Tying Knots:
Lending to Win Equity Underwriting Business

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This article examines the practice of "tying," which occurs when an underwriter lends to an issuer around the time of public securities offering in order to secure underwriting business. We examine the following questions: (i) How far do investment banks compete directly in tying? (ii) How does tying affect issuers, and in particular, their financing costs? (iii) Why do underwriters tie lending to underwriting? We find that investment banks engage in a substantial amount of tying, contrary to concerns that they are disadvantaged by tying practices. We find that tying allows firms to reduce their financing costs, as tied issuers receive lower underwriter fees on seasoned equity offerings and discounted loan yield spreads. These results are robust to matching methodology developed by Heckman, Ichimura, and Todd (1997, 1998). Lower financing costs are consistent with informational economies of scope from combining lending with underwriting. From the underwriters' perspective, we find that tying helps build relationships that augment an underwriter's expected investment banking revenues by increasing the probability of receiving both current and future equity underwriting business.

1. Introduction

For many years, the 1933 Glass-Steagall Act prevented commercial banks from underwriting corporate bonds and equities. By the end of 1996, the Federal Reserve relaxed some of the most restrictive provisions, and in 1999, the Gramm-Leach-Bliley Financial Modernization Act effectively repealed the Glass-Steagall Act. As a result, in the late-1990s, commercial banks acquired investment banks, or developed investment-banking capabilities internally, to create universal banks that can offer an array of financial services.

While universal banks can provide multiple services to their clients, laws prohibit banks from offering credit "in a coercive manner to gain a competitive advantage in markets for non-banking products or services."[1] This would seem to preclude explicitly tying the provision or pricing of credit to the use of their investment banking services. However, recent commentary by the Federal Reserve suggests that banks have leeway in linking loans to other products, particularly if customers express an interest in bundling of products.[2] Nonetheless, tie-ins have been a source of controversy, in part because commercial banks have access to the government's safety net, which might provide banks with market power over credit that could put investment banks at a disadvantage.[3] On the other hand, tying might allow for potential gains from firms contracting with the same counterparty to arrange simultaneous transactions. In a tied transaction, lower costs could arise due to informational economies of scope, as the bank can jointly deliver services and use the same client-specific information for multiple purposes (see e.g. Benston, 1990; Saunders and Walter, 1994). Also, in a tied deal, the issuer may have lower

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[1] Section 106 of the Bank Holding Company Act Amendments of 1970 prohibits a bank from explicitly extending credit or varying the terms of credit on the condition that a customer purchase another product or service from the bank or its affiliates. Section 23B of the Federal Reserve Act requires that transactions involving a bank and its affiliate be on market terms.

[2] The Fed stated that the laws "do not prohibit a bank from granting credit or providing any other product to a customer based solely on a desire or a hope (but not a requirement) that the customer will obtain additional products from the bank or its affiliates in the future." Also, clients are free to use "their own bargaining power" to seek a bundle of banking services. For more information, see "Fed seeks to clarify the rules on 'tying'," *Financial Times*, August 26, 2003.

[3] Fair access to credit is important for both large and small borrowers. Houston and James (2001) and Saidenberg and Strahan (1999) show that large public firms benefit from bank loans and credit lines because the bank can provide liquidity. Berger and Udell (1995) and Petersen and Rajan (1994) provide direct evidence on the importance of lending relationships for small borrowers. U.S. House Representative Dingell highlights some regulatory concerns in a letter to Chairman Greenspan and Comptroller Hawke (see "Letter to FRB and OCC re: 'pay to play' practices," July 11, 2002).

search costs that result from using a single entity, instead of multiple banks, to complete a series of related transactions.

The popular press often reports that banks have implicit agreements where the client chooses the bank to underwrite its securities and in return, the bank provides credit. For example, in one of many cases reported by *The Wall Street Journal*, Morgan Stanley was not selected to underwrite Primedia's May 2001 bond issue despite leading previous bond issues for the company. Instead, Primedia selected the commercial banks that provided a credit line at around the time of the offering.[4] Our calculations indicate that implicit tying - where lending and underwriting occur at about the same time - is prevalent amongst equity offerings, with over 20% of seasoned equity offerings (SEOs) in the first half of 2001 involving a loan from the underwriter to the issuer.[5]

This paper investigates the implicit tying of loans to seasoned equity offerings. In particular, we examine the following questions: (i) Is the tying of lending to underwriting empirically relevant? How far do investment banks compete directly in tying? (ii) How does tying affect issuers? Does tying reduce financing costs? (iii) Why do underwriters tie lending to underwriting? Does tying help underwriters to build relationships that can lead to additional business? To the best of our knowledge, ours is the first paper to investigate these issues.

To address these questions, we use a unique data set that is carefully assembled from multiple databases and augmented by hand collected data. We gather data on seasoned equity issuers, including each firm's credit rating, stock returns, issuance history, and lending history. We identify prior underwriting and lending relationships between each issuer and potential underwriter, as well as each underwriter's ranking and level and quality of analyst coverage. Further, we collect data on underwriter fees, loan pricing, and lending terms.

We find that, between 1996 and 2001, a substantial number of issuers received a loan from their equity underwriter at around the time of the SEO. Furthermore, the practice became more prevalent over time. Interestingly, while tying practices are commonly associated with

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[4] See "Deals & Deal Makers: Banks' Lending Clout Stings Securities Firms," *The Wall Street Journal*, June 15, 2001, C1. Other examples include the September 2001 spinoff of Genuity by Verizon Communications and the June 2002 Nortel Networks equity issuance (see "Banks Find Linking of Loans to Other Business Has Perils," *The Wall Street Journal*, September 19, 2002, A1.)

[5] Table 1 reports that between January 1, 2001 and May 31, 2001, 21% of SEO issuers received a loan from their underwriter between six-months before and six-months after the equity issuance.

commercial banks, we discover that investment banks underwrote a significant portion of tied deals. This suggests that investment banks have now developed the organizational infrastructure to tie lending and underwriting.[6]

We examine the impact of tying on issuers' financing costs, and our results suggest that tying lowers issuers' financing costs through two main dimensions – (i) a reduced underwriter fee for the equity offering, and (ii) discounted yield spreads of tied loans as compared with "matched" non-tied loans. To ensure that matching biases are not driving the yield spread discount, we use the econometric techniques developed by Heckman, Ichimura and Todd (1997, 1998). These econometric methods effectively take into account the fact that the characteristics of tied loans may differ significantly from non-tied loans and ensure that such observed characteristics are not driving the results. Using a variety of matching models, we confirm that tied loans are significantly cheaper than comparable loans. These results are consistent with informational economies of scope from combining lending and underwriting.

Why do underwriters tie lending to underwriting? To answer this question, we examine the impact of tying on the underwriter's relationship with the firm. In particular, we investigate if the same bank is selected for current and future equity underwriting mandates. We find that tying significantly increases the probability of securing current equity underwriting business. We also find that tied issuers go back to the equity market more frequently than non-tied issuers, and issuers who are tied to investment bank underwriters are more likely to keep the same underwriter. The result is consistent with tied loans helping to build relationships that increase an underwriter's expected investment banking revenues.

Our results suggest that commercial banks and investment banks both compete for tied deals. However they seem to compete through different components of the tied deals -- commercial banks are more likely to offer discounted yield spreads on tied loans while investment banks are more likely to discount the underwriter spread for the SEO. This is consistent with each type of underwriter competing more aggressively in its area of expertise and

[6] For example, Morgan Stanley participated in a $6.5 billion bank loan for Lucent Technologies and was subsequently awarded the role of underwriter on Lucent's spinoff of Agere Technologies (see "Lucent Deal Shows Wall Street Takes on Greater Risk," *The Wall Street Journal*, February 23, 2001, C1). Moreover, investment banks are increasing their lending capacity, with Merrill Lynch, Lehman Brothers, and Morgan Stanley forming bank subsidiaries (see "Morgan Stanley Injects About $2 Billion Into Bank Unit, Aiming to Boost Lending," *The Wall Street Journal*, August 16, 2001, B7).

in the area where it is more likely to generate future business. Investment banks discount underwriter spreads and receive more future underwriting business. Commercial banks discount loan yield spreads, which is consistent with establishing a lending relationship that helps generate other banking business.

This paper adds to the literature on universal banking and the implications of allowing banks to underwrite securities. Regulators have recently raised questions on the firm-level and competitive effects of the relaxation and repeal of the Glass-Steagall Act (see e.g., Berger, et. al, 1999; Santomero and Eckles, 2000). Related to these issues, there is some event-study evidence on the relaxation of various regulatory constraints on banks' activities (see e.g., Carow and Kane, 2001; Narayanan et. al, 2001). The theoretical literature has examined the potential for commercial banks and investment banks to co-exist, as well as the implications of such a scenario (see e.g., Boot and Thakor, 1997; Kanatas and Qi, 1998, 2002; Puri, 1999). However, the possibility that investment banks might respond by expanding into lending activities has generally not received much attention. On lending, James (1987), Lummer and McConnell (1989), Best and Zhang (1993), and Billett, Flannery and Garfinkel (1995), among others, find that new loans, loan renewals, and lender identity carry (positive) private information to the outside equity market about a borrowing firm's financial condition.[7] Much of the empirical literature that examines when banks lend and underwrite investigates the effect of bank lending, and the private information contained therein, on the banks' underwriting of public securities. These effects are ascertained through the pricing of underwritten securities (see e.g., Gande et. al, 1997; Puri, 1996; Yasuda, 2001) or through long run performance (see e.g., Ang and Richardson, 1994; Kroszner and Rajan, 1994; and Puri, 1994). An important but unexplored issue is the reverse question – how do potential underwriting opportunities affect banks' lending, and how does this affect the financing costs of the issuing firm? This paper provides a first step in addressing this question.

The remainder of the paper is organized as follows. Section 2 describes the data and our sample selection process. We present the major empirical findings in Section 3. Section 4 concludes.

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[7] See James and Smith (2000) for a comprehensive review of the past and recent research on the special nature of bank loan financing.

2. Data and Sample Selection

A natural way to capture the implicit tying of loans and underwritings is to take all instances when a financial institution underwrites a firm's public securities and lends to the firm simultaneously. However, in practice even if there is an implicit agreement to this effect, there may be a few months lag between the reported transactions. Hence, the definition we adopt is if the firm received a loan from the underwriter of the SEO between six months prior to and six months after the SEO, we classify the loan as a "tied loan" and the SEO as a "tied deal." As a robustness check to this definition, we also reran our estimations where we defined tied loans to be those loans that were originated between three months prior to and three months after the SEO. This sample produces qualitatively similar results.

We select our sample period based on the following factors. First, we hope to capture an active period of tying. Table 1 shows that tied deals were nearly non-existent before 1996, and with the exception of the year 2000, the proportion of tied deals increases each year. The decline in tied deals in the year 2000 may be due to a noticeable decline in telecom and cable SEOs, which account for around one-third of all tied deals, and a very high proportion of technology offerings, which account for only a small percentage of tied deals. Second, since we will be examining if the issuers proceed with a subsequent SEO, we must provide enough time to capture the decisions of end of sample issuers. Based on these considerations, we define our sample period as January 1, 1996 through May 31, 2001.

We construct a unique database using eight different data sources and hand-collected data. Data on seasoned equity offerings comes from Thomson Financial's SDC *Platinum* United States New Issues database, from which we download underwritten, seasoned, US Common Stock issues. Since we wish to study industrial firms, we remove financial firms (companies with a one-digit SIC code of 6). The sample consists of 2301 issues. We hand match, by issuer name, each of the 2301 issuers to the Loan Pricing Corporation's (LPC) *DealScan* database to identify if the firm received a tied loan from their underwriter and in doing so, we identify if the SEO is a tied deal.[8] There are 201 tied deals in the sample and 2100 non-tied deals.

[8] LPC *DealScan* collects its loan data from SEC filings, and it receives data from large loan syndicators and from a staff of reporters. As such, *DealScan* is well-suited to studying the borrowing activity of companies with public

We classify each underwriter as an "investment bank" or a "commercial bank" based on the status of the parent/holding company of the underwriter at the time of the issue.[9] Due to the many mergers and acquisitions in the financial sector, we use the mergers and acquisitions database from SDC *Platinum* to aid in classification. For example, NationsBank acquired Montgomery Securities on 10/1/1997. Montgomery Securities is classified as an investment bank prior to 10/1/1997, but after 10/1/1997, we classify it as a commercial bank. Commercial banks underwrote 91 tied SEOs and 591 non-tied SEOs, while investment banks underwrote the remaining 110 tied SEOs and 1509 non-tied SEOs.

We will study how tying affects the pricing of bank services and the ability of the underwriter to generate equity underwriting business. As a result, we need to control for factors that may alter fees, pricing, or the likelihood that an issuer selects an underwriter. Prior lending and underwriting relationships are likely to be important in both the selection of a bank and the pricing of banking services because the existence of prior relationships provides a bank with private information that is not transferable to other banks, which can create lock-in effects (see e.g., Williamson, 1979; James, 1992). Furthermore, if there are economies of scope in lending and underwriting, then a prior lending relationship may result in a reduced underwriter fee or other pricing differences. From SDC *Platinum*, we identify 90 tied issuers and 830 non-tied issuers that use an underwriter that had underwritten a prior equity offering. From *DealScan*, we identify 83 tied issuers and 103 non-tied issuers that have a prior lending relationship with the selected underwriter.

Previous research indicates that we need to incorporate the reputation of the underwriter and the level and quality of analyst coverage into our models because these factors are likely to affect the firm's decision to select an underwriter or to switch underwriters in the future. On bank reputation, Booth and Smith (1986) find that the underwriter's reputation is important in determining underwriter choice because a more prestigious underwriter has a higher ability to

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equity and debt. Since all of the companies in our sample have public equity, we should observe the vast majority of their lending activity. *Dealscan* has been used in previous studies for many purposes, including examining the effect of lending on bond yield spreads (see e.g. Gande et. al 1999) and bank effects in lending rates (Hubbard et. al 2002).

[9] We do not separate commercial banks that internally developed investment-banking capabilities from those that acquired investment banks because almost all of the commercial banks developed underwriting operations by acquiring investment banks. Chaplinsky and Erwin (2001) note that for commercial banks who developed underwriting capabilities internally, only JP Morgan acquired market share in equity underwriting that is above

certify an issue, and Carter and Manaster (1990) show that an underwriter with a higher reputation tends to underwrite less risky initial public offerings. On analyst coverage, Clarke et. al (2003) find that all-star analysts significantly affect investment banking deal flow, and Krigman et. al (1999) find that firms are more likely to switch to underwriters who provide all-star coverage.

We capture the influence of reputation through the underwriter's market share. For each year, we compute each underwriter's SEO market share by adding the principal amounts of all SEOs in which the bank was the underwriter and dividing this total by the principal amounts of all SEOs during the year. If a merger between underwriters occurred during the year, we use the combined market share of the underwriters. We rank the underwriters on a yearly basis, based on the market share in the previous year.[10] For example, Goldman Sachs had the highest market share in 1995, so in our models, issuers who have an SEO in 1996 consider Goldman Sachs to be the top ranked underwriter.

We measure the level of equity analyst coverage by using the I/B/E/S Detail History, which contains over twelve years of forecast changes and encompasses earnings estimates from more than 200 brokerage houses and 2000 individual analysts. We match any estimate of earnings per share from any analyst in the I/B/E/S database to each of the 2301 firms in our sample. If the underwriter provided an earnings recommendation within one-year prior to the SEO date, then the underwriter provided "coverage." To capture the quality of analyst coverage, we use Institutional Investor magazine's All-America Research Team, which is published yearly and lists the top three analysts in each sector. Since the report is published towards the end of each year, the inclusion of an analyst in the publication will most likely have its greatest impact on underwriter choice for issues that occur in the following year. As a result, we define that the analyst (and corresponding underwriter) provided "all-star coverage" for a firm if the analyst is included in the All-America Research Team for the year prior to the equity issuance and provided an earnings recommendation within one-year prior to the SEO date.

0.02% during the post-1996 period. This investment bank / commercial bank classification scheme has been used in other papers (see e.g. Roten and Mullineaux 2002).

[10] An endogenity problem would arise if we used the market shares from the current year to rank the underwriters because when an issuer selects an underwriter in the current year, the decision simultaneously increases the underwriter's market share.

Since it is necessary to control for financial characteristics and risk factors, we obtain financial data for each firm from the Compustat Industrial Quarterly database from Standard and Poor's. The financial data used in this study corresponds to the quarter and year of the SEO issue date. The incorporation date for each firm was hand collected from Moody's / Mergent's Industrial and Transportation Manuals and Standard & Poor's Corporation Records. From the Center for Research in Security Prices (CRSP) daily stock database, we download daily return, price, and outstanding share data to compute the equity volatility and market capitalization for each firm.

For each of the 201 tied deals, we gather the associated lending facilities from LPC *DealScan.* There are 358 tied lending facilities. The sample of tied lending facilities consists of 116 notes, 111 revolving lines of credit, 99 term loans, seventeen 364-day facilities, 13 bridge loans, and two other types of facility.

To examine differences between tied loans and non-tied loans, we create two separate samples. In the hand-matching sample, for each of the tied loan facilities, we create a control group of non-tied loans that were originated at around the same time as the tied loan, with firms that belong to the same industry and have the same credit rating. We use all loans in *DealScan* that occur between six months prior to and six months after the term facility active date of the tied loan.[11] We keep only those non-tied loans that have the same 2-digit SIC code and credit rating as the corresponding tied loan. We remove any loan that is missing information for the all-in spread drawn and / or the length of the loan.[12] All bridge loans and loans with an issuer that is not rated are removed. This sample has 107 tied loans that can be matched to a similar non-tied loan, and it is comprised of 56 revolving lines of credit, 40 term loans, ten 364-day facilities, and one other type of facility.

To construct the econometric-matching sample, we download all lending facilities in *DealScan* that occur between January 1, 1996 and May 31, 2001. We remove any facility that is missing information for the all-in spread drawn and / or the length of the facility, and we remove any facility where the borrower is a financial firm (companies with a one-digit SIC code of 6). As before, all bridge loans and loans to non-rated borrowers are excluded. This sample consists

[11] We also use a sample of loans that occur between three months prior to and three months after the SEO date. Results using this sample are similar and are not reported.

of 166 tied loans that can be matched to a sample of 6919 non-tied loans. Seventy-four revolving lines of credit, 77 term loans, fourteen 364-day facilities, and one other type of facility form the sample of 166 tied loans. Seventy-nine of the 166 tied loans are from commercial bank underwriters while the remaining 87 tied loans are provided by investment bank underwriters. From the sample of 6919 non-tied loans, we classify 145 lending facilities as "simultaneous loans," which are loans to an issuer of an SEO that are originated between six months prior to and six months after the SEO, where the lender could have been selected to underwrite the SEO but is not provided with underwriting responsibilities.

3. Methodology and Results

Table 1 displays trends in tying over time. It can be seen that tying increased over time from about 1% in 1994 to over 20% in 2001. However, before 1996, while tying was nearly non-existent, many issuers received loans from another bank at about the same time as the issuance of public securities.[13] As commercial banks have gained market share in equity underwriting, issuers have shifted from using a commercial bank for lending and an investment bank for equity underwriting to employing a single entity for both of the simultaneous transactions.

Table 2 reports summary statistics for the tied and non-tied SEO samples. Commercial banks are underwriters on 45% of tied deals and only 28% of non-tied deals. While this provides some evidence that commercial banks are using tied lending to gain market share, investment banks are also heavily involved in tied lending. Also, commercial banks and investment banks are providing tied loans to similar clients. These are interesting facts, which suggest that investment banks have now developed the organizational structure to lend. It also raises the issue that if regulation was now to cause commercial banks to exit this market, since investment banks have incurred the fixed costs of developing lending capabilities, investment banks may continue to tie lending with underwriting and may not necessarily revert to their earlier mode of operations.

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[12] The all-in spread drawn is rate the borrower pays to the lender each year for each dollar drawn off the credit line, quoted in basis points over LIBOR.

[13] In 1994, over 30% of SEO issuers received a loan from some bank within a period of six months before and six months after the issuance, even though only 1.4% of these loans came from the underwriter of the issuance.

Tied issuers are highly leveraged, with debt-to-equity ratios that are, on average, five times higher than non-tied issuers. Furthermore, tied lenders have low credit ratings, with 71% of investment bank tied deals and 60% of commercial bank tied deals for junk rated issuers, and another 12% of investment bank deals and 27% of commercial bank deals involving issuers that are not rated. Since duplication of information will be particularly costly for risky firms because they will be subject to extensive due diligence in both lending and underwriting, tying may be extremely beneficial for these issuers because a single bank can use the collected information for both transactions.

3.1. Equity Underwriter Spreads

We wish to determine if tying lowers issuers' financing costs. One possibility is that the firm pays a lower fee to the bank for underwriting its equity offering. An underwriter could charge a lower fee in a tied deal because the bank may face lower underwriting costs due to informational economies of scope that arise from the joint delivery of services and the reusability of information gathered during the lending process. We examine differences between tied and non-tied underwriting fees by analyzing the underwriter spread, which is the compensation paid to the underwriter for selling the firm's security issue, expressed as a percent of the capital raised. Consistent with the existence of scope economies, the univariate descriptive statistics in Table 2, Panel A indicate that the average underwriter spread of tied SEOs is 78 basis points lower than the mean underwriter spread of non-tied SEOs, a difference that is significant at the 1% level.

3.1.1. U-shaped Underwriter Spreads

The initial evidence indicates that tied issuers receive lower underwriter spreads. We wish to see if this result withstands a multivariate specification. Following Altinkilic and Hansen (2000), we estimate a model of the underwriter spread that can be a U-shaped function of the amount of new capital raised. Theoretically, a U-shaped function could arise because fixed costs cause scale economies initially, but as issue size increases, diseconomies of scale arise in the spread due to rising placement costs. Altinkilic and Hansen find strong evidence of U-shaped curves in a sample of 1,325 SEOs from 1990 through 1997.

As a model for the underwriter spread, we use Altinkilic and Hansen's expanded spread linear model in which the underwriter spread is the sum of a fixed cost and a variable cost component. In order to generate U-shaped spreads, the variable cost component must be allowed to rise over a relevant range of proceeds. This condition is satisfied by dividing the SEO principal amount by the firm's equity market capitalization, which holds firm size fixed as the size of the offering expands, thus allowing variable costs of underwriting to increase at an increasing rate. We control for the volatility of equity returns because higher volatility can cause more uncertainty, which may be reflected in a higher underwriter spread. The model captures any variation in underwriter costs that are due to the volume of issuance in the seasoned equity market.

We extend the model to include variables to capture tied lending and prior lending relationships. Since an existing lending relationship can lower setup costs and provide the bank with access to additional information, tied deals involving prior lenders may be less costly. To capture this potential effect, we control for interactions between prior lending and tied lending. A negative coefficient on the tied lending variables would be consistent with the existence of scope economies.

We estimate two variations of the expanded spread model. In model A, we do not allow for differences between investment bank variables and commercial bank variables while in model B, we relax this restriction.

3.1.2. Results

Results of ordinary least squares regressions are presented in Table 3. For both models, we find support for U-shaped spreads. As more capital is raised the variable cost is rising. As expected, higher stock return volatility increases the variable spread.

In model A, the coefficients on the tied lending and the prior lending variables are all negative and significant. A tied loan without a prior lending relationship provides an 18 basis point reduction in the underwriter spread, which is significant at the 10% level. A prior lending relationship, both with and without a tied loan, translates into a 36 basis point reduction in the underwriter spread. On a $200 million equity offering, an 18 basis point reduction in the underwriter fee provides a cost savings of $360,000 to the issuer, while a 36 basis point decrease saves the issuer $720,000. These results are consistent with the existence of economies of scope.

The results of model B show that investment banks account for most of the tied lending and underwriting relationship discount. For tied issuers, investment banks provide a discount of 26 basis points if no prior lending relationship existed and 44 basis points if there is a prior lending relationship, both significant at the 5% level. On a $200 million equity offering with an investment bank, on average, the issuer saves $520,000 to $880,000. For commercial bank underwritten issues, the coefficients for tied deals are negative but insignificant. It is interesting to note that both investment banks and commercial banks provide significant discounts in the underwriter spread to firms that do not receive a tied loan but with which a prior lending relationship is in place, which further supports the existence of informational economies of scope between lending and equity underwriting.

Overall, we find that tied deals have lower underwriter spreads than non-tied deals and that most of the discount can be attributed to investment bank underwriters. Tied deals in which there was a prior lending relationship in place receive a larger discount. This supports the existence of economies of scope between lending and equity underwriting. Further supporting the existence of scope economies, a prior lending relationship with a commercial bank translates into an underwriter spread discount. This result is also present for investment banks.

3.2. The Pricing of Tied Loans

We now study the pricing of tied loans to address two issues. First, we wish to determine if there is additional evidence that tying reduces issuers' financing costs. To examine this question, we compare the yield spreads of tied loans and non-tied loans.[14] Lower yield spreads for tied loans would be consistent with the existence of informational economies of scope. Second, we wish to examine how investment banks and commercial banks are competing for tied deals. Considering the result from the last section in which we found that investment banks are discounting underwriter spreads, any differences between investment bank and commercial bank pricing of tied loans will provide insight into how these two underwriter types compete.

Therefore, we compare the yield spreads of tied loans in which the lender is a commercial bank with tied loans from investment banks.

3.2.1. Hand Matching

To examine pricing differences between tied and non-tied loans, we hand match tied loans to non-tied loans on four dimensions – (i) loan origination date, (ii) industry, (iii) credit rating, and (iv) length of the loan. Ideally, we would like to find a non-tied loan that matches the tied loan on all four dimensions. However, it is unlikely that we will find an exact match. Instead, for each of the 107 tied lending facilities in the hand-matching sample, we select the non-tied loan with the closest term length, given that the non-tied loan was originated between six months before and six months after the tied loan origination date, and the non-tied borrower belongs to the same industry and has the same credit rating as the tied borrower.[15] Therefore, any selected non-tied loan will be an exact match on two of the four dimensions (industry and credit rating) and will have a very similar term length and loan origination date.

We examine the mean difference between tied and non-tied yield spreads using three estimators.[16] The "twelve-month estimator" uses all matches in which the absolute value of the difference between the term lengths of the matched pair of loans is less than 12 months. The "six-month estimator" is the same as the twelve-month estimator except that the difference cannot exceed six months. The "exact estimator" only includes matches where each loan in a matched pair has the same term length. For all three estimators, on average, the tied loan yield spreads are more than 20 basis points lower than the matched non-tied loan yield spreads, a significant difference at the 5% level.

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[14] The yield spread is the loan yield, quoted in basis points over LIBOR. By using yield spreads instead of yields, we remove economy-wide factors that could affect the results.

[15] We also restrict the selection of non-tied loans to those that are originated between three months prior to and three months after the term facility origination date. The results are similar and are not reported. Also, we match on the credit rating of the borrower at the loan origination date. If the bank acts rationally, it should consider the effect that the loan will have on the credit risk of the firm when determining the price and structure of the loan. Therefore, we also examine the credit rating of the firm at two quarters after the loan. In our sample of tied loans, only two rated borrowers had a credit rating change during the two quarters, so both measures of credit rating provide a nearly identical sample.

[16] If multiple non-tied loans share the closest term length to the non-tied loan, we use the average yield spread of the non-tied loans.

3.2.2. Econometric Matching

There are a few problems with the hand matching method. First, we match on only four dimensions and ignore variables that may be relevant in determining yield spread differences, such as the size of the lending facility and the type of lending facility. Second, for matching to occur, there must exist at least one non-tied loan that meets these four criteria. As a result, we do not generate matches for all of the tied loans in our sample. Based on these comments, it would be better to use a method that enlarges the number of matching dimensions while increasing the number of tied loans for which we can find a match. Econometric matching techniques that were developed by Rubin and Rosenbaum (1983) and extended by Heckman and Robb (1986), and Heckman, Ichimura, and Todd (1997, 1998) provide such an improvement.[17] Below, we provide a summary of their results.

We consider the case where a loan can belong to one of two groups, numbered 1 and 0. Let $D=1$ denote the treatment, which in this case is if the loan is a tied loan, and let $D=0$ represent the control, which is if the loan is a non-tied loan. In principle, the ith of the N loans under study has both a yield spread Y_{1i} that would result if it had received treatment and another yield spread Y_{0i} that would result if it did not receive the treatment. The effect of interest is a mean effect of the difference between Y_1 and Y_0. However, since we only observe Y_1 for our sample of tied loans, we have a missing data problem that cannot be solved at the level of the individual, so we reformulate the problem at the population level. We focus on the mean effect of the difference between tied loans and non-tied loans with characteristics X:

$$E(Y_1 - Y_0 \mid D=1, X) \tag{1}$$

While the mean $E(Y_1 \mid D=1, X)$ can be identified from data on tied loans, some assumptions must be made to identify the unobservable counterfactual mean, $E(Y_0 \mid D=1, X)$. The observable outcome of self-selected non-tied loans $E(Y_0 \mid D=0, X)$ can be used to approximate $E(Y_0 \mid D=1, X)$. The selection bias that arises from this approximation is

$$B(X) = E(Y_0 \mid D=1, X) - E(Y_0 \mid D=0, X)$$

[17] Previous papers in economics and finance use the Heckman et. al matching methodology. McMillen and McDonald (2002) apply the method to study land valuation in a newly zoned city while Dearden, Ferri, and Meghir (2002) and Blundell, Dearden, Goodman, and Reed (2000) use the matching methods to study the effect of education on wages. Bharath (2002) uses these methods to evaluate the agency costs of debt.

We use a method of matching that solves the evaluation problem. Following Heckman and Robb (1986), we assume that all relevant differences between tied loans and non-tied loans are captured by their observable characteristics *X*. Let

$$(Y_0, Y_1) \perp D \mid X \tag{2}$$

denote the statistical independence of (Y_0, Y_1) and D conditional on X. Rosenbaum and Rubin (1983) establish that when *(2)* and

$$0 < P(D=1 \mid X) < 1 \tag{3}$$

(which are referred to as the strong ignorability conditions) are satisfied, then $(Y_0, Y_1) \perp D \mid P(D=1 \mid X)$. While it is often difficult to match on high dimension *X,* this result allows us to match based on the one-dimensional $P(D=1 \mid X)$ alone. $P(D=1 \mid X)$, known as the propensity score, can be estimated using probit or logit models.

Heckman, Ichimura, and Todd (1998) extend this result by showing that the strong ignorability conditions are overly restrictive for the estimation of *(1).* Instead, a weaker mean independence condition

$$E(Y_0 \mid D=1, P(D=1 \mid X)) = E(Y_0 \mid D=0, P(D=1 \mid X)) \tag{4}$$

is all that is required.

To determine if econometric matching is a viable method of evaluation, Heckman et. al identify four features of the data and matching techniques that can substantially reduce bias – (i) Participants and controls have the same distributions of unobserved attributes; (ii) They have the same distributions of observed attributes; (iii) Outcomes and characteristics are measured in the same way for both groups; and (iv) Participants and controls are from the same economic environment. Items (iii) and (iv) are met very well for this study because the loan yield spreads and other loan characteristics are measured in the same way for both tied and non-tied loans, and the non-tied loans are from the same time period as the tied loans. To satisfy condition (ii), we use loan characteristics to match tied loans to non-tied loans. Feature (i) cannot be achieved in a non-experimental evaluation. However, Heckman, Ichimura, and Todd (1997) note that feature (i) is only a small part of bias in their experimental study. Thus, the method of matching non-tied loans to tied loans can produce a viable estimate of the difference between non-tied loan and tied loan yield spreads.

3.2.3. Matching Estimators

In Section 3.2.1., we hand matched tied loans to non-tied loans based on the loan origination date, the industry, the credit rating, and the length of the loan. By using the propensity score, we can match on more dimensions, such as the notional value of the facility size and the type of lending facility, while increasing the number of tied loans for which we can find a matched non-tied loan. The econometric methods effectively take into account the fact that the characteristics of tied loans may differ significantly from non-tied loans and ensure that such observed characteristics are not driving the results.

For each of the 166 tied loans and 6919 non-tied loans in the econometric-matching sample, we compute a propensity score *P(D=1 | X)* via the probit model:

$$P(TIED = 1 \mid X) = \Phi\left(\begin{array}{l} \beta_0 + \beta_1 * RATING + \beta_2 * FACSIZE + \beta_3 * LENGTH \\ \qquad + \beta_{type} * TYPE + \beta_{year} * YEAR + \beta_{ind} * INDUSTRY \end{array} \right) \qquad (5)$$

where *TIED* is a dummy variable that equals one if the lending facility is a tied loan and zero if the loan is a non-tied loan, *RATING* is the credit rating of the firm at the loan origination date, *FACSIZE* is the notional value of the loan facility, *LENGTH* is the term length of the loan, *TYPE* are dummy variables that indicate if the lending facility is a term loan, 364-day facility, revolving line of credit, or other loan, *YEAR* are dummy variables that indicate the year of the origination of the lending facility, and *INDUSTRY* are dummy variables that correspond to the 2-digit SIC code of the borrower.

As described above, the propensity score is used to match tied loans to non-tied loans. We use four propensity score matching methods: (i) nearest neighbor matching with 10 neighbors, (ii) nearest neighbor matching with 50 neighbors, (iii) Gaussian kernel based matching, and (iv) Epanechnikov kernel based matching.[18] Let Y_{1i} be the yield spread of a tied loan, Y_{0j} be the yield spread of a non-tied loan, and let $\overline{Y}_{0j}^{z}$ represent the (weighted) average of yield spreads of the non-tied loans using estimator z. We match the yield spreads of non-tied

[18] All propensity score matching methods are discussed in greater detail in Heckman et. al (1997, 1998)

loans to the yield spreads of tied loans using the various estimators. For each i, we compute $Y_{1i} - \overline{Y}_{0j}^{z}$.

For each tied loan, the nearest neighbor matching estimator chooses the n non-tied loans with closest propensity scores to the tied loan propensity score. The estimator computes the arithmetic average of the yield spreads of these n non-tied loans. For each Y_{1i}, we match

$$\overline{Y}_{0j}^{NN} = \frac{1}{n} \sum_{j \in N} Y_{0j}$$

where N is the set of non-tied loans that are nearest neighbors. We set $n = 10$ and $n = 50$.

The kernel estimators construct matches for each tied loan by using weighted averages of yield spreads of multiple non-tied loans. If weights from a typical symmetric, non negative, unimodal kernel $K(\bullet)$ are used, then the kernel places higher weight on loans close in terms of $P(D=1 \mid X)$ and lower or zero weight on more distant observations. Let

$$K_{ij} = K\left(\frac{P(X_{1i}) - P(X_{0j})}{h} \right)$$

where h is a fixed bandwidth and $P(X) = P(D=1 \mid X)$. For each Y_{1i}, we match a corresponding $\overline{Y}_{0j}^{K}$ where

$$\overline{Y}_{0j}^{K} = \frac{\sum_{j} K_{ij} Y_{0j}}{\sum_{j} K_{ij}} .$$

We use two different kernels to compute $\overline{Y}_{0j}^{K}$. The Gaussian kernel uses all non-tied loans while the Epanechnikov kernel only uses non-tied loans with a propensity score $P(X_{0j})$ that falls within the fixed bandwidth h of $P(X_{1i})$. We set $h = 0.01$.

We extend the methodology to capture differences between commercial bank tied loans and investment bank tied loans. We compare commercial bank tied loans to non-tied loans by restricting the tied lending sample to include only commercial bank loans. Separately, we examine differences between investment bank tied loans and non-tied loans.

3.2.4. Results

Each of the estimators provides a sample of yield spread differentials, with each yield spread differential representing the discount (if negative) or premium (if positive) that a tied lender pays. We calculate the sample average and standard error for each estimation and display the results in Table 4.

First, we provide evidence that is consistent with the existence of economies of scope in tied deals. All estimators indicate the tied loans have significantly lower yield spreads, with the average discount ranging between 9.97 and 14.81 basis points. On a $200 million dollar, 6-year loan, a reduction of 9.97 basis points represents a present value savings of $770,000 while a 14.81 basis point reduction provides a present value savings of $1.15 million.[19]

We attempt to determine the effect of prior lending relationships on the yield spread differential between tied and non-tied loans. For each estimator, we regress the sample of estimated yield spread differentials on a dummy variable that indicates if the borrower of the tied loan had a prior lending relationship with the bank. Our results indicate that a prior lending relationship does not significantly affect the size of the discount.

Second, we find that commercial banks provide cheaper loans to tied borrowers. Yield spreads on commercial bank tied loans are discounted by between 16.35 and 22.72 basis points relative to non-tied yield spreads, and the differences are highly significant for all four estimators. On a $200 million dollar, 6-year loan, a tied borrower earns a present value savings of between $1.27 million and $1.76 million through a discounted loan spread that is provided by its commercial bank.[20] While commercial banks reduce tied loan yield spreads, we find that yield spreads on investment bank tied loans are insignificantly different from those of non-tied loans. Tying by commercial banks, as opposed to investment banks, largely drives the difference between the yield spreads of tied and non-tied loans.

These results, in combination with the results from Section 3.1., indicate that in comparison to similar non-tied issuers and borrowers, tied issuers pay lower underwriter spreads on the SEO and receive lower loan yield spreads. Both results are consistent with informational economies of scope. However, we find that the form of the savings depends on the type of bank

[19] This calculation assumes a yearly discount rate of 15%.
[20] Again, this calculation assumes a yearly discount rate of 15%.

that is involved in the transaction, with investment banks providing lower underwriter spreads on the equity offering and commercial banks providing lower loan yield spreads. These savings are economically substantive. As an illustration, tied issuers who use investment banks receive an average savings of between $520,000 to $880,000 on a $200 million dollar equity offering. Those who use commercial banks receive an average saving of between $1.27 million and $1.76 million on a $200 million dollar, 6-year loan.

3.2.5. Robustness – Simultaneous Loans

An additional concern is that tied issuers are simultaneously raising equity and receiving loans and may therefore differ from other issuers. To address this concern, within the sample of non-tied loans, we identify simultaneous loans, which are loans to an issuer of an SEO that are originated between six months prior to and six months after the SEO, where the lender could have been selected to underwrite the SEO but is not provided with underwriting responsibilities.[21] We then compare tied loan yield spreads with simultaneous loan yield spreads to determine if the results in Section 3.2.4. are robust.

In Section 3.2.4., we show that most of the discounting of tied loans comes from commercial banks. Hence, we compare commercial bank tied loans with commercial bank simultaneous loans. Extending the previously employed methodology, we match commercial bank tied loans to other non-tied loans as well as commercial bank simultaneous loans to other non-tied loans by computing propensity scores using equation *(5)*.[22] We use the estimators that are described in Section 3.2.3. to calculate yield spread differences.

We compute sample averages for the tied loan matched pairs and the simultaneous loan matched pairs and report the mean difference in the yield spread between the two groups in Table 4. The results of all four estimations indicate that commercial bank tied loans are discounted more than commercial bank simultaneous loans. On average, tied loan yield spreads are less than simultaneous loan yield spreads by 16.43 to 28.42 basis points, and the difference is

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[21] We also extend this sample to include loans from any bank, not just those who could be selected to underwrite the SEO. The results are qualitatively similar.

[22] Of course, equation (5) must be modified slightly. For simultaneous loans, we replace TIED with SIMULTANEOUS, which is a dummy variable that equals one if the loan is a simultaneous loan and zero if it is a non-simultaneous loan.

significant when using three of the four estimators. Relative to simultaneous loans, the discount that is provided by commercial banks to tied issuers remains significant.

3.3. Underwriter Relationships

In Sections 3.1. and 3.2., we found that the issuers who participate in a tied deal have lower financing costs in the form of lower underwriter spreads and lower loan yield spreads. Now, we examine potential reasons for underwriters to tie lending to underwriting. Tying may help build relationships that improve the bank's chances of capturing the current or future underwriting business. Hence we first investigate if tying significantly increases the probability that the bank wins the current equity underwriting mandate. Then we investigate if tying lending to underwriting increases the likelihood that the bank will receive future underwriting business from the firm, thereby increasing expected future revenues.

3.3.1. McFadden's Choice Model

In this section, we study the influence tying has on the likelihood that a bank is selected as equity underwriter. We use McFadden's (1974) choice model to capture the effect.

Each issuing firm i chooses an underwriter j from a set of J underwriters. The choice of underwriter will depend on the characteristics of the issuer and attributes of the underwriter. The utility of choice j is

$$U_{ij} = \boldsymbol{\alpha}' \boldsymbol{w_i} + \boldsymbol{\beta}' \boldsymbol{x_{ij}} + \varepsilon_{ij}$$

where $\boldsymbol{w}_i$ is a vector of issuer characteristics and $\boldsymbol{x}_{ij}$ is a matrix of choice attributes. If the issuing firm makes a choice j, then we assume that U_{ij} is the maximum among the J utilities. Let Y_i be a random variable that indicates the firm's choice. McFadden (1973) shows that if the J disturbances are independent and identically distributed with Weibull distribution, then

$$\Pr(Y_i = j) = \frac{\exp(\boldsymbol{\alpha}' \boldsymbol{w}_i + \boldsymbol{\beta}' \boldsymbol{x_{ij}})}{\sum_{j=1}^{J} \exp(\boldsymbol{\alpha}' \boldsymbol{w}_i + \boldsymbol{\beta}' \boldsymbol{x_{ij}})}.$$

We assume that each firm has 21 potential choices – each of the top 20 underwriters and a single choice of any of the underwriters that are not ranked in the top 20. Since the attributes of the potential underwriters can influence an issuer's choice, we track underwriting relationships, lending relationships, analyst coverage, and all-star analyst coverage for each of the issuer's potential choices.[23] By including this information, we more accurately control for relationship-specific and underwriter-specific factors that could affect the probability of a firm selecting an underwriter. In addition, we modify our definition of "tied loans" to include loans from *potential* underwriters that are originated between six months prior to the SEO and six months after the SEO. Technically, this modification is needed because, otherwise, tied lending perfectly predicts an issuer's choice of underwriter. This methodology allows us to address the question on hand – does lending at the time of the SEO improve the probability of getting the underwriting business.

In our models, we assume that the relevant issuer specific characteristics ($\boldsymbol{w}_i$) are the logarithm of the SEO principal amount, the age of the firm, the long-term debt to equity ratio of the firm in the quarter of the SEO, and the industry of the issuer. These variables are chosen to control for differences between tied and non-tied issuers that are shown in Table 2, Panel A. For the choice-specific attributes ($\boldsymbol{x}_{ij}$), we include variables to capture tied lending, prior lending relationships, prior underwriting relationships, as well as the reputation of the underwriter and the level and quality of equity analyst coverage. We expect that prior lending and underwriting relationships between a firm and an underwriter will increase the probability of selection. Also, we expect that the reputation of the underwriter and the level and quality of equity analyst coverage will be positively related to underwriter selection (see e.g. Booth and Smith, 1986; Clarke et. al, 2002). In model A, we do not consider differences between investment banks and commercial banks, while in model B we relax this restriction.

3.3.2. Results

In Table 5, we present the results of the underwriter selection models. In both models, the control variables have the expected signs and most are highly significant. The coefficients of the tied lending variables are positive and statistically significant at the 1% level. This indicates that

[23] For example, even though AMC Entertainment selected Goldman Sachs to underwrite its August 1998 SEO, we capture that it could have selected Morgan Stanley and that Morgan Stanley provided all-star analyst coverage for the firm. Our final dataset consists of 48,321 firm-underwriter pairs (2301 firms X 21 choices).

providing a tied loan increases the probability of winning the underwriting mandate, even after controlling for other factors that significantly influence underwriter selection. The effect is present for both commercial and investment bank underwriters. The results demonstrate that providing a tied loan increases a bank's expected investment banking revenues.

3.4. Probability of Keeping Future Business

Tying lending to underwriting may also allow for a durable relationship that can boost expected future revenues by increasing the likelihood that the issuer will use the bank in the future. Theoretically, this could occur because a tied deal is a source of both a lending and underwriting relationship. The practice allows the bank to generate private information that can be used in future transactions with the bank and may create a lock-in effect, as described in Williamson (1979). In this section, we determine if expected future revenues increase by examining if those firms that participate in a tied deal go back to the market more frequently and do not switch underwriters as often as issuers who do not receive a tied loan.

In Table 6, we present a univariate analysis of switching probabilities. For our sample of 2301 issuers, 37% of tied issuers proceed with a subsequent equity offering while only 22% of non-tied issuers go back to the equity market.[24] More importantly, of those firms that have a follow-up equity offering, 57% of tied issuers and 44% of non-tied issuers keep the same underwriter, a significant difference at the 10% level. However, there is a disparity between investment bank and commercial bank underwriters. While tying significantly increases the probability of retaining future business for investment banks, the effect is not present for commercial banks. This result indicates that commercial banks may not be able to leverage their tying practices into extended underwriting relationships.

3.4.1. Nested Logit Model

To determine if these results withstand a multivariate specification, we use a nested logit model. As shown in Figure 1, we assume that each issuer makes a two-stage decision. First, the issuer decides if it will proceed with a subsequent SEO or if it will not issue again. Second, if the issuer chooses to issue again, then it can keep the same underwriter or switch to a new underwriter.

Following Maddala (1983), let k index the first-level alternative and l index the second-level alternative.[25] Also, let $\boldsymbol{Y}_{\mathbf{kl}}$ and $\boldsymbol{Z}_{\mathbf{k}}$ be vectors of explanatory variables specific to the categories (k, l) and (k), respectively. Then each issuer will have a utility U_{kl} for alternative (k,l) that is a function of the explanatory variables. We set $U_{kl} = \boldsymbol{\alpha}'\boldsymbol{Y}_{\boldsymbol{kl}} + \boldsymbol{\beta}'\boldsymbol{Z}_{\boldsymbol{k}} + \varepsilon_{kl}$, and then the probability of choosing l, conditional on first choosing k is

$$\Pr_{l|k} = \frac{\exp(\boldsymbol{\alpha}'\boldsymbol{Y}_{\boldsymbol{kl}})}{\sum_{l=1}^{L}\exp(\boldsymbol{\alpha}'\boldsymbol{Y}_{\boldsymbol{kl}})}.$$

Define the inclusive values for category (k) as

$$IV_{\boldsymbol{k}} = \ln\left(\sum_{l=1}^{L}\exp(\boldsymbol{\alpha}'\boldsymbol{Y}_{\boldsymbol{kl}})\right),$$

which leaves us with

$$\Pr_{\boldsymbol{k}} = \frac{\exp(\boldsymbol{\beta}'\boldsymbol{Z}_{\boldsymbol{k}} + \tau_{\boldsymbol{k}} IV_{\boldsymbol{k}})}{\sum_{k=1}^{K}\exp(\boldsymbol{\beta}'\boldsymbol{Z}_{\boldsymbol{k}} + \tau_{\boldsymbol{k}} IV_{\boldsymbol{k}})}.$$

In our models, we assume that the variables that only affect the decision to re-issue ($\boldsymbol{Z}_{\boldsymbol{k}}$) are the logarithm of the SEO principal amount, the age of the firm, the long-term debt to equity ratio of the firm in the quarter of the SEO, and the industry of the issuer. For the variables that affect both the decision to re-issue and the decision to keep or switch underwriters ($\boldsymbol{Y}_{\boldsymbol{kl}}$), we include variables to capture tied lending, prior lending relationships, prior underwriting relationships, as well as differences in the level and quality of equity analyst coverage and differences in the ranking of underwriters. Due to lock-in effects, we expect that prior lending and underwriting relationships will be positively related to keeping future business. Also, previous papers indicate

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[24] We examine subsequent SEOs that took place before March 31, 2002. Extending the sample end date allows issuers from the later part of the sample to potentially re-issue.

[25] For our model, k can be "Repeat" or "No-Repeat" while l can be "Switch" or "No-Switch"

that firms will be more likely to switch to an underwriter who has higher quality equity analyst coverage and is ranked above the original underwriter (see e.g. Krigman et. al, 2001). In model A, we do not consider differences between investment banks and commercial banks, while in model B we relax this restriction. Based on the univariate results, we expect a previous tied deal with an investment bank underwriter to increase the probability that the investment bank keeps future underwriting business. We also expect that a previous tied deal with a commercial bank will not significantly affect the probability that the bank can retain equity underwriting business in the future.

3.4.2. Results

In Table 7, we present the results of the nested logit models. The base category is that the issuer does not have a subsequent equity offering, so variables that are interacted with *KEEP* provide the effects of choosing to re-issue and keep the same underwriter instead of not re-issue at all. We also determine the effect of the variables on keeping the same underwriter instead of switching to a new underwriter through t-tests for differences between keeping and switching.

In model A, we find that a prior tied deal increases the probability of an issuer choosing to re-issue and keep the same lead underwriter relative to not reissuing. The t-tests for differences between keeping and switching indicate that a previous tied deal also increases the probability of keeping an underwriter instead of switching to a new underwriter, although this result is insignificant.

In model B, a prior tied deal (without the existence of a prior lending relationship) with an investment bank significantly increases the probability of keeping the same underwriter in the subsequent equity offering. The results indicate that for commercial bank underwriters, a tied deal does not significantly affect the probability that an underwriter will keep the same underwriter instead of switch to a new underwriter in the subsequent equity offering. These results are consistent with the univariate statistics in Table 6.

Combined with our previous findings, the results suggest that both commercial banks and investment banks tie lending with underwriting to win the current equity underwriting business, and that tying reduces an issuer's financing costs. However, the type of price discount that is given to the firm varies by underwriter type, with investment banks providing lower underwriter spreads on the SEO and commercial banks discounting the yield spreads on the loan. This is consistent with each type of underwriter competing more aggressively in its area of expertise and in the area where they are more likely to generate future business. We find that investment banks discount underwriter spreads and that tying increases the probability of retaining future underwriting business from the firm. Commercial banks, on the other hand, discount loan yield spreads, which helps establish lending relationships. It is well known that commercial banks' prior lending relationships lead to other fee-based lending business (such as letters of credit, guarantees, etc.). Hence commercial banks compete more aggressively on this dimension.

4. Conclusion

We use a unique data set drawn from multiple data sources and augmented by hand collected data to examine the practice of "tying," which occurs when a bank lends to an issuer around the time of a public security offering in order to secure the underwriting mandate. We find the practice of tying to be widespread and increasing over time. Our results suggest that the tying of lending and underwriting reduces issuers' financing costs, as tied issuers receive a lower underwriter fee for the equity offering and a discounted yield spread on the tied loan. These results, which are robust to the matching methodology developed by Heckman, Ichimura, and Todd (1997, 1998), are consistent with banks achieving economies of scope through the joint delivery of services and the reusability of information.

Underwriters tie lending to underwriting because this helps build a relationship that improves the probability of getting business. A tied loan raises their expected revenues by increasing the likelihood of receiving the current equity underwriting business; it also helps generate other business from the issuers. Investment bank underwriters can expect future underwriting fees from tied issuers, as we find that issuers that are tied to investment banks go back to the equity market and keep the same underwriter more frequently than non-tied issuers. While investment banks do not compete with commercial banks on lending terms, the durability of the underwriting relationship allows investment banks to aggressively price the gross spreads associated with the tied SEO. Commercial banks, on the other hand, compete more aggressively on lending terms by offering discounted loan yields. This finding is consistent with an intention to create a lending relationship, which is well known to help generate other fee-based, lending related business from the firm.

We find, contrary to the perception of the popular press, tying is not limited to commercial banks. Investment banks have responded by also tying loans to equity underwriting. We find that investment bank and commercial bank tied deals involve similar clients. Both investment banks and commercial banks are tying lending to underwriting and offering price discounts, albeit in different ways. This suggests that regulators who are trying to determine the impact of tying has on the financial system need to expand their analysis beyond commercial banks to include investment banks as well.

References

Ang, J., Richardson, T., 1994. The underwriting experience of commercial bank affiliates prior to the Glass-Steagall act: a re-examination of evidence for passage of the act, *Journal of Banking and Finance* 18, 351-395.

Altinkilic, O., Hansen, R., 2000. Are there economies of scale in underwriting fees? Evidence of rising external financing costs, *Review of Financial Studies* 13, 191-218.

Benston, G., 1990. *The Separation of Commercial and Investment Banking*, New York: Oxford University Press.

Berger, A., Demsetz, R. S., Strahan, P.E., The consolidation of the financial services industry: Causes, consequences, and implications for the future, *Journal of Banking and Finance* 23, 135-194.

Berger, A., Udell G., 1995. Relationship lending and lines of credit in small firm finance, *Journal of Business* 68, 351-381.

Best, R., Zhang, H., 1993. Alternative information sources and the information content of bank loans, *Journal of Finance* 48, 1507-1522.

Bharath, S., 2002. Agency costs, bank specialness and renegotiation, Working paper, New York University.

Billet, M. T., Flannery, M. J., Garfinkel, J. A., 1995. The effect of lender identity on a borrowing firm's equity return, *Journal of Finance* 50, 699-718.

Blundell, R., Dearden, L., Goodman, A., Reed, H., 2000. The returns to higher education in Britain: evidence from a British cohort, *Economic Journal* 110 (461), F82-F99.

Boot, A., Thakor, A., 1997. Banking scope and financial innovation, *Review of Financial Studies* 10(4), 1099-1131.

Booth, J., Smith, R., 1986. Capital raising, underwriting and the certification hypothesis, *Journal of Financial Economics* 15, 261-281.

Carter, R., Manaster, S., 1990. Initial public offerings and underwriter reputation, *Journal of Finance* 45, 1045-1067.

Carow, K.A., Kane, E., 2001, Event-study evidence of the value of relaxing longstanding regulatory restraints of banks, 1970-2000, NBER working paper.

Chaplinsky, S., and Erwin G., 2001. Commercial banks as equity underwriters, Working Paper, University of Virginia.

Clarke, J., Khorana, A., Patel, A., and Rau, R., 2002. Do all-star analysts drive investment banking deal flow? Working Paper, Wake Forest University.

Dearden, L., Ferri, J., Meghir, C., 2002. The effect of school quality on educational attainment and wages, *Review of Economics and Statistics* 84(1), 1-20.

Dingell, J., 2002. Letter to FRB and OCC re: “pay to play” practices, Jul 11. Available from www.house.gov/commerce_democrats/press/107ltr179.htm.

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

Gande, A., Puri, M., Saunders, A., Walter, I., 1997. Bank underwriting of debt securities: Modern evidence, *Review of Financial Studies* 10, 1175-1202.

Greene, W., 2000. *Econometric Analysis*, 4th ed., New Jersey: Prentice-Hall.

Hansen, R., Torregrosa, P., 1992. Underwriter compensation and corporate monitoring, *Journal of Finance* 47, 1537-1555.

Heckman, J., Ichimura, H., Todd, P., 1997. Matching as an econometric evaluation estimator: evidence from evaluating a job training programme, *Review of Economic Studies* 64, 605-654.

Heckman, J., Ichimura, H., Todd, P., 1998. Matching as an econometric evaluation estimator, *Review of Economic Studies* 65, 261-294.

Heckman, J., Robb, R., 1986. Alternative method for solving the problem of selection bias in evaluating the impact of treatments on outcomes, in H. Wainer (ed.), *Drawing Inferences from Self-Selected Samples*, New York: Springer-Verlag.

Houston, J., James, C., 2001. Do relationships have limits? Banking relationships, financial constraints, and investment, *Journal of Business* 74, 347-374.

Hubbard, R., Kuttner, K., Palia, D., 2003. Are there bank effects in borrowers' costs of funds? Evidence from a matched sample of borrowers and banks, *Journal of Business* 75, 559-582.

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

James, C., 1992. Relationship-specific assets and the pricing of underwriter services, *Journal of Finance* 47, 1865-1885.

James, C., Smith, D. C., 2000. Are banks still special? New evidence on their role in the corporate capital-raising process, *Journal of Applied Corporate Finance* 13, 395-422.

Kanatas, G., Qi, J., 1998. Underwriting by commercial banks: incentive conflicts, scope economies, and project quality, *Journal of Money, Credit, and Banking* 30, 119-133.

Kanatas, G., Qi, J., 2003. Integration of lending and underwriting: implications of scope economies, *Journal of Finance* 58, 1167-1191.

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

Kroszner, R., Rajan, R., 1994. Is the Glass-Steagall act justified? A study of the U.S. experience with universal banking before 1933, *American Economic Review* 84, 810-832.

Lummer, S., McConnell, J., 1989. Further evidence on bank lending process and capital market response to bank loan agreements, *Journal of Financial Economics* 25, 52-63.

Maddala, G., 1983. *Limited Dependent and Qualitative Variables in Econometrics*, New York: Cambridge University Press.

McFadden, D., 1973. Conditional logit analysis of qualitative choice behavior, in P. Zarembka (ed.) *Frontiers in Econometrics,* New York: Academic Press.

McMillen, D. P., McDonald, J. F., 2002. Land values in a newly zoned city, *Review of Economics and Statistics* 84(1), 62-72.

Narayanan, R., Nanda, R., Sundaram, S., 2001. Relaxing Glass-Steagall: Welfare implications of bank entry into securities underwriting, *Quarterly Review of Economics and Finance* 43, 505-527.

Petersen, M., Rajan, R., 1994. The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3-37.

Puri, M., 1994. The long term default performance of bank underwritten security issues, *Journal of Banking and Finance* 18, 397-418.

Puri, M., 1996. Commercial banks in investment banking: conflict of interest or certification role? *Journal of Financial Economics* 40, 373-401.

Puri, M., 1999. Commercial banks as underwriters: implications for the going public process. *Journal of Financial Economics* 54, 133-163.

Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects, *Biometrika* 70, 41-55.

Roten, I., and Mullineaux, D., 2002. Debt underwriting by commercial bank-affiliated firms and investment banks: more evidence, *Journal of Banking and Finance* 26, 689-718.

Saidenberg, M., Strahan P., 1999. Are banks still important for financing large businesses?, *Federal Reserve Bank of New York Current Issues in Economics and Finance* 5, 1-6.

Santomero, A., Eckles, D.L., 2000. The determinants of success in the new financial services environment, *FRBNY Economic Policy Review*, October, 11-23.

Saunders A., Walter, I., 1994. Universal banking in the United States. What could we gain? What could we lose? Oxford University Press, New York.

Sapsford, J., Beckett, P., 2002. Banks find linking of loans to other business has perils, *Wall Street Journal*, Sep 19, A1.

Silverman, G., Michaels, A., 2003. Fed seeks to clarify the rules on 'tying', *Financial Times*, Aug 26.

Smith, R., 2001. Lucent deal shows wall street takes on greater risk, *Wall Street Journal*, Feb 23, C1.

Smith, R., 2001. Morgan Stanley injects about $2 billion into bank unit, aiming to boost lending, *Wall Street Journal*, Aug 16, B7.

Smith, R., McGee, S., 2001. Deals & deal makers: banks' lending clout stings securities firms, *Wall Street Journal*, Jun 15, C1.

Williamson, O., 1979. Transaction cost economics: the governance of contractual relations, *Journal of Law and Economics* 22, 233-261.

Yasuda, A., 2001. Relationship capital and competition in the corporate securities underwriting market, Working paper, Wharton School, University of Pennsylvania.

Appendix A
Detailed Descriptions of the Variables

Underwriter Spread Regressions (Section 3.1.)

USPREAD: The underwriter spread, which is the compensation paid to the underwriter for selling the firm's security issue, expressed as a percent of the capital raised

TIELOAN: A dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter had never provided a loan to the issuer in the past

TIEPLEND: A dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter provided a loan to the issuer prior to six months before the SEO

PRIORLEND: A dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO

PRIORUND: A dummy variable that equals one if the underwriter had been the underwriter on any prior equity offering by the issuer

IB: A dummy variable that equals one if the parent/holding company of the underwriter at the time of the issue is an investment bank

CB: A dummy variable that equals one if the parent/holding company of the underwriter at the time of the issue is an commercial bank

(1/SEOSIZE): The inverse of the principal amount of the offering, in millions of dollars. This variable captures the fixed cost component of underwriter spreads

(SEOSIZE / MKTCAP) : The principal amount of the offering divided by the market capitalization of the issuer at the date of the SEO. This variable captures the variable cost component of underwriting spreads

VOL: The daily standard deviation of the issuer's common stock rate of return over the 220 trading days ending 40 days before the offering

MKTACT: The dollar volume of issuance by non-SIC6 firms in the US seasoned equity market during the three months prior to the SEO date

Propensity Score / Estimating Yield Spread Differences (Section 3.2.)

YSPREAD: The yield spread of the loan, measured as the rate the borrower pays to the lender, quoted in basis points over LIBOR. We use the *DealScan* item "all-in spread drawn," which adds the spread of the loan with any fees that have to be paid back to the bank.

TIED: A dummy variable that equals one if the lending facility is a tied loan and zero if the loan is a non-tied loan

SIMULTANEOUS: A dummy variable that equals one if the lending facility is a simultaneous loan and zero if the loan is a non-simultaneous loan

RATING: A variable that provides the Standard & Poor's credit rating of the firm at the date of the lending facility. Each rating is given a numerical counterpart: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, CCC = 7, CC = 8, C = 9

FACSIZE: The notional value of the loan facility between the lender and the borrower, expressed in millions of dollars

LENGTH: The term length of the loan, measured as the difference between the term facility active date and the term facility expiration date, measured in months

TYPE: Dummy variables that correspond to the type of lending facility. The dummy variables indicate if the facility is a term loan, 364-day facility, revolving line of credit, or other type

YEAR: Dummy variables that correspond to the year of the origination date of the lending facility

INDUSTRY: Dummy variables that equal one if the borrower is in the corresponding two-digit SIC group

McFadden Choice Model / Underwriter Relationships (Section 3.3.)

TIELOAN: A dummy variable that equals one if a potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO and the potential underwriter had never provided a loan to the issuer in the past

TIEPLEND: A dummy variable that equals one if the potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the potential underwriter provided a loan to the

issuer prior to six months before the SEO
PRIORLEND: A dummy variable that equals one if a loan between the potential underwriter and the issuer was originated at any time prior to six months before the SEO *and* the potential underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO
PRIORUND: A dummy variable that equals one if the potential underwriter had been the underwriter on any prior equity offering by the issuer
COVERAGE: A dummy variable that is one if the potential underwriter provided an earnings per share estimate for the firm during the year prior to the SEO
ALLSTAR: A dummy variable that is one if COVERAGE is one and the analyst was ranked as an all-star by Institutional Investor magazine for the year prior to the SEO
RANK: We compute each underwriter's yearly SEO market share by adding the principal amounts of all SEOs in which the bank was a underwriter and dividing this total by the principal amounts of all SEOs during the year. To avoid potential endogenity problems, we rank the underwriters on a yearly basis, based on the market share in the previous year. If a merger between underwriters occurred during the year, we use the combined market share of the underwriters. The top-ranked underwriter is given a score of 20, the second-ranked underwriter is 19, and so on. Underwriters not ranked in the top 20 are given a score of zero
Nested Logit Model / Keeping Future Business (Section 3.4.)
TIELOAN: A dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the original SEO and six months after the original SEO and the underwriter had never provided a loan to the issuer in the past
TIEPLEND: A dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the original SEO and six months after the original SEO *and* the underwriter provided a loan to the issuer prior to six months before the original SEO
PRIORLEND: A dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the original SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the original SEO and six months after the original SEO
PRIORUND: A dummy variable that equals one if the underwriter had been the underwriter on any equity offering prior to the original SEO by the issuer
REPEAT: A dummy variable that is one if the issuer has a subsequent offering
KEEP: A dummy variable that is one if the issuer keeps the same underwriter in the subsequent offering
SWITCH: A dummy variable that is one if the issuer switches underwriters in the subsequent offering
CNGCOV: For "switchers," the difference between the coverage provided by the new underwriter and the original underwriter during the year prior to the subsequent SEO. The variable can take on the values of –1, 0, or 1. By definition, for all non-repeaters and keepers, it has a value of zero
CNGSTAR: For "switchers," the difference between the all-star coverage provided by the new underwriter and the original underwriter during the year prior to the subsequent SEO. The variable can take on the values of –1, 0, or 1. By definition, for all non-repeaters and keepers, it has a value of zero
CNGRANK: For "switchers," the difference between the subsequent underwriter's ranking in the year before the subsequent issue date and the original underwriter's ranking in the year before the subsequent issue date. For keepers and non-repeaters, the variable is zero
IB: A dummy variable that equals one if the parent/holding company of the potential underwriter at the time of the issue is an investment bank
CB: A dummy variable that equals one if the parent/holding company of the potential underwriter at the time of the issue is an commercial bank
Control Variables
LNSIZE: The logarithm of the principal amount of the offering
DE-LTDEBT: The long-term debt to equity ratio in the quarter of the SEO
AGE: The firm's age, measured as the difference between the SEO date and the incorporation date, expressed in years
SICx: Dummy variables that equal one if the issuer is in the corresponding one-digit SIC group
IGRADE: A dummy variable that equals one if the issuer is rated AAA, AA, A, or BBB in the quarter of the SEO by Standard & Poor's
JUNK: A dummy variable that equals one if the issuer is rated BB, B, CCC, CC, or C in the quarter of the SEO by Standard & Poor's

Table 1

Tied Deals, by year

This table presents the percentage of SEOs that are tied deals. A tied deal is any SEO in which the underwriter provides a loan to the issuer between six months prior to the SEO and six months after the SEO.

Year	1994	1995	1996	1997	1998	1999	2000	2001*
Number of SEOs	363	493	596	515	340	389	375	86
Number of Tied Deals	5	5	19	48	37	52	27	18
% Tied Deals	1.38%	1.01%	3.19%	9.32%	10.88%	13.37%	7.20%	20.93%

* Through May 31

Table 2

Univariate Tests for Differences in the Sample of SEOs between Jan. 1996 and May 2001

This table tests for differences between tied deals and non-tied deals and for differences between investment bank tied deals and commercial bank tied deals. Panels A and C use a difference in means t-test and Wilcoxon rank test. A tied deal is any SEO in which the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO. The underwriter is an IB (CB) if the parent or holding company of the underwriter is an investment bank (commercial bank) at the time of the SEO. The variables are defined as follows: USPREAD is the underwriter spread, which is compensation paid to the underwriter for selling the firm's security issue, expressed as a percent of the capital raised. LNSIZE is the logarithm of the SEO principal amount, expressed in millions of dollars. DE-LTDEBT is the long-term debt to common equity ratio in the quarter of the SEO. AGE is the firm's age, measured as the difference between the date of the SEO and the incorporation date, measured in years. PRIORLEND is one if a loan between underwriter and the issuer was originated at any time before six months prior to the SEO. PRIORUND is one if the underwriter had been the underwriter on any prior equity offering by the issuer. COVERAGE is one if the underwriter had provided an earnings per share estimate for the firm within the year prior to the SEO. ALLSTAR is one if COVERAGE is one and the analyst was ranked as an all-star by Institutional Investor magazine for the year prior to the SEO. A firm has an issuer rating of IGRADE if it is rated AAA, AA, A, or BBB by Standard & Poor's in the quarter of the SEO. A firm has an issuer rating of JUNK if it is rated BB, B, CCC, CC, or C by Standard & Poor's in the quarter of the SEO.

Panel A: Tied vs. Non-Tied Deals – Issuer and Issuance Variables

Variable	Tied Deal Mean	Non-Tied Deal Mean	T-ratio		Wilcoxon test p-value	
USPREAD	4.33	5.11	-8.63	***	0.0000	***
LNSIZE	5.09	4.28	9.94	***	0.0000	***
DE-LTDEBT	2.57	0.55	2.96	***	0.0000	***
AGE	21.78	17.87	2.12	**	0.1845	

Panel B: Tied vs. Non-Tied Deals – Relationship Variables

Variable	Percent of Tied Deals	Percent of Non-Tied Deals
CB	45.3	28.1
IB	54.7	71.9
PRIORLEND	41.3	4.9
PRIORUND	44.8	39.5
COVERAGE	77.1	63.0
ALLSTAR	21.4	12.9

Table 2 (continued)

Panel C: IB vs. CB Tied Deals – Issuer and Issuance Variables				
Variable	IB Tied Deal Mean	CB Tied Deal Mean	T-ratio	Wilcoxon test p-value
USPREAD	4.25	4.43	0.98	0.2792
LNSIZE	5.28	4.92	2.24 **	0.0110 **
DE-LTDEBT	2.83	2.31	0.39	0.4189
AGE	20.50	23.35	0.79	0.1148

Panel D: IB vs. CB Tied Deals – Relationship Variables		
Variable	Percent of IB Tied Deals	Percent of CB Tied Deals
PRIORLEND	36.4	47.3
PRIORUND	48.2	40.7
COVERAGE	78.2	75.8
ALLSTAR	23.6	18.7

Panel E: IB vs. CB Tied Deals – Issuer Rating		
Variable	Percent of IB Tied Deals	Percent of CB Tied Deals
IGRADE	17.27	13.19
JUNK	70.91	60.44

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Table 3
Underwriter Fee Regressions

In this table, we provide estimates of an ordinary least squares regression of the following model based on Altinkilic and Hansen (2000):

$$
\begin{aligned}
USPREAD = {} & \beta_0 + \beta_1 * TIELOAN + \beta_2 * TIEPLEND + \beta_3 * PRIORLEND + \beta_4 * PRIORUND + \beta_5 * IB \\
& + \beta_6 * IB\ X\ TIELOAN + \beta_7 * CB\ X\ TIELOAN + \beta_8 * IB\ X\ TIEPLEND + \beta_9 * CB\ X\ TIEPLEND \\
& + \beta_{10} * IB\ X\ PRIORLEND + \beta_{11} * CB\ X\ PRIORLEND + \beta_{12} * IB\ X\ PRIORLEAD + \beta_{13} * CB\ X\ PRIORLEAD \\
& + \beta_{14} * (1/SEOSIZE) + \beta_{15} * (SEOSIZE/MKTCAP) + \beta_{16} * VOL + \beta_{17} * MKTACT + \beta_{SIC} * SICx + \varepsilon
\end{aligned}
$$

In model A, we do not allow for differences between investment bank and commercial bank variables by imposing that $\beta_i = 0$ *for* $i = 5, 6, \ldots, 13$.

In model B, we relax this restriction by setting $\beta_i = 0$ *for* $i = 1, 2, 3,$ *and* 4.

The dependent variable is USPREAD, which is the compensation paid to the underwriter for selling the firm's security issue, expressed as a percentage of the principal amount. The independent variables are: TIELOAN is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if the underwriter had been the underwriter on any prior equity offering by the issuer. IB (CB) is one if the parent / holding company of the underwriter is an investment bank (commercial bank). To capture the fixed cost component of spreads, we include (1/SEOSIZE), the inverse of the principal amount of the equity offering, measured in millions of dollars. Variable costs are captured by (SEOSIZE / MKTCAP), the principal amount of the offering divided by the market capitalization of the issuer at the date of the SEO. VOL is the daily standard deviation of the issuer's common stock rate of return over the 220 trading days ending 40 days before the offering. MKTACT is the dollar volume of issuance in the US SEO market for the three months prior to each offering. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. Coefficients for the industry variables (SICx) are not reported.

	MODEL A			**MODEL B**		
	Coefficient	T-ratio		Coefficient	T-ratio	
Intercept	4.247	33.12	***	4.231	31.57	***
TIELOAN	-0.182	-1.74	*			
TIEPLEND	-0.360	-2.31	**			
PRIORLEND	-0.360	-3.04	**			
PRIORUND	-0.217	-4.19	***			
IB				0.021	0.29	
IB X TIELOAN				-0.263	-2.00	**
CB X TIELOAN				-0.070	-0.43	
IB X TIEPLEND				-0.440	-2.20	**
CB X TIEPLEND				-0.321	-1.43	
IB X PRIORLEND				-0.324	-2.49	**
CB X PRIORLEND				-0.454	-1.81	*
IB X PRIORUND				-0.248	-4.39	***
CB X PRIORUND				-0.135	-1.45	
1 / SEOSIZE	17.270	6.04	***	17.259	5.98	***
SEOSIZE / MKTCAP	0.242	1.43		0.241	1.42	
VOL	12.274	10.26	***	12.226	9.96	***
MKTACT	-7.581	-2.34	**	-7.652	-2.36	**
R-Squared	0.4029			0.4040		

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Table 4

Estimated Yield Spread Differences, in basis points

This table provides estimates of the mean difference between the yield spread (YSPREAD) of (a) Tied loans and non-tied loans, (b) CB tied loans and non-tied loans, and (c) CB tied loans and CB simultaneous loans, using various estimators. YSPREAD is the yield spread – the rate that the borrower pays to the lender, quoted in basis points over LIBOR. Tied (Simultaneous) loans are loans to the issuer of an SEO between six months prior to and six months after the SEO where the lender is (not, but could have been selected as) the underwriter of the SEO. To examine mean yield spread differences, we control for six characteristics – (i) Credit rating (ii) Lending facility size (iii) Length of the loan (iv) Type of lending facility (v) Loan origination date and (vi) Industry. We compute propensity scores using the following probit model:

$$P(TIED = 1 \mid X) = \Phi\left(\begin{array}{l} \beta_0 + \beta_1 * RATING + \beta_2 * FACSIZE + \beta_3 * LENGTH \\ \qquad + \beta_{type} * TYPE + \beta_{year} * YEAR + \beta_{ind} * INDUSTRY \end{array}\right)$$

TIED is a dummy variable that equals one if the lending facility is a tied loan and zero if the loan is a non-tied loan. RATING provides the Standard & Poor's credit rating of a firm at the date of the loan. Each rating is given a numerical counterpart: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, CCC = 7, CC = 8, C = 9. FACSIZE is the notional value of the loan facility between the lender and the borrower, expressed in millions of dollars. LENGTH is the difference between the term facility active date and the term facility expiration date, measured in months. TYPE stands for a set of dummy variables based on the type of lending facility, as classified by LPC *Dealscan*. Each facility is classified as "term loan," "revolving line of credit," "364 day facility," or "other type," and we create four corresponding dummy variables. YEAR stands for a set of dummy variables based on the loan origination date of the lending facility. For this sample, we define six dummy variables, one for each year between 1996 and 2001. INDUSTRY stands for a set of industry dummy variables based on two-digit primary SIC code. The estimators, which are described in detail in Heckman, Ichimura, and Todd (1997, 1998), are defined as follows: NEAR NEIGHBOR chooses for each tied loan, the n non-tied loans with closest propensity scores, and uses the arithmetic average of the n non-tied yield spreads. We use n = 10 and n = 50. GAUSSIAN and EPANECHNIKOV use a weighted average of non-tied loans, with more weight given to non-tied loans with propensity score that are closer to the tied loan propensity score. GAUSSIAN uses all non-tied loans, while for EPANECHNIKOV, we specify a propensity score bandwidth (h) that limits the sample of non-tied loans. We specify that h = 0.01.

To compute yield spread differences between tied loans and non-tied loans, we use the estimators to match tied loans to non-tied loans. The sample averages and T-ratios are presented in columns 2 and 3. To compute yield spread differences between CB tied loans and non-tied loans, we remove IB tied loans from the sample, compute propensity scores, and use the estimators to find non-tied loan matches for CB tied loans and compute yield spread differences. The sample averages and T-ratios are presented in columns 4 and 5. To compute yield spread differences between CB tied and CB simultaneous loans, we remove all simultaneous loans and IB tied loans from the sample, compute propensity scores, match non-tied loans to each CB tied loan, and compute yield spread differences. For CB simultaneous loans, we remove all tied loans and IB simultaneous loans from the sample. We compute propensity scores using the above probit model by replacing TIED with SIMULTANEOUS, which is one if the loan is simultaneous and zero if it is non-simultaneous. We use the estimators to find matches and compute yield spread differences for each simultaneous loan. Column 6 presents the mean difference between the CB tied sample average and CB simultaneous sample average, with the T-ratio displayed in column 7. Standard errors are computed by bootstrapping the matching procedures with 50 replications.

Estimator	Mean Yield Spread Difference between Tied and Non-Tied	T-ratio	Mean Yield Spread Difference between CB Tied and Non-Tied	T-ratio	Mean Yield Spread Difference between CB Tied and CB Simultaneous	T-ratio
NEAR NEIGHBOR (n=10)	-14.811	-2.09 **	-22.713	-2.38 **	-28.422	-1.92 *
NEAR NEIGHBOR (n=50)	-12.081	-2.38 **	-19.052	-2.31 **	-28.202	-1.96 **
GAUSSIAN	-9.966	-1.93 *	-16.347	-2.23 **	-16.430	-1.12
EPANECHNIKOV	-14.772	-2.27 **	-21.223	-2.57 **	-26.409	-1.83 *

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Table 5
Multivariate Model of Underwriter Selection (McFadden's Choice Model)

Each issuing firm i chooses an underwriter j from a set of J underwriters. The utility of choice j is

$$U_{ij} = \boldsymbol{\alpha}' \boldsymbol{w}_{\boldsymbol{i}} + \boldsymbol{\beta}' \boldsymbol{x}_{\boldsymbol{ij}} + \varepsilon_{ij}$$

where $\boldsymbol{w}_i$ is a vector of issuer characteristics and $\boldsymbol{x}_{ij}$ is a matrix of choice attributes. If the issuing firm makes a choice j, then we assume that U_{ij} is the maximum among the J utilities. In both models, the relevant issuer specific characteristics are $\boldsymbol{w}_i$ = {LNSIZE, AGE, DE-LTDEBT, SICx}. We use two different specifications for $\boldsymbol{x}_{ij}$. In model A, we do not consider differences between investment banks and commercial banks. We specify that $\boldsymbol{x}_{ij}$ = {TIELOAN, TIEPLEND, PRIORLEND, PRIORUND, COVERAGE, ALLSTAR, RANK1, . . ., RANK20}. In model B, we allow for differences between investment banks and commercial banks by setting $\boldsymbol{x}_{ij}$ = {IB X TIELOAN, CB X TIELOAN, IB X TIEPLEND, CB X TIEPLEND, IB X PRIORLEND, CB X PRIORLEND, IB X PRIORUND, CB X PRIORUND, IB, COVERAGE, ALLSTAR, RANK1, . . ., RANK20}. The issuer characteristics are defined as follows: LNSIZE is the logarithm of the SEO principal amount, expressed in millions of dollars. AGE is the firm's age, measured as the difference between the date of the SEO and the incorporation date, measured in years. DE-LTDEBT is the long-term debt to common equity ratio in the quarter of the SEO. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. The choice attributes are defined as follows: TIELOAN is a dummy variable that equals one if a potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the potential underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if a potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the potential underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the potential underwriter and the issuer was originated at any time prior to six months before the SEO *and* the potential underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if a potential underwriter had been the underwriter on any prior equity offering by the issuer. IB (CB) is one if the potential underwriter of the SEO is an investment bank (commercial bank). COVERAGE is one if the potential underwriter had provided an earnings per share estimate for the firm during the year prior to the SEO. ALLSTAR is one if COVERAGE is one and the analyst was ranked as an all-star by Institutional Investor magazine for the year prior to the SEO. RANK1 through RANK20 are 20 dummy variables, one for each potential choice. The issuer characteristics are interacted with the 20 choice-specific dummy variables in order to be included in the model. Estimated coefficients for the choice specific constants and the issuer characteristics are not reported.

	MODEL A			**MODEL B**		
	Coefficient	T-ratio		Coefficient	T-ratio	
TIELOAN	1.765	9.73	***			
TIEPLEND	1.236	5.92	***			
PRIORLEND	0.513	3.28	***			
PRIORUND	2.693	37.43	***			
IB X TIELOAN				1.853	7.96	***
CB X TIELOAN				1.587	6.16	***
IB X TIEPLEND				1.521	4.80	***
CB X TIEPLEND				1.120	4.49	***
IB X PRIORLEND				0.885	4.37	***
CB X PRIORLEND				0.097	0.40	
IB X PRIORUND				2.879	33.60	***
CB X PRIORUND				2.188	15.47	***
IB				-0.171	-1.85	*
COVERAGE	1.609	20.02	***	1.646	20.37	***
ALLSTAR	0.557	4.73	***	0.531	4.50	***
Psuedo R-squared	0.4150			0.4174		
Log Likelihood	3405.48			3391.31		

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Table 6

Univariate Analysis of Keeping the Same Underwriter in a Subsequent SEO

This table summarizes the probability that an issuer will proceed with a subsequent SEO and, if so, the probability that the issuer will keep the underwriter, based on if the initial SEO was a tied deal. A tied deal is any SEO in which the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO. The underwriter is an IB (CB) if the parent or holding company of the underwriter is an investment bank (commercial bank) at the time of the SEO. Panel A provides a full sample analysis. Panel B examines those SEOs in which the underwriter was an investment bank. Panel C examines those SEOs in which the underwriter is a commercial bank. P-values for the difference in proportions is provided in the last column.

	Tied Deals	Non-Tied Deals	Proportion test p-value	
PANEL A: Full Sample				
# in Sample	201	2100		
# that Repeat	74	462		
% of Sample that Repeat	36.82%	22.00%	0.0000	***
# Keep Same Lead	42	207		
% of Repeaters that Keep Same Lead	56.76%	44.81%	0.0556	*
PANEL B: Underwriter is an IB				
# in Sample	110	1509		
# that Repeat	43	347		
% of Sample that Repeat	39.09%	23.00%	0.0001	***
# Keep Same Lead	28	148		
% of Repeaters that Keep Same Lead	65.12%	42.65%	0.0049	***
PANEL C: Underwriter is a CB				
# in Sample	91	591		
# that Repeat	31	115		
% of Sample that Repeat	34.07%	19.46%	0.0018	***
# Keep Same Lead	14	59		
% of Repeaters that Keep Same Lead	45.16%	51.30%	0.5162	

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Table 7

Multivariate Model of Keeping the Same Underwriter in a Subsequent SEO

In this table, we present results of two nested logit models of the probability of keeping or switching underwriters in a subsequent SEO. Let the alternatives of "Repeat" and "Not Repeat" belong to category *k* and the alternatives of "Keep" and "Switch" belong to category *l*. We define $\boldsymbol{Y_{kl}}$ and $\boldsymbol{Z_k}$ be vectors of explanatory variables specific to the categories (*k*, *l*) and (k), respectively. The utility of choosing alternative *(k,l)* is

$$U_{kl} = \boldsymbol{\alpha' Y_{kl}} + \boldsymbol{\beta' Z_k} + \varepsilon_{kl}$$

In both models, $\boldsymbol{Z_k}$ = {LNSIZE, AGE, DE-LTDEBT, SICx}. In model A, we do not consider differences between investment banks and commercial banks by specifying that $\boldsymbol{Y_{kl}}$ = {TIELOAN, TIEPLEND, PRIORLEND, PRIORUND, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. In model B, we allow for differences between investment banks and commercial banks by setting $\boldsymbol{Y_{kl}}$ = {IB X TIELOAN, CB X TIELOAN, IB X TIEPLEND, CB X TIEPLEND, IB X PRIORLEND, CB X PRIORLEND, IB X PRIORUND, CB X PRIORUND, IB, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. The variables in $\boldsymbol{Z_k}$ are defined as follows: LNSIZE is the logarithm of the original SEO principal amount, expressed in millions of dollars. AGE is the firm's age, measured as the difference between the date of the original SEO and the incorporation date, measured in years. DE-LTDEBT is the long-term debt to common equity ratio in the quarter of the original SEO. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. The variables in $\boldsymbol{Y_{kl}}$ are: TIELOAN is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the original SEO and six months after the original SEO *and* the underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if the underwriter had been the underwriter on any equity offering by the issuer prior to the original SEO. IB is one if the underwriter of the original SEO is an investment bank. CB is one if the underwriter of the original SEO is a commercial bank. CNGCOV is the difference between the coverage provided by the subsequent underwriter and the original underwriter in the year prior to the subsequent SEO. CNGSTAR is the difference between the all-star coverage provided by the subsequent underwriter and the original underwriter in the year prior to the subsequent SEO. CNGRANK is the difference between the subsequent underwriter's ranking in the year before the subsequent issue date and the original underwriter's ranking in the year before the subsequent issue date. KEEP and SWITCH are choice-specific dummy variables. TIELOAN, PRIORUND, PRIORLEND, and IB are interacted with KEEP and SWITCH in order to be included in the model. LNSIZE, AGE, DE-LTDEBT, and SICx are interacted with REPEAT in order to be included in the model. Estimated coefficients for the industry variables (SICx) are not reported.

	MODEL A		MODEL B	
	Coefficient	T-ratio	Coefficient	T-ratio
Variables that affect the choice of "REPEAT" or "NO REPEAT"				
REPEAT X LNSIZE	0.124	2.29 **	0.139	2.55 **
REPEAT X AGE	0.003	1.20	0.002	0.74
REPEAT X DE-LTDEBT	0.010	1.05	0.010	1.08
Variables that affect the choice of "NO REPEAT", "(REPEAT, KEEP)", or "(REPEAT, SWITCH)"				
Tied Lending / No Prior Lending Relationship				
KEEP X TIELOAN	0.434	2.52 **		
KEEP X IB X TIELOAN			0.727	3.70 ***
KEEP X CB X TIELOAN			-0.188	-0.44
SWITCH X TIELOAN	0.095	0.45		
SWITCH X IB X TIELOAN			-0.083	-0.27
SWITCH X CB X TIELOAN			0.478	1.74 *
Tied Lending with Prior Lending Relationship				
KEEP X TIEPLEND	0.380	1.87 *		
KEEP X IB X TIEPLEND			0.071	0.19
KEEP X CB X TIEPLEND			0.603	2.23 **
SWITCH X TIEPLEND	-0.008	-0.03		
SWITCH X IB X TIEPLEND			0.014	0.04
SWITCH X CB X TIEPLEND			0.125	0.36

Table 7 (continued)

	MODEL A		MODEL B	
	Coefficient	T-ratio	Coefficient	T-ratio
Tied Lending with Prior Lending Relationship				
KEEP X TIEPLEND	0.380	1.87 *		
KEEP X IB X TIEPLEND			0.071	0.19
KEEP X CB X TIEPLEND			0.603	2.23 **
SWITCH X TIEPLEND	-0.008	-0.03		
SWITCH X IB X TIEPLEND			0.014	0.04
SWITCH X CB X TIEPLEND			0.125	0.36
Prior Lending Relationship / No Tied Lending				
KEEP X PRIORLEND	0.320	1.71 *		
KEEP X IB X PRIORLEND			0.161	0.64
KEEP X CB X PRIORLEND			0.632	2.18 **
SWITCH X PRIORLEND	0.018	0.08		
SWITCH X IB X PRIORLEND			0.053	0.19
SWITCH X CB X PRIORLEND			0.025	0.05
Prior Underwriting Relationship				
KEEP X PRIORUND	0.282	2.77 ***		
KEEP X IB X PRIORUND			0.159	1.31
KEEP X CB X PRIORUND			0.557	2.91 ***
SWITCH X PRIORUND	-0.112	-1.08		
SWITCH X IB X PRIORUND			-0.188	-1.53
SWITCH X CB X PRIORUND			0.072	0.35
Coverage and Reputation				
SWITCH X CNGCOV	0.120	0.62	0.097	0.49
SWITCH X CNGSTAR	0.737	2.36 **	0.704	2.26 **
SWITCH X CNGRANK	0.146	7.72 ***	0.146	7.55 ***
Bank Classification and Constants				
KEEP X IB			0.250	1.38
SWITCH X IB			0.312	1.85 *
KEEP	-1.494	-8.41 ***	-1.730	-7.14 ***
SWITCH	-1.303	-8.32 ***	-1.582	-6.78 ***
IV(REPEAT)	2.490	6.83 ***	2.441	6.68 ***
LR Test of Homoskedasticity [IV(Repeat) = 1]	34.97 ***		32.30 ***	
Log Likelihood	1315.01		1301.27	
T-tests for differences between keeping and switching				
KEEP X TIELOAN – SWITCH X TIELOAN	0.339	1.05		
KEEP X IB X TIELOAN – SWITCH X IB X TIELOAN			0.810	1.92 *
KEEP X CB X TIELOAN – SWITCH X CB X TIELOAN			-0.667	-1.10
KEEP X TIEPLEND – SWITCH X TIEPLEND	0.388	1.00		
KEEP X IB X TIEPLEND – SWITCH X IB X TIEPLEND			0.057	0.09
KEEP X CB X TIEPLEND – SWITCH X CB X TIEPLEND			0.478	0.93
KEEP X PRIORLEND – SWITCH X PRIORLEND	0.303	0.82		
KEEP X IB X PRIORLEND – SWITCH X IB X PRIORLEND			0.108	0.23
KEEP X CB X PRIORLEND – SWITCH X CB X PRIORLEND			0.608	0.97
KEEP X PRIORUND – SWITCH X PRIORUND	0.394	2.21 **		
KEEP X IB X PRIORUND – SWITCH X IB X PRIORUND			0.347	1.62
KEEP X CB X PRIORUND – SWITCH X CB X PRIORUND			0.485	1.44

*** indicates significantly different than zero at the 1% level (2-sided)
** indicates significantly different than zero at the 5% level (2-sided)
* indicates significantly different than zero at the 10% level (2-sided)

Figure 1

Nesting Structure

This figure presents the nesting structure for the nested logit model of keeping the same underwriter in a subsequent SEO. Each issuer has a first-level choice of re-issuing ("Repeat") or not re-issuing ("No Repeat"). If the issuer decides to re-issue, the issuer has a second level choice of keeping the underwriter of the current SEO ("Keep") or switching to a new underwriter ("Switch") in the subsequent offering.