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ABSTRACT

This article examines the practice of "tying," which occurs when an underwriter lends to an issuer around the time of a public securities offering. We examine whether there are efficiencies from tying lending and underwriting which lead to benefits for issuers and underwriters. We find evidence consistent with tying occurring for issues when there are informational economies of scope from combining lending and underwriting. Firms benefit from tying through lower financing costs, as tied issuers receive lower underwriter fees on seasoned equity offerings and discounted loan yield spreads. These financing costs are significantly reduced for non-investment grade issuers, where informational economies of scope from combining lending with underwriting are likely to be large. These results are robust to matching methodology developed by Heckman, Ichimura, and Todd (1997, 1998). For underwriters, tying helps build relationships that augment an underwriter's expected revenues by increasing the probability of receiving both current and future business. Both commercial banks and investment banks tie lending and underwriting and offer price discounts, albeit in different ways, with commercial banks discounting loan yield spreads and investment banks offering reduced underwriter spreads.

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1. Introduction

For many years, the 1933 Glass-Steagall Act prevented commercial banks from underwriting corporate bonds and equities. Due to the recent relaxation and eventual repeal of the Act, commercial banks acquired investment banks, or developed investment-banking capabilities internally, to create universal banks that can offer an array of financial services.

The entry of commercial banks into underwriting markets has increased the potential for financial institutions to tie products, such as packaging loans with underwriting services. In fact, tying has increased substantially over time -- in 1994, only 1% of seasoned equity issuers received a loan from their underwriter at around the time of issuance, but by 2001, over 20% of all deals were tied. The tying of lending and underwriting raises a host of interesting questions. First, why are deals tied? Are there efficiencies resulting from the tying of lending and underwriting? Tying might allow for potential efficiency gains due to informational economies of scope that can result from the bank jointly delivering services and using the same client-specific information for multiple purposes (see e.g. Benston, 1990; Saunders and Walter, 1994). Therefore, tying might be useful when there are large potential economies of scope from combining lending and underwriting. This would suggest that certain kinds of deals are tied, but not others. Second, who benefits from tying? Lower costs could arise due to informational economies of scope, and issuers can benefit if the bank passes along these savings. For the underwriter, tying might help build relationships that improve the probability of securing current and future business from the firm. Third, do the benefits from tying vary by the type of underwriter involved in the transaction? It is possible that commercial banks are able to generate larger economies of scope than investment banks due to their well-established lending businesses. Therefore, there may exist differences in tied deals that are underwritten by investment banks as opposed to commercial banks.

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

We find that there is a distinct profile of issues that are tied. The majority of tied deals involve clients that are highly leveraged and are non-investment grade rated. One explanation for this is that for lower rated and highly leveraged firms, there are larger potential efficiency gains that arise due to informational economies of scope from combining lending and underwriting. Therefore, tying lending and underwriting for these issuers could produce substantial benefits. To study if issuers actually benefit from tying, we examine the impact of tying on issuers' financing costs. Our results suggest that tying lowers issuers' financing costs through two main dimensions – (i) a reduced underwriter fee for the equity offering, and (ii) discounted yield spreads of tied loans as compared with "matched" non-tied loans. Interestingly, we find that the cost reductions are more pronounced amongst issuers that are non-investment grade rated, where the expected informational economies of scope are relatively large.

To ensure that matching biases are not driving the yield spread discount, we use the econometric techniques developed by Heckman, Ichimura and Todd (1997, 1998). These econometric methods effectively take into account the fact that the characteristics of tied loans may differ significantly from non-tied loans and ensure that such observed characteristics are not driving the results. Using a variety of matching models, we confirm that tied loans are significantly cheaper than comparable loans.

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

We also examine if the benefits from tying vary by the type of underwriter involved in the transaction. Interestingly, while commercial banks are well positioned to tie lending and underwriting due to their existing lending businesses, we discover that investment banks underwrote a significant portion of tied deals. This suggests that investment banks have now developed the organizational infrastructure to tie lending and underwriting and is consistent with there being potential gains from a single entity offering both lending and underwriting services.[1] Our results indicate that commercial banks and investment banks both compete for tied deals. However they seem to compete through different components of the tied deals -- commercial banks are more likely to offer discounted yield spreads on tied loans while investment banks are more likely to discount the underwriter spread for the SEO. This is consistent with each type of underwriter competing more aggressively in its area of expertise and in the area where it is more likely to generate future business. Investment banks discount underwriter spreads and receive more future underwriting business. Commercial banks discount loan yield spreads, which is consistent with establishing a lending relationship that helps generate other banking business.

This paper adds to the growing literature on how underwriters and issuers associate with each other. An important question is what determines the pairing of firms and underwriters for current as well as for future deals. Studies suggest that underwriter reputation is an important determinant of the choice of underwriter (Booth and Smith, 1986; Carter and Manaster, 1990), and high quality issuers are more likely to associate with high quality underwriters (Fernando et. al, 2003). Underwriter capability in terms of all-star analyst coverage has been found to be important in affecting investment banking deal flow (Clarke et. al., 2003; Corwin and Schultz, 2003) and for switching from one underwriter to another (Krigman et. al, 2001), though there is little evidence to suggest that aggressive analyst recommendations increase the bank's probability of winning an underwriting mandate (Ljungqvist et. al, 2003). In this paper, we find that prior lending as well as simultaneous lending by the underwriter to the firm significantly affect firm-underwriter pairings and the pricing of underwriting services. Lending activities are important not just for current firm-underwriter association but also for future transactions and help create durable relationships that can benefit the issuer through lower financing costs.[2] Our findings also underscore that firm-underwriter pairings can differ by underwriter type and not simply by underwriter reputation and analyst coverage, as we find important differences between commercial bank and investment bank underwriters.

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

[2] See also Ljungqvist et. al (2003) for additional sources of durability in bank-issuer relationships.

This paper also contributes to the literature on universal banking and the implications of allowing banks to underwrite securities. Regulators have recently raised questions on the firm-level and competitive effects of the relaxation and repeal of the Glass-Steagall Act (see e.g., Berger, et. al, 1999; Santomero and Eckles, 2000) as well as the implications of tie-ins.[3] Related to these concerns, 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, 2003; Puri, 1999; Rajan, 2002; Stefanadis, 2004). However, the possibility that investment banks might respond by expanding into lending activities has generally not received much attention. Our results bring to light some similarities and differences in the ways that investment banks and commercial banks compete for underwriting business. We also add to the evidence on implications of combining lending with underwriting. 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.[4] These effects are ascertained through the pricing of underwritten securities (see e.g., Puri, 1996; Gande et. al, 1997; Yasuda, 2003; Benzoni and Schenone, 2004) or through long run performance (see e.g., Ang and Richardson, 1994; Kroszner and Rajan, 1994; Puri, 1994). An important but unexplored issue is the reverse question – how do potential underwriting opportunities affect banks' lending, and how does this affect the financing cost of the issuing firm? This paper provides a first step in addressing this question.

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

[3] U.S. House Representative Dingell highlights some regulatory concerns in a letter to Chairman Greenspan and Comptroller Hawke (see "Letter to FRB and OCC re: 'pay to play' practices," July 11, 2002).
[4] In related literature, James (1987), Lummer and McConnell (1989), Best and Zhang (1993), and Billett, Flannery and Garfinkel (1995), among others, find that new loans, loan renewals, and lender identity carry (positive) private information to the outside equity market about a borrowing firm's financial condition. See James and Smith (2000) for a comprehensive review of the past and recent research on the special nature of bank loan financing. This literature examines the effect of bank lending absent an underwriting role for the bank.

2. Data and Sample Selection

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

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

We construct a unique database using eight different data sources and hand-collected data. Data on seasoned equity offerings comes from Thomson Financial's SDC *Platinum* United States New Issues database, from which we download underwritten, seasoned, US Common Stock issues. Since we wish to study industrial firms, we remove financial firms (companies with a one-digit SIC code of 6). The sample consists of 2301 issues. We hand match, by issuer name, each of the 2301 issuers to the Loan Pricing Corporation's (LPC) *DealScan* database to identify if the firm received a tied loan from their underwriter and in doing so, we identify if the SEO is a tied deal.[5] There are 201 tied deals in the sample and 2100 non-tied deals.

[5] LPC *DealScan* collects its loan data from SEC filings, and it receives data from large loan syndicators and from a staff of reporters. As such, *DealScan* is well-suited to studying the borrowing activity of companies with public equity and debt. Since all of the companies in our sample have public equity, we should observe the vast majority of

We classify each underwriter as an "investment bank" or a "commercial bank" based on the status of the parent/holding company of the underwriter at the time of the issue.[6] Due to the many mergers and acquisitions in the financial sector, we use the mergers and acquisitions database from SDC *Platinum* to aid in classification. For example, NationsBank acquired Montgomery Securities on 10/1/1997. Montgomery Securities is classified as an investment bank prior to 10/1/1997, but after 10/1/1997, we classify it as a commercial bank. Commercial banks underwrote 91 tied SEOs and 591 non-tied SEOs, while investment banks underwrote the remaining 110 tied SEOs and 1509 non-tied SEOs.

We will study how tying affects the pricing of bank services and the ability of the underwriter to generate equity underwriting business. As a result, we need to control for factors that may alter fees, pricing, or the likelihood that an issuer selects an underwriter. Prior underwriting relationships are likely to be important in both the selection of a bank and the pricing of banking services (see e.g., Baker, 1990; James, 1992; Crane and Eccles, 1993; Ljungqvist et. al, 2003). Furthermore, it is possible that prior lending relationships could also influence underwriter selection and the pricing of services. In particular, if there are economies of scope in lending and underwriting, then a prior lending relationship may result in a reduced underwriter fee or other pricing differences. When identifying prior lending and underwriting relationships, we account for mergers between potential underwriters. For example, Fleet Bank merged with BankBoston / Robertson Stephens on 10/1/1999. When tracking relationships, we assume that Fleet Bank acquired all of BankBoston's and Robertson Stephens' prior lending and underwriting relationships. From SDC *Platinum*, we identify 90 tied issuers and 830 non-tied issuers that use an underwriter that had underwritten a prior equity offering. From *DealScan*, we identify 83 tied issuers and 103 non-tied issuers that have a prior lending relationship with the selected underwriter.

Previous research indicates that we need to incorporate the reputation of the underwriter and the level and quality of analyst coverage into our models because these factors are likely to

their lending activity. *Dealscan* has been used in previous studies for many purposes, including examining the effect of lending on bond yield spreads (see e.g. Gande et. al 1997) and bank effects in lending rates (Hubbard et. al 2002).

[6] We do not separate commercial banks that internally developed investment-banking capabilities from those that acquired investment banks because almost all of the commercial banks developed underwriting operations by acquiring investment banks. Chaplinsky and Erwin (2001) note that for commercial banks who developed underwriting capabilities internally, only JP Morgan acquired market share in equity underwriting that is above 0.02% during the post-1996 period.

affect the firm's decision to select an underwriter or to switch underwriters in the future. We capture the influence of reputation through the underwriter's market share. For each year, we compute each underwriter's SEO market share by adding the principal amounts of all SEOs in which the bank was the underwriter and dividing this total by the principal amounts of all SEOs during the year. If a merger between underwriters occurred during the year, we use the combined market share of the underwriters. We rank the underwriters on a yearly basis, based on the market share in the previous year.[7] For example, Goldman Sachs had the highest market share in 1995, so in our models, issuers who have an SEO in 1996 consider Goldman Sachs to be the top ranked underwriter.

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

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

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

price, and outstanding share data to compute the equity volatility and market capitalization for each firm.

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

To examine differences between tied loans and non-tied loans, we create two separate samples. In the hand-matching sample, for each of the tied loan facilities, we create a control group of non-tied loans that were originated at around the same time as the tied loan, with firms that belong to the same industry and have the same credit rating. We use all loans in *DealScan* that occur between six months prior to and six months after the term facility active date of the tied loan.[8] 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.[9] All bridge loans and loans with an issuer that is not rated are removed. This sample has 107 tied loans that can be matched to a similar non-tied loan, and it is comprised of 56 revolving lines of credit, 40 term loans, ten 364-day facilities, and one other type of facility.

To construct the econometric-matching sample, we download all lending facilities in *DealScan* that occur between January 1, 1996 and May 31, 2001. We remove any facility that is missing information for the all-in spread drawn and / or the length of the facility, and we remove any facility where the borrower is a financial firm (companies with a one-digit SIC code of 6). As before, all bridge loans and loans to non-rated borrowers are excluded. This sample consists of 166 tied loans that can be matched to a sample of 6919 non-tied loans. Seventy-four revolving lines of credit, 77 term loans, fourteen 364-day facilities, and one other type of facility form the sample of 166 tied loans. Seventy-nine of the 166 tied loans are from commercial bank underwriters while the remaining 87 tied loans are provided by investment bank underwriters.

In addition, we classify 340 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

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

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

SEO, where the lender could have been selected to underwrite the SEO but is not provided with underwriting responsibilities. Of the 6919 non-tied loans in the econometric-matching sample, 145 lending facilities are simultaneous loans.

3. Methodology and Results

Table 1 displays trends in tying over time. It can be seen that tying increased over time from about 1% in 1994 to over 20% in 2001. However, before 1996, while tying was nearly non-existent, many issuers received loans from another bank at about the same time as the issuance of public securities.[10] Over time, issuers have shifted from using a commercial bank for lending and an investment bank for equity underwriting to employing a single entity for both of the simultaneous transactions.

Table 2 reports summary statistics for the tied and non-tied SEO samples. Tied issuers are highly leveraged, with debt-to-equity ratios that are, on average, five times higher than non-tied issuers. Furthermore, tied lenders have low credit ratings, with 71% of investment bank tied deals and 60% of commercial bank tied deals for junk rated issuers, and another 12% of investment bank deals and 27% of commercial bank deals involving issuers that are not rated. Since duplication of information will be particularly costly for risky firms because they will be subject to extensive due diligence in both lending and underwriting, tying can be extremely beneficial for these issuers because a single bank can use the collected information for both transactions. In addition, for lower rated and highly leveraged firms, debt has similar characteristics to equity. As a result, information gathered in the lending process will be relevant to the equity issuance, which may enhance the certification ability of the underwriter. Therefore, economies of scope are likely to be high for these firms, and tying may be an efficient response to banks' ability to use information across product lines.

Commercial banks are underwriters on 45% of tied deals and investment banks underwrite the remaining 55% of tied deals. Also, commercial banks and investment banks are providing tied loans to similar clients. These are interesting facts, which suggest that investment banks have now developed the organizational structure to lend. The expansion into lending by

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

investment banks is consistent with there being potential gains from a single entity offering both lending and underwriting services.

3.1. Equity Underwriter Spreads

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

3.1.1. U-shaped Underwriter Spreads

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

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

We extend the model to include variables to capture tied lending and prior relationships. Since an existing lending relationship can lower setup costs and provide the bank with access to additional information, tied deals involving prior lenders may be less costly. To capture this potential effect, we control for interactions between prior lending and tied lending. A negative coefficient on the tied lending variables would be consistent with the existence of scope economies. We estimate two variations of the expanded spread linear model – in the first model we do not consider differences between investment banks and commercial banks while we relax this restriction in the second model. Further, we examine differences between non-investment grade and investment grade issuers. Since economies of scope are likely to be high for non-investment grade firms, we expect discounts to be concentrated amongst these deals.

3.1.2. Results

Results of ordinary least squares regressions are presented in Table 3. We find support for U-shaped spreads. As more capital is raised the variable cost is rising. As expected, higher stock return volatility increases the variable spread and there is a large fixed cost component to underwriter spreads. In the first column of Table 3, we present the results of the model in which we do not consider differences in the fees charged by investment banks and commercial banks. The coefficients on the tied lending and the prior lending variables are all negative and significant. A tied loan without a prior lending relationship provides an 18 basis point reduction in the underwriter spread, which is significant at the 10% level. A prior lending relationship, both with and without a tied loan, translates into a 36 basis point reduction in the underwriter spread. On a $200 million equity offering, an 18 basis point reduction in the underwriter fee provides a cost savings of $360,000 to the issuer, while a 36 basis point decrease saves the issuer $720,000. These results are consistent with the existence of economies of scope.

As previously argued, economies of scope between lending and underwriting are likely to be pronounced when the issuer is junk rated or not rated. We restrict the sample of SEOs to include only junk rated and not rated issuers and display the results of the model in the second column of Table 3. Consistent with the existence of informational economies of scope, we find that amongst these issuers, significant underwriter spread discounts are provided when the issuer receives a tied loan or has a prior lending relationship with the underwriter. In the third column of Table 3, we present the results of the model when we restrict the sample to include only investment grade issuers. Amongst investment grade issuers, where private information is likely to be less important, we do not find significant underwriter spread discounts. These results highlight that the underwriter spread discounts are driven by deals in which, ex-ante, tying is likely to be efficient.

The results in the fourth and fifth columns of Table 3 show that investment banks account for most of the tied lending and underwriting relationship discount. For tied issuers, investment banks provide a discount of 26 basis points if no prior lending relationship existed and 44 basis points if there is a prior lending relationship, both significant at the 5% level. On a $200 million equity offering with an investment bank, on average, the issuer saves $520,000 to $880,000. For commercial bank underwritten issues, the coefficients for tied deals are negative but insignificant. It is interesting to note that both investment banks and commercial banks provide significant discounts in the underwriter spread to firms that do not receive a tied loan but with which a prior lending relationship is in place, which further supports the existence of informational economies of scope between lending and equity underwriting.

Overall, we find that tied deals have lower underwriter spreads than non-tied deals and that tied deals in which there was a prior lending relationship in place receive a larger discount. Importantly, we find that the discounts are driven by deals that involve junk rated and not rated issuers, where economies of scope between lending and underwriting are likely to be large. Consequently, the results are consistent with the view that tying is an efficient response to banks' ability to use information across product lines. We find additional support for the existence of economies of scope between lending and equity underwriting, as a prior lending relationship translates into an underwriter spread discount. Further, we find that most of the underwriter spread discount can be attributed to investment bank underwriters.

3.2. The Pricing of Tied Loans

We now study the pricing of tied loans to address two issues. First, we wish to determine if there is additional evidence that tying reduces issuers' financing costs. To examine this question, we compare the yield spreads of tied loans and non-tied loans.[11] Lower yield spreads for tied loans would be consistent with the existence of informational economies of scope. Second, we wish to examine if the benefits provided to tied issuers vary by the type of underwriter. Considering the result from the last section in which we found that investment banks are discounting underwriter spreads, any differences between investment bank and commercial bank pricing of tied loans will provide insight into how these two underwriter types compete. Therefore, we compare the yield spreads of tied loans in which the lender is a commercial bank with tied loans from investment banks.

3.2.1. Hand Matching

To examine pricing differences between tied and non-tied loans, we hand match tied loans to non-tied loans on four dimensions – (i) loan origination date, (ii) industry, (iii) credit rating, and (iv) length of the loan. Ideally, we would like to find a non-tied loan that matches the tied loan on all four dimensions. However, it is unlikely that we will find an exact match. Instead, for each of the 107 tied lending facilities in the hand-matching sample, we select the non-tied loan with the closest term length, given that the non-tied loan was originated between six months before and six months after the tied loan origination date, and the non-tied borrower belongs to the same industry and has the same credit rating as the tied borrower.[12] Therefore, any selected non-tied loan will be an exact match on two of the four dimensions (industry and credit rating) and will have a very similar term length and loan origination date.

[11] The yield spread is the rate that the borrower pays to the lender (inclusive of fees), quoted in basis points over LIBOR.
[12] We also restrict the selection of non-tied loans to those that are originated between three months prior to and three months after the term facility origination date. The results are similar and are not reported. We match on the credit rating of the borrower at the loan origination date. If the bank acts rationally, it should consider the effect that the loan will have on the credit risk of the firm when determining the price and structure of the loan. Therefore, we also examine the credit rating of the firm at two quarters after the loan. In our sample of tied loans, only two rated borrowers had a credit rating change during the two quarters, so both measures of credit rating provide a nearly identical sample.

We examine the mean difference between tied and non-tied yield spreads using three estimators.[13] The “twelve-month estimator” uses all matches in which the absolute value of the difference between the term lengths of the matched pair of loans is less than 12 months. The “six-month estimator” is the same as the twelve-month estimator except that the difference cannot exceed six months. The “exact estimator” only includes matches where each loan in a matched pair has the same term length. For all three estimators, on average, the tied loan yield spreads are more than 20 basis points lower than the matched non-tied loan yield spreads, a significant difference at the 5% level.

3.2.2. Econometric Matching

There are a few problems with the hand matching method. First, we match on only four dimensions and ignore variables that may be relevant in determining yield spread differences, such as the size of the lending facility and the type of lending facility. Second, for matching to occur, there must exist at least one non-tied loan that meets these four criteria. As a result, we do not generate matches for all of the tied loans in our sample. To reduce these problems, we rely on econometric matching techniques that were developed by Rosenbaum and Rubin (1983) and extended by Heckman and Robb (1986), and Heckman, Ichimura, and Todd (1997, 1998).[14] In Appendix A, we provide a summary of these techniques and a detailed description of how we apply the methods to our data.

Essentially, instead of facing the difficult task of matching directly on multiple dimensions, econometric matching allows us to match non-tied loans to tied loans based on a one-dimensional propensity score, which is a function of loans’ observable characteristics. As a result, we effectively match loans based on many observable characteristics while not reducing the number of tied loans for which we can find matches. Furthermore, the methods 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.

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

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

We choose to use econometric matching techniques instead of the alternative approach of employing a multivariate regression model because matching employs fewer restrictions than the regression approach, and many studies have confirmed that propensity score matching methods can allow for a more accurate analysis (see e.g. Rubin, 1997; Conniffe et. al, 2000). A key restriction in using multivariate regressions to study the pricing of loans is that the covariates are assumed to be linearly related to the yield spread. In the propensity score approach, the researcher does not need to specify the actual relationship between yield spreads and the characteristics that can affect loan pricing.

In our models, the propensity score is a function of the firm's credit rating, the notional value of the loan facility, the term length of the loan, the type of lending facility, the year of the facility origination, and the firm's industry. Using propensity scores and econometric matching estimators, we calculate average yield spread differences between tied loans and matched non-tied loans. Further, we split our sample to allow for a comparison of junk rated tied loans with matched junk rated non-tied loans and to enable tied loans to investment grade rated borrowers to be matched with non-tied loans to similar, investment grade rated borrowers. Also, we extend the methodology to capture differences between commercial bank tied loans and investment bank tied loans. We compare commercial bank tied loans to non-tied loans by restricting the tied lending sample to include only commercial bank loans. Separately, we examine differences between investment bank tied loans and non-tied loans.

3.2.3. Results

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

First, we provide evidence that is consistent with the existence of economies of scope in tied deals. As displayed in the first column of Table 4, all estimators indicate that tied loans have significantly lower yield spreads, with the average discount ranging between 9.97 and 14.81 basis points. On a $200 million dollar, 6-year loan, a reduction of 9.97 basis points represents a present value savings of $770,000 while a 14.81 basis point reduction provides a present value savings of $1.15 million.[15]

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

Second, we find that the lower yield spreads on tied loans are concentrated amongst borrowers that have lower credit quality. The results in the second column of Table 4 show that yield spreads on tied loans to junk rated borrowers are discounted, on average, by between 12.10 and 15.96 basis points relative to matched non-tied loans to junk rated borrowers, and the discounts are strongly significant for all four estimators. In comparison, we find that investment grade borrowers do not receive significantly lower yield spreads on tied loans relative to matched non-tied loan yield spreads. These results are consistent with economies of scope between lending and underwriting being more pronounced for issuers with lower credit ratings.

Third, we find that commercial banks provide cheaper loans to tied borrowers. In the third column of Table 4, we show that yield spreads on commercial bank tied loans are discounted by between 16.35 and 22.72 basis points relative to non-tied yield spreads, and the differences are highly significant for all four estimators. On a $200 million dollar, 6-year loan, a tied borrower earns a present value savings of between $1.27 million and $1.76 million through a discounted loan spread that is provided by its commercial bank.[16] Again, the savings provided by commercial banks are pronounced amongst junk rated borrowers. While commercial banks reduce tied loan yield spreads, we find that yield spreads on investment bank tied loans are insignificantly different from those of non-tied loans.[17] Tying by commercial banks, as opposed to investment banks, largely drives the difference between the yield spreads of tied and non-tied loans.

These results, in combination with the results from Section 3.1., indicate that in comparison to similar non-tied issuers and borrowers, tied issuers pay lower underwriter spreads

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

on the SEO and receive lower loan yield spreads. Furthermore, we find that the cost reductions are large and significant for issuers who are not investment grade rated. These results are consistent with the existence of informational economies of scope. In addition, the concentration of savings amongst these firms helps explain why all deals are not tied, as tying is economically justified only when there are sufficient informational economies of scope.

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

3.2.4. Robustness – Simultaneous Loans

An additional concern is that tied issuers are simultaneously raising equity and receiving loans and may therefore differ from other issuers. To address this concern, within the sample of non-tied loans, we identify simultaneous loans, which are loans to an issuer of an SEO that are originated between six months prior to and six months after the SEO, where the lender could have been selected to underwrite the SEO but is not provided with underwriting responsibilities.[18] We then compare tied loan yield spreads with simultaneous loan yield spreads to determine if the results in Section 3.2.3. are robust.

In Section 3.2.3., we show that most of the discounting of tied loans comes from commercial banks. Hence, we compare commercial bank tied loans with commercial bank simultaneous loans. Extending the previously employed methodology, we match commercial bank tied loans to other non-tied loans as well as commercial bank simultaneous loans to other non-tied loans by computing propensity scores and calculating yield spread differences.

We compute sample averages for the tied loan matched pairs and the simultaneous loan matched pairs and report the mean difference in the yield spread between the two groups in the

[17] In unreported estimations, we find that investment bank tied loan yield spreads are insignificantly discounted between zero and six basis points relative to matched non-tied loan yield spreads.

fourth column of Table 4. The results of all four estimations indicate that commercial bank tied loans are discounted more than commercial bank simultaneous loans. On average, tied loan yield spreads are less than simultaneous loan yield spreads by 16.43 to 28.42 basis points, and the difference is significant when using three of the four estimators. Relative to simultaneous loans, the discount that is provided by commercial banks to tied issuers remains significant.

3.3. Underwriter Relationships

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

3.3.1. McFadden's Choice Model

In this section, we study the influence tying has on the likelihood that a bank is selected as equity underwriter. We use McFadden's (1973) choice model to capture the effect.[19]

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

$$U_{ij} = \boldsymbol{a}' \boldsymbol{w_i} + \boldsymbol{ß}' \boldsymbol{x_{ij}} + \boldsymbol{e}_{ij}$$

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

[18] 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.
[19] See Greene (2000) for a discussion of models for choices between multiple alternatives.

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

$$\Pr(Y_i = j) = \frac{\exp(\boldsymbol{a}'\boldsymbol{w}_i + \boldsymbol{ß}'\boldsymbol{x}_{ij})}{\sum_{j=1}^{J}\exp(\boldsymbol{a}'\boldsymbol{w}_i + \boldsymbol{ß}'\boldsymbol{x}_{ij})}.$$

We assume that each firm has 21 potential choices – each of the top 20 underwriters and a single choice of any of the underwriters that are not ranked in the top 20. Since the attributes of the potential underwriters can influence an issuer's choice, we track underwriting relationships, lending relationships, analyst coverage, and all-star analyst coverage for each of the issuer's potential choices.[20] By including this information, we more accurately control for relationship-specific and underwriter-specific factors that could affect the probability of a firm selecting an underwriter. In addition, we modify our definition of "tied loans" to include loans from *potential* underwriters that are originated between six months prior to the SEO and six months after the SEO. This adjustment amounts to adding the 340 simultaneous loans to the sample of 358 tied loans.[21] Technically, this modification is needed because, otherwise, tied lending perfectly predicts an issuer's choice of underwriter. This methodology allows us to address if conditional on a firm issuing seasoned equity, lending at the time of the SEO improves the probability of getting the underwriting business.

In our models, we assume that the relevant issuer specific characteristics ($\boldsymbol{w}_i$) are the logarithm of the SEO principal amount, the age of the firm, the long-term debt to equity ratio of the firm in the quarter of the SEO, and the industry of the issuer. These variables are chosen to control for differences between tied and non-tied issuers that are shown in Table 2, Panel A. For the choice-specific attributes ($\boldsymbol{x}_{ij}$), we include variables to capture tied lending, prior lending relationships, prior underwriting relationships, as well as the reputation of the underwriter and the level and quality of equity analyst coverage. Our priors are that prior lending and underwriting relationships between a firm and an underwriter will increase the probability of

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

[21] Since multiple underwriters can be lenders on a given lending facility, the number of underwriters that provide "tied loans" exceeds the total number of "tied loans." A total of 1154 firm-underwriter pairs have at least one loan that is originated between six months prior to the SEO and six months after the SEO, of which 201 underwriters are selected to underwrite deals. Of the 1154 pairs, an unranked underwriter provided a loan around the equity issuance on 106 occasions.

selection. Also, we expect that the reputation of the underwriter and the level and quality of equity analyst coverage will be positively related to underwriter selection. We estimate two models – in the first model we do not consider differences between investment banks and commercial banks while we relax this restriction in the second model.

3.3.2. Results

In Table 5, we present the results of the underwriter selection models. In both models, the control variables have the expected signs and most are highly significant. The coefficients of the tied lending variables are positive and statistically significant at the 1% level. This indicates that after controlling for other factors that significantly influence underwriter selection, providing a tied loan increases the probability of winning the underwriting mandate, conditional on a firm issuing seasoned equity. The effect is present for both commercial and investment bank underwriters. The results demonstrate that providing a tied loan increases a bank's expected investment banking revenues and raises the likelihood of building relationships with issuers.

3.4. Probability of Keeping Future Business

Tying lending to underwriting may also foster a durable relationship that can boost expected future revenues by increasing the likelihood that the issuer will use the bank repeatedly. Future interactions could become more likely because tying allows the bank to generate private information that can be used in ongoing transactions with the bank, thereby providing the bank with a source for both lending and underwriting relationships.[22] In this section, we determine if tying enhances an underwriter's ability to cultivate relationships by examining if those firms that participate in a tied deal go back to the market more frequently and do not switch underwriters as often as issuers who do not receive a tied loan.

In Table 6, we present a univariate analysis of switching probabilities. For our sample of 2301 issuers, 37% of tied issuers proceed with a subsequent equity offering while only 22% of non-tied issuers go back to the equity market.[23] Of those firms that have a follow-up equity

[22] Access to firm-specific information is well known to be a key factor in developing and maintaining lending relationships (see Ongena and Smith, 2000 for a survey of the literature). Private information is also a key determinant of investment banking relationships (see e.g. Crane and Eccles, 1993).
[23] We examine subsequent SEOs that took place before March 31, 2002. Extending the sample end date allows issuers from the latter part of the sample to potentially re-issue.

offering, 57% of tied issuers and 45% of non-tied issuers keep the same underwriter, a significant difference at the 10% level. However, there is a disparity between investment bank and commercial bank underwriters. While tying significantly increases the probability of retaining future business for investment banks, the effect is not present for commercial banks. This result indicates that commercial banks may not be able to leverage their tying practices into extended underwriting relationships.

3.4.1. Nested Logit Model

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

Following Maddala (1983), let k index the first-level alternative and l index the second-level alternative.[24] Also, let $\boldsymbol{Y_{kl}}$ and $\boldsymbol{Z_k}$ 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 $U_{kl} = \boldsymbol{a}'\boldsymbol{Y_{kl}} + \boldsymbol{ß}'\boldsymbol{Z_k} + e_{kl}$, and then the probability of choosing l, conditional on first choosing k is

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

Define the inclusive values for category (k) as

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

which leaves us with the probability of choosing k is

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

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

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 principal amount, the age of the firm, the long-term debt to equity ratio of the firm in the quarter of the SEO, and the industry of the issuer. For the variables that affect both the decision to re-issue and the decision to keep or switch underwriters ($\boldsymbol{Y_{kl}}$), we include variables to capture tied lending, prior lending relationships, prior underwriting relationships, as well as differences between the original underwriter and the subsequent underwriter in the level and quality of equity analyst coverage and underwriter ranking. We expect that prior lending and underwriting relationships will be positively related to keeping future business. Also, previous papers indicate that firms will be more likely to switch to an underwriter who has higher quality equity analyst coverage and is ranked above the original underwriter (see e.g. Krigman et. al, 2001; Fernando et. al, 2003). As in the previous section, we estimate one model in which we do not consider differences between investment banks and commercial banks and a second model where we relax this restriction. Based on the univariate results, we expect a previous tied deal with an investment bank underwriter to increase the probability that the investment bank keeps future underwriting business. We also expect that a previous tied deal with a commercial bank will not significantly affect the probability that the bank can retain equity underwriting business in the future.

3.4.2. Results

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

In the first column of Table 7, we present the results of the model in which we do not consider differences between investment banks and commercial banks. We find that a prior tied deal increases the probability of an issuer choosing to re-issue and keep the same lead underwriter relative to not reissuing. The t-tests for differences between keeping and switching indicate that a previous tied deal also increases the probability of keeping an underwriter instead of switching to a new underwriter, although this result is insignificant. Furthermore, we find that prior lending relationships (both with and without a tied loan) increase the probability of an issuer choosing the keep the same lead underwriter. These results highlight the importance of lending in generating future investment banking business.

The second column of Table 7 shows the results where we allow the coefficients to reflect disparities between investment banks and commercial banks. We find that a prior tied deal (without the existence of a prior lending relationship) with an investment bank significantly increases the probability of keeping the same underwriter in the subsequent equity offering. The results indicate that for commercial bank underwriters, a tied deal does not significantly affect the probability that an underwriter will keep the same underwriter instead of switch to a new underwriter in the subsequent equity offering. These results are consistent with the univariate statistics in Table 6.

Combined with our previous findings, we find that investment banks discount underwriter spreads and that tying increases the probability of retaining future underwriting business from the firm. Commercial banks, on the other hand, discount loan yield spreads, which can help establish lending relationships that are well-known to lead to other fee-based lending business (for some recent evidence, see Bharath et. al, 2004). Therefore, the results are consistent with each type of underwriter competing more aggressively in its area of expertise and in the area where it is more likely to generate future business.

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 securities offering. We find evidence that is consistent with tying occurring when there are large potential efficiency gains that can arise due to informational economies of scope from combining lending and equity underwriting. This is supported by the preponderance of tied deals involving highly leveraged and non-investment grade issuers, and the substantial benefits that tying brings to such issuers. For issuers, these benefits come in the form of lower financing costs, as tied issuers receive a lower underwriter fee for the equity offering and a discounted yield spread on the tied loan. The cost reductions are large and significant for issuers who are non-investment grade rated, where the expected informational economies of scope are sizeable. Interestingly, the benefit that an issuer receives varies by the type of underwriter involved in the transaction. Investment banks offer reduced underwriter spreads on tied SEOs, while commercial banks offer discounted loan yield spreads, which is consistent with each type of underwriter competing more aggressively in its area of expertise. In addition to benefiting issuers, tying lending and equity underwriting produces gains for underwriters. We find that providing a tied loan increases the likelihood of receiving the current equity underwriting business, and it also helps generate other business from the issuers, with investment bank underwriters more likely to receive future equity underwriting mandates from tied issuers. These results are consistent with tied loans helping to build ongoing, durable relationships that increase an underwriter's expected revenues. Our finding of substantial benefits to issuers and underwriters from combining lending with underwriting indicates that tying is likely to continue in the future and that lending will remain an important factor in determining firm-underwriter pairings as well as influence the pricing of financial products and services.

Appendix A
Econometric Matching Methodology

Econometric matching techniques were developed by Rosenbaum and Rubin (1983) and extended by Heckman and Robb (1986), and Heckman, Ichimura, and Todd (1997, 1998). Below, we provide a summary of their results and how we apply these methods to our data.

Let $D=1$ if the loan is a tied loan, and let $D=0$ if the loan is a non-tied loan. In principle, the ith tied loan has its observed "tied" yield spread Y_{1i} and another yield spread Y_{0i} that would result if it were a non-tied loan. To determine the average effect of tying on yield spreads, one would calculate the mean difference between Y_{1i} and Y_{0i} for all tied loans. However, since we do not observe Y_{0i} 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 $E(Y_1 - Y_0 \mid D=1, X)$, the mean effect of the difference between tied loans and non-tied loans with characteristics X. 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 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 $(Y_0, Y_1) \perp D \mid X$ denote the statistical independence of (Y_0, Y_1) and D conditional on X. Rosenbaum and Rubin (1983) establish that when $(Y_0, Y_1) \perp D \mid X$ and $0 < P(D=1 \mid X) < 1$ (which are referred to as the strong ignorability conditions), then $(Y_0, Y_1) \perp D \mid P(D=1 \mid X)$. While it is often difficult to match on high dimension X, this result allows us to match based on the one-dimensional $P(D=1 \mid X)$ alone. $P(D=1 \mid X)$, known as the propensity score, can be estimated using probit or logit models. Heckman, Ichimura, and Todd (1998) extend this result by showing that the strong ignorability conditions are overly restrictive for the estimation of $E(Y_1 - Y_0 \mid D=1, X)$. Instead, a weaker mean independence condition $E(Y_0 \mid D=1, P(D=1 \mid X)) = E(Y_0 \mid D=0, P(D=1 \mid X))$ is all that is required.

To implement econometric matching, we compute propensity scores for each of the tied loans and non-tied loans. There may be loans that have propensity scores that are outside of the common support of tied loan and non-tied loan propensity scores. Using loans that fall outside of the common support can substantially bias the results (see e.g. Heckman et. al 1997). As a result, we remove all loans that are outside of the common propensity score support.

We use two classes of propensity score matching estimators: (i) nearest neighbor matching, and (ii) kernel based matching.[25] Let Y_{1i} be the yield spread of a tied loan, Y_{0j} be the yield spread of a non-tied loan, and let $\overline{Y}_{0i}^{z}$ represent the (weighted) average of yield spreads of the non-tied loans using estimator *z* that is matched with Y_{1i}. We compute the sample average of yield spread differences $Y_{1i} - \overline{Y}_{0i}^{z}$.

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

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

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

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

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

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

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

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

We use two different kernels to compute $\bar{Y}_{0i}^{K}$. The Gaussian kernel uses all non-tied loans while the Epanechnikov kernel only uses non-tied loans with a propensity score $P(X_{0j})$ that falls within the fixed bandwidth h of $P(X_{1i})$. We set h = 0.01. As a robustness check, we also tried different values of h and obtained similar results.

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

Appendix B
Detailed Descriptions of the Variables

Underwriter Spread Regressions (Section 3.1.)

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

McFadden Choice Model / Underwriter Relationships (Section 3.3.)

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

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

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

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

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

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

RANK: We compute each underwriter's yearly SEO market share by adding the principal amounts of all SEOs in which the bank was an underwriter and dividing this total by the principal amounts of all SEOs during the year. To avoid potential simultaneity problems, we rank the underwriters on a yearly basis, based on the market share in the previous year. If a merger between underwriters occurred during the year, we use the combined market share of the underwriters. The top-ranked underwriter is given a score of 20, the second-ranked underwriter is 19, and so on. Underwriters not ranked in the top 20 are given a score of zero

Nested Logit Model / Keeping Future Business (Section 3.4.)

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

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

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

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

REPEAT: A dummy variable that is one if the issuer has a subsequent offering

KEEP: A dummy variable that is one if the issuer keeps the same underwriter in the subsequent offering

SWITCH: A dummy variable that is one if the issuer switches underwriters in the subsequent offering

CNGCOV: For "switchers," the difference between the coverage provided by the new underwriter and the original underwriter during the year prior to the subsequent SEO. The variable can take on the values of –1, 0, or 1. By definition, for all non-repeaters and keepers, it has a value of zero

CNGSTAR: For "switchers," the difference between the all-star coverage provided by the new underwriter and the original underwriter during the year prior to the subsequent SEO. The variable can take on the values of –1, 0, or 1. By definition, for all non-repeaters and keepers, it has a value of zero

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

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

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

Control Variables

LNSIZE: The logarithm of the principal amount of the offering

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

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

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

IGRADE: A dummy variable that equals one if the issuer is rated AAA, AA, A, or BBB in the quarter of the SEO by Standard & Poor's

JUNK: A dummy variable that equals one if the issuer is rated BB, B, CCC, CC, or C in the quarter of the SEO by Standard & Poor's

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Table 1

Tied Deals, by year

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

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

* Through May 31

Table 2

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

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

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

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

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

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

Table 2 (continued)

Panel C: IB vs. CB Tied Deals – Issuer and Issuance Variables				
Variable	IB Tied Deal Mean	CB Tied Deal Mean	T-ratio	Wilcoxon test p-value
USPREAD	4.25	4.43	0.98	0.2792
LNSIZE	5.28	4.92	2.24 **	0.0110 **
DE-LTDEBT	2.83	2.31	0.39	0.4189
AGE	20.50	23.35	0.79	0.1148
Panel D: IB vs. CB Tied Deals – Relationship Variables				
Variable	Percent of IB Tied Deals	Percent of CB Tied Deals		
PRIORLEND	36.4	47.3		
PRIORUND	48.2	40.7		
COVERAGE	78.2	75.8		
ALLSTAR	23.6	18.7		
Panel E: IB vs. CB Tied Deals – Issuer Rating				
Variable	Percent of IB Tied Deals	Percent of CB Tied Deals		
IGRADE	17.27	13.19		
JUNK	70.91	60.44		

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

Table 3
Underwriter Spread Regressions

This table provides ordinary least squares estimates of a model of the underwriter spread that can be a U-shaped function of the amount of new capital raised. The model is based on Altinkilic and Hansen's (2000) expanded spread linear model. The dependent variable is USPREAD, which is the compensation paid to the underwriter for selling the firm's security issue, expressed as a percentage of the principal amount. The independent variables are: TIELOAN is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if the underwriter had been the underwriter on any prior equity offering by the issuer. IB (CB) is one if the parent / holding company of the underwriter is an investment bank (commercial bank). To capture the fixed cost component of spreads, we include (1/SEOSIZE), the inverse of the principal amount of the equity offering, measured in millions of dollars. Variable costs are captured by (SEOSIZE / MKTCAP), the principal amount of the offering divided by the market capitalization of the issuer at the date of the SEO. VOL is the daily standard deviation of the issuer's common stock rate of return over the 220 trading days ending 40 days before the offering. MKTACT is the dollar volume of issuance in the US SEO market for the three months prior to each offering. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. In columns (1) and (4), we estimate the models using the full sample of issues. In columns (2) and (5), the sample is restricted to SEOs by non-investment grade issuers. Non-investment grade issuers are either not rated or have a Standard & Poor's long term debt rating of BB, B, CCC, or CC in the quarter of the SEO. In columns (3) and (6), the sample is restricted to SEOs by investment grade issuers. Investment grade issuers have a Standard & Poor's long term debt rating of AAA, AA, A, or BBB in the quarter of the SEO. Coefficients for the industry variables (SICx) are not reported. T-ratios are in parentheses.

	Full Sample (1)		Non-Investment Grade (2)		Investment Grade (3)		Full Sample (4)		Non-Investment Grade (5)		Investment Grade (6)	
Intercept	4.247	***	4.599	***	3.439	***	4.231	***	4.565	***	3.185	***
	(33.12)		(35.74)		(7.38)		(31.57)		(34.28)		(5.64)	
TIELOAN	-0.182	*	-0.179	*	-0.034							
	(-1.74)		(-1.76)		(-0.11)							
TIEPLEND	-0.360	**	-0.329	**	-0.474							
	(-2.31)		(-2.26)		(-1.02)							
PRIORLEND	-0.360	***	-0.358	***	-0.069							
	(-3.04)		(-3.17)		(-0.23)							
PRIORUND	-0.217	***	-0.263	***	-0.028							
	(-4.19)		(-5.19)		(-0.17)							
IB							0.021		0.043		0.238	
							(0.29)		(0.64)		(0.67)	
IB X TIELOAN							-0.263	**	-0.343	**	0.303	
							(-2.00)		(-2.40)		(0.92)	
CB X TIELOAN							-0.070		0.022		-0.760	
							(-0.43)		(0.17)		(-1.61)	
IB X TIEPLEND							-0.440	**	-0.413	**	-1.382	
							(-2.20)		(-2.44)		(-1.55)	
CB X TIEPLEND							-0.321		-0.283		0.003	
							(-1.43)		(-1.27)		(0.00)	
IB X PRIORLEND							-0.324	**	-0.328	***	0.046	
							(-2.49)		(-2.67)		(0.15)	
CB X PRIORLEND							-0.454	*	-0.427	*	-0.441	
							(-1.81)		(-1.84)		(-0.48)	
IB X PRIORUND							-0.248	***	-0.299	***	-0.122	
							(-4.39)		(-5.29)		(-0.72)	
CB X PRIORUND							-0.135		-0.173	**	0.178	
							(-1.45)		(-2.02)		(0.42)	
1 / SEOSIZE	17.270	***	15.377	***	24.680	***	17.259	***	15.328	***	24.783	***
	(6.04)		(5.99)		(2.91)		(5.98)		(5.92)		(2.74)	
SEOSIZE / MKTCAP	0.242		0.225		-0.049		0.241		0.223		-0.052	
	(1.43)		(1.13)		(-0.37)		(1.42)		(1.12)		(-0.39)	
VOL	12.274	***	7.570	***	17.273		12.226	***	7.532	***	18.625	*
	(10.26)		(6.73)		(1.57)		(9.96)		(6.55)		(1.73)	
MKTACT	-7.581	**	-4.071		-2.042		-7.652	**	-3.957		-2.173	
	(-2.34)		(-1.44)		(-1.38)		(-2.36)		(-1.42)		(-1.49)	
R-Squared	0.4029		0.4003		0.1644		0.4040		0.4026		0.2048	

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

Table 4

Estimated Yield Spread Differences, in basis points

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

$$P(TIED = 1 \mid X) = \Phi\begin{pmatrix} b_0 + b_1 * RATING + b_2 * FACSIZE + b_3 * LENGTH \\ + b_{type} * TYPE + b_{year} * YEAR + b_{ind} * INDUSTRY \end{pmatrix}$$

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

In column (1), we compute yield spread differences between tied loans and non-tied loans by using the estimators to match tied loans to non-tied loans. In column (2), we compute yield spread differences between junk rated tied loans and non-tied loans by removing all investment grade-rated loans from the sample, computing propensity scores, and using the estimators to find non-tied loan matches for each junk rated tied loan. In column (3), we compute yield spread differences between CB tied loans and non-tied loans by removing IB tied loans from the sample, computing propensity scores, and using the estimators to find non-tied loan matches for CB tied loans. In column (4), we compute yield spread differences between CB tied and CB simultaneous loans. We remove all simultaneous loans and IB tied loans from the sample, compute propensity scores, match non-tied loans to each CB tied loan, and compute yield spread differences. Then, we remove all tied loans and IB simultaneous loans from the sample and compute propensity scores using the above probit model by replacing TIED with SIMULTANEOUS, which is one if the loan is simultaneous and zero if it is non-simultaneous. We use the estimators to find matches and compute yield spread differences for each CB simultaneous loan. We examine the difference between CB tied yield spread differences and CB simultaneous yield spread differences. For all estimations, we present the sample averages. We report t-ratios in parentheses, which are calculated using standard errors that are computed by bootstrapping with 50 replications.

Estimator	**Mean Yield Spread Difference between Tied and Non-Tied (1)**	**Mean Yield Spread Difference between Junk Rated Tied and Non-Tied (2)**	**Mean Yield Spread Difference between CB Tied and Non-Tied (3)**	**Mean Yield Spread Difference between CB Tied and CB Simultaneous (4)**
NEAR NEIGHBOR	-14.811 **	-13.690 **	-22.713 **	-28.422 *
(n=10)	(-2.09)	(-2.23)	(-2.38)	(-1.92)
NEAR NEIGHBOR	-12.081 **	-12.104 **	-19.052 **	-28.202 **
(n=50)	(-2.38)	(-2.24)	(-2.31)	(-1.96)
GAUSSIAN	-9.966 *	-13.041 **	-16.347 **	-16.430
	(-1.93)	(-2.38)	(-2.23)	(-1.12)
EPANECHNIKOV	-14.772 **	-15.959 **	-21.223 **	-26.409 *
	(-2.27)	(-2.06)	(-2.57)	(-1.83)

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

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

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

$$U_{ij} = \boldsymbol{a}' \boldsymbol{w}_i + \boldsymbol{ß}' \boldsymbol{x}_{ij} + e_{ij}$$

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. The relevant issuer specific characteristics are $\boldsymbol{w}_i$ = {LNSIZE, AGE, DE-LTDEBT, SICx}. We use two different specifications for $\boldsymbol{x}_{ij}$. In column (1), we do not consider differences between investment banks and commercial banks. We specify that $\boldsymbol{x}_{ij}$ = {TIELOAN, TIEPLEND, PRIORLEND, PRIORUND, COVERAGE, ALLSTAR, RANK1, . . ., RANK20}. In column (2), we allow for differences between investment banks and commercial banks by setting $\boldsymbol{x}_{ij}$ = {IB X TIELOAN, CB X TIELOAN, IB X TIEPLEND, CB X TIEPLEND, IB X PRIORLEND, CB X PRIORLEND, IB X PRIORUND, CB X PRIORUND, IB, COVERAGE, ALLSTAR, RANK1, . . ., RANK20}. The issuer characteristics are defined as follows: LNSIZE is the logarithm of the SEO principal amount, expressed in millions of dollars. AGE is the firm's age, measured as the difference between the date of the SEO and the incorporation date, measured in years. DE-LTDEBT is the long-term debt to common equity ratio in the quarter of the SEO. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. The choice attributes are defined as follows: TIELOAN is a dummy variable that equals one if a potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the potential underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if a potential underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the potential underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the potential underwriter and the issuer was originated at any time prior to six months before the SEO *and* the potential underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if a potential underwriter had been the underwriter on any prior equity offering by the issuer. IB (CB) is one if the potential underwriter of the SEO is an investment bank (commercial bank). COVERAGE is one if the potential underwriter had provided an earnings per share estimate for the firm during the year prior to the SEO. ALLSTAR is one if COVERAGE is one and the analyst was ranked as an all-star by Institutional Investor magazine for the year prior to the SEO. RANK1 through RANK20 are 20 dummy variables, one for each potential choice. The issuer characteristics are interacted with the 20 choice-specific dummy variables in order to be included in the model. Estimated coefficients for the choice specific constants and the issuer characteristics are not reported.

	(1)			(2)		
	Coefficient	T-ratio		Coefficient	T-ratio	
TIELOAN	1.945	10.34	***			
TIEPLEND	1.385	6.51	***			
PRIORLEND	0.513	3.29	***			
PRIORUND	2.698	37.46	***			
IB X TIELOAN				2.106	8.54	***
CB X TIELOAN				1.699	6.51	***
IB X TIEPLEND				1.867	5.59	***
CB X TIEPLEND				1.188	4.75	***
IB X PRIORLEND				0.874	4.36	***
CB X PRIORLEND				0.104	0.43	
IB X PRIORUND				2.881	33.60	***
CB X PRIORUND				2.197	15.50	***
IB				-0.176	-1.89	*
COVERAGE	1.601	19.90	***	1.640	20.26	***
ALLSTAR	0.561	4.76	***	0.535	4.52	***
Psuedo R-squared	0.4161			0.4187		
Log Likelihood	3398.72			3383.64		

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

Table 6
Univariate Analysis of Keeping the Same Underwriter in a Subsequent SEO

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

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

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

Table 7

Multivariate Model of Keeping the Same Underwriter in a Subsequent SEO

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

$$U_{kl} = \boldsymbol{a}'\boldsymbol{Y_{kl}} + \boldsymbol{\beta}'\boldsymbol{Z_k} + e_{kl}$$

We specify that $\boldsymbol{Z_k}$ = {LNSIZE, AGE, DE-LTDEBT, SICx}. In column (1), we do not consider differences between investment banks and commercial banks by specifying that $\boldsymbol{Y_{kl}}$ = {TIELOAN, TIEPLEND, PRIORLEND, PRIORUND, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. In column (2), we allow for differences between investment banks and commercial banks by setting $\boldsymbol{Y_{kl}}$ = {IB X TIELOAN, CB X TIELOAN, IB X TIEPLEND, CB X TIEPLEND, IB X PRIORLEND, CB X PRIORLEND, IB X PRIORUND, CB X PRIORUND, IB, CNGCOV, CNGSTAR, CNGRANK, KEEP, SWITCH}. The variables in $\boldsymbol{Z_k}$ are defined as follows: LNSIZE is the logarithm of the original SEO principal amount, expressed in millions of dollars. AGE is the firm's age, measured as the difference between the date of the original SEO and the incorporation date, measured in years. DE-LTDEBT is the long-term debt to common equity ratio in the quarter of the original SEO. SICx are industry dummy variables, which are one if the firm has the corresponding one-digit SIC. The variables in $\boldsymbol{Y_{kl}}$ are: TIELOAN is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the SEO and six months after the SEO *and* the underwriter had never provided a loan to the issuer in the past. TIEPLEND is a dummy variable that equals one if the underwriter provided a loan to the issuer between six months prior to the original SEO and six months after the original SEO *and* the underwriter provided a loan to the issuer prior to six months before the SEO. PRIORLEND is a dummy variable that equals one if a loan between the underwriter and the issuer was originated at any time prior to six months before the SEO *and* the underwriter does not provide a loan to the issuer between six months prior to the SEO and six months after the SEO. PRIORUND is one if the underwriter had been the underwriter on any equity offering by the issuer prior to the original SEO. IB is one if the underwriter of the original SEO is an investment bank. CB is one if the underwriter of the original SEO is a commercial bank. CNGCOV is the difference between the coverage provided by the subsequent underwriter and the original underwriter in the year prior to the subsequent SEO. CNGSTAR is the difference between the all-star coverage provided by the subsequent underwriter and the original underwriter in the year prior to the subsequent SEO. CNGRANK is the difference between the subsequent underwriter's ranking in the year before the subsequent issue date and the original underwriter's ranking in the year before the subsequent issue date. KEEP and SWITCH are choice-specific dummy variables. TIELOAN, PRIORUND, PRIORLEND, and IB are interacted with KEEP and SWITCH in order to be included in the model. LNSIZE, AGE, DE-LTDEBT, and SICx are interacted with REPEAT in order to be included in the model. Estimated coefficients for the industry variables (SICx) are not reported.

	(1)		(2)	
	Coefficient	T-ratio	Coefficient	T-ratio
Variables that affect the choice of "REPEAT" or "NO REPEAT"				
REPEAT X LNSIZE	0.124	2.29 **	0.139	2.55 **
REPEAT X AGE	0.003	1.20	0.002	0.74
REPEAT X DE-LTDEBT	0.010	1.05	0.010	1.08
Variables that affect the choice of "NO REPEAT", "(REPEAT, KEEP)", or "(REPEAT, SWITCH)"				
Tied Lending / No Prior Lending Relationship				
KEEP X TIELOAN	0.434	2.52 **		
KEEP X IB X TIELOAN			0.727	3.70 ***
KEEP X CB X TIELOAN			-0.188	-0.44
SWITCH X TIELOAN	0.095	0.45		
SWITCH X IB X TIELOAN			-0.083	-0.27
SWITCH X CB X TIELOAN			0.478	1.74 *
Tied Lending with Prior Lending Relationship				
KEEP X TIEPLEND	0.380	1.87 *		
KEEP X IB X TIEPLEND			0.071	0.19
KEEP X CB X TIEPLEND			0.603	2.23 **
SWITCH X TIEPLEND	-0.008	-0.03		
SWITCH X IB X TIEPLEND			0.014	0.04
SWITCH X CB X TIEPLEND			0.125	0.36

Table 7 (continued)

	(1)		(2)	
	Coefficient	T-ratio	Coefficient	T-ratio
Prior Lending Relationship / No Tied Lending				
KEEP X PRIORLEND	0.320	1.71 *		
KEEP X IB X PRIORLEND			0.161	0.64
KEEP X CB X PRIORLEND			0.632	2.18 **
SWITCH X PRIORLEND	0.018	0.08		
SWITCH X IB X PRIORLEND			0.053	0.19
SWITCH X CB X PRIORLEND			0.025	0.05
Prior Underwriting Relationship				
KEEP X PRIORUND	0.282	2.77 ***		
KEEP X IB X PRIORUND			0.159	1.31
KEEP X CB X PRIORUND			0.557	2.91 ***
SWITCH X PRIORUND	-0.112	-1.08		
SWITCH X IB X PRIORUND			-0.188	-1.53
SWITCH X CB X PRIORUND			0.072	0.35
Coverage and Reputation				
SWITCH X CNGCOV	0.120	0.62	0.097	0.49
SWITCH X CNGSTAR	0.737	2.36 **	0.704	2.26 **
SWITCH X CNGRANK	0.146	7.72 ***	0.146	7.55 ***
Bank Classification and Constants				
KEEP X IB			0.250	1.38
SWITCH X IB			0.312	1.85 *
KEEP	-1.494	-8.41 ***	-1.730	-7.14 ***
SWITCH	-1.303	-8.32 ***	-1.582	-6.78 ***
IV(REPEAT)	2.490	6.83 ***	2.441	6.68 ***
LR Test of Homoskedasticity [IV(Repeat) = 1]	34.97 ***		32.30 ***	
Log Likelihood	1315.01		1301.27	
T-tests for differences between keeping and switching				
KEEP X TIELOAN – SWITCH X TIELOAN	0.339	1.05		
KEEP X IB X TIELOAN – SWITCH X IB X TIELOAN			0.810	1.92 *
KEEP X CB X TIELOAN – SWITCH X CB X TIELOAN			-0.667	-1.10
KEEP X TIEPLEND – SWITCH X TIEPLEND	0.388	1.00		
KEEP X IB X TIEPLEND – SWITCH X IB X TIEPLEND			0.057	0.09
KEEP X CB X TIEPLEND – SWITCH X CB X TIEPLEND			0.478	0.93
KEEP X PRIORLEND – SWITCH X PRIORLEND	0.303	0.82		
KEEP X IB X PRIORLEND – SWITCH X IB X PRIORLEND			0.108	0.23
KEEP X CB X PRIORLEND – SWITCH X CB X PRIORLEND			0.608	0.97
KEEP X PRIORUND – SWITCH X PRIORUND	0.394	2.21 **		
KEEP X IB X PRIORUND – SWITCH X IB X PRIORUND			0.347	1.62
KEEP X CB X PRIORUND – SWITCH X CB X PRIORUND			0.485	1.44

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

Figure 1
Nesting Structure

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