in 1999 under the Gramm-Leach-Bliley Act.

Our objective is to study differences in loan interest costs and underwriting fees among borrowers that use different types of financial intermediaries, have different financing needs and characteristics, and exhibit different relationship bundling patterns. We thus classify firms' financing patterns and banking relationship patterns through time. To this end, we develop the concept of the "financing window"—a set of financial transactions that are temporally close together—to capture differences in risk and financing needs, and to separate customer-level effects associated with combinations and sequences of financings, per se, from the effects of relationship bundling decisions.

3.1 Defining financing windows

As discussed in Section 2, existing studies on the effects of relationship bundling focus on one or two types of transactions and define banking relationships with respect to only those transactions. This approach ignores other transactions that may affect the conclusions reached about relationships. For example, when a study focuses on a debt underwriting transaction and defines the existing banking relationship as any lending transaction prior to the debt underwriting transaction, a low fee on a debt underwriting may not be a consequence of the existing lending relationship if, for example, there are other equity or debt offerings prior to the current debt underwriting deal, as well. That is, the low fee may reflect prior security offerings that are ignored in the construction of the proxies for the banking relationship. We will distinguish between patterns of financing according to the type, combination, and sequence in which various transactions occur.

Table 1 This table presents the number and the dollar volume of loans to non-financial, non-regulated, and non-governmental borrowers in the U.S. from Loan Pricing Corporation's DealScan database. Specifically, we exclude all borrowers with first-digit SIC code 6 and 9 and highly regulated industries with first 2-digit SIC code 43, 45 and 49. In Panel A, the data are broken down by various types of lending financial institutions for the period from 1992 to 2002. Panel B classifies loans by type of loan.Panel C classifies loans by distribution method. Only loans from borrowers that can be matched to financial data from Compustat are included in this table. The upper rows of data are number of loans as % of total and the lower rows are dollar volume as % of total

Number of loans (% Total) Dollar volume (% Total)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
Panel A: Loans classified by type of lender												
Banks Only	93%	95%	95%	94%	92%	88%	87%	83%	85%	80%	83%	88%
	88%	95%	96%	81%	89%	83%	83%	70%	70%	66%	71%	78%
IBs Only	1%	1%	1%	1%	1%	1%	1%	1%	2%	1%	1%	1%
	1%	3%	1%	2%	2%	1%	1%	1%	2%	1%	0%	1%
Joint Banks & IBs	0%	0%	0%	2%	3%	6%	7%	11%	9%	13%	12%	7%
	8%	0%	2%	17%	9%	15%	15%	28%	28%	32%	28%	19%
Other Lenders	5%	4%	4%	3%	4%	4%	5%	5%	4%	6%	4%	4%
	3%	2%	1%	1%	1%	1%	1%	1%	1%	2%	1%	1%
Panel B: Loans classified by loan type												
Bridge Loans	1%	1%	1%	1%	1%	1%	2%	2%	2%	2%	2%	1%
	1%	3%	0%	2%	1%	2%	4%	4%	3%	6%	6%	3%
364 day Facility	1%	4%	7%	6%	4%	6%	9%	12%	16%	17%	18%	10%
	12%	15%	21%	17%	11%	14%	28%	36%	42%	36%	44%	28%
Letter of Credit	4%	4%	3%	2%	2%	2%	1%	1%	1%	1%	1%	2%
	1%	1%	1%	1%	0%	2%	2%	2%	2%	2%	0%	1%
Lease	0%	0%	0%	0%	1%	1%	1%	1%	2%	2%	1%	1%
	0%	0%	0%	0%	0%	0%	1%	0%	1%	1%	0%	0%
Other	5%	4%	3%	2%	1%	1%	1%	4%	3%	3%	2%	3%
	1%	1%	1%	1%	1%	1%	1%	2%	2%	1%	1%	1%
Revolver	67%	66%	65%	69%	71%	67%	61%	52%	51%	52%	50%	60%
	72%	71%	69%	73%	78%	71%	49%	40%	38%	44%	35%	55%
Term Loan	22%	21%	21%	19%	21%	22%	26%	29%	26%	23%	26%	24%
	14%	9%	9%	7%	8%	9%	16%	16%	12%	10%	13%	11%
Panel C: Loans classified by distribution method												
Sole Lender	42%	36%	26%	18%	24%	23%	19%	15%	7%	8%	7%	18%
	3%	2%	1%	1%	1%	1%	1%	0%	0%	1%	0%	1%
Syndication	58%	64%	74%	82%	76%	77%	81%	85%	93%	92%	93%	82%
	97%	98%	99%	99%	99%	99%	99%	100%	100%	99%	100%	99%
Total Number of Loans	965	1,145	1,358	1,361	1,738	1,955	1,906	1,934	1,869	1,798	1,548	17,577
Total Dollar Volume (Billion)	113	175	248	310	337	437	369	415	464	482	395	3,744

Table 2 Summary of SDC public offering sample. This table presents the number and the dollar volume of debt and public equity offerings (both IPO and SEO) by non-financial, non-regulated, and non-governmental borrowers in the U.S. from Securities Data Corporation's underwriting database. Specifically, we exclude all borrowers with first-digit SIC code 6 and 9 and highly regulated industries with the first 2-digit SIC code 43, 45 and 49. The data are broken down by security type and type of underwriting financial institution for the period 1992- 2002. The upper rows of data are number of offerings as % of total and the lower rows are dollar volume as % of total

Number of offerings (% total) Dollar volume (% total)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
Panel A: debt underwritings												
Banks Only	10%	11%	13%	20%	22%	16%	34%	33%	38%	47%	58%	26%
	7%	7%	7%	12%	16%	15%	24%	31%	34%	48%	57%	28%
IBs Only	90%	89%	87%	80%	78%	84%	66%	66%	60%	49%	35%	72%
	93%	93%	93%	88%	84%	85%	74%	67%	63%	44%	28%	68%
Joint Banks & IBs	0%	0%	0%	0%	0%	0%	1%	1%	2%	4%	8%	1%
	0%	0%	0%	0%	0%	0%	2%	2%	3%	7%	15%	4%
Total Number of Offerings	417	511	315	397	565	657	749	403	308	401	340	5,063
Total Dollar Volume (Billion)	70	84	44	58	78	84	114	114	100	169	122	1,039
Panel B: Equity Underwritings												
Banks Only	0%	1%	3%	3%	5%	12%	29%	27%	33%	30%	30%	13%
	0%	2%	4%	3%	3%	8%	26%	22%	20%	18%	20%	13%
IBs Only	100%	99%	97%	97%	95%	87%	70%	72%	62%	61%	64%	86%
	100%	98%	96%	97%	96%	90%	72%	75%	69%	62%	72%	82%
Joint Banks & IBs	0%	0%	0%	0%	0%	0%	1%	2%	5%	8%	6%	1%
	0%	0%	0%	0%	1%	1%	2%	3%	10%	20%	8%	5%
Total Number of Offerings	663	884	705	820	1,141	858	531	743	649	310	295	7,599
Total Dollar Volume (Billion)	36	48	35	56	81	66	64	111	125	65	49	736

A window is defined as a cluster of financing events[5] that are at most 1 year apart from their closest neighboring transaction, and for which there are no other financing events (outside the window) happening within 1 year before or after the window.[6] Using this definition, the window can have a length ranging from 1 year (with two financing events, one at the beginning and one at the end of the window) to as long as the total length of the study period (1992–2002). The vast majority of financing windows have a length of less than 2 years. Table 3 provides a summary of financing windows constructed by this method.[7] For example, there are 138 financing windows that involved a loan and debt

[5] A financial event can be a loan, or a debt or equity underwriting. IPOs are included in the windows for the purpose of defining an event, but we restrict ourselves to seasoned equity offerings (SEOs) in our analysis of underwriting fees for equity offerings, for two reasons: (1) some data about firms in years preceding their IPOs may not be available; and (2) underwriting costs are much higher for IPOs than for SEOs, and are a much smaller fraction of the total cost of the offering, since IPOs also entail significant underpricing.

[6] We also defined the financing window with a 6-month events gap, as opposed to one year. The conclusions of the paper are insensitive to that alternative specification.

[7] Because our dataset is left-truncated in 1992, we exclude all windows where the first event we observe occurs in 1992, since it is unclear whether those windows actually start in 1992 or at an earlier date.

Table 3 Classification of financing windows. This table presents the number of financing windows constructed from the history of financing activities of 7,315 firms during 1992 to 2003. The history of financing activities for each firm is assembled from loan and underwriting data from DealScan and Loan Pricing Corporation (LPC) databases detailed in Tables 1 and 2. Loans in DealScan are matched with Compustat using ticker symbol as well as manual name matching. The underwriting deals in SDC Platinum are matched with loans from LPC using CUSIP. Then the financing history of a firm is constructed by sorting all loans and underwriting deals by date for each matched GVKEY variable in Compustat. A financing window is defined as a cluster of events that are at most 1 year apart and for which there is no other financing event happening within 1 year before and after the window. By this definition, financing windows can have variable length with different numbers of events in a window. The table then classifies windows by the number of events that belong to them. Furthermore, we classify windows according to the sequence of events within the window defined as follows:

Type of Events in the Windows	Number of events in window					
	1	2	3	4	>4	Total
Loan only	4,658	808	226	74	52	5,818
Debt only	500	73	23	4	20	620
Equity only	3,700	377	32	4		4,113
Loan and Debt		138	84	61	185	468
Loan and Equity		661	345	162	155	1,323
Debt and Equity		98	29	13	14	154
Loan, Debt, and Equity			26	32	134	192
Total	8,858	2,155	765	350	560	12,688
Average Length of Windows in Months		15	30	43	84	31

offering pair, as shown in the fourth row and the second column in the table. Most windows contain a pair of events occurring less than 1 year apart. This fact explains why varying the definition of windows has little effect on our findings.

3.2 Determining lead financial institutions

We define "lead" financial institutions as those that matter for relationship banking. The mergers, acquisitions, and reorganizations among financial institutions make it difficult to identify all banks and subsidiaries within a bank holding structure through time. To overcome this challenge, we develop an additional dataset containing the identities of large bank holding companies, their subsidiaries, and merger histories, which uniquely identifies each financial institution in the dataset through time.[8] We assign a unique ID to *all* banks and subsidiaries within the same holding company. When mergers occur, the IDs are updated to reflect the new holding company. Similarly, unique IDs are assigned to all investment banks in our dataset.

Financial institutions sometimes participate in loan syndications or joint security underwritings. However, the degree of participation and the influence in deal pricings vary according to their roles in the transaction. We credit a financial institution with a transaction

[8] Merger data are available from the BHC database provided at the Federal Reserve Bank of Chicago website. We also manually verify bank merger history and holding company structure with the website of the National Information Center of the Federal Reserve System for accuracy.

only if it has a *leading* role as the originator or underwriter of the transaction.[9] Specifically, lead lenders are defined as lenders with agent title in loan syndication documentation (e.g., managing agent, syndication agent, documentation agent, administrative agent) or the party that acts as the lender and arranger in non-syndicated loans. For underwriting deals, we adopt the definition of lead managers from the *SDC* database, where lead managers are defined as those with the role of book runner, joint book runner, or joint lead manager. Therefore, it is possible in our dataset that a loan or underwriting has multiple lead lenders or lead underwriters, which may give rise to ambiguity in defining the bank-firm relationship. We devise a robust approach to dealing with the potential problem of multiple lead banks about which we will elaborate below.

3.3 Constructing control variables for firm financing patterns

We control for firm financing patterns using the following six dummy variables that capture different combinations and sequencing of firm financings by describing the temporal relationship between the current event and all the other events in the same window: *PL*, *PD*, *PE*, *SL*, *SD*, and *SE*. The variables *PL*, *PD*, and *PE* equal one, respectively, if there are other loan, debt, or equity events *preceding* the current event within the financing window. *SL*, *SD*, and *SE* equal one, respectively, if there are other loan, debt, and equity events *subsequent* to the current event within the financing window. These six dummy variables are clearly defined for each event in a financing window regardless of the identities of the lenders/underwriters involved in the event and can be used in the regressions to control for unobserved heterogeneity among firms related to differences in the patterns of their financial sequencing, per se. We provide some examples of financing windows to demonstrate how these financing pattern control variables are assigned toward the end of this section.

3.4 Constructing proxies for relationship variables

We define a relationship between a bank and a firm as the repetition of this bank-firm pairing in multiple events within the financing window. Therefore, a bank-firm relationship can take the form of repeating loans, repeating debts, repeating equities, or any combination of these transactions by this bank-firm pair within a window.

When *all* of the lead lenders and underwriters for *all* events within a financing window are unique, we identify this window as an *unmatched window*. In this case, a firm uses different lenders and underwriters for all events in the window and there is no identifiable relationship in the window. A financing window is a *matched window* when *one or more* lead lenders or underwriters in the window (as identified by their unique IDs defined earlier) lead *more than one* transaction within the window. Therefore, it is possible to have several relationships embedded within a matched window. Figure 1 provides a diagram depicting the classification of events for different types of windows.

First, consider the case of unmatched windows. By definition, all events in these windows are *unmatched events*. When an unmatched event involves a single lead financial

[9] Our definition of lending relationships is narrower than Drucker and Puri (2005), who include all loan participants. Our definition in the underwriting context is broader; they use the first name listed in the underwriting syndicate, which can exclude joint book runners. These definitional differences are a more important source of differences in findings regarding matching effects in our underwriting spread regressions than in our loan spread regressions. The sources of differences in results are reviewed in a “Appendix A2-Comparison Appendix (ESM),” available upon request from the authors.

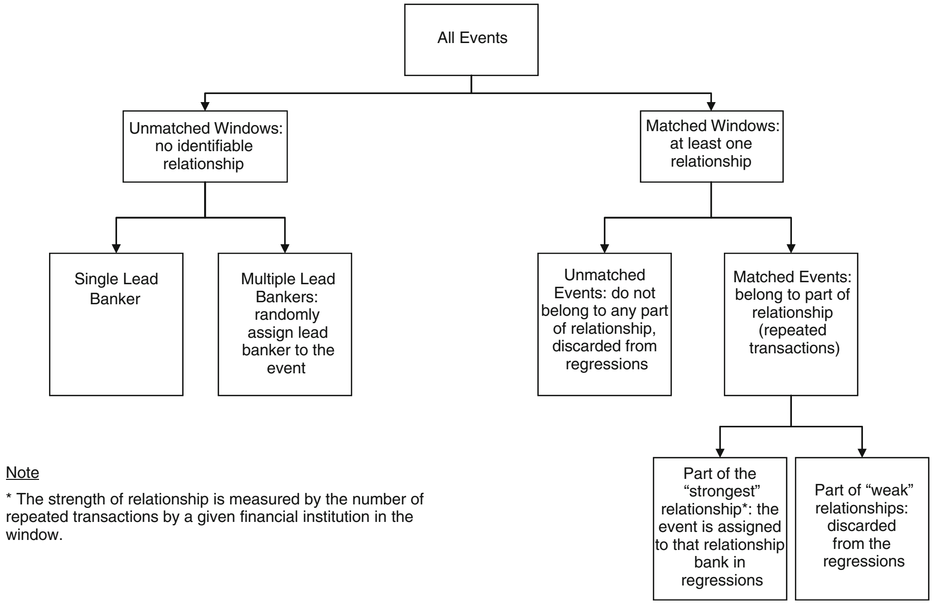

Fig. 1 Classification of events

institution, the identity of the lead institution to be used in the regressions is obvious. However, it is less clear when there are multiple lead bankers in the event. One possible approach for the regression analysis is to include all possible bank-firm pairings from each event in the regressions. For example, a two-event window comprised of a loan (with two lead lenders) followed by a debt underwriting (with two lead underwriters) creates four possible observations for the regression analysis (two observations for loan regressions and two observations for debt regressions). This approach essentially double-counts some events, and thus may suffer from non-random sampling bias induced by the correlation among observations from the same event. To avoid this problem, we deal with unmatched loans with multiple lead institutions by randomly assigning a lead institution to each event in order to create a unique bank-firm matching. This approach to assigning bank-firm matches to the unmatched group does not introduce any systematic bias in measuring the effects of relationships on deal pricings, which is evident in our robustness tests.[10]

In a matched window, if *only one* financial institution is involved in multiple events in the window, then there is a *unique relationship* in this window, in which case we assign these matched events to the relationship bank and discard any unmatched events from the analysis. When *more than one* financial institution leads (or jointly leads) multiple events in the window, we include only events from the financial institution with the *strongest*

[10] In results not reported here, we perform the following robustness tests of our approach to randomly assigning a lead banker to each event. For the first robustness test, we redraw several trials of the random assignment of a banker-firm match for the set of unmatched loans. Our regression results are practically unchanged from one trial to another. For the second test, we average lender/underwriter characteristics across all banks and assign the average value to that event in the regressions. In our specification, the only lender/underwriter characteristic used in the regressions is the lending/underwriting market share. In addition to the *IB* dummy variable, whose value indicates the fact that the event involves exclusively investment banks, we also include a dummy variable *MIX* to indicate mixed commercial and investment banks deal (the base case regression corresponds to deals that are done exclusively by commercial banks). The regression results for these robustness tests are very similar to the ones reported in the paper.

relationship in the regressions, where the strength of a bank-firm relationship is measured by the number of repeated transactions done by that bank (see specific examples below).[11]

In 2,377 of our 4,411 matched window observations for loans, we identify unique matches within the window (transactions involving a matched bank-firm relationship where there is no other bank-firm matching occurring within the window). In 1,533 other transactions, there is more than one matched relationship within the window, but we are able to identify a dominant matched relationship. In the remaining 501 cases where more than one institution has the same number of repeated events in the window, we randomly select one of the bank-firm relationships as the matched relationship for that window. As in the case of the random assignment of unmatched bank-firm relationships, this method avoids double counting of matched observations. We test, and confirm, the robustness of our reported results to alternative random choices of bank-firm matches, and also to the alternative sampling method of using only the 2,377 unique matches in our sample.[12]

Once we identify the strongest relationship bank within the matched windows, we define six indicators, *MPL*, *MPD*, *MPE*, *MSL*, *MSD*, and *MSE*, to capture the pattern of matching within the window. These variables, *MPL*, *MPD*, *MPE*, *MSL*, *MSD*, and *MSE*, equal one when the corresponding events (i.e. *PL*, *PD*, *PE*, *SL*, *SD*, and *SE*) involve the same financial institution as the one in the current event. For instance, both *MPD* and *PD* equal one if the current loan event is preceded by a debt offering that is underwritten by the same bank as the current loan. Tables 4, 5 and 6 provide descriptions for all twelve relationship variables defined earlier, along with the definitions of other variables used in this study.

3.5 Financing window examples

In Table 4, example 1 illustrates a financing window with the following sequence of transactions that are, at most, a year apart: loan, debt offering, loan, seasoned equity offering, and loan. Each transaction in the window has a unique lender/underwriter and we can identify two relationships within the *matched window*, namely repeated loans from bank A and a debt, equity, and loan sequence by bank B. Because bank B is involved in three matched transactions, compared to two transactions by bank A, we identify bank B as having the stronger relationship in this financing window. Therefore, only transactions by bank B would be included in the regression (one observation each in the loan, debt, and equity regressions). To further illustrate how we assign values to financing pattern and relationship variables, consider the debt offering event in example 1. PL, SE, and SL equal one because there is a loan prior to this debt offering and there is an equity offering and another loan transaction after this debt offering. In addition, MSE and MSL are set to one because the subsequent equity and loan transactions are done by the same bank as in this debt transaction.

Example 2 in Table 5 illustrates the case of multiple lead bankers within a window with multiple relationships. This financing window includes a sequence of three transactions: a

[11] For an event with multiple lead bankers, it can simultaneously be part of several relationships within a window. Therefore, the approach we adopt here in defining the strongest relationship also handles the issues that arise from the events with multiple lead financial institutions.

[12] In a "Loan Regressions Robustness Appendix (ESM)," available upon request from the authors, we present our loan spread regressions where we restrict our samples to include only events from unmatched windows and matched windows with a *unique* bank relationship, to test whether our conclusions are sensitive to our assumptions about assigning a relationship bank to a matched window when there are multiple relationships. The regression results in this case are similar to what we report in the next section of the paper. We conclude that our method of ranking the intensity of relationships when there are multiple relationships is not important in driving our results.

Table 4 Matched financing window examples. Example 1. Each Event has Only One Banker. This example illustrates how we assign values to vectors of relationship dummy variables associated with events in a given financing windows (LDLEL window). Table 6 provides the definitions of these dummy variables

Sequence of events Single Lead Banker	Loan → Bank A	Debt → Bank B	Loan → Bank A	Equity → Bank B	Loan Bank B
Variables	Assigned Values				
PL	0	1	1	1	1
PD	0	0	1	1	1
PE	0	0	0	0	1
MPL	0	0	1	0	0
MPD	0	0	0	1	1
MPE	0	0	0	0	1
SL	1	1	1	1	0
SD	1	0	0	0	0
SE	1	1	1	0	0
MSL	1	1	0	1	0
MSD	0	0	0	0	0
MSE	0	1	0	0	0
Obs Used in Regs	✕	✔	✕	✔	✔

loan, a debt offering, and another loan. There are two bankers involved in each transaction with a total of two relationships within this window: repeated loans by bank A and a loan-debt sequence by bank B. Again, we include only the observations led by bank B in the regressions based on the criterion that bank B has the highest number of repeated events within the window. In particular, we include all three events in the regressions but only associate these events to bank B.

4 Loan market regressions

The endogenous variables of interest for the loan regressions are the loan spread (all-in-spread) and the loan amount. We choose a log specification to be consistent with positivity of loan spread and quantity, and to transform these variables to be closer to a normal distribution.[13] We allow the loan spread and loan amount to be determined jointly in the following system of simultaneous equations, where Eq. 1 is the Loan Supply Equation, and Eq. 2 is the Loan Demand Equation. By employing a structural approach to the loan market, we are able to separate Supply and Demand effects related to relationships.

$$LNSPREAD_i = \beta_0^s + \beta_1^s REL_i + \beta_2^s LEC_i + \beta_3^s LOC_i + \beta_4^s BC_i + \beta_5^s SUP_i + \gamma_1 LNAMT_i + \varepsilon_{1i} \tag{1}$$

$$LNAMT_i = \beta_0^d + \beta_1^d REL_i + \beta_2^d LEC_i + \beta_3^d LOC_i + \beta_4^d BC_i + \beta_5^d DEM_i + \gamma_2 LNSPREAD_i + \varepsilon_{2i} \tag{2}$$

[13] Our results are not sensitive to this log transformation. We obtain very similar results using the basis point spread and the dollar loan amount.

Table 5 Example 2. Each event has multiple bankers but one dominant relationship for the window. This example illustrates how we assign values to vectors of relationship dummy variables associated with events in a given financing windows (LDL window) when there are multiple bankers in some deals and one dominant relationship

Sequence of events	Loan →		Debt →		Loan	
Joint Lead Bankers	Bank A	Bank B	Bank B	Bank C	Bank A	Bank B
Variables	Assigned Values					
PL	0	0	1	1	1	1
PD	0	0	0	0	1	1
PE	0	0	0	0	0	0
MPL	0	0	1	0	1	1
MPD	0	0	0	0	0	1
MPE	0	0	0	0	0	0
SL	1	1	1	1	0	0
SD	1	1	0	0	0	0
SE	0	0	0	0	0	0
MSL	1	1	1	0	0	0
MSD	0	1	0	0	0	0
MSE	0	0	0	0	0	0
Obs Used in Regs	✕	✓	✓	✕	✕	✓

where:

– *LNSPREAD* is the natural log of the loan all-in-spread (DealScan's measure of cost that combines all interest payments and fees on a loan into a single, comparable cost measure),
– *LNAMT* is the natural log of loan amount,
– *REL* is a vector of 12 dummy variables for financing needs and relationship variables (defined above) which can interact with dummies for the type of financial institution, which can affect supply and demand,
– *LEC* is a vector of lender characteristics that can affect supply and demand,
– *LOC* is a vector of loan characteristics that can affect supply and demand,
– *BC* is a vector of borrower characteristics that can affect supply and demand,
– *SUP* is a vector of two loan supply shifters unrelated to loan demand, and
– *DEM* is a vector of two loan demand shifters unrelated to loan supply.

Crucial to our ability to identify Eqs 1 and 2 as Loan Supply and Loan Demand is our ability to construct plausible sets of instruments, *SUP* and *DEM*. We include *PRIME* and *SIC2LESH* in *SUP*. *PRIME* equals one when loans are indexed to prime rate instead of other, market-based indexes, such as Libor. Calomiris and Pornrojnangkool (2005) and Beim (1996) document a pricing premium for prime-indexed loans which they argue reflects greater lender pricing power. The variable *SIC2LESH* is the previous year's lending market share of the lender (for the transaction under consideration) to all borrowers with the same two-digit SIC code as the borrower. This is constructed based on all loans in the *DealScan* database. Lenders that acquire lending specialization in a certain industry (measured by two-digit SIC code) may be able to price loans in their specialized industries more competitively. Both variables are assumed to primarily influence loan-supply terms and to be unrelated to demand.

We include two measures of lender characteristics (*LEC*) in both the Loan Supply and Loan Demand equations. These are the variables *MULTLEND*, and *LTOTLEND*.

Table 6 Definition and summary statistics of variables

Variables	Description	Equation	25th pct	Median	75th pct	Mean	Std	Count
PANEL A: VARIABLES USED IN REGRESSIONS								
LNSPREAD	log of loan all-in-spread	Pricing	3.912	4.828	5.470	4.632	0.945	21,579
LTOTSPDT	log of total debt underwriting spread	Pricing	4.266	4.531	5.076	4.686	0.704	2,132
LTOTSPEQ	log of total equity underwriting spread	Pricing	6.312	6.505	6.690	6.521	0.380	1,864
ADJMKTLV	leverage ratio adjusted for market value of equity	Loan	0.215	0.354	0.504	0.369	0.193	21,579
		Debt	0.178	0.273	0.410	0.306	0.167	2,132
		Equity	0.008	0.088	0.246	0.150	0.167	1,864
LNAMT	log of principle amount of loan or offering	Loan	18.315	19.337	20.253	19.150	1.691	21,579
		Debt	18.826	19.337	20.030	19.429	1.020	2,132
		Equity	17.084	17.736	18.400	17.748	1.086	1,864
LNASSET	log of total assets	Loan	19.929	21.225	22.588	21.209	1.956	21,579
		Debt	21.070	22.207	23.331	22.127	1.686	2,132
		Equity	17.513	18.417	19.612	18.631	1.672	1,864
LNMATURE	log of the number of days to maturity	Loan	5.897	6.999	7.510	6.843	0.805	21,579
		Debt	7.849	8.204	8.385	8.158	0.865	2,132
LNMVE	log of market value of equity	Equity	18.254	19.028	20.009	19.109	1.446	1,864
LTOTLEND	last year log total dollar lending	Loan	23.674	24.822	25.575	24.319	1.970	21,579
LTOTDUND	last year log total debt underwriting	Debt	22.289	22.961	23.495	22.663	1.381	2,132
LTOTEUND	last year log total equity underwriting	Equity	19.519	21.070	22.067	20.636	1.864	1,864
MVEOBVE	market to book ratio of equity	Loan	1.356	2.264	3.835	3.273	1.810	21,579
		Debt	1.520	2.333	3.611	2.061	4.167	2,132
		Equity	1.989	3.142	5.475	2.962	6.115	1,864
SALEGRWT	growth of sales over the past year	Loan	0.012	0.091	0.229	0.152	0.336	21,579
		Debt	0.016	0.076	0.179	0.135	0.295	2,132
		Equity	0.102	0.245	0.481	0.335	0.584	1,864
SIC2LESH	lender market share in 2-digit SIC sector	Loan	0.019	0.049	0.100	0.074	0.090	21,579
VOL	volatility using last 250 days stock returns	Equity	0.406	0.526	0.672	0.566	0.243	1,864
PANEL B: INDICATORS VARIABLES								
PL	=1 if event is followed by another loan event in the window	Loan				0.498		
		Debt				0.476		
		Equity				0.269		
PD	=1 if event is followed by another debt event in the window	Loan				0.260		

Table 6 (continued)

Variables	Description	Equation	25th pct	Median	75th pct	Mean	Std	Count
		Debt				0.415		
		Equity				0.071		
PE	=1 if event is followed by another equity event in the window	Loan				0.176		
		Debt				0.167		
		Equity				0.252		
SL	=1 if event is preceded by another loan event in the window	Loan				0.441		
		Debt				0.478		
		Equity				0.231		
SD	=1 if event is preceded by another debt event in the window	Loan				0.225		
		Debt				0.436		
		Equity				0.092		
SE	=1 if event is preceded by another equity event in the window	Loan				0.130		
		Debt				0.120		
		Equity				0.116		
MPL	=1 if event is preceded by matched debt event in the window	Loan				0.279		
		Debt				0.129		
		Equity				0.013		
MPD	=1 if event is preceded by matched equity event in the window	Loan				0.026		
		Debt				0.245		
		Equity				0.042		
MPE	=1 if event is preceded by matched equity event in the window	Loan				0.008		
		Debt				0.068		
		Equity				0.171		
MSL	=1 if event is followed by matched loan event in the window	Loan				0.271		
		Debt				0.125		
		Equity				0.012		
MSD	=1 if event is followed by matched debt event in the window	Loan				0.031		
		Debt				0.254		
		Equity				0.049		

Table 6 (continued)

Variables	Description	Equation	25th pct	Median	75th pct	Mean	Std	Count
MSE	=1 if event is preceded by matched loan event in the window	Loan				0.007		
		Debt				0.050		
		Equity				0.074		
AAA	=1 for AAA S&P senior debt credit ratings	Loan				0.004		
AA	=1 for AA S&P senior debt credit ratings	Loan				0.033		
A	=1 for A S&P senior debt credit ratings	Loan				0.169		
BBB	=1 for BBB S&P senior debt credit ratings	Loan				0.289		
BB	=1 for BB S&P senior debt credit ratings	Loan				0.274		
B	=1 for B S&P senior debt credit ratings	Loan				0.203		
ACQLOB	=1 if loan is acquisition line of credit	Debt				0.034		
		Equity				0.055		
BRIDGE	=1 if loan is bridge loan	Loan				0.019		
CALLABLE	=1 if debt issue is callable	Debt				0.319		
CAPRESTRUC	=1 if loan is for capital restructuring	Loan				0.024		
COMBODL	=1 if multiple types of loans are offered at the same time	Loan				0.345		
COMPBID	=1 if the underwriting fee is set by competitive bidding process	Debt				0.013		
CPBACKUP	=1 if loan is for commercial paper backup	Loan				0.186		
DEBTREPAY	=1 if loan is for repay debts	Loan				0.236		
FLOAT	=1 if debt issue has floating rate	Debt				0.024		
IB	=1 if the lender or underwriter is investment bank	Loan				0.047		
		Debt				0.762		
		Equity				0.915		
INVGRADE	=1 if its senior debts are investment grade	Debt				0.738		
	Equity					0.065		
LISTED	=1 if company stocks are listed	Debt				0.142		
MTNPROG	=1 if debt issue is a part of Medium-term Note program	Debt				0.004		
MULTBANK	=1 if the offering is joint underwritten	Debt				0.222		

Table 6 (continued)

Variables	Description	Equation	25th pct	Median	75th pct	Mean	Std	Count
		Equity				0.046		
		Loan				0.950		
PERFPRC	=1 if loan has performance pricing provision (i.e. pricing grid)	Loan				0.480		
PRIME	=1 if loan is indexed of prime rate	Loan				0.039		
PUTABLE	=1 if debt issue is putable	Debt				0.217		
RATED	=1 if the issuer has credit rating	Equity				0.366		
REFIDEBT	=1 if equity offering is for refinancing outstanding debt	Debt				0.200		
		Equity				0.065		
REPAYBK	=1 if equity or debt offering is used to repay bank loan	Debt				0.269		
		Equity				0.196		
REVOLVER	=1 for revolver loan	Loan				0.494		
SECURE	=1 if loan is secured by assets	Loan				0.402		
SHELFREG	=1 if debt or equity offering has been shelf-registered	Debt				0.776		
		Equity				0.046		
STREVOLV	=1 if loan is revolver loan with maturity less than 1 year	Loan				0.304		
SUBORDIN	=1 if loan is subordinated to more senior loans	Loan				0.001		
TAKEOVER	=1 if loan is for takeover financing	Loan				0.221		
TERMB	=1 if loan is tranch B term loan	Loan				0.050		
TERMBSUB	=1 if loan is term loan with tranch lower than B	Loan				0.012		
WORKCAP	=1 if loan is for working capital	Loan				0.092		

MULTLEND is an indicator variable for a syndicated loan. The lead lender in a syndicated loan may have less pricing power due to the fact that other members of the syndicate may insist that the loan is priced at market terms. *LTOTLEND* is the log of the aggregate amount of lending made by the lead lender for a given year. This variable is a proxy for the lender's reputation and any lender size effect. We expect these two *LEC* variables to have negative impacts on Loan Supply.

For Loan Demand, the variables *SALEGRWT* and *MVEOBVE* (the ratio of the market value of equity to the book value equity) are used as instruments that capture growth and hence the funding needs of borrowers, which affect demand. We assume that these two variables do not influence loan supply beyond the default risk that has already been captured by other control variables in the system with which they may be correlated (which are captured, inter alia, by debt ratings and leverage). If these identifying assumptions are reasonable, then the coefficients of this system can be consistently estimated using two-stage least squares, where *DEM* is used to instrument *LNAMT* in Eq. 1 and *SUP* is used to instrument *LNSPREAD* in Eq. 2. Alternatively, the coefficients of these equations can potentially be estimated more efficiently by GMM. The results are quite similar. We focus on the GMM estimates, together with various specification tests for the validity of the instruments and the overidentification restrictions. The 2SLS results and their corresponding specification tests are available from the authors upon request in a "Two-Stage Least Squares Appendix (ESM)" to this paper.

The other control variables used are as follows. *REL* is a vector of variables which consists of the variables *PL*, *PD*, *PE*, *SL*, *SD*, *SE, MPL*, *MPD*, *MPE*, *MSL*, *MSD*, *MSE*, and their interaction with the variable *IB* (a dummy variable which equals one if the lead financial institution in the event is an investment bank, and zero otherwise).

We include the following loan characteristic variables in *LOC*: *LNMATURE*, *TERMB*, *TERMBSUB*, *REVOLVER*, *STREVOLV*, *BRIDGE*, *COMBODL, PERFPRC*, and *SECURE*, together with the following indicator variables that capture the purpose of the loan: *TAKEOVER*, *CAPRESTR*, *CPBACKUP*, *DEBTRPAY*, *BUYOUT*, and *WORKCAP*. Most of these are standard control variables for loan characteristics that are used successfully in previous loan pricing studies (e.g., Calomiris and Pornrojnangkool 2005). Definitions are provided in Table 6, together with the rest of the variables used in this paper. We also distinguish revolvers of less than 1 year from those of more than 1 year. Bank capital regulation requires additional capital against undrawn revolvers with a maturity greater than 1 year. We thus expect *STREVOLV* to have negative impact on loan spread in the Loan Supply Equation.

The variables included in *BC* control for borrower characteristics that influence loan terms. *LNASSET* captures the effect of borrower size. *ADJMKTLV* is the market value measure of leverage, and is adjusted for any loan, debt, and equity transactions that have occurred since the last available financial statements, in order to better reflect the borrower's riskiness at the time of the loan event. We include dummies for S&P's long-term senior credit ratings. Roughly one-third of our observations have no rating data. We employ an ordered Probit model to impute credit ratings for observations where no rating data are available.[14] The indicator variable *RATEFORE*, which indicates whether ratings are forecasted by the model rather than provided by the ratings agency, captures any systematic difference between firms that are rated and firms that are not.

4.1 Loan supply findings

Table 7 presents the GMM estimates of the Loan Supply Eq. 1, reported as two *LNSPREAD* regressions. We also include time and industry dummies, which are omitted from the table. Model A presents estimates of the Loan Supply (*LNSPREAD)* regression in which

[14] We include rating and industry dummies in our ordered Probit regression together with additional control variables that influence credit standing of the borrowers. We do not include the Probit regression result here but it is available in an unpublished appendix from the authors upon request. As a robustness check, we also repeat the analysis of this paper using only loan observations with rating information. The results are similar to what we present here. Selected results are also included in the unpublished appendix.

financing needs and relationship variables (*REL*) do not interact with the investment bank indicator variable (*IB*). Model B allows *REL* to interact with *IB*. Using *SALEGRWT* and *MVEOBVE* as instruments for *LNAMT* in this regression works well; as shown in the overidentification tests in the table, the value of the chi-sq(2) test statistic based on the GMM objective function is 2.08 for model A and 2.05 for model B, indicating that one cannot reject the null of instruments exogeneity.[15]

The coefficient of *LNAMT* from the GMM estimate differs from the ordinary least squares estimate (not reported). The coefficient for *LNAMT* in the ordinary least squares regression is significantly *negative* whereas the coefficient for *LNAMT* in the structural GMM regression is *positive* and significant. Since we interpret our spread regression as a Loan Supply equation (by including supply shifter variables (*SUP*)), we expect an upward sloping supply curve (a positive *LNAMT* coefficient). The ordinary least squares estimator clearly is not consistent and suffers from simultaneity bias. This result confirms the validity of modeling Loan Supply and Loan Demand as a system of equations.

The coefficients for most variables in the Loan Supply equation are of the expected signs and significant. Having multiple lenders (*MULTLEND*) participating in the syndication significantly reduces the costs of borrowing. Larger and more diversified lenders (*LTOTLEND*) can lend to borrowers at lower costs. Loan characteristics also affect loan pricing in expected ways. In tranch B term loans (*TERMB*), where lenders carry lower seniority than other lenders in the same term loan, loan pricing is higher. The pricing premium is even greater for loans in lower tranches (*TERMBSUB*).[16] We document a substantial *PRIME* premium in our sample, as found in Beim (1996). The coefficient for *SIC2LESH* is also significant and negative in our sample as expected, reflecting lender cost savings from sectoral specialization.

4.2 Effects of the patterns of financing needs and relationships on loan prices

As discussed in our review of the literature, omitting financing pattern variables (*PL*, *PD*, *PE*, *SL*, *SD*, and *SE)* from the regressions can make estimates inconsistent and provide misleading estimates of the effects of bundling on loan pricing. We find several consistent results across our specifications, which indicate the importance of controlling for financing patterns. First, with regard to loan-supply effects, loans that occur around the time of debt offerings receive pricing discounts from both universal and investment banks, regardless of whether the lender and underwriter are matched (the coefficients of *PD* and *SD* are negative). Interestingly, we do not find the same result for loans around the time of equity offerings. This finding is consistent with a "road-show" effect, in which information regarding the creditworthiness of borrowers is transmitted to the market surrounding a debt offering in a way that reduces information gathering costs for the

[15] In an unpublished appendix (available upon request), we report alternative estimates of loan supply and demand using two-stage least square regressions. Results are similar to GMM.

[16] Revolvers carry lower spreads than term loans (tranch A) and short-term revolvers have even lower spreads, perhaps reflecting lower regulatory capital requirements. The indicator variable *SECURE* is significantly positive, as found in previous studies. This reflects unobserved (higher) riskiness of borrowers that borrow with secured loans. In addition, borrowers are charged higher rates when term and revolving loans are packaged together in one deal (*COMBODL*). The discount for "performance pricing" of loans is significant but smaller than the discount reported in prior studies (e.g., Beatty and Weber 2000).

Table 7 Generalized method of moments estimates of loan supply and demand regressions. This table presents the generalized method of moment estimates of a system of equations where log all-in-spread (LNSPREAD) and log loan amount (LNAMT) are allowed to be determined jointly. Models A and C include the IB dummy but it does not interact with financing pattern and relationship variables. Models B and D allow IB interaction. Both loan supply and demand equations are overidentified with SALEGRWT and MVEOBVE as instruments for LNAMT in the loan supply equation, whereas PRIME and SIC2LESH are instruments for LNSPREAD in the loan demand equations. Under GMM framework, the estimators utilize cross equations correlation in estimation and are fully robust to heteroskdasticity. An overidentification test based on the objective function of the GMM is reported at the end of the table

	Loan supply regressions (LNSPREAD)					Loan demand regressions (LNAMT)			
	A: No IB interaction		B: IB interaction			C: No IB interaction		D: IB interaction	
	Coefficient	Std Err	Coefficient	Std Err		Coefficient	Std Err	Coefficient	Std Err
INTERCEPT	5.8508	0.3315***	5.8603	0.3317***	INTERCEPT	9.6719	0.8027***	9.6792	0.8037***
LNAMT	0.0767	0.0228***	0.0769	0.0228***	LNSPREAD	-0.9253	0.1068***	-0.9250	0.1067***
PL	0.0238	0.0180	0.0183	0.0185	PL	0.0056	0.0334	0.0017	0.0343
PD	-0.0639	0.0202***	-0.0591	0.0204***	PD	-0.0597	0.0349*	-0.0597	0.0351*
PE	0.0213	0.0249	0.0380	0.0248	PE	0.2832	0.0316***	0.2826	0.0316 ***
MPL	-0.0076	0.0164	0.0007	0.0169	MPL	-0.0659	0.0290**	-0.0728	0.0304
MPD	0.0102	0.0260	0.0043	0.0283	MPD	-0.0706	0.0408*	-0.0988	0.0463**
MPE	-0.0720	0.0293**	-0.0125	0.0558	MPE	-0.2227	0.0634***	-0.2468	0.0952***
SL	0.0304	0.0176*	0.0119	0.0210	SL	0.0053	0.0367	0.0008	0.0377
SD	-0.1691	0.0236***	-0.1704	0.0237***	SD	0.0162	0.0379	0.0147	0.0383
SE	-0.0284	0.0232	-0.0269	0.0232	SE	0.1351	0.0376***	0.1324	0.0379***
MSL	-0.0003	0.0200	0.0036	0.0207	MSL	-0.0815	0.0335**	-0.0880	0.0351**
MSD	-0.0294	0.0216	-0.0258	0.0232	MSD	-0.0681	0.0342**	-0.0662	0.0365*
MSE	0.1590	0.0421***	0.2198	0.0606***	MSE	-0.0756	0.0856	0.0735	0.0791
IB	0.0821	0.0258***	0.1301	0.0453***	IB	0.2351	0.0390***	0.2531	0.0773***
IB*PL			0.0591	0.0596	IB*PL			0.0334	0.0980
IB*PD			-0.0868	0.0626	IB*PD			-0.0223	0.0955
IB*PE			0.0919	0.0814	IB*PE			-0.0087	0.0971

IB*MPL			-0.0818	0.0558	IB*MPL			-0.0744	0.0833
IB*MPD			0.0774	0.0702	IB*MPD			0.1271	0.1022
IB*MPE			-0.2004	0.1010**	IB*MPE			-0.1950	0.1490
IB*SL			-0.0351	0.0688	IB*SL			0.0391	0.1133
IB*SD			0.1187	0.0696*	IB*SD			0.1760	0.1042*
IB*SE			-0.0639	0.0653	IB*SE			0.0819	0.1126
IB*MSL			-0.0389	0.0670	IB*MSL			-0.0518	0.1058
IB*MSD			-0.0479	0.0843	IB*MSD			-0.1453	0.1164
IB*MSE			-0.0662	0.0925	IB*MSE			-0.1269	0.1958
MULTEND	-0.1730	0.0583***	-0.1727	0.0583***	SALEGRWT	0.0534	0.0306*	0.0543	0.0307*
LTOTLEND	-0.0116	0.0033***	-0.0117	0.0033***	MVEOBVE	0.0010	0.0001***	0.0010	0.0001***
LNMATURE	-0.1023	0.0206***	-0.1023	0.0205***	MULTIPLELENDER	0.6237	0.0507***	0.6242	0.0507***
TERMB	0.2404	0.0323***	0.2385	0.0324***	LTOTEND	0.0110	0.0057*	0.0109	0.0057*
TERMBSUB	0.3910	0.0423***	0.3938	0.0420***	LNMATURTE	0.1015	0.0275***	0.1015	0.0275***
REVOLVER	-0.0670	0.0302**	-0.0565	0.0302*	TERMB	0.5505	0.0603***	0.5505	0.0602***
STREVOLV	-0.2351	0.0418***	-0.2346	0.0416***	TERMBSUB	0.3368	0.01023***	0.3392	0.1024***
BRIDGE	0.0650	0.0848	0.0625	0.0846	REVOLVER	0.3339	0.0292***	0.3340	0.0291***
COMBODL	0.2462	0.0338***	0.2455	0.0338***	STREVOLV	0.2236	0.0556***	0.2232	0.0555***
SECURE	0.3550	0.0187***	0.3551	0.0187***	BRIDGE	0.8690	0.0963***	0.8659	0.0964***
PERFPRC	-0.0751	0.0209***	-0.0749	0.0209***	COMBODL	-0.2044	0.0383***	-0.2050	0.0382***
PRIME	0.4995	0.0396***	0.5003	0.0397***	SECURE	0.2182	0.0483***	0.2182	0.0483***
SIC2LESH	-0.0783	0.0393**	-0.0790	0.0392**	PERFPRC	-0.0321	0.0247	-0.0323	0.0247
TAKEOVER	-0.0463	0.0483	-0.0464	0.0483	TAKEOVER	0.5678	0.0391***	0.5684	0.0391***
CAPRESTR	0.0219	0.0447	0.0214	0.0446	CAPRESTR	0.3264	0.0733***	0.3262	0.0734***
CPBACKUP	-0.2503	0.0281***	-0.2508	0.0281***	CPBACKUP	-0.0071	0.0454	-0.0064	0.0454
DEBTRPAY	-0.0531	0.0232**	-0.0527	0.0231**	DEBTRPAY	0.1700	0.0323***	0.1702	0.0323***
BUYOUT	0.1579	0.0449***	0.1552	0.0447***	BUYOUT	0.3749	0.0896***	0.3748	0.0896***
WORKCAP	-0.0066	0.0206	-0.0071	0.0206	WORKCAP	0.0002	0.0377	-0.0004	0.0377
LNASSET	-0.0652	0.0204***	-0.0656	0.0204***	LNASSET	0.5191	0.0144***	0.5188	0.0145***

Table 7 (continued)

	Loan supply regressions (LNSPREAD)					Loan demand regressions (LNAMT)			
	A: No IB interaction		B: IB interaction			C: No IB interaction		D: IB interaction	
	Coefficient	Std Err	Coefficient	Std Err		Coefficient	Std Err	Coefficient	Std Err
ADJMKTLV	0.3598	0.0983***	0.3563	0.0985***	ADJMKTLV	1.7360	0.0945***	1.7358	0.0943***
AAA	-1.6924	0.0813***	-1.6927	0.0813***	AAA	-1.2023	0.2388***	-1.1982	0.2387***
AA	-1.6554	0.0676***	-1.6589	0.0677***	AA	-0.7844	0.0257***	-0.7885	0.2059***
A	-1.2179	0.0499***	-1.2187	0.0499***	A	-0.7528	0.1569***	0.7508	0.1569***
BBB	-0.5927	0.0354***	-0.5941	0.0354***	BBB	-0.4150	0.0980***	-0.4144	0.0981***
BB	-0.1991	0.0289***	-0.1997	0.0289***	BB	-0.1476	0.0672**	-0.1465	0.0674**
B	-0.0794	0.0291***	-0.0796	0.0291***	B	-0.2536	0.0599***	-0.2532	0.0600***
RATEFORE	0.0273	0.0257	0.0282	0.0257	RATEFORE	-0.1542	0.0310***	-0.1548	0.0310***
N		14,439		14,439	N		14,439		14,439
GMM Obj Fn		30,046		29,652	GMM Obj Fn		30,046		29,652
Specification Tests									
1. Overidentification test for validity of instruments (H0:instruments are exogenous) based on GMM Objective Function/N									
jointly	Chi-sq(2)	2.0809		2.0536	Chi-sq(2)		2.0809		2.0536

*, **, *** denote 90%, 95%, and 99% significance respectively

surrounding loans.[17] Second, a loan that is followed by another loan (*SL*) is priced slightly higher than a single loan. This occurs regardless of whether the loans are matched. Third, investment banks price loans higher than universal banks, in general (the coefficient for *IB* is positive and significant). That effect is larger (0.13) in model B, where we allow *IB* interactions. This finding indicates that investment banks suffer a cost disadvantage relative to commercial banks in originating loans. Commercial banks' access to deposits and the payment system may reduce their costs of originating loans.[18]

Turning to the key question of the loan-supply effect of relationship bundling of lending and underwriting, our results for matched loans (whose lenders also underwrite other transactions within the same financing windows) differ from the results of other studies. Matched loans, whose lenders provide other loans or underwrite other *debt* issues within the same financing windows, are priced similarly to unmatched loans, ceteris paribus. That finding is inconsistent with the findings of Fraser et al. (2007) who find that prior matched debt offerings are associated with higher loan interest rates. For loans that are matched to *equity* underwritings, our findings contradict those of Drucker and Puri (2005). We find that matching has differing effects on loan pricing depending on the sequencing of the transactions and the identities of the lenders. If matched loans occur before equity underwritings, both universal banks and investment banks price these loans significantly *higher* than their unmatched counterparts. However, if loans are granted after matched equity offerings, then there is a loan pricing *discount* that *only* investment banks provide (as shown in Model B of Table 7). In contrast, Drucker and Puri (2005) report discounts rather than premiums charged on loans with relationship bundling, and that *only* universal banks (not investment banks) provide discounts for loans to the borrowers who also use their equity underwriting services around the time of loans, without distinguishing *MSE* from *MPE* matches.

Our finding of a loan pricing *premium* preceding matched *MSE* equity underwritings indicates that both universal and investment banks are able to extract quasi rents in the loan market from relationship bundling. Our finding that loan pricing discounts are offered only by relationship bundling investment banks, and only when loans are preceded by matched equity underwritings (MPE sequencings), is consistent with the evidence that investment banks suffer a cost disadvantage relative to commercial banks in providing loans (i.e., the positive coefficient for the *IB* indicator). Investment banks appear to compete with universal banks by providing loan interest rate "rebates" to customers that have already used their equity underwriting services. The sum of the coefficients on IB (0.13 and statistically significantly different from zero) plus IB*PE (0.09 and insignificant) is roughly equal to IB*MPE (-0.20 and significant).

Our findings suggest that loan pricing in the presence of an underwriting relationship does not merely reflect physical scope economies; banks price in a *strategic* way to extract value from existing relationships (by selectively charging "premiums"), and also as a tool to compete with competitors (by selectively offering "rebates").

[17] A somewhat similar result is found in Pagano et al. (1998), which finds a reduction in interest rates on loans following the public listing of a firm in Italy. They interpret this finding as either reflecting the result of the improved information related to a new stock listing, per se, or improvements in the bargaining power of the borrower as the result of the change in the status of the firm.

[18] At least two possible influences may be important. The payment system may afford information to banks about borrowers by virtue of the fact that banks can monitor debits and credits flowing in and out of the firm's accounts. A second possibility, which applies to revolving lines of credit, is that linking the line with a checking account may economize on transaction costs of accessing the line. Our finding that investment banks charge more than commercial banks for loans raises the question of why a borrower would borrow from an investment bank, despite this higher cost. Part of the answer may relate to search and switch costs.

4.3 Loan demand specifications

GMM estimates of the Loan Demand equation are presented in models C and D in Table 7. We include time and industry dummies, which are omitted from the table. The sign of *LNSPREAD* is negative and significant, confirming the demand interpretation of the equation. One cannot reject the GMM overidentification test. Several more specification tests in the 2SLS context confirm the validity of our instruments (a "Two-stage Least Square Regressions Appendix (ESM)" is available from the authors upon request).

Our demand shifter variables (*SALEGRWT* and *MVEOBVE*) are both positive and significant. Borrowers who have their loans secured tend to have higher demand for credit than those who do not. Borrowers tend to demand larger loans when the loans are for a specific purpose such as a takeover loan, a capital restructuring loan, or a debt repayment. Borrowers with better credit ratings tend to have less demand for credit, and more leveraged borrowers tend to have higher demand for credit.

4.4 Effects of patterns of financing needs and relationships on loan demand

Firms that recently issued debts (*PD*) have lower demand for loans. Firms that recently issued equities or plan to issue equities (*PE* or *SE*) have higher demand for loans.

For relationship variables, we observe consistently negative effects on Loan Demand for matched loans regardless of which particular transactions are matched with these loans (i.e., negative signs for *MPL*, *MPD*, *MPE*, *MSL*, *MSD*, and *MSE*). We restrict the model by combining all the relationship bundling dummies (i.e. defining the variable *MATCH* to equal one when any of the matching relationship variables, *MPL*, *MPD*, *MPE*, *MSL*, *MSD*, or *MSE,* equals one). The coefficient on *MATCH* in Loan Demand is significantly negative. This holds for both universal banks and investment banks. We interpret this result as lending support to the real-option view (as in Ramirez 1995) that universal banking relationships provide liquidity insurance to firms in the form of implicit lines of credit that reduce their need to maintain explicit lines of credit.[19] Borrowers who maintain close relationships with their banks (as reflected in matched transactions) enjoy cost savings from foregone fees on unused credit lines. The savings borrowers receive from lower Loan Demand (and hence lower fees in support of credit lines) in the context of relationship banking can explain why borrowers would be willing to build relationships with bankers, even though relationships entail higher spreads on loans. We perform several additional tests for robustness and variation across sub-samples for our loan regressions, which are available in a "Loan Regressions Robustness Appendix (ESM)" from the authors upon request.

5 Debt and equity underwriting regressions

In the loan market, we observe the amount and the full cost of borrowing in the form of loan spreads (time dummies capture temporal variation in Libor, and our regressions

[19] Several other studies of relationship advantages in banking (not specifically related to bundling) also suggest that relationships may create real options that are valuable to firms. Jiangli et al. (2008) find that relationships increase the probability of access to credit in difficult times. Chakravarty and Yilmazer (2007) also find that relationships improve access to credit. Brick and Palia (2007) find that relationships mitigate the need to post collateral.

explain spreads over Libor). That allows us to model Loan Supply and Loan Demand and identify relationship effects on Supply and Demand separately. In the case of underwritings, we only observe the amount of funds raised and the underwriting fee, which is not a measure of the firm's cost of capital (unlike an interest rate). We also lack some of the identifying instruments available in the context of the loan market. Most importantly, unlike the case of loan demand (where reductions of loan needs would be reflected in lower levels of maintained lines of credit due to increased real options from relationship banking), there is unlikely to be a real option relationship effect associated with reduced quantities of securities underwritten, given potential economies of scale in underwriting. For these three reasons we do not construct a structural estimation of securities markets supplies and demands. Instead, we estimate the following, non-structural regression for total debt underwriting spreads, where total spreads include management fees, underwriting fees, selling concessions, and other direct expenses related to the administration and marketing of the offering. We include these direct expenses in the definition of underwriting spreads to better reflect total costs associated with security offerings.

$$LNDSPREAD_i = \beta_0^D + \beta_1^D REL_i + \beta_2^D DBC_i + \beta_3^D DFC_i + \beta_4^D DIC_i + \varepsilon_{3i} \tag{3}$$

LNDSPREAD is the natural log of the debt underwriting spread relative to the amount of proceeds raised, expressed in basis points of the total amount of proceeds. *REL* is defined similarly to the way it was defined in the loan regressions. *DBC* is a vector of underwriter (bank) characteristics, which is comprised of *MULTBANK and LTOTDUND*. They are defined similarly to the control variables for lender characteristics (*LEC*) in the Loan Supply equation, but are specific to the debt underwriting market. *DFC* is a vector of firm characteristics, which includes the log of firm assets (*LNASSET*), a market-value measure of adjusted leverage (*ADJMKTLV*) defined similarly to the measure used in the loan regressions, and an indicator variable for an investment grade-rated firm (*INVGRADE*). Lastly, we include debt issue characteristics in *DIC*, namely *LNMATURE, LNAMT, REPAYBK*, *REFIDEBT*, *ACQLOB*, *MTNPROG*, *FLOAT*, *SHELFREG*, *CALLABLE*, *PUTABLE*, *LISTED*, and *COMPBID*. Their definitions are presented in Table 6.

5.1 Equity underwriting regression

We employ similarly specified regressions for the equity underwriting spread:

$$LNESPREAD_i = \beta_0^E + \beta_1^E REL_i + \beta_2^E EBC_i + \beta_3^E EFC_i + \beta_4^E EIC_i + \varepsilon_{3i}, \tag{4}$$

LNESPREAD is the log of the equity underwriting spread. *REL* is the vector of financing needs and relationship variables defined previously. *EBC* is defined similarly to *DBC* in the debt regression but is specific to the equity underwriting market. We include *LNASSET*, *ADJMKTLV*, *RATED*, *INVGRADE, LNMVE, and VOL* in the vector of firm characteristics *EFC*. Equity volatility is calculated from previous 250-day daily equity returns, as of the offering date. *LNAMT, REPAYBK, REFIDEBT*, *ACQLOB* and *SHELFREG*) are included in the vector of issue characteristics (*EIC*).

5.2 Regression results for debt and equity spreads

Our debt and equity underwriting spread regressions, shown in Table 8, have high explanatory power, with adjusted R-squareds of 0.78 and 0.74 for the debt and equity underwriting spread regressions, respectively. Our control variables in the debt underwriting spread regressions have the expected signs and most are significant. Large underwriters (*LTOTDUND*) underwrite debt issues at lower cost, although it is also possible that the underwriter size effect reflects unobserved heterogeneity of clients (riskier, and therefore, hard-to-underwrite firms may be attracted to smaller underwriters). Larger firm size (*LNASSET*) is associated with reduced underwriting costs for debt issuers. Higher leverage (*ADJMKTLV*) is associated with higher debt underwriting costs, while having long-term debt rated as investment grade (*INVGRADE*) reduces debt underwriting costs.[20] In general, it costs more to use specialized investment banks than universal banks to underwrite debts.

With respect to relationship bundling, we find that debt offerings matched with loans are associated with higher spreads than unmatched counterparts (i.e., significantly positive coefficients for *MPL* and *MSL*) for both universal and investment banks. This finding reinforces the conclusion from the loan-supply results that banks can extract quasi rents from relationship bundling. Recall the results from the loan-supply regressions, where we found significant discounts for loans surrounding debt offerings due to a “road show” effect, whether these loans are matched or not. But Table 8 indicates that those discounts are offset by higher debt underwriting costs on matched (*MPL* or *MSL*) transactions. In addition, we find that issuers pay less when debt offerings are done consecutively (when *PD* equals one), a variation on the “road show” effect.

As in the debt underwriting regressions, in the equity regressions larger underwriters underwrite at lower cost (*LTOTEUND*). Using joint underwriters (*MULTBANK*) increases cost. Market capitalization (*LNMVE*), asset size (*LNASSET*), and the size of the equity offering (*LNAMT*) are associated with significantly reduced underwriting costs, whereas leverage (*ADJMKTLV*) and equity volatility (*VOL*) are associated with higher underwriting costs for equity offerings. The negative coefficient for *SHELFREG* and the positive coefficient for *ACQLOB* are similar to those in the debt spread regressions. As with debt, investment banks generally underwrite equity at higher costs than universal banks.

With respect to relationship bundling, we also find results that are similar to the debt underwriting regressions. When there are matched loans surrounding equity offerings, both universal banks and investment banks underwrite the issues at higher cost than unmatched transactions. This finding reinforces the findings from the debt underwriting regression and the Loan Supply regressions that both universal and investment banks are able to extract value from relationship bundling. Recall that we find a significant negative coefficient for *IB*MPE* in the loan spread regressions. Our equity underwriting regressions show, however, that investment banks provide that loan pricing “rebate” only after they capture an underwriting fee premium for matched transactions. The debt and equity underwriting spread regression results (not reported) from sub-samples are extremely similar to those for the whole sample.

[20] In addition, the underwriting costs are lower when the proceeds of the debt offerings are used for existing debt repayments or refinancings (*REPAYBK* or *REFIDEBT*). Having floating interest debt (*FLOAT*), being registered in an MTN program (*MTNPROG*), or using a competitive bidding process (*COMPBID*) for selecting underwriters reduces underwriting costs. Finally, more complex debt structures such as callable and puttable features (*CALLABLE* and *PUTABLE*) increase underwriting costs for the issues.

Table 8 Debt and equity underwriting spread regressions. This table presents OLS regressions of log equity and log debt total spread (LNTOTSPREAD) for all equity and debt issues in our database. Models A and C include the IB dummy but do not interact it with the financing pattern and relationship variables. Models B and D allow IB interaction. Total underwriting spread consists of gross spread and other direct expenses related to underwriting, which capture total underwriting costs. Time and industry dummies are included but not shown

	Debt total spread regressions					Equity total spread regressions			
	A: No IB interaction		B: IB interaction			C: No IB interaction		D: IB interaction	
	Coefficient	Std Err	Coefficient	Std Err		Coefficient	Std Err	Coefficient	Std Err
INTERCEPT	7.7963	0.2102***	7.8689	0.2121***	INTERCEPT	11.2370	0.1119***	11.2288	0.1142***
PL	-0.0102	0.0183	-0.0588	0.0488	PL	-0.0088	0.0124	0.0111	0.0456
PD	-0.0719	0.0228***	-0.0866	0.0377**	PD	0.0115	0.0301	-0.1256	0.0773
PE	0.0179	0.0259	-0.0241	0.0444	PE	-0.0409	0.0179**	-0.0472	0.0433
MPL	0.0732	0.0298**	0.1539	0.0440***	MPL	0.1422	0.0499***	0.1855	0.0826**
MPD	0.0463	0.0341	-0.0432	0.0471	MPD	-0.0200	0.0368	0.1033	0.1347
MPE	0.0084	0.0376	0.1135	0.0916	MPE	0.0193	0.0201	0.0622	0.0623
SL	0.0041	0.0182	-0.0229	0.0426	SL	0.0172	0.0126	0.0198	0.0513
SD	0.0066	0.0217	-0.0151	0.0378	SD	0.0150	0.0253	0.1385	0.0815*
SE	0.0145	0.0295	0.0499	0.0577	SE	-0.0238	0.0235	-0.0235	0.0916
MSL	0.0665	0.0288**	0.1218	0.0461***	MSL	0.1083	0.0496**	0.1206	0.0580**
MSD	-0.0591	0.0231**	-0.0829	0.0457*	MSD	-0.0061	0.0321	-0.0481	0.1288
MSE	0.0067	0.0434	0.0530	0.1261	MSE	0.0409	0.0283	0.0936	0.1170
IB	0.0862	0.0213***	0.0697	0.0335**	IB	0.0429	0.0186**	0.0491	0.0243**
IB*PL			0.0550	0.0488	IB*PL			-0.0212	0.0472
IB*PD			0.0152	0.0462	IB*PD			0.1637	0.0829**
IB*PE			0.0632	0.0543	IB*PE			0.0087	0.0473
IB*MPL			-0.0914	0.0646	IB*MPL			-0.0419	0.1033
IB*MPD			0.1121	0.1553	IB*MPD			-0.1519	0.1410
IB*MPE			-0.1270	0.1011	IB*MPE			-0.0460	0.0662
IB*SL			0.0319	0.0471	IB*SL			-0.0012	0.0528
IB*SD			0.0287	0.0454	IB*SD			-0.1424	0.0854*

Table 8 (continued)

	Debt total spread regressions					Equity total spread regressions			
	A: No IB interaction		B: IB interaction			C: No IB interaction		D: IB interaction	
	Coefficient	Std Err	Coefficient	Std Err		Coefficient	Std Err	Coefficient	Std Err
IB*SE			-0.0511	0.0671	IB*SE			0.0020	0.0947
IB*MSL			-0.0545	0.0626	IB*MSL			0.0969	0.1099
IB*MSD			0.0285	0.0531	IB*MSD			0.0534	0.1332
IB*MSE			-0.0456	0.1345	IB*MSE			-0.0583	0.1207
MULTBANK	0.0049	0.0253	0.0008	0.0253	MULTBANK	0.0657	0.0266**	0.0678	0.0271**
LTOTDUND	-0.0171	0.0067**	-0.0193	0.0068***	LTOTEUND	-0.0158	0.0036***	-0.0153	0.0036***
LNASSET	-0.1031	0.0080***	-0.1033	0.0080***	LNASSET	-0.0351	0.0080***	-0.0343	0.0080***
ADJMKTLV	0.2276	0.0544***	0.2271	0.0545***	LNMVE	-0.0409	0.0087***	-0.0407	0.0087***
INVGRADE	-0.6666	0.0281***	-0.6632	0.0282***	VOL	0.1903	0.0247***	0.1943	0.0247***
LNMATURE	0.0712	0.0088***	0.0717	0.0088***	ADJMKTLV	0.1677	0.0474***	0.1670	0.0475***
LNAMT	-0.0236	0.0115**	-0.0230	0.0115**	LNAMT	-0.1800	0.0086***	-0.1820	0.0087***
RPAYBANK	-0.0619	0.0183***	-0.0620	0.0183***	RATED	-0.0117	0.0115	-0.0117	0.0116
REFIDEBT	-0.0542	0.0202***	-0.0527	0.0204	INVGRADE	0.0073	0.0210	0.0084	0.0211
ACQLOB	0.0783	0.0423*	0.0795	0.0424*	RPAYBANK	0.0058	0.0128	0.0068	0.0129
MTNPROG	-0.0978	0.1203	-0.0779	0.1206	REFIDEBT	0.0315	0.0196	0.0331	0.0196*
FLOAT	-0.3319	0.0492***	-0.3241	0.0493***	ACQLOB	0.0448	0.0209**	0.0433	0.0210**
SHELFREG	-0.2019	0.0246***	-0.2054	0.0247***	SHELFREG	-0.0884	0.0246***	-0.0867	0.0254***
CALLABLE	0.1184	0.0206***	0.1194	0.0207***					
PUTABLE	0.0901	0.0244***	0.0894	0.0244***					
LISTED	0.0808	0.0228***	0.0869	0.0229***					
COMPBID	-0.5856	0.0669***	-0.5833	0.0668***					
Adj R-sq		0.7765		0.7776	Adj R-sq		0.7348		0.7348
N		2,132		2,132	N		1,844		1,844

*, **, *** denote 90%, 95%, and 99% significance respectively

Table 9 Summary of key economic impacts. This table summarizes economic impacts of our key findings in this paper. Panel A summarizes the findings from loan supply and demand regressions, whereas panel B relates to underwriting regressions. The "% Premium" columns translate the coefficients of the relevant dummy variables in our semilog specifications into percentage premium (+) and discount (-) on the mean spread using exp(b)-1 transformation to interpret the coefficients β from the semilog regressions. The average fee impacts (in basis points) for loans, and debt and equity underwritings, are calculated by multiplying the "% Premium" column with the sample averages for loan all-in-spread, and debt and equity total underwriting spreads, of 150, 143 and 737 bps, respectively. The average dollar impact per transaction is calculated by multiplying the average bps fee impact by the sample averages of deal sizes for loans, and debt and equity offerings, of $640, $520 and $95 million, respectively

		Commercial bank			Investment bank		
	Source table: variable name	% Premium	Average bps	Average $ (mil)	% Premium	Average bps	Average $ (mil)
Panel A: loan regression							
1) Road show effects	Table 7: PD, PD*IB	-5.7%	-9	-0.6 ***	-13.6%	-20	-1.3 ***
	Table 7: SD, SD*IB	-15.6%	-23	-1.5***	-5.0%	-8	-0.5*
2) Investment bank premium	Table 7: IB	n/a	n/a	n/a	13.9%	21	1.3***
3) Quasi-rent prior to matched equity deal	Table 7: MSE, MSE*IB	24.6%	37	2.4***	16.6%	25	1.6***
4) Rebate after matched equity deal	Table 7: MPE, MPE*IB	-1.2%	-2	-0.1	-19.2%	-29	-1.8**
5) Liquidity insurance provision	Table A3-1: MATCH, MATCH*IB	-8.5%	n/a	-54.5**	-9.2%	n/a	-58.9***
Panel B: underwriting regression							
1) Investment bank premium	Table 8: IB	9.0%	13	0.7***	4.4%	32	0.3**
2) Quasi-rent for matched loan deal	Table 8: MPL	7.6%	11	0.6**	15.3%	113	1.1***
	Table 8: MSL	6.9%	10	0.5**	11.4%	84	0.8**

*, **, *** denote 90%, 95%, and 99% significance respectively

The effects of relationships on loan interest rates and on debt and equity underwriting costs reported in Tables 7 and 8 differ in interesting ways. First, relationship effects only appear to involve the joint production of lending and underwriting (not the joint production of debt and equity underwriting), and second, relationship effects involving lending and underwriting are stronger for equity underwriting than for debt. In Table 8, underwriting debt (equity) within the same relationship does not matter for the cost of underwriting equity (debt), but lending relationships do matter in the pricing of both debt and equity underwriting services. In Table 7, equity, but not debt, underwriting relationships matter for the pricing of loans when relationships include both lending and underwriting. These findings may reflect the role of information in the intensity of relationship formation. The essential role of lending in relationship banking may reflect the greater information intensivity of the private debt market. Furthermore, underwriting public debt offerings (senior contracts in the public market) is a less information-intensive (and less expensive) activity than either equity underwriting (a junior contract) or bank lending (a private debt contract), and thus debt underwriting does not contribute as much to relationship formation (or quasi rent extraction) as equity underwriting.

6 Conclusions

We investigate how the bundling of financial services that occurs within banking relationships affects the pricing of loans and the underwriting costs of issuing securities. Our research methodology addresses several shortcomings in previous studies.

First, we incorporate important control variables into the analysis of the effects of relationships on pricing, and in particular, we consider the pricing of financial transactions within the context of the sequential patterns of financing transactions undertaken by firms (the "financing window" of the firm). Firm and deal characteristics, as well as the sequencing of transactions, turn out to be important sources of firm heterogeneity, and incorporating these effects has significant consequences for measuring the effects of relationships on pricing. Second, we consider the pricing of several financial services supplied within financial relationships: loans, debt underwriting, and equity underwriting. Third, we model loan supply and demand, which allows us to investigate relationship benefits associated with reduced credit demand.

Table 9 summarizes some of the most important results from our study, and measures the economic importance of the various effects we identify in our analyses of lending and underwriting transactions. Effects are measured in terms of basis points of interest cost or fee cost (evaluated at sample means), and also the dollar magnitudes of these and other effects (evaluated at sample means).

We find evidence of strategic pricing. Banks use relationships to *over*-price loans that precede equity underwritings (by 37 basis points). We also find pricing premiums for both debt and equity underwritings that are relationship bundled with loans within the same financing windows (by 10–11 basis points for debt underwriting fees, and 84–113 basis points for equity underwriting fees, depending on the sequencing of deals within the windows).

Investment banks have different pricing strategies than universal banks, reflecting an apparent cost disadvantage. Investment banks tend to price loans and underwriting services higher than universal banks (21 basis points higher on loans, 13 basis points higher on debt underwriting fees, and 32 basis points higher on equity underwriting fees). Further study is needed to understand the relative efficiency of universal banks. Access to deposits and the payment system enjoyed by commercial banks may provide favorable information processing capabilities about borrowers and lower transaction costs for providing revolving lines of credit.

The cost disadvantage of investment banks may explain why they price bundled transactions somewhat differently from universal banks. Investment banks compete with universal banks in the loan market by providing loan pricing discounts as "rebates" to borrowers who had employed them in preceding equity underwriting transactions (the size of rebates evaluated at the sample mean is 29 basis points).

Our finding that banks appear to be able to extract quasi rents from their relationships does not imply that relationships are harmful to bank customers. There may be offsetting gains to borrowers from relationships, including superior pricing of securities offered for sale, which we plan to investigate in future research. One benefit we are able to observe is a reduction in Loan Demand associated with relationship bundling (indicating an implicit free credit line associated with the relationship, which translates into a savings on the credit line amount maintained of $54.5 million in lines with commercial banks and $58.9 million in lines with investment banks). Evidence of real-option value in the form of greater access to credit as the result of stronger banking relationships has been found in other studies, as well (Ramirez 1995; Brick and Palia 2007; Chakravarty and Yilmazer 2007; Jiangli et al. 2008).

We also find evidence of “road show” effects for debt underwritings. The similarity between the information produced in debt underwritings and loans seems to result in pricing discounts of 9–23 basis points for loans by commercial banks that occur near debt issues, and 8–20 basis points for investment banks, and these results hold whether the loans are bundled with the offerings or not. Similarly, we find that consecutive debt offerings entail lower underwriting costs.

Our findings suggest little reason for concern about relationship bundling from a prudential regulatory perspective. Recent concerns about “tying” have been associated with claims that banks offer discounts on their loans in exchange for receiving underwriting business. Prudential regulators have been concerned that commercial banks may abuse the bank safety net by transforming lending income (within an insured bank) into underwriting income of an affiliate (that is, a part of the bank holding company outside of the insured bank) by offering discounts on loans in exchange for higher underwriting fees. Our results on loan pricing provide evidence against the prevalence of that practice, since matched loans that precede underwritings are charged a premium.

Acknowledgment The authors thank Haluk Unal, an anonymous referee, Paul Efron, Mark Carey, Stas Nikolova, Steve Drucker, and seminar participants at Yale, Columbia, Tulane, George Mason, the University of Western Ontario, the Federal Reserve Board, the New York Fed, the FDIC, and the American Enterprise Institute for helpful comments.

Data appendix

This Data Appendix explains our approach to combining loan data from Loan Pricing Corporation’s *DealScan* database and underwriting data from Securities Data Corporation (*SDC*) into a single dataset that contains available information on the history of bank loans and public offerings for 7,315 U.S. firms during the period 1992 to 2002. Our data include deal pricing information, firm characteristics, and information about the identity of lenders and underwriters for each deal.

We exclude private placements of securities from our dataset due to the lack of pricing data for such deals. We do not regard the omission of private placements as a major shortcoming since private placements constitute a small portion of listed firms’ financing transactions. Commercial paper offerings are also excluded, since these offerings are generally part of a long-term financing program (making the timing of the financing decision hard to measure) and because commercial paper offerings are accessible only to a select group of firms (for further discussion, see Calomiris et al. 1995). To the best of our knowledge, we are the first to construct such a nearly complete dataset of bank loans and public offerings and to use it to systematically address the issue of how relationship banking affects the pricing of financing transactions.

Loan data

We searched the *DealScan* database for all bank loan deals for U.S. borrowers from 1992 to 2002. Since we are interested in industrial firms, we excluded all transactions related to financial institutions (firms with SIC 6) from the search. We also followed the precedent of many other studies by excluding regulated industries (those with SIC code starting with 43, 45, and 49) [21] and government-related deals (those with SIC code starting with 9) from the search. We further exclude borrowers with no stock ticker information to restrict our study to listed borrowers. In each deal, the data contain all loan facilities associated with the deal along with the list of lenders and their roles for each facility in the deal. Data on the all-in-spread cost of loans and other loan characteristics are also available from this source. Table 2 in the text provides a summary of loan observations broken down by lender types, loan classifications, and loan distribution method.

There are several points worth noting about the loan data. First, over the sample period, 1992 to 2002, the lending market is dominated by commercial banks. Roughly 99% of loans in the sample have commercial banks in the leading roles. Investment banks participate in the lending market primarily through relatively large loan syndications where commercial banks act as joint lead lenders. Second, there is an increased usage of short-term revolver facilities instead of longer-term ones as a result of a favorable regulatory capital requirement rule for lines of credit with less than 1 year to maturity.[22] Third, an increasing number of loans are syndicated over time. In light of this and other time-varying practices in lending during our sample period, we include time effects in our regressions, and also explore robustness of our results to sample subperiods.

Underwriting data

Detailed data for all public offerings of common equity and bonds during 1992–2002 are obtained from the *SDC* database. The data contain gross underwriting spreads (total fees paid by the issuer to the underwriters) and the other expenses associated with the offerings. As before, we exclude issuers with SIC codes starting with 6, 9, 43, 45, and 49 from our sample. Table 2 in the text provides a summary of underwriting deals in our sample broken down by type of financial institutions.

Combining the datasets

To link data in the different datasets, by firm, we utilize a unique identification number, namely *GVKEY*, assigned by *Compustat* to the each firm in its database. This unique identification numbering system eliminates the problem associated with changes in firms' names and stock ticker symbols during the study period. It also facilitates our matching of financing transaction data from *SDC* and *DealScan* with *Compustat* data on firm characteristics and market pricing data in the *CRSP* database.

To associate loan observations to *GVKEY* in *Compustat*, we match stock ticker information from *DealScan* to the ticker variable in *Compustat* and combine data dated for the same quarter and year of the loan date, when available. This approach ensures that loan deals are assigned to the current owner of the ticker symbol at the time of the loan.[23] Not all loan deals find a match in *Compustat.* Borrowers that cannot be matched through the easy

[21] We do not exclude all firms with SIC 4 to ensure that some high-tech and telecom industry firms are included in our study. These firms are a focus of tying accusations in the financial press and were active issuers during our study period.

[22] As we show, banks in fact charge lower spreads and provide larger credit lines for short-term revolving lines of credit.

[23] More than one firm may use the same ticker symbol at the different point in time. Care is necessary to match the current owner of the symbol (in the DealScan data) with the correct firm in the Compustat data.

method are searched manually, by name, for a possible match to the *Compustat* database. For underwriting deals from the *SDC* database, the issuers' CUSIP numbers are available and can be used to match with firms in *Compustat*. When matching cannot be accomplished using this method, the CUSIP numbers of the issuer's immediate parent or ultimate parent are used.

The resulting dataset can be used to track the history of financing transactions of a firm by sorting all transactions associated with a particular *GVKEY* by loan and underwriting dates. We have 7,315 firms with "complete" histories of financing transactions (i.e., all bank loans and securities offerings from *DealScan* and SDC) in our final dataset.[24] Once firms are matched, accounting information from *Compustat* and the market equity price from *CRSP* are added to the final dataset.

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