Tying Knots:
Lending to Win Equity Underwriting Business

Steven Drucker & Manju Puri[ξ]

Graduate School of Business
Stanford University
Stanford, CA 94305-5015

December 2002

[ξ] Corresponding author, Stanford University and NBER. Email; puri_manju@gsb.stanford.edu. Tel: 650-723-3402.
Puri is grateful to the Sloan Foundation for partial funding of this research.

Tying Knots:
Lending to Win Equity Underwriting Business

This article examines the practice of "tying," which occurs when an underwriter lends to an issuer around the time of a public securities offering in order to secure underwriting business. We examine the following questions: (i) Does the issuing firm benefit from tying practices? (ii) If so, what is the source of these benefits? Why do underwriters tie lending to underwriting? (iii) How has tying affected the competitive structure of the market? We find firms benefit both from a lower gross spread on tied seasoned equity offerings, as well as from discounted loan yields. These results are robust to matching methodology developed by Heckman, Ichimura, and Todd (1997, 1998). We find that underwriters tie lending to underwriting because a tied loan increases the probability of receiving the current equity underwriting business and can also increase the likelihood of being selected to underwrite future equity issues for the tied issuer. The benefits to the firm are consistent with informational economies of scope from combining lending with underwriting. We find that investment banks engage in a substantial amount of tying, contrary to concerns that they are disadvantaged by tying practices. Investment banks and commercial banks are remarkably similar in that they tie lending with underwriting for similar deals and provide price discounts to tied issuers, but they offer price reductions through different channels.

1. Introduction

For many years, the investment banking industry was protected by the 1933 Glass-Steagall Act, which 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some of the most restrictive provisions, and in 1999, the Gramm-Leach-Bliley Financial Modernization Act effectively repealed the Glass-Steagall Act.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.

Commercial banks have made significant progress in equity underwriting. According to Thomson Financial, in 1996, commercial banks underwrote approximately 5% of the total dollar volume of seasoned equity issues, while in 2001, the proportion had risen to nearly 50%. Academicians such as Benston (1990) and Saunders and Walter (1994) reason that some of the gain in market share could be due to universal banks achieving economies of scope through information they can use for several purposes, joint delivery of services, and savings to consumers in terms of lower search and other transaction costs. The popular press has insinuated that commercial banks have gained market share through the practice of providing loans to an issuer at the time of a public securities issue in return for high fee underwriting business, which is commonly referred to as "tying." As an example of the power of tying, despite leading previous bond issues for Primedia Inc., Morgan Stanley was not selected to underwrite the May 2001 issue, while the commercial banks that provided a credit line to Primedia were selected as managers.[1]

Regulators, such as John D. Dingell, ranking member of the Committee on Energy and Commerce Democrats, have raised questions about the pricing of tied loans, claiming that commercial banks may be providing credit to borrowers at reduced rates to get compensated by high fee business.[2] It could be that commercial banks are using their lending prowess, the availability of deposit insurance, and easy access to capital to provide tied loans with discounted yields in order to gain lucrative underwriting business. Such undercutting of the market can help improve penetration in new markets and increase long-run market share and power. However,

[1] "Deals & Deal Makers: Banks' Lending Clout Stings Securities Firms," *The Wall Street Journal*, June 15, 2001, C1.

regulators are concerned that tying may have an "adverse impact on consumers and the financial system as a whole."[3] Such a claim could be substantiated if investment banks are unable to compete with commercial banks, or if lending to win underwriting business is an overly risky practice. However, while regulators and the press have focused on the potential negatives of tying lending and underwriting, the possible gains have been ignored.

Our paper investigates the tying of loans to seasoned equity offerings (SEOs). In particular, we examine the following questions: (i) Does the issuing firm benefit from tying practices? (ii) What are the benefits to the underwriter from tying? (iii) How has tying affected the competitive structure of the market? What are the mechanisms through which investment banks have responded or are they disadvantaged by tying practices? 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 gross spreads, loan pricing, and lending terms. We find that tying benefits the issuing firm. In particular, a tied issuer gains on two main dimensions – (i) a reduced gross spread of the SEO, and (ii) discounted yields of tied loans as compared with similar "matched" loans. To ensure that our pricing results are not driven by matching biases, 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.

What are the benefits to the underwriter from tying? To understand this question, we also examine the impact of tying on underwriter selection for current and future equity underwriting buisness. We determine that tying has a significant effect on the probability of securing current

[2] "Letter to FRB and OCC re: 'pay to play' practices," July 11, 2002.

equity underwriting business. Also, tying may serve as a gateway to future fees if tied issuers are more likely to go back to the market and keep the same underwriter. Our results show 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.

We also examine the effect of tying on the competitive structure of the market for underwriting securities by analyzing differences between commercial and investment bank deals. While the popular press generally associates tying practices with commercial banks, we find investment banks underwrote a substantial portion of tied deals. This suggests that investment banks have now developed the organizational infrastructure to tie lending and underwriting.[4] Further, we find that investment bank and commercial bank tied deals involve similar clients. However, while both commercial and investment banks tie lending with underwriting, they seem to compete on different components of the tied deals. Investment banks are more likely to provide benefits via a lower gross spread on the SEO while commercial banks are more likely to offer a discounted yield on the loan. This is consistent with each type of underwriter using its comparative strength to generate future business in their primary business. Investment banks discount gross spreads and receive more future underwriting business, while commercial banks discount loan yields, and the consequent lending relationship developed helps them 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 Financial Modernization Act (see e.g., Berger, et. al, 1999; Santomero and Eckles, 2000). Related to this there is some event-study evidence on the relaxation of various regulatory constraints on banks' activities (see e.g., Carow and Kane, 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

---

[3] ibid.

[4] For example, Morgan Stanley participated in a $6.5 billion bank loan for Lucent Technologies and was subsequently awarded the role of lead manager 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).

by expanding into lending activities has generally not received much attention. James (1987), Lummer and McConnell (1989); Best and Zhang (1993); 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.[5] 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 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.

2. Data and Sample Selection

We construct a unique database using eight different data sources and hand-collected data. 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." This captures implicit tying that is likely to be occurring at the time of the underwriting.[6] 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,

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

[6] Section 106 of the Bank Holding Company Act Amendments of 1970 prohibits a bank from explicitly tying and extending credit or varying the terms of credit on the condition that a customer purchase another product or service

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. Data on seasoned equity offerings comes from Thomson Financial's SDC *Platinum*. Using the "Global New Issues: United States" database, we download underwritten, seasoned, US Common Stock issues, excluding those with an SIC code of "6xxx." The sample consists of 2301 issues.

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. Ratings information in the quarter of the SEO is taken from Compustat. 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.

We classify each potential 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. Due to the many mergers and acquisitions in the financial sector, we use the mergers and acquisitions database from SDC New Issues database 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. The chosen lead manager was a commercial bank for 682 issues, and an investment bank underwrote the remaining 1619 issues.

We use Loan Pricing Corporation's (LPC) *DealScan* database to gather lending data. Each of the 2301 issuers is hand matched by issuer name to the *DealScan* database and we identify if the firm received a tied loan from their underwriter and in doing so, we identify if the SEO is a tied deal. There are 201 tied deals in the sample. There are 358 lending facilities

---

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.

associated with the 201 tied deals. 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.[7] 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.[8] 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 has an SIC code of "6xxx." As before, all bridge loans and loans to non-rated borrowers are excluded. This sample consists of 166 tied loans that can be matched to a sample of 4534 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. Of the 4534 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.

From SDC *Platinum*, we identify 1005 issuers that used a lead manager that had underwritten a prior equity offering. From *DealScan*, we identify 186 issuers with a prior lending relationship with the selected lead manager. The establishment of an underwriting or

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

credit relationship with a bank produces a durable transactor-specific asset, which is an asset that is required for the transaction but not marketable or transferable to transactions involving different parties (see e.g., Williamson (1979); James (1992)). The existence of prior relationships can create lock-in effects, which may influence the choice of underwriter. Furthermore, if there are economies of scope in lending and underwriting, then a prior lending relationship may result in a reduced gross spread or other pricing differences.

Booth and Smith (1986) find that the lead manager's reputation is important in determining underwriter choice because a more prestigious underwriter has a higher ability to certify an issue. Carter and Manaster (1990) show that an underwriter with a higher reputation tends to underwrite less risky initial public offerings. To control for reputation effects, we use the underwriter's market share to proxy for reputation. For each year *x*, we rank the underwriters by using the principal amount of the offerings from our sample of 2301 firms and computing the market share for each lead manager in year *x-1*.

We control for 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. By using a translation file that is provided by I/B/E/S, 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.[9] If the underwriter provided an earnings recommendation within one-year prior to the SEO date, then the underwriter provided "coverage." To control for 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" in year *x*, provided an earnings recommendation within one-year prior to the SEO date, and the SEO date of the firm is in year *x+1*.

---

[8] 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.

[9] The standard download from I/B/E/S provides a broker code that corresponds to a specific bank and an analyst code that corresponds to a specific analyst. The translation file allows us to decode the output.

To implement our models of underwriter selection in the current SEO, we substantially extend our data set. For each of the 2301 firms in our sample, we create a choice set that consists of the twenty highest ranked underwriters at the time of the SEO and a generic, unranked underwriter. Therefore, our data set consists of over 48,000 firm-underwriter pairs. For each firm-underwriter pair, we determine if the firm had received a loan around the time of the SEO, if the firm had a prior lending or underwriting relationship with the underwriter, if the potential underwriter provided analyst coverage, and if an all-star analyst provided coverage.

For our models of underwriter selection in a subsequent SEO, we classified each of the 2301 issues as a "repeater" if the issuer had another SEO between the issue date and March 31, 2002 or as a "non-repeater" otherwise. This yields 536 repeaters and 1765 non-repeaters. A repeater is classified as a "switcher" if the lead manager in the current SEO differs from the lead manager in the subsequent SEO. Otherwise, the repeater is classified as a "keeper." Of the 536 repeaters, 287 are switchers and 249 are keepers. For "switchers", we calculate differences between the subsequent lead manger and original lead manager's rank, coverage, and all-star coverage in the year prior to the subsequent equity offering.

Appendix A to this article provides a detailed description of the variables that are used in this paper.

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.[10] As commercial banks have gained market share in equity underwriting, there has been shift from issuers' 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 shows that tied issuers have debt-to-equity ratios that are, on average, three to five times higher than non-tied issuers, and are slightly older. Furthermore, tied lenders have

[10] Interestingly, there was a low level of tying in 1994, despite the fact that many issuers took out loans at about the same time as the underwriting. 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 SEO, but only 1.4% of SEO issuers received a tied loan from the underwriter of the SEO.

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. Only 17% of investment bank tied deals and 13% of commercial bank tied deals involve investment grade rated issuers.

Commercial banks are lead managers 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. In fact, commercial banks and investment banks are providing tied loans to similar clients, with the only noticeable difference being that investment bank tied deals have slightly larger SEOs than commercial bank tied deals.

3.1 Gross Spread

If there are informational economies of scope present in tied deals, then we may find a reduction in the gross spread of the SEO. The univariate descriptive statistics in Table 2, Panel A indicate that the average gross spread of tied SEOs is 78 basis points lower than the mean gross spread of non-tied SEOs, a difference that is significant at the 1% level.

3.1.1. U-shaped Gross Spreads

We wish to see if this result withstands a multivariate specification. Following Altinkilic and Hansen (2000), we estimate a model of the gross 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 gross spread, we use a variation of Altinkilic and Hansen's expanded spread linear model in which the gross spread is the sum of a fixed cost and a variable cost component. Based on Altinkilic and Hansen's theoretical model, the fixed cost component requires that the spread model include the inverse of the gross proceeds. 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 gross proceeds by the firm's equity market capitalization, which holds firm size fixed as proceeds expand and allows 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 gross spread. The model captures any variation in underwriter costs that are due to the volume of issuance in the seasoned equity market.

We include variables to capture tied lending and prior lending relationships. Since it is possible that the effect of tied lending on gross spread may be different if the underwriter and issuer have a prior lending relationship, we control for interactions between prior lending and tied lending.

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. The coefficient of the inverse of the proceeds coefficient implies a fixed cost component of about $170,000. 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 gross 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 gross spread. These results are consistent with the economies of scope hypothesis. A prior underwriting relationship provides a 22 basis point reduction in the gross spread.

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. For commercial bank underwritten issues, the coefficients for tied deals are negative but insignificant.

Both investment banks and commercial banks provide significant discounts in the gross spread to firms that do not receive a tied loan but with which a prior lending relationship is in place, indicating potential informational economies of scope. The reduction in gross spread associated with commercial bank lending is in line with Roten and Mullineaux (2002) who find that commercial bank lending is negatively related to gross spread in the debt underwriting market. However, they did not examine the effects of investment bank prior lending, which we find also produces a significant reduction in gross spread.

Overall, we find that tied deals have lower gross 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. As in the debt underwriting market, a prior lending relationship with a commercial bank translates into a gross spread discount. This result is also present for investment banks.

3.2. The Pricing of Tied Loans

We now investigate if tied loans have lower yields than similar non-tied loans, a result that would be consistent with informational economies of scope. Regulators are concerned that commercial banks may be able to provide cheaper loans than investment banks by using their extensive expertise in lending, the benefit of deposit insurance, and more capital to provide to borrowers. In the last section, we found evidence of tied SEOs having lower gross spreads, with investment bank underwriters providing a larger discount. Given this finding, any differences between investment bank and commercial bank pricing of tied loans will provide insight into how these two underwriter types compete for tied deals.

3.2.1. Hand Matching

First, we attempt to 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. As explained in

Section 2, we generate a hand-matched sample of tied loans and non-tied loans. For a sample of 107 tied loans, we are able to create a sample of non-tied loans that were originated within a twelve-month window around the start of the tied loan with firms that belong to the same industry and have the same credit rating. The length of the loans, however, varies across loans in the control group and may be different than the length of the tied loan.

There are two features of the lending sample that are worth mentioning. First, we match on the credit rating of the borrower at the time of the loan origination date. However, 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. Once the loan is originated, the market must reassess the credit risk of the firm. 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. Second, *Dealscan* does not provide the all-in spread drawn for lending facilities that are classified as notes. Therefore, we are unable to analyze this class of tied lending facility, so our analysis focuses on term loans, 364-day facilities, and revolving lines of credit.

We hand match to each tied loan the non-tied loan with the closest term length and record the difference between tied all-in spread drawn and non-tied all-in spread drawn.[11] We examine the mean difference between tied and non-tied yields using three estimators. 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 yields were more than 20 basis points lower than the matched non-tied loan yields, a significant difference at the 5% level.

While the estimates indicate that tied loan yields are discounted, 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 differences, such as the size of the lending facility and the type of lending facility. Second, by using only non-tied loans that meet these four criteria, we restrict the sample of potential non-tied loan matches. As a result, we do not generate

[11] In the case of a tie amongst non-tied loans, we take the average all-in spread drawn of the tied non-tied loans.

matches for some of the tied loans in our sample. Based on these comments, it may seem like we cannot simultaneously enlarge the number of matching dimensions while increasing the number of tied loans for which we can find a match. However, econometric matching techniques that are developed by Heckman, Ichimura, and Todd (1997, 1998) allow us to solve this dilemma. Previous papers in economics and finance use the Heckman et. al matching methodology.[12]

3.2.2. Econometric Matching

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 yields and 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 yields.

The formal econometric methods of matching are developed in Rosenbaum and Rubin (1983), Heckman and Robb (1986), and Heckman, Ichimura and Todd (1998). 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

[12] For example, 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

under study has both a yield Y_{1i} that would result if it had received treatment and another yield 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:

$$E(Y_1 - Y_0 \mid D=1, X) \qquad (1)$$

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

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

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

$$(Y_0, Y_1) \perp D \mid X \qquad (2)$$

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

$$0 < P(X) < 1 \qquad (3)$$

(which are referred to as the strong ignorability conditions) are satisfied, then $(Y_0, Y_1) \perp D \mid P(X)$, where $P(X) = Pr(D = 1 \mid X)$. While it is often difficult to match on high dimension X, this result allows us to match based on the one-dimensional $P(X)$ alone. $P(X)$, 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

---

methods to study the effect of education on wages. Bharath (2002) uses these methods to evaluate the agency costs of debt.

$$E(Y_0 \mid D=1, P(X)) = E(Y_0 \mid D=0, P(X)) \qquad (4)$$

is all that is required.

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.

To employ propensity score matching methods, we use the econometric matching data sample of tied and non-tied loans that was discussed in Section 2. This methodology allows us to match more loans, and the sample consists of 166 tied loans and a large number of non-tied loans, from which we can potentially find matches. There are 4534 such non-tied loans to rated, non-financial borrowers, which were originated between January 1, 1996 and May 31, 2001. As in the hand-matched sample, the econometric data sample largely consists of term loans, 364-day facilities, and revolving lines of credit because *Dealscan* does not provide an all-in spread drawn for notes. The propensity score *P(X)* for each loan is calculated using the probit model:

$$\begin{aligned} TIED \;=\; & \beta_0 + \beta_1 * RATING \;+ \beta_2 * FACSIZE \;+ \beta_3 * LENGTH \\ & + \beta_{type} * TYPE \;+ \beta_{year} * YEAR \;+ \beta_{ind} * INDUSTRY \;+ \varepsilon \end{aligned} \qquad (5)$$

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.

We use four propensity score matching methods: (i) nearest neighbor matching, (ii) kernel based matching, (iii) local linear least squares matching, and (iv) regression adjusted local linear matching.[13] Let Y_{1i} be the all-in spread drawn of a tied loan, Y_{0j} be the all-in spread drawn of a non-tied loan, and let $\overline{Y}^{z}_{0j}$ represent the (weighted) average of all-in spread drawns of the non-tied loans using estimator *z*. We match the yields of non-tied loans to the yields of tied loans using the various estimators. For each *i*, we compute $Y_{1i} - \overline{Y}^{z}_{0j}$.

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 yields of these *n* non-tied loans. For each Y_{1i}, we match

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

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 yields 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 $P(X)$ 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. For each Y_{1i}, we match a corresponding $\overline{Y}^{K}_{0j}$ where

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

We use two different kernels to compute $\overline{Y}^{K}_{0j}$. 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 $h = 0.01$.

As in kernel matching, local linear least squares matching uses weighted averages of the

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

yields of multiple non-tied loans. However, this method uses different weights to allow for faster convergence at boundary points. For each Y_{1i}, we match a corresponding $\overline{Y}_{0j}^{LS}$ where

$$W_{0j}^{LS} = \frac{K_{ij}\sum_{z\in J} K_{iz}\left[P(X_{0z}) - P(X_{1i})\right]^2 - \left\{K_{ij}\left[P(X_{0j}) - P(X_{1i})\right]\right\}\sum_{z\in J} K_{iz}\left[P(X_{0z}) - P(X_{1i})\right]}{\sum_{j\in J} K_{ij}\sum_{z\in J} K_{iz}\left[P(X_{0z}) - P(X_{1i})\right]^2 - \left\{\sum_{z\in J} K_{iz}\left[P(X_{0z}) - P(X_{1i})\right]\right\}^2}$$

and

$$\overline{Y}_{0j}^{LS} = \sum_j W_{0j}^{LS}\, Y_{0j}\ .$$

The regression adjusted local linear matching combines local linear matching with a regression adjustment on X by using the following procedure. Assume that non-tied loan yields are additively separable in the observables and unobservables: $Y_0 = X\beta_0 + U_0$. Using partial linear regression methods, estimate the components of:

$$E(Y_0 \mid D = 0, X) = X\beta_0 + E(U_0 \mid D = 0, X)\,.$$

Let $H_{1i} = Y_{1i} - X_i\hat{\beta}_0$ and $H_{0j} = Y_{0j} - X_j\hat{\beta}_0$. For each H_{1i}, we match

$$\overline{H}_{0j}^{RA} = \sum_j W_{0j}^{LS} H_{0j}\ .$$

For each tied loan i, we compute $H_{1i} - \overline{H}_{0j}^{RA}$.

We extend the methodology to capture differences between investment bank tied loans and commercial bank tied loans. We compare investment bank tied loans and commercial bank tied loans to other non-tied loans to find differences in the yields.

3.2.4. Results

Each of the estimators provides a sample of yield differentials, with each yield 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 estimated sample and display the results in Table 4. All estimators indicate the tied loans have significantly lower yields, with the average discount ranging between 9.5 and 14.1 basis points.

Also, we attempt to determine the effect of prior lending relationships on the yield differential between tied and non-tied loans. For each estimator, we regress the sample of estimated yield 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.

We compute sample averages for the commercial bank matched pairs and the investment bank matched pairs and report the mean difference in the all-in spread drawn between the two groups in Table 4. Yields on investment bank tied loans are insignificantly different from those of non-tied loans. In all six samples, commercial bank tied loans are discounted more than investment bank tied loans. On average, commercial banks reduce yields by between 19.2 and 26.3 basis points more than investment banks, and the difference is significant in all six samples. Tying by commercial banks, as opposed to investment banks, largely drives the difference between yields 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 gross spreads on the SEO and receive lower loan yields. Both results are consistent with informational economies of scope. However, we find that the form of the savings depends on the type of underwriter that is involved in the transaction, with investment banks providing lower gross spreads on the SEO and commercial banks providing lower loan yields. The evidence suggests that each type of underwriter uses its comparative strength to compete with the other type of underwriter.

3.2.5. Robustness – Simultaneous Loans

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.[14] It is important to determine if tied loan yields are discounted relative to simultaneous loan yields because both types of loans are provided to firms that are raising funds in the seasoned equity market.

[14] 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.

In Section 3.2.4, we show that commercial banks are discounting tied loans while investment banks are not discounting, so we wish to compare commercial bank tied loans with commercial bank simultaneous loans. We find 145 simultaneous non-tied loans. One-hundred eleven of these loans are commercial bank simultaneous loans, which are simultaneous loans where only commercial banks lead the transaction. There are 79 commercial bank tied loans in our sample.

To compare tied loans and simultaneous loans, we extend the methodology from Section 3.2.3. We compare commercial bank tied loans to other non-tied loans as well as commercial bank simultaneous loans to other non-tied loans. In both cases we compute propensity scores using equation *(5)* and find matches for each commercial bank simultaneous loan and tied loan using the estimators that are described in Section 3.2.3.[15]

We compute sample averages for the tied loan matched pairs and the simultaneous loan matched pairs and report the mean difference in the all-in spread drawn between the two groups in Table 4. The results of all six estimations indicate that commercial bank tied loans are discounted more than commercial bank simultaneous loans. On average, tied loan yields are less than simultaneous loan yields by 16.6 to 31.7 basis points, and the difference is significant at the 10% level in two samples and at the 5% level in two samples. Relative to simultaneous loans, the discount that is provided by commercial banks to tied issuers remains significant.

3.3. Underwriter Selection

In Sections 3.1. and 3.2., we found that the firm receives benefits in the form of lower gross spreads or lower loan yields. For the underwriter, a loan creates credit related risks and generates low fees. To undertake the credit risks and offer benefits to the firm, the obvious implication is that the underwriter believes that the tied loan increases the probability of receiving the current equity underwriting business. We examine the influence of tied lending on the probability that an underwriter is chosen. We use McFadden's (1974) choice model to capture the effect.

3.3.1. McFadden's Choice Model

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. In our models, we assume that the relevant issuer specific characteristics ($\boldsymbol{w}_i$) are the logarithm of the SEO gross proceeds, 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 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 level and quality of equity analyst coverage will be positively related to underwriter selection. In model A, we do not consider differences between investment banks and commercial banks, while in model B we relax this restriction.

[15] Of course, equation (5) must be modified slightly. 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.

3.3.2. Results

In Table 5, we present the results of the underwriter selection models. In both models, most of the control variables have the expected signs and are highly significant. The coefficients of the tied lending variables are positive and statistically significant at the 1% level. As expected, a tied loan increases the probability of an issuer choosing that particular underwriter, and the effect is present for both commercial and investment bank underwriters. Therefore, one source of the benefits that are provided to tied issuers is that a tied loan increases the probability that an underwriter will win the current equity underwriting business.

3.4. Probability of Keeping Future Business

A tied deal is a source of both a lending and underwriting relationship and may create a lock-in effect, as described in Williamson (1979). As a result, a potential benefit for the underwriter of a tied deal is that it could increase the probability of generating future business from the issuer. In this section, we determine if those firms that receive a tied loan from the lead manager go back to the market more frequently and do not switch lead managers 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. 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 lead manager, a significant difference at the 10% level. However, there is a disparity between investment bank and commercial bank underwriters. While tied issues significantly increase the probability of retaining future business for investment banks, the effect is not present for commercial banks.

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 lead manager.

Following Maddala (1983), let *k* index the first-level alternative and *l* index the second-level alternative.[16] 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 $U_{kl} = \boldsymbol{\alpha' Y_{kl}} + \boldsymbol{\beta' Z_k} + \varepsilon_{kl}$, and then the probability of choosing *l*, conditional on first choosing *k* is

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

Define the inclusive values for category *(k)* as

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

which leaves us with

$$\Pr_k = \frac{\exp(\boldsymbol{\beta}' \boldsymbol{Z}_k + \tau_k IV_k)}{\sum_{k=1}^{K} \exp(\boldsymbol{\beta}' \boldsymbol{Z}_k + \tau_k IV_k)}.$$

In our models, we assume that the variables that only affect the decision to re-issue ($\boldsymbol{Z_k}$) are the logarithm of the SEO gross proceeds, 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 ($\boldsymbol{Y_{kl}}$), 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, we expect 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. 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 tied lending by an investment bank to increase the probability of keeping future business, but that commercial bank tied lending will be insignificant.

3.4.2. Results

In Table 7, we present the results of the nested logit models. The base category is "Not Repeat," 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 tied lending 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 tied lending also increases the probability of keeping an underwriter instead of switching to a new underwriter, although this result is insignificant.

In model B, consistent with the univariate results, a 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 suggest 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. However, it is important to recognize that only 31 issuers who are tied to a commercial bank have a subsequent issue and merely 14 of these issuers keep the same lead manager, so we are using a small sample.

Combined with our previous findings, the results suggest that both commercial banks and investment banks tie lending with underwriting, and tying benefits the issuer. However, the type of price discount that is given to the firm varies by underwriter type, with investment banks

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

providing lower gross spreads on the SEO and commercial banks discounting the yields on the loan. This is consistent with each 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 gross spreads and that tying increases the probability of retaining underwriting business from the firm in the future. Commercial banks, on the other hand, discount loan yields to help 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. Banks who tie lending and underwriting can achieve economies of scope through the joint delivery of services and may pass benefits along to firms through lower transaction costs or superior lending terms. We find evidence of scope economies, as gross spreads are lower on tied deals, and further, we find that tied loans' yields are also at a discount. These results are robust to matching methodology developed by Heckman, Ichimura, and Todd (1997, 1998).

Underwriters take on credit risks from the tied loan, but are able to offer benefits to the issuer because the tied loan increases the probability of receiving the current equity underwriting business. Furthermore, 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 if tying has an adverse impact 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

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., and Kane, Ed, 2001, Event-study evidence of the value of relaxing longstanding regulatory restraints of banks, 1970-2000, NBER working paper.

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. and 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.

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., 2002. Integration of lending and underwriting: implications of scope economies, *Journal of Finance*, forthcoming.

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.

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.

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., and I. Walter, 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.

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

Source of Data: *SDC Platinum*

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

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

GSPREAD: The gross spread, which is the difference between the SEO principal amount and the proceeds to the issuer, expressed as a percentage of the principal amount.

LNSIZE: The logarithm of the principal amount of the offering

RANK: For each year *x*, we rank the underwriters by using the principal amount of the offerings from our sample of 2301 firms and computing the market share for each lead manager in year *x-1*. 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

CNGRANK: For switchers, the difference between the subsequent lead manager's ranking in the year before the subsequent issue date and the original lead manager's ranking in the year before the subsequent issue date. For keepers and non-repeaters, the variable is zero.

SEOSIZE: The principal amount of the offering, in millions of dollars

SICx: Dummy variables that equal one if the issuer is in the corresponding one-digit SIC group

CHOSEN: An indicator variable in the McFadden model that is one for each issuer's choice of underwriter

REISSUE: An indicator variable in the nested logit model that is one for each issuer's choice between "repeat" or "no-repeat"

KSCHOICE: An indicator variable in the nested logit model that is one for each issuer's choice between "NO REPEAT", "{REPEAT, KEEP}", or "{REPEAT, SWITCH}"

Source of Data: *LPC DealScan*

DRAWN: The all-in spread drawn of the loan, measured as the rate that the borrower pays to the lender each year for each dollar drawn off the credit line, quoted in basis points over LIBOR.

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

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

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.

LOANSIZE: The notional value of the combined facilities in a lending agreement, expressed in millions of dollars.

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.

Source of Data: *SDC Platinum* and *LPC DealScan*

TIELOAN: 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 had never provided a loan to the issuer in the past. Words in parentheses apply only to the McFadden choice model.

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. Words in parentheses apply only to the McFadden choice model.

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. Words in parentheses apply only to the McFadden choice model.

PRIORLEAD: A dummy variable that equals one if the (potential) underwriter had been the lead manager on any prior equity offering by the issuer. Words in parentheses apply only to the McFadden choice model.

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. This variable is used to compute propensity score's that are necessary to do econometric matching.

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. This variable is used to compute propensity score's that are necessary to do econometric matching.

Source of Data: *Compustat*

DE-LTDEBT: The long-term debt to equity ratio in the quarter of the SEO

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

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

Source of Data: *Mergent's / Moody's Manuals* and *Standard & Poor's Corporation Records*

AGE: The firm's age, measured as the difference between the SEO date and the incorporation date, expressed in years.

Source of Data*: CRSP*

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

MKTCAP: The market value of equity at the time of the offering, computed using the price and shares outstanding in the most recent recorded observation prior to the equity offering

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

Source of Data: *I/B/E/S* and *Institutional Investor*

COVERAGE: A dummy variable that is one if the underwriter provided an earnings per share estimate for the firm during the year prior to the SEO

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.

ALLSTAR: A dummy variable that is one if COVERAGE is one and the analyst was ranked as an all-star by Institutional Investor magazine in the year prior to the SEO.

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.

Choice Model Dummy Variables

RANKx: Dummy variables for the top-20 underwriters, which equal one for the corresponding RANK. For example, RANK1 is a dummy variable indicating the top-ranked underwriter

KEEP: A dummy variable that is one for the choice of "keep" in the nested logit models

SWITCH: A dummy variable that is one for the choice of "switch" in the nested logit models

REPEAT: A dummy variable that is one if SWITCH or KEEP is one

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 lead manager provided 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 lead manager provided a loan to the issuer between six months prior to the SEO and six months after the SEO. The Lead Manager is an IB (CB) if the parent or holding company of the lead manager is an investment bank (commercial bank) at the time of the SEO. The variables are defined as follows: GSPREAD is the gross spread, which is the difference between the SEO principal amount and the proceeds to the issuer, expressed as a percentage of the principal amount. 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. LOANSIZE is the notional value of the combined facilities in a lending agreement, expressed in millions of dollars. FACSIZE is the notional value of the loan facility between the lender and the borrower, expressed in millions of dollars. LENGTH is 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. PRIORLEND is one if a loan between the lead manager and the issuer was originated at any time before six months prior to the SEO. PRIORLEAD is one if the lead manager had been the lead manager on any prior equity offering by the issuer. COVERAGE is one if the lead manager 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 in 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
GSPREAD	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
PRIORLEAD	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	
GSPREAD	4.25	4.43	0.98		0.2792	
LNSIZE	5.28	4.92	2.24	**	0.0110	**
DELTDEBT	2.83	2.31	0.39		0.4189	
AGE	20.50	23.35	0.79		0.1148	
LOANSIZE	589.14	959.55	-1.88	***	0.9453	
FACSIZE	82.99	69.00	1.08		0.1297	
LENGTH	92.76	71.18	3.91	***	0.0000	***

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
PRIORLEAD	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
Gross Spread Regressions

In this table, we provide estimates of an ordinary least squares regression of the following model:

$$GSPREAD = \beta_0 + \beta_1 * TIELOAN + \beta_2 * TIEPLEND + \beta_3 * PRIORLEND + \beta_4 * PRIORLEAD + \beta_5 * IB$$
$$+ \beta_6 * IB\ X\ TIELOAN + \beta_7 * CB\ X\ TIELOAN + \beta_8 * IB\ X\ TIEPLEND + \beta_9 * CB\ X\ TIEPLEND$$
$$+ \beta_{10} * IB\ X\ PRIORLEND + \beta_{11} * CB\ X\ PRIORLEND + \beta_{12} * IB\ X\ PRIORLEAD + \beta_{13} * CB\ X\ PRIORLEAD$$
$$+ \beta_{14} * (1 / SEOSIZE) + \beta_{15} * (SEOSIZE / MKTCAP) + \beta_{16} * VOL + \beta_{17} * MKTACT + \sum_x \delta_x * SIC_x + \varepsilon$$

The dependent variable is GSPREAD, which is the difference between the SEO principal amount and the proceeds to the issuer, 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 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 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. PRIORLEAD is one if the lead manager had been the lead manager on any prior equity offering by the issuer. IB is one if the lead manager of the SEO is an investment bank. CB is one if the lead manager of the SEO is a commercial bank. SEOSIZE is the principal amount of the equity offering, measured in millions of dollars. MKTCAP is 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 are not reported.

In model A, we impose that $\beta_i = 0\ for\ i = 5, 6, \ldots, 13$. In model B, $\beta_i = 0\ for\ i = 1, 2, 3, and\ 4$.

	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 **		
PRIORLEAD	-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 PRIORLEAD			-0.248	-4.39 ***
CB X PRIORLEAD			-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 all-in spread drawn of (a) Tied loans and non-tied loans, (b) CB tied loans and IB tied loans, and (c) CB tied loans and CB simultaneous loans, using various estimators. The all-in spread drawn is the rate that the borrower pays to the lender each year for each dollar drawn off the credit line, 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 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:

$$TIED = \beta_0 + \beta_1 * RATING + \beta_2 * FACSIZE + \beta_3 * LENGTH$$
$$+\beta_{type} * TYPE + \beta_{year} * YEAR + \beta_{ind} * INDUSTRY + \varepsilon$$

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. TREATMENT is a dummy variable, which varies by application. We remove from the sample all facilities in which the all-in spread drawn or LENGTH is unavailable, the type of facility is a bridge loan, or the borrower is not rated. 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 yields. 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. LOCAL LINEAR uses local linear weights instead of kernel weights because local linear estimators converge at a faster rate at boundary points. REGRESS ADJUSTED combines local linear matching on propensity scores and a regression adjustment on the variables used to compute the propensity score. We specify that $h = 0.01$.

To compute yield differences between tied and non-tied loans, we use the estimators to match tied loans to non-tied loans and compute the yield difference. The sample averages and T-ratios are presented in columns 2 and 3. To compute yield differences between IB and CB Tied loans, we remove IB tied loans from the sample, compute propensity scores, find non-tied loan matches for CB tied loans, and compute yield differences. Then, we replace the IB tied loans with CB tied loans, compute propensity scores, find non-tied loan matches for IB tied loans, and compute yield differences. Column 4 presents the mean difference between CB-sample average and IB-sample average, and the T-ratio is displayed in column 5. To compute yield 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 differences. For CB simultaneous loans, we remove all tied loans and IB simultaneous loans from the sample. We compute propensity scores 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 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.

Estimator	Mean Yield Difference between Tied and Non-Tied	T-ratio	Mean Yield Difference between CB Tied and IB Tied	T-ratio	Mean Yield Difference between CB Tied and CB Simultaneous	T-ratio
NEAR NEIGHBOR (n=10)	-14.084	-2.01 **	-23.556	-1.82 *	-22.936	-1.50
NEAR NEIGHBOR (n=50)	-14.087	-2.36 **	-24.487	-2.07 **	-26.809	-1.85 *
GAUSSIAN	-9.463	-1.64 *	-19.235	-1.67 *	-16.671	-1.15
EPANECHNIKOV	-13.819	-2.36 **	-22.491	-1.94 *	-24.908	-1.74 *
LOCAL LINEAR	-13.188	-2.20 **	-26.304	-2.25 **	-31.717	-2.21 **
REGRESS ADJUSTED	-12.254	-2.11 **	-24.918	-2.11 **	-29.139	-2.03 **

*** 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
Results of McFadden 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, PRIORLEAD, 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 PRIORLEAD, CB X PRIORLEAD, IB, COVERAGE, ALLSTAR, RANK1, . . ., RANK20}. The Dependent Variable is CHOSEN, which is a dummy variable that is one for a given firm's choice of underwriter. 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. PRIORLEAD is one if a potential lead manager had been the lead manager on any prior equity offering by the issuer. IB is one if the potential lead manager of the SEO is an investment bank. CB is one if the potential lead manager of the SEO is a commercial bank. COVERAGE is one if the potential lead manager 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 in 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	2.035	10.96 ***		
TIEPLEND	1.426	6.48 ***		
PRIORLEND	0.584	3.46 ***		
PRIORLEAD	2.761	35.92 ***		
IB X TIELOAN			2.141	7.98 ***
CB X TIELOAN			1.538	5.96 ***
IB X TIEPLEND			2.099	5.30 ***
CB X TIEPLEND			1.200	4.81 ***
IB X PRIORLEND			1.155	4.81 ***
CB X PRIORLEND			0.122	0.51
IB X PRIORLEAD			3.000	31.89 ***
CB X PRIORLEAD			2.200	15.61 ***
IB			-0.181	-1.95 *
COVERAGE	1.579	19.63 ***	1.609	19.94 ***
ALLSTAR	0.576	4.85 ***	0.544	4.55 ***
Psuedo R-squared	0.4046		0.4058	
Log Likelihood	3465.97		3458.83	

*** 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 6

Univariate Analysis of Keeping the Same Lead Manager 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 lead manager, based on if the initial SEO was a tied deal. A tied deal is any SEO in which the lead manager provided a loan to the issuer between six months prior to the SEO and six months after the SEO. The Lead Manager is an IB (CB) if the parent or holding company of the lead manager 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 lead manager was an investment bank. Panel C examines those SEOs in which the lead manager 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: Lead Manager 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: Lead Manager 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 Lead Manager in a Subsequent SEO

In this table, we present results of two nested logit models of the probability of keeping or switching lead managers 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 $\boldsymbol{Y}_{\mathbf{kl}}$ and $\boldsymbol{Z}_{\mathbf{k}}$ be vectors of explanatory variables specific to the categories (*k*, *l*) and (k), respectively. The utility of choosing alternative *(k,l)* is

$$U_{kl} = \boldsymbol{\alpha}' \boldsymbol{Y}_{\boldsymbol{kl}} + \boldsymbol{\beta}' \boldsymbol{Z}_{\boldsymbol{k}} + \varepsilon_{kl}$$

In both models, $\boldsymbol{Z}_{\boldsymbol{k}}$ = {LNSIZE, AGE, DE-LTDEBT, SICx}. In model A, we do not consider differences between investment banks and commercial banks by specifying that $\boldsymbol{Y}_{\boldsymbol{kl}}$ = {TIELOAN, TIEPLEND, PRIORLEND, PRIORLEAD, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. In model B, we allow for differences between investment banks and commercial banks by setting $\boldsymbol{Y}_{\boldsymbol{kl}}$ = {IB X TIELOAN, CB X TIELOAN, IB X TIEPLEND, CB X TIEPLEND, IB X PRIORLEND, CB X PRIORLEND, IB X PRIORLEAD, CB X PRIORLEAD, IB, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. To generate estimates of $\boldsymbol{\alpha}$ and of IV_k, we use the dependent variable KSCHOICE, which is a dummy variable that is one for a given firm's choice of *(k,l)*. To estimate $\boldsymbol{\beta}$, we use the dependent variable REISSUE, which is a dummy variable that is one for the issuer's choice of *(k)*. The variables in $\boldsymbol{Z}_{\boldsymbol{k}}$ 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 $\boldsymbol{Y}_{\boldsymbol{kl}}$ 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 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. PRIORLEAD is one if the lead manager had been the lead manager on any equity offering by the issuer prior to the original SEO. IB is one if the lead manager of the original SEO is an investment bank. CB is one if the lead manager of the original SEO is a commercial bank. CNGCOV is the difference between the coverage provided by the subsequent lead manager and the original lead manager in the year prior to the subsequent SEO. CNGSTAR is the difference between the all-star coverage provided by the subsequent lead manager and the original lead manager in the year prior to the subsequent SEO. CNGRANK is the difference between the subsequent lead manager's ranking in the year before the subsequent issue date and the original lead manager's ranking in the year before the subsequent issue date. KEEP and SWITCH are choice-specific dummy variables. TIELOAN, PRIORLEAD, 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 *

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 PRIORLEAD	0.282	2.77 ***		
KEEP X IB X PRIORLEAD			0.159	1.31
KEEP X CB X PRIORLEAD			0.557	2.91 ***
SWITCH X PRIORLEAD	-0.112	-1.08		
SWITCH X IB X PRIORLEAD			-0.188	-1.53
SWITCH X CB X PRIORLEAD			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 PRIORLEAD – SWITCH X PRIORLEAD	0.394	2.21 **		
KEEP X IB X PRIORLEAD – SWITCH X IB X PRIORLEAD			0.347	1.62
KEEP X CB X PRIORLEAD – SWITCH X CB X PRIORLEAD			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 lead manager 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.