Do Bank-Firm Relationships affect Bank Competition in the Corporate Bond Underwriting Market?

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Abstract

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Abstract

This paper empirically examines how bank-firm relationships affect post-deregulation competition among underwriters in the U.S. corporate bond underwriting market. I find that there is a trade-off between relationships and price in the demand equation and that this trade-off is sharply higher for junk bond issuers and first-time issuers. This finding is consistent with the certification effect of commercial bank underwriting. Commercial bank entry has increased bank competition to the extent that their client-specific relationships have increased product differentiation in the market. Since issuers with low reputation value the relationships more, the deregulation has increased competition the most in these segments.
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1 Introduction

Following the historic deregulatory trend in the financial industry, commercial banks in the U.S. have re-entered the underwriting markets for corporate stocks and bonds in recent years, to compete with the incumbent investment banks. Prior to deregulation, these underwriting markets were characterized by a small number of banks to perform the bulk of the business and by a high level of transaction fees. Thus the fact that the commercial banks entered the market successfully at all raise the following questions: What is different about these entrant commercial banks that enabled them to enter this seemingly oligopolistic market? And, to the extent that they did, how has their entry changed the competitive structure of this market? These are the questions I investigate in this paper.

There have been a number of academic papers that examine the effect of underwriter type on security pricing in the corporate securities underwriting markets. In this literature, there have been two main empirical findings with respect to the effect of commercial bank underwriting. One is that, ceteris paribus, commercial bank underwriting has had a positive effect on pricing of the underwritten corporate bond issues. ¹ A typical econometric analysis in this body of research involves a regression of pricing of bonds on various bond characteristics plus an indicator variable for the type of underwriter (commercial bank or investment house), and finds this coefficient to be negative in sign.

In another important paper, (Gande, Puri, and Saunders 1999) studies the effect of commercial bank entry and finds that the general fee level went down in this market as the market share of commercial banks went up. It also finds that there are no differences in fees charged by commercial bank and investment house underwriters, i.e. it finds no evidence that commercial bank entrants are either undercutting the incumbent investment houses or charging higher fees to extract rent from issuing firms. The latter finding is based on the econometric analysis where the micro-level transaction fee variable is regressed on various control variables (such as bond characteristics and a trend) and an indicator variable for the

¹See (Kroszner and Rajan 1994), (Puri 1994), (Puri 1996), and (Gande, Puri, Saunders, and Walter 1997).
type of underwriter (commercial bank or investment house). This last coefficient is found to be not significantly different from zero.

These empirical findings are somewhat at odds with implications of the underlying equilibrium model of economic agents with strategic behavior. In a pioneer work that provides a theoretical foundation for the analysis of underwriting markets, (Puri 1999) finds that commercial banks and investment houses will co-exist in the equilibrium if either (1) they fetch the same pricing for the issuers (no differentiation in certification ability), or (2) commercial banks fetch higher pricing for the security, and investment houses discount their fees to the level where issuing firms are indifferent between choosing either type of underwriters (differentiation). Empirical papers on the certification effect document that commercial banks fetch higher pricing from investors on behalf of issuers. Yet, in the empirical paper studying the competition, it finds that commercial banks and investment houses charge the same fees. If commercial banks deliver better quality in the form of higher certification, why would any firms choose investment houses at the same fee level? And to the extent that firms (consumers of the underwriting service) are willing to pay higher fees for higher quality, why would profit-maximizing commercial banks not charge a higher fee?

This paper seeks to reconcile these empirical and theoretical findings by focusing on the issuing firm’s underwriter choice problems and explicitly modeling product differentiation and heterogeneous tastes for certification among issuing firms. Use of demand estimates to infer imperfect competition among sellers of differentiated products has become a standard analytical tool in the empirical industrial organizational literature in the recent years. Surprisingly, this method has not been applied in studies of the financial service industry. This paper conducts the first investigation on the nature of competition among banks in the financial service markets using the differentiated product, imperfect competition model framework.

In this demand analysis framework, a given issuing firm chooses one from multiple underwriting banks, both commercial banks and investment houses, for underwriting service. This approach is useful in directly answering the following questions: (1) For a given fee level, does having a loan relationship increase the likelihood of a commercial bank to be chosen by a given firm? (Or, does presence of a commercial bank with a loan relationship decrease the likelihood of other commercial banks and investment houses to be chosen?) In other words, is there a trade-off between fee and loan relationship, a measure of certification? (2) Is the effect of a loan relationship on choice probability greater when the issuing firm

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(Bresnahan 1989) provides a survey of this literature.
has lesser reputation in the market? In other words, is the fee-relationship tradeoff greater for issuing firms with lesser reputation? Answers for these empirical questions provide an economic explanation for the effect of commercial bank entry in this deregulated market that is consistent with the existing theoretical understanding of the underwriting markets.

In order to estimate this model, I have constructed a data set consisting of 1,536 U.S. domestic corporate bond issues in the period 1993-1997. This data set combines individual issue-level and firm-level data with firm- and bank-specific data on previous loan arrangements. The underwriting fees in this market are quoted individually in each issue, and thus the fees of unchosen underwriters are unobserved and need to be imputed. Exogenous imputation based on observed prices alone will lead to systematic underestimation of imputed prices and will bias the price coefficient accordingly. To address this data issue, I jointly estimate the demand equations and prices using an Expectation-Maximization (EM) algorithm framework.

I find that there is a significant trade-off between fees and loan relationships in the demand model. Moreover, I find that this trade-off is sharply higher for junk-bond issuers and first-time issuers, i.e. firms with lesser reputation of their own in the capital markets. These empirical findings are consistent with a post-entry equilibrium where entrant commercial banks are differentiated from incumbent investment banks in their certification ability which they possess for a subset of the issuing firms (because they have had previous loan relationships with them). In this firm-bank specific differentiated product setting, competitive effect of commercial bank entry is the greatest for segments of issuers with lesser market reputation where these relationships are more likely to be present and also where these relationships are valued more by the issuers. We are less certain about the pro-competition effect of commercial bank entry in the other segments of issuers where certification is valued less. In other words, we still do not understand very well what binds in determining the structure of these segments of the market.

The remainder of the paper is organized as follows. Section 2 reviews related branches of the corporate finance literature. A model of the underwriting service market is described in Section 3. Section 4 explains the empirical specification used to estimate the demand model. Section 5 describes the data and defines the explanatory variables to be included in the estimation, and Section 6 presents the estimation results and discusses analytical interpretations of these demand and price estimates. Section 7 concludes.
2 Prior and Related Literature

In the first subsection I discuss related works in the corporate finance literature. In the second subsection I discuss the previous research on underwriter competition.

2.1 Related Literature in Corporate Finance

2.1.1 The Informational Roles of Commercial Banks

The theory of financial intermediation has stressed the unique informational function of commercial banks. A number of papers argue that banks have scale economies and comparative cost advantages over other lenders (including individual bondholders) in producing information about the borrowers.\(^3\) Other papers attribute the monitoring ability of banks to their incentive to build their own reputations as lenders. For example, (Chemmanur and Fulghieri 1994) model a firm’s choice between bank loans and bonds, allowing for debt renegotiation in the event of financial distress. The main implication of the model is that the desire of the banks to acquire a reputation for making the “right” renegotiation versus liquidation decisions gives them an endogenous incentive to devote more resources towards evaluating a firm’s value than bondholders. These papers suggest that commercial banks have closer, longer-term, and more exclusive relationships with their borrowers than other types of lenders. These views support the use of pre-existing relationship variables in my model as a measure of effectiveness in information production as underwriters. In a related empirical study, (Datta, Iskandar-Datta, and Patel 1999) find that the existence of bank debt (with any bank and not necessarily with the underwriting bank) lowers the at-issue yield for first public straight bond offers.

2.1.2 The Firm’s Debt Choice Model Based on Its Reputation

(Diamond 1991) uses the borrowing firm’s reputation in explaining the choice between bank loans and bonds. The main result of the paper is that firm reputation and bank monitoring (of the firm’s investment decisions) are substitutes. The intuition for this result is as follows: Young firms and old firms without reputations tend to rely more on bank loans, because they do not have reputations to lose and therefore bank monitoring is needed to enforce efficient investment decisions. Large established firms with good reputations, on the other hand, do

\(^3\)(Leland and Pyle 1977), (Diamond 1984), (Fama 1985).
have a reputation to lose and therefore have sufficient incentive to choose efficient investment decisions. Since bank monitoring is costly, this class of firms prefers to issue bonds.

The paper also implies that there is an intertemporal linkage between bank loans today and the firm’s decision to issue bonds in the future: “A borrower’s credit record acquired when monitored by a bank serves to predict future actions of the borrower when not monitored” (p.690). This suggests that the monitoring of firms by commercial banks in the loan market can become an asset in another market, i.e., when such banks become underwriters in the bond market.

2.2 Prior Research on Commercial Bank Underwriting

Several papers \(^4\) analyze the implications of commercial bank underwriting using game-theoretic models. They demonstrate that even with the assumption of rational investors, a potential social cost to the combining of investment banking and commercial banking cannot be ruled out. The existence and magnitude of the conflict of interest problem in these models depends on the cost of information production by the two types of banks, the timing of their access to a firm’s private information, investors’ beliefs about the quality of the firms underwritten by commercial banks, etc. Since these variables are not directly measurable, empirical studies on the subject have taken the route of measuring the association between pricing of the bond and the instance of commercial bank underwriting. \(^5\) They conclude that generally there is no detectable conflict of interest in the data \(^6\) and in some cases there is a net certification effect. (Gande, Puri, and Saunders 1999) measure the association between the commercial bank entry and change in underwriting fees and ex ante yield of the bonds and conclude that the deregulation has enhanced competition in the market in the short-run. In contrast, I examine underwriter competition by estimating how issuers choose underwriters in the framework of the empirical methods developed in the industrial organization literature. This approach is aimed at providing the missing piece, i.e. the issuer-side economic analysis of this market and thus complementing the prior research.

\(^5\)See (Ang and Richardson 1994), (Kroszner and Rajan 1994), and (Puri 1994) for default rate studies using pre-Glass-Steagall historical data. See (Puri 1996), (Gande, Puri, Saunders, and Walter 1997), and (Hamao and Hoshi 1999) for studies on ex ante yield.
\(^6\)One exception is (Hamao and Hoshi 1999), which examine the Japanese market and conclude there might be a conflict of interest.
3 The Underwriting Service Market

When a firm decides to issue a bond, it hires an underwriting bank to market, price and distribute the security. For a relatively small offering and/or if the firm is a frequent issuer, the issuer typically calls up a number of potential underwriting banks and obtains individual quotations from them. For a large issue and/or if the firm issues infrequently, it is more likely that a “beauty contest” takes place. In such cases the issuing firm invites a certain number of potential underwriting banks to make detailed proposals in formal presentations. After being presented with these multiple proposals, the firm then decides which bank will underwrite its bond.

To examine how the banks compete in this market, we need to first understand the nature of the product that is bought and sold. Security underwriting is a financial service. By hiring an underwriting bank, the issuing firm effectively buys an insurance for unsold securities, and pays for utilizing the bank’s capability for documentation, marketing, pricing, and sales of the security.

How do banks price this mix of services? Do prices vary across transactions, and do they vary across banks in a given transaction? The price variation across transactions is easily observed, and is strikingly high, especially compared to the oft-discussed “7 % fix” in the equity IPO market. (See Figure 1). What accounts for these variations in fees?

For the underwriting bank underlying a given firm, it is predicted that the costs of providing these two services are both negatively correlated with the reputation of the issuing firm. For example, if the issuer is a “hot”, well-regarded name in the market, not only is the probability of unsold securities very low, but the physical cost of marketing and selling the security is also fairly low. In contrast, it is more expensive both to insure (against unsold securities) and to market and distribute an obscure, less well-known issuer’s bond. Investors need to be educated and persuaded harder to purchase the bond (even after controlling for higher yield of the bond), which requires that the bank’s sales force also needs to be educated. Thus the first implication of the analysis is that the reputation characteristics of the issuing firms and bonds are factored into the price of underwriting services. Credit ratings and previous issue experience of the firms are examples of such characteristics.

Similarly, cost of underwriting is likely to be associated with some features of the

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7I am abstracting away from the syndicate structure here for expositional clarity. The syndicate structure will be discussed in Section 5.

8See (Chen and Ritter 2000) and (Hansen 2001).
bonds, such as the maturities and the shelf registration status. Long-maturity bonds are less liquid and the prices are more volatile over course of the maturity of the bond, so the fees are expected to be higher the longer the maturity of the bond is. Shelf registration (e.g. Medium-Term Notes Programs), on the other hand, simplifies the issuance procedures and allows for flexible timing of issuance, and is therefore expected to lower the fee.

Second, these two services share a common cost component, that is, the cost of assessing the issuer’s creditworthiness and certifying the findings to the investors. I refer to this assessment and certification aspect of the underwriting service as information production. When certain banks are perceived by investors as more effective in information production, they can build up demand faster for the securities they sell and thus will face lower risk of unsold securities and lower marginal cost of marketing and sales as well. Therefore, if there is heterogeneity among banks in their information production effectiveness, they face different profit functions even after controlling for the issuer and bond characteristics, which leads to a prediction that prices vary across banks for a given firm as well.

Issuing firms may prefer banks with superior information production effectiveness for two reasons. First, since unsold securities or otherwise failed transactions are likely to hurt their reputation in the capital markets for future transactions, they value informational effectiveness of underwriting banks to lower the risk. Second, the superior effectiveness of banks in building up demand for the security may indicate that they can negotiate a lower yield for the bond than other underwriting banks can. So the product in this market is expected to be differentiated mainly along two dimensions—price and information production effectiveness.

One way in which banks come to possess more effective information production technology is by having built relationships with the firms. Having already networked and established communication channels with an issuer increases a bank’s effectiveness in producing information about that particular issuer. As reviewed in Section 2, the financial intermediation literature provides explanations for why commercial banks may play a unique informational role with respect to the firms to which they lend. The effect of this relationship on the underwriter demand may be positive or negative or zero, depending on the issuing firms’ valuation of the relationships. As with prices, there are variations in these relationships both across issuers and across banks. Because these entrant banks have had pre-existing relationships with some of the issuers built through their loan business prior to the deregulation, I treat these relationships as predetermined and exogenous to the competi-

\footnote{(Leland and Pyle 1977), (Diamond 1984), (James 1987), (Rajan 1992a).}
tion in the underwriting market, and use the variation in price and relationship to estimate a model of underwriting demand.

The price competition literature has used estimates of the demand function to quantify the ability of sellers (banks in this paper) to set prices in product differentiated industries. The first-order condition of a bank’s profit maximization problem gives the basis for using own-price elasticities to estimate the mark-ups that sellers charge. If there is a high trade-off between relationships and price in the demand equation, that implies low price elasticities for firms with relationships and thus high market power.

Lastly, the analysis of price determination and demand behavior yields another prediction that this trade-off between price and relationship varies with reputation of the firm. Firms with low reputation stand to have the most gain from choosing an underwriting bank whose effective information production capability can certify them. For firms with high reputation, on the other hand, the information production capability of banks is largely redundant, since their security can sell easily in the market regardless of who the underwriter is. In other words, it is predicted that there is a higher trade-off between relationship and price for firms with lower reputation to the extent that pre-existing relationships make commercial banks more effective information producers. If true, this indicates that not only are the pre-existing relationships a source of market power for the entrant commercial banks, but their significance is inversely related to the reputation of issuing firms.

So to summarize, I investigate the following research questions:
(1) Do issuing firms value the effectiveness of banks with relationships to produce information about the issuers for investors?
(2) If the answer to question 1 is yes, then how much are the issuers willing to trade off price for the value of the relationship?
(3) Does this trade-off vary across the reputation characteristics of the issuing firms?
(4) How do the abilities of banks to set prices differ between the entrant commercial banks and incumbent investment banks, and how do they vary across the reputation characteristics of the issuers?
4 Underwriter Choice Model

4.1 Underlying Demand Model

The central component of my analysis is a discrete choice model of a firm’s underwriter demand. The approach taken here is transaction-based, rather than capital stock-based. This is similar to the pecking-order financing model \(^\text{10}\) and is consistent with the premises of other debt choice models as well.

Firms are assumed to maximize an indirect value function of the form

\[ V_{ij} = \bar{V}_{ij} + \epsilon_{ij} \]  \hspace{1cm} (1)

where the banks are numbered \(1..J\), indexed by \(j\) and the firms are numbered \(1..N\), indexed by \(i\). \(^\text{11}\) \(\bar{V}_{ij}\), the predetermined component of the value function, is assumed to depend on product characteristics \(x_{ij}\) and price \(p_{ij}\). \(^\text{12}\) Thus

\[ V_{ij} = x_{ij}\beta - \alpha p_{ij} + \epsilon_{ij} \]  \hspace{1cm} (2)

4.2 Modeling Issues

When the error term \(\epsilon_{ij}\) is assumed to be homoskedastic with the above model specification, this leads to a problem of unreasonable substitution patterns between alternative choices.

\(^{10}\)In this well-known partial equilibrium model of the firm’s financing behavior, the firm optimizes with respect to each financial transaction, taking its need for external finance as given. See (MacKie-Mason 1990); (Helwege and Liang 1996) for use of similar discrete-choice models.

\(^{11}\)There is no outside good in the model in this paper. The chief reason for this is that it is not obvious what the market \(M\) —appropriate pool of firms—is. It is not readily observed and needs to be estimated. (Berry 1994) gives a discussion of how this is a commonly found problem in industry studies, with no clear-cut solutions. Since the results of this paper suggest that commercial bank entry potentially induced shift away from loan markets to bond markets by junk-bond issuers and new issuers, explicitly modeling outside good would be a valuable extension, but I did not try to take on additional task in this particular paper.

\(^{12}\)The fact that these variables are indexed by \(i\) as well as by \(j\) is a unique feature of this market. This is because the underwriting service, the good in this market, has an underlying product, the bond, which varies with both the choices (e.g. maturity) and the attributes (e.g. credit rating) of issuers. See the data section for more discussion of this.
The result is that cross-elasticities depend only on mean utility levels in the model for iid consumer tastes. \(^{13}\)

4.2.1 Empirical Approach—market share model or micro-level model?

There have been two proposed solutions to this modeling problem. One is the so-called BLP approach, after (Berry, Levinsohn, and Pakes 1995). In BLP, taste coefficients on product characteristics are assumed to be random—this amounts to the error term being heteroskedastic. It is assumed that the econometrician may not observe the decisions of individual consumers. Instead, product market shares are derived as the aggregate outcome of consumer decisions, and instrumental variable (IV) estimation is then applied to this market share equations. Presence of unobserved product characteristics is key to the interpretation of error terms in this approach.

In contrast, many studies using micro-level data (with observations of individual purchase decisions) have solved the above problem by interacting the product characteristics with consumer characteristics. Differences between consumers will then have a systematic effect on their preferences, while the taste coefficients are treated as non-random.

The question is: Which approach should be taken in investigating this market? The key variable in this paper—the bank- and firm-specific relationship variable, \(x_{ij}\), cannot enter the product-level demand equation a-la-BLP, because it not only varies across banks but also across firms, by definition. Even if it is possible to somehow use summary statistics of the empirical distribution of this "product attributes" at product-level equations, it is a less appealing approach for the purpose of this paper than using the variable directly in the micro-data analysis. In contrast, by interacting this variable with issuer attributes, I can naturally implement the remedy suggested in the second approach. So the nature of this variable made the latter approach a more appealing modeling choice.

4.2.2 Nested-Logit

While logit error specification is a computationally convenient choice for estimating discrete choice models, the literature has pointed out the unattractive substitution property of logit models. Nested-logit model improves upon it by relaxing this feature. The relaxation of the Independence of Irrelevant Alternatives (IIA) property translates into more reasonable sub-

\(^{13}\)See (Berry 1994).
stitution patterns for nested-logit models as compared to simple logit models. Following this, and the previous discussion of the relationship variable \( x_{ij} \), the indirect value function for firm \( i \) choosing bank \( j \) which belongs to upper nest \( m \) (see Figure 2) is now given by:

\[
V_{i,(m,j)} = [d_j^T \mu + \alpha_p x_{i,j} + \beta x_{i,j}] + w_i^T \delta_m + \epsilon_{i,(m,j)} \tag{3}
\]

\( p_{i,j} \) is the underwriting fee charged by the bank
\( x_{i,j} \) is a prior loan relationship variable
\( d_j \) is a bank dummy vector
\( w_i \) are the bond/issuer characteristics
\( \epsilon_{i,(m,j)} \) is the idiosyncratic firm-bank error

### 4.2.3 Interaction of Product Characteristics with Consumer Characteristics

Furthermore, as suggested above, I interact observed characteristics of consumers with product characteristics. This further avoids the problem of unreasonable substitution pattern because differences between consumers have a systematic effect on their preferences. In particular, I interact the reputation characteristics of issuers with the relationship variable and prices. The indirect value function for firm \( i \) choosing bank \( j \) which belongs to upper nest \( m \) is now given by:

\[
V_{i,(m,j)} = \sum_r Y_r [d_j^T \mu + \alpha_r p_{i,j} + \beta_r x_{i,j}] + w_i^T \delta_m + \epsilon_{i,(m,j)} \tag{4}
\]

\( Y_{i,r} \) is an indicator variable for the reputation characteristics of the issuer

Assume that the error term \( \epsilon \) follows the Generalized Extreme-Value (GEV) distribution. McFadden (1978 and 1981) showed that the assumption of the GEV distribution implies

- The lower-nest choice probability:

\[
\Pr(j|m, Y_{i,r}) = \frac{e^{d_j^T \mu + \alpha_r p_{i,j} + \beta_r x_{i,j}}}{\sum_{k=1}^\kappa e^{d_k^T \mu + \alpha_r p_{i,k} + \beta_r x_{i,k}}} \tag{5}
\]

\(^{14}\text{See (Maddala 1983)}\)
The upper-nest choice probability:

\[
Pr(m) = \frac{e^{w_m^T \delta_m + \lambda I_{i,m}}}{\sum_t e^{w_t^T \delta_t + \lambda I_{i,t}}}
\]

where \( I_{i,t} = \log(\sum_{t \in L_t} e^{d_t^T \mu + \alpha p_{i,t} + \beta x_{i,t}}) \)

The inclusive value \( I_{i,t} \) measures the expected aggregate value of subset \( t \) and the coefficient \( \lambda \) reflects the dissimilarity of alternatives within a specific subset.

### 4.3 Data Issues

In calculating transaction prices for each bond issue, I use multi-variate imputations by various bond and issuer characteristics (e.g. maturity, Medium-Term Notes (MTN) status, etc.), by which the underwriting fees are known to vary. More discussions of these characteristics are given in the data section. The price is assumed to be exogenous in the model because essentially, a single firm (consumer in this market) is assumed to be too insignificant to affect the average price. \(^{15}\) This follows the practice of micro-data studies of other industries. \(^{16}\)

In particular, I impute the prices as follows:

\[
p_{i,j} = z_{i} T_{j}^{1} + z_{i,j} T_{j}^{2} + \delta_{i,j}
\]

where \( \delta_{i,j} \sim N(0, \sigma^2) \) iid. \( z_{i} \) and \( z_{i,j} \) are various firm and bond characteristics (See Section 5.4 for discussions of individual variables.)

\(^{15}\)I control for correlation of prices with quality variables that are not included in the demand equations by using the same product categories for prices of alternative banks in each observation. In other words, if a given observation is a short-maturity, investment grade, first-time issue without MTN registration, I use the imputed prices for that product category for all banks. Again this is a unique feature of this market that consumer characteristics (e.g. credit rating of the issuer) make up the product characteristics. In other words, in studying this market, we cannot make the usual operating assumption that product mix by a given seller (banks in our market) is fixed in the short-run. This is true of many service markets, in contrast with manufacturing industries like automobiles.

\(^{16}\)For example, (Goldberg 1995).
4.3.1 Choice bias

A data issue arises in studying this market because prices vary across both issuers and banks, but only one price per issue, that is, the price offered by the bank which is hired to underwrite the bond, is observed. Though the price is assumed to be exogenous in the model, the observations I have on price to compute the average prices are not a random subset, but the prices that are charged when they are chosen. To illustrate how not treating this feature of the data will lead to biased estimates of prices, let $c_i$ represent the index of the bank chosen by firm $i$. Since price enters the value function of the issuing firm negatively, the fact that a given bank was chosen over other banks in the choice set implies that these observed prices, $(p_{i,j}; j = c_i)$, are on average lower than the unconditional distribution of $p_{i,j}$. As a result, if we impute unobserved prices by obtaining estimates of $\gamma$ from Equation 8 using observed prices as dependent variables, we will be systematically underestimating unobserved prices and biasing the price coefficient $\alpha$ toward zero, or even positive.

4.3.2 Remedy: Expectation-Maximization algorithm

To correct for the bias using this information (on their choice), it was advantageous to compute them iteratively and jointly with the demand model. I use Expectation-Maximization Algorithm, which provides an appealing framework for this task. The main idea is to estimate price estimates $\gamma, \sigma$ and demand estimates $\alpha, \beta, \mu$ jointly in an iterative algorithm where price imputation is done conditional on the information on $c_i, i = 1..N$. The main appeal of using this framework for my data problem is that it provides an iterative procedure where, if not for the systematic absence of some data, the Maximum Likelihood estimation is straightforward. The demand estimates obtained from this estimation method are then used to estimate the upper level of the nested-logit model. Details of this method are found in the Appendix.

4.4 Research Hypotheses Revisited

The empirical demand model as specified above corresponds to my research questions as follows:

(1) Do issuing firms value the effectiveness of banks with relationships to produce information about the issuers for investors? This is captured by coefficient $\beta$ in Equation 5.

\footnote{See (Dempster, Laird, and Rubin 1977); and (McLachlan and Krishnan 1997).}
(2) How much are the issuers willing to trade off price for the value of the relationship? This is measured by the ratio of the coefficient $\frac{\beta}{\alpha}$.

(3) Does this trade-off vary across the reputation characteristics of the issuing firms? This hypothesis is tested by interacting the demand function with the reputation characteristics of the issuers, thus allowing the valuations of relationships and price to vary across these characteristics.

(4) How do the abilities of banks to set prices differ between the entrant commercial banks and incumbent investment banks, and how do they vary across the reputation characteristics of the issuers? This is measured by calculating own-price elasticities of individual banks from the demand estimates.

5 The Data

5.1 Data Sources

I construct the dataset using two data sources. One is U.S. Domestic New Issues Database by Thomson Financial Securities Data which compiles new issues information from company filings, press releases, and news sources. The other is the Loanware Database compiled by Euromoney, which is a global database on syndicated loan markets that contains U.S. domestic syndicated loan transactions as well as non-syndicated, single-bank transactions. A full list of variables used in the estimation is provided in the Appendix.

5.2 Data Selection

I choose the sample period to be from January 1, 1993 to August 31, 1997—for roughly 4 2/3 years. The criteria I used are as follows. First, the sample should begin after January 1989, when the first commercial bank underwriting of a public corporate bond took place. Second, the economic and regulatory environment surrounding the underwriters and issuers should also remain relatively stable. The decision to omit data after August 1997 is primarily due to the merger in September 1997 of Salomon Brothers and Smith Barney, as a result of the acquisition of Salomon by Travelers, Smith Barney’s parent company. Both Salomon and Smith Barney were leading investment banks in the U.S. corporate bond underwriting market at the time of the merger. It is of course quite infeasible to omit all mergers and acquisitions activities involving underwriters from any reasonably long sample period. In the
wake of financial globalization, there have been a flurry of cross-border and cross-industry mergers between major players. A few examples include the Paine Webber Group’s purchase of Kidder, Peabody & Co. in Oct. 1994, and Swiss Bank Corp.’s double acquisitions of the investment-banking unit of S.G. Warburg in May 1995 and of Dillon, Read & Co. in May 1997. However, none of these earlier M&A events involved two firms ranked in the top ten of the corporate bond underwriting market. Rather, they are characterized as acquisitions of veteran Wall Street players by commercial banks just entering the underwriting market, so one can argue that ownership changes of these firms had no substantial impact on the competitive environment in the underwriting market. In contrast, the Salomon-Smith Barney merger represented the first merger of two existing major investment banks, thus affecting the overall market structure.

I exclude financial firms (one-digit SIC code 6) and regulated industries (one-digit SIC code 4) from my study. I also concentrate on the top sixteen underwriters of fixed-rate, non-convertible corporate debt. Fixed-rate debt comprises about 90% of all non-convertible issues. Moreover, I find that both the composition and the sum of market shares of top underwriters are virtually uniform between fixed-rate and other coupon-type bonds. For my sample, five of the sixteen underwriters are Section 20 subsidiaries of bank holding companies, namely J.P. Morgan, Chase Manhattan Bank, Bankers Trust, Citicorp, and Nations Bank. Using the above criteria results in a sample of 1,536 non-convertible, fixed-rate corporate bond issues.

5.3 Variables in the Demand Equation

5.3.1 The Price Variable

The price variable (PRICE) used in the estimation is a gross spread expressed as a percentage of the size of the bond. The gross spread is the fee that underwriters receive, or the difference between the price at which securities are sold to investors and the price paid by the underwriters to the issuing firm. A typical public bond offering consists of multiple

---

18 The rankings were based on the dollar value of underwritings and gave full credit to the book-runner(s).
19 The name is derived from Section 20 of the Glass-Steagall Act, which prohibits member banks in the Federal Reserve System to be affiliated with firms which are engaged “principally” in the securities business. These subsidiaries were permitted to enter the investment banking business by meeting various requirements, such as a ceiling on their security-related revenues.
underwriters forming a selling syndicate. As shown in Figure 3, one underwriter serves as the book-runner (or the lead-manager) who organizes and manages the deal. I identified the book-runner (or the lead-manager) as the underwriter of a given issue. Given the syndicate and fee structure as illustrated below and shown in Figure 3, this seems to be a reasonable assumption. This rule is also consistent with the perception of practitioners who advertise their bank’s market position in terms of “book-runner ranking”.

5.3.2 The Loan Variable

I constructed dummy variables LOAN1-LOAN16 (for 16 underwriting banks in the sample) using transactions data from the Loanware database. A loan agreement frequently (but not always) consists of participation by a number of banks in a way that is analogous to the structure of a selling syndicate in a public bond offering. I use arrangership of loan agreements rather than capital participation in a loan as an indication of a “prior banking relationship”. I chose this definition of a relationship variable given the well-known fact that a top banker position earns a bank a disproportionate share of the profit.

These variables capture the presence of pre-existing loan relationships between a given firm and individual commercial banks that were established prior to the entry of the banks into the underwriting market (see Appendix A for the exact variable definitions). I treat these relationships as predetermined and exogenous to the competition in the underwriting market.

On rare occasions, some top-tier investment banks also act as arrangers of syndicated loans. This variable needs to be interpreted differently from an arrangership of syndicated loans by commercial banks, because investment banks do not participate in the syndicate as creditors, whereas a commercial bank arranger is usually the top lender in the syndicate as well (this is another justification for using an arrangership as a measure of a relationship). My

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20 In a small number of cases where there were two co-book-runners, each was counted separately as if they underwrote separate issues.

21 Alternatively, we can use a concave functional form such as the log function to capture the diminishing returns to relationship as they go down in rankings. I did not do this here because I did not have data on actual take-downs of these loans by individual banks. Instead I had data on the initial loan arrangements and identity of banks acting as arrangers. I run the estimation with alternative variable specifications using the more comprehensive Japanese data in (Yasuda 2001), and find that results are robust to various variable specifications.
interpretation is that this variable for investment banks is potentially an indirect measure of their closeness to the issuer through their investment banking activities, of which loan syndication is a relatively small but recently growing part. But it is also plausible that they are being chosen as arrangers only because they know other banks well instead of being committed to knowing the borrowing firm. If the latter factor dominates the former, the LOAN variable for investment banks should not be significant in the demand model.

5.4 Variables in the Price Equation

As discussed in Section 1, underwriting fees are determined in part by various costs, including distribution costs, the expected cost of taking market and reputation risks, and information production costs. I estimate my model using various specifications for the price equations. The basic variables that I include in all specifications are a constant term, CREDIT (a dummy variable for a junk-bond category), and some maturity variables that are non-linear in the year of maturity. Being in the junk-bond category means issuers have less financial strength and in general are lower reputation than those in the non-junk bond category. This increases the risk-related cost for the underwriter. It might also mean that it is more costly to distribute these bonds because the company is less well-known and investors need to be marketed more intensively (which also feeds back to create potentially greater market risk). For similar reasons, investors require substantially higher yields for junk bonds.

In general, underwriters also demand higher underwriting fees for longer maturity bonds. This makes sense to the extent that a normal yield curve is also upward sloping; in addition, the secondary market for 30-year corporate bonds is much less liquid than for 30-year treasury bonds. This is measured by including some non-linear functions (dummy variables, log, etc.) of maturity in years.

In some specifications, I also include a variable that represents the previous issue experience of firms in the bond market. From the underwriter’s point of view, frequent issuers are easier to market than first-time or infrequent issuers. They are also less likely to lead to failed transactions because the track record of previous issues gives a reputation to the name of the issuer. Thus the price is expected to be decreasing in this variable. Another indicator of frequency of issues is whether the bond was issued under shelf registration or the Medium-Term Notes (MTN) program. Registering for this program simplifies the filing process and reduces the legal and accounting costs of incremental issues. I used the sample of observed (and thus chosen) prices to check whether these variables affect the price in the
predicted direction, and in fact they do.  

5.5 Descriptive Statistics of the Sample

The tables presented here give descriptive statistics for the sample used in the estimation. In all of these tables, the first two columns segment the data according to whether the underwriter was a commercial bank or an investment bank.

In Table 1 the sample is tabulated by issue size, maturity, and credit rating. Several observations can be made. First, bank-underwritten issues are relatively small compared to investment bank-underwritten issues. Their maturity also tends to be slightly shorter, but no better or worse in terms of credit ratings. There are a few plausible reasons for this. For example, if a smaller, younger firm is more likely to choose the commercial bank with which it had built close ties, the issue size might be proxying for characteristics of that firm. Or if commercial banks have a smaller distribution capability relative to investment banks, the issue size might then be reflecting the supply-side constraint.

In Table 2, the sample is tabulated first by previous issue experience and then by the issuer’s SIC code. Commercial bank issues are relatively more frequent among first-time issuers. This observation is consistent with the first explanation given above for the size difference. In contrast, there is little difference between bank and investment bank subsamples in terms of the distribution of issuers across different industries (Table 3).

6 Estimation Results

6.1 Basic Model

The estimation results of the basic model are presented in Table 4.  

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22 I used these OLS estimates as starting values for price equation parameters in the estimation. Coefficients have the predicted signs and are significant.

23 For this and all other model specifications, the nested-logit demand model was estimated using a sequential estimation method consisting of two successive logit steps. The standard errors in the second stage were calculated using the formula given in (McFadden 1981).
The price coefficient $\alpha$ is negative and significant, whereas the relationship coefficient $\beta$ is positive and significant. Thus both price and prior loan relationships are significant determinants of demand in the underwriting market. The dissimilarity coefficient of the nested-logit model ($\lambda$) is 0.8317, which is not significantly different from one at the 5% significant level by the Wald test. It is significantly different from zero. $\lambda = 1$ statistically implies that the nesting as specified in Figure 2 is redundant. Besides the inclusive value variables, I also include issuer and bond characteristics in the upper nest. Since these are chooser-specific variables, parameters are estimated separately for each choice. However, the coefficients for one choice (in this case investment banks) are normalized to zero, so the reported coefficients are for the choice of commercial banks.

The estimates of equations determining prices, $\gamma$, are reported for each bank. Commercial banks and investment banks are listed separately, and within each category the banks are listed in the order of their market shares in the sample. Bank1 is therefore the top-ranking commercial bank underwriter, whereas Bank6 is the top-ranking investment bank underwriter and is the top-ranking bank overall. Coefficients for the maturity and junk bond variables are mostly positive, whereas those for the past issue experience and shelf-registration variables are mostly negative. These findings are consistent with the analysis of price determination in Section 3 and with the discussions of variables entering pricing equations in Section 5.

Of these four reputation characteristics of issuers/bonds, the coefficients for junk bond variables are much larger in absolute values than others. JUNK BOND and MTN are indicator variables, and the sample mean of variables for maturity and past issue experience are 2.338 and 1.118, respectively. Thus the effect of being in the junk bond category on price dominates the other categories. This coefficient also tends to be smaller for top-ranking banks.

Some of the coefficients also vary significantly across banks within a given category. For example, Bank1 and Bank2 have a differential of almost 0.8 for the junk bond variable. As JUNK BOND is an indicator variable, this translates to a price differential of 0.801 expressed in percentage of the issue amount, or, evaluated at the mean issue size of $180 million, approximately $1.44 million. The difference between Bank3 and Bank8 for the maturity variable is similarly large, at 0.3237. The sample mean value for the maturity variable is 2.338, so this translates to about $1.36 million. The coefficients for pre-existing loan relationship variables are mixed in sign and vary widely in magnitudes as well.
6.2 Junk vs. Non-Junk Model

Table 5 reports the estimation results of one of the interacted models where price and relationship coefficients are allowed to vary across the reputation characteristics of issuers, namely, credit rating. The criterion I use is whether the issuer’s credit rating is in the junk-bond category at the time of the issuance. Being in the junk-bond category means issuers have less financial strength and in general lower reputation than those in the non-junk bond category. The price coefficient $\alpha_1$ for non-junk (i.e. “high quality”) issuers is sharply more negative at -2.599, whereas the price coefficient for junk-bond issuers (“low quality”) is negative but a lot smaller in magnitude at -0.425. The loan coefficients $\beta_r$ are both positive as predicted, though essentially equal in size.

The dissimilarity coefficient $\lambda$ is again not significantly different from one. $\delta_1$ is positive, indicating that first-time issuers are more likely to choose a commercial bank than seasoned issuers. $\delta_2$ is negative. If the issue amount is proxying for the size of the firm, this suggests that smaller firms are more likely to choose a commercial bank underwriter than larger firms.

The price estimates presented in Table 5 are qualitatively similar to those in the base model in Table 4. The quantitative changes in estimates from the base model to interacted model, however, are concentrated in the commercial bank category and Bank11. Bank11 is not a high-ranking bank overall, but is the top-ranking underwriting bank in the junk bond category. Thus we can see that allowing for variation in the demanders’ trade-off between relationship and price in the model specifications affect the price estimates of certain banks more than others.

6.3 First-Time vs. Seasoned Model

In Table 6, I report the estimation results of another interaction model, where the trade-off between price and relationship in the demand equation is allowed to vary along newness of

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$^{24}$I also ran a different specification of the upper nest where there are two separate nests for banks with and without pre-existing loan relationships. While the coefficient for FST\_TIME for banks with pre-existing relationships is significantly positive and even larger than the coefficient in the basic model, the coefficient for FST\_TIME for banks without relationships is negative. This indicates that the first-time issuers are more likely to choose commercial banks over investment banks despite the formers’ recent entry into the market, but only if they have had pre-existing relationships with these banks.
the issuers in the corporate bond market. Investors are less likely to be familiar with or even recognize the name of first-time issuers in the market, so these firms are worse off than seasoned issuers in terms of their market reputation. Seasoned issuers, on the other hand, have a track record of issuing public debt, which contributes positively to their reputation. The price coefficient $\alpha_1$ for non-first-time (i.e. “high reputation”) issuers is negative at -1.418, whereas the price coefficient $\alpha_2$ for first-time issuers (“low reputation”) is negative at -0.661, less than half in size. The loan coefficients $\beta_1$ and $\beta_2$ are both positive as predicted, with $\beta_2$ being about 50% larger. Both results are consistent with the prediction of the model.

The size of the dissimilarity coefficient $\lambda$ is close to 1, as in the two previous specifications. Price estimates are also qualitatively similar to the other specifications.

6.4 The Economic Implications of Estimation Results

The demand estimates presented in Table 4–6 are consistent with the predictions of the model. Both relationships and price are significant determinants of underwriter demand in the market. The trade-off between relationships and price indicates that issuers are willing to pay higher price for underwriting services from banks with pre-existing relationships. The trade-off is quantified by the ratio of the two coefficients, $\frac{\beta}{\alpha}$.

In the base model reported in Table 4, this ratio is -0.805. Since price is expressed as a percentage and the relationship is an indicator variable, this ratio has a unit of 0.805%. In terms of the underlying demand model, a bank with a relationship can charge a premium of up to 0.805% before an issuer prefers a bank without a relationship (holding all else constant). Evaluated at the sample mean issue size of about $180 million, this translates to about $1.45 million in dollar value. Since the level of the underwriting fee paid by the issuers in the sample ranges anywhere from $200,000 to several million dollars, the value of a relationship implied by the results is quite substantial, and at the same time reasonable.

In Table 5 where this trade-off is allowed to differ between non-junk bond and junk bond issuers, the ratios $\frac{\beta}{\alpha}$ are -0.501 and -3.051 for high- and low-quality issuers, respectively. Evaluated again at the mean issue size of $180 million, the valuation of pre-existing relationships for two classes of issuers are approximately $900,000 and $5.5 million, respectively. The 0.501% for high-quality issuers roughly matches the mean of the underwriting fee in that category, whereas 3.051% is on the high end of the range of underwriting fees paid by junk bond issuers. The large difference in the values of $\frac{\beta}{\alpha}$ confirms the prediction that there is an inverse relationship between the reputation of issuing firms and their valuation of the
ability of underwriting banks to certify them for investors.

Similar implications are obtained from results reported in Table 6, with the ratios $\frac{q}{a}$ being -0.518 and -0.991 for non-first-time and first-time issuers, respectively. Evaluated at the mean issue size of $180 million, the valuation of pre-existing relationships for these two classes of issuers are approximately $900,000 and $1.8 million, respectively.

### 6.4.1 Price Elasticities

The higher trade-offs for low-reputation firms suggest that banks derive greater market power from these pre-existing relationships when providing services to low-reputation firms. To quantify this economic implication, I calculated the own-price elasticities of individual banks from the demand estimates. Table 7 reports the results of calculations based on the estimates reported in Table 5. In the first column I report the mean own-price elasticities of sixteen individual banks where all observations were used for calculations. On average the entrant commercial banks face a higher price elasticity of -1.780 compared to the investment bank average of -1.557, indicating less market power than the incumbents. When calculations are done separately for non-junk and junk bond issuers, however, a more subtle picture of competition emerges.

First, the price elasticities that banks face when supplying underwriting services to junk bond issuers are sharply lower, roughly half of the elasticities for non-junk bond issuers. Second, comparing the means of two peer groups, I find that the price elasticities that commercial banks face with respect to junk bond issuers are as low as those of investment banks (-0.944 and -0.953, respectively), whereas the entrants face higher price elasticities relative to incumbents, -2.148 compared to -1.823, when facing non-junk bond issuers. Therefore, the pre-existing relationships with low-reputation firms are a significant source of market power for the entrant commercial banks. Despite their recent entry into the market, the commercial banks are on a par with the incumbent investment banks when selling their services to low-reputation issuers. In Table 8, I calculate a percentage change in own total demand from 1% increase in price across the sample. The results and implications are qualitatively quite similar to Table 7.

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25Since $\lambda$ was not significantly different from one, the elasticities were calculated with only the lower-est results. So these calculations are essentially based on a logit model specification.
6.4.2 Discussion

It is also notable that there is a significant variety in the banks’ ability to set their price within each group. There seem to be two tiers within the investment bank group, with Bank 6 to Bank 10 constituting the first-tier with greater market power, with Bank 12 to Bank 16 lagging behind. The only exception is Bank 11, which does well in the junk bond category but not in the non-junk bond category. In the commercial bank group, only Bank 1 seems to belong to the “first-tier” class. Bank 3 and Bank 5 seem to fit the analytical prediction of the entrant commercial banks the best, enjoying comparably greater market power with respect to junk bond issuers but not with respect to non-junk bond issuers. Bank 2 and Bank 4, on the other hand, seem to lag behind overall.

In fact, once I control for firm-and-bank-specific certification ability of commercial banks, I find that there does not seem to be any organizational form-specific “quality” left that makes the entrant commercial banks different from the incumbent investment banks. This is reflected in the size of λ, the dissimilarity coefficient. Commercial banks as a group per se are neither closer substitutes for each other nor more imperfect substitutes for investment banks. Instead, what matters is the client-specific relationship capital that makes them locally more effective in producing information, and the valuation of such relationships by issuers, which in turn depends on the reputation of the issuers in the capital market.

Finally, the price estimates reported in Table 4-6 are open to some economic interpretations. It is interesting to note that coefficients for JUNK BOND are all positive but tend to be smaller in size for top-ranking banks. This might be because the top-ranking underwriting banks are also the largest banks with the best and largest staff, and that enables them to be much more effective in their production, leading to lower cost. It is possible that their cost savings are sufficiently large that their junk bond premium in fee is lower even with the higher mark-ups implied by their lower price elasticities. Another possibility is that there is sorting and matching between reputation of underwriters and quality of firms, and therefore the firms that I observe to be underwritten by low-ranking underwriters did not have top-ranking underwriters in their choice sets. In other words, the high JUNK BOND coefficients of lower-ranking banks relative to high-ranking banks reflect the lower debt quality of firms that end up being underwritten by these banks. While it is conceptually appealing to relax the assumption of a fixed choice set across all issuers, it is not clear whether there is any publicly available data that enables researchers to make inference about issuer-specific choice sets. And this second interpretation is still consistent with the assertion that all banks, including even the low-ranking banks, exercise significant market
power in the junk bond category.

7 Conclusion

This paper has found significant evidence that product differentiation and heterogeneous tastes (valuations) for bank certification among firms explain the co-existence of commercial banks and investment banks in the post-deregulation equilibrium in the corporate bond underwriting market. I have argued that if commercial banks are differentiated from incumbent investment banks because of their previous loan relationships with issuing firms, presence of such relationships will be a significant determinant of own-demand. Further, if firms are heterogeneous in their tastes (or valuations) for bank certification, the positive effect of relationships on firms choice will be greater for firms with lesser reputation of their own. Confirmation of the second result strengthens the economic reasoning of the first result, because the directions of the results both point toward an advantage of entrant commercial banks to mitigate asymmetric information problems of these issuing firms (e.g. junk-bond issuers and first-time issuers) with which they had relationships, and thus the relative dominance of commercial banks in these segments of the market.

However, more than adverse selection (on issuer side) may be at play in determining the post-deregulation equilibrium outcome of the market. For example, adverse selection explains little about the dominance of several investment banks in underwriting blue-chip, seasoned corporate issuers. In fact, why do these issuers want to hire underwriters at all? Why not directly place their bonds to institutional investors with which they have a good track record? Below I will suggest some conjectures as a way of extending the investigation of this market. It might be that there are economies of both scale and scope in having a few top banks handling the volumes of these issues. Economies of scale would exist to the extent that building books for these bonds actually requires high fixed cost (e.g. in specialized personnel) and low marginal cost (of doing an extra issue). Furthermore, economies of scope might exist between providing services in both primary and secondary markets. Since bond secondary markets are not centralized, investment banks acting as market makers for these issues often control liquidity in the secondary market. Investors may thus prefer to buy bonds in the primary market from investment banks which later will agree to buy back the bonds as market makers if necessary. These are interesting empirical questions which do not seem to have been explored. This paper did not seek to explicitly identify existence and importance of these factors. In essence, the findings in this paper explain why commercial
banks succeeded in entering this concentrated market, taking the initial concentration as a given. Since the findings suggest that commercial banks are unlikely to be active in blue-chip segment of the market (unless they outright buy the investment banks through M&A—which have happened to lower-tier investment banks but not to the top ones), it seems especially important to investigate these other determinants of competitive structure in this market.

Appendix

A List of Variables

(A) Dependent Variables

.BOOK: Takes a value of i if the issuing firm chooses bank i in the given observation. (i = 1-16)

.BANK_DUM: Takes a value of 1 if the chosen bank in the given issue is a commercial bank; 0 otherwise.

(B) Choice Characteristics:

.LOAN1-LOAN16: .LOAN i Takes a value of 1 if bank i ever acted as an arranger in a loan agreement for the firm in the given issue in the period prior to the sample period (1980-1992); 0 otherwise.

.PRICE1-PRICE16: .PRICE i is the gross spread (expressed as a percentage of the issue amount) charged by bank i for the given issue.

(C) Issuer/Bond Characteristics:

.FIRST TIME: Takes a value of 1 if the issuing firm in the given observation never issued a non-convertible bond in the domestic U.S. bond market between 1973-1992; 0 otherwise.

.AMOUNT: The size of the issue in 100 millions of U.S. dollars.

.LMAT: natural log(maturity of bonds in number of years).
.JUNK BOND: Takes a value of 1 if the given issue’s credit rating is below Baa based on Moody’s credit rating; 0 otherwise.

.LNBOND: natural log(number of previous bond issues + 1).

.MTN: = 1 if the issue is under the Medium-Term Notes (MTN) program, or else 0.

(D) Other:

.INC0-INCl: INC1 is the inclusive value for Commercial Banks at the C-Bank/I-Bank node of the nest. INC0 is the inclusive value for Investment Bank at the C-Bank/I-Bank node.

B Estimation Method

In the EM framework, the observed data are viewed as being “incomplete”, and are augmented by unobserved data to make up the “complete data”. Each EM iteration involves an E-step where the conditional expectation of the complete-data log likelihood given the observed data is computed using the previous estimates \( \theta(0) \), and an M-step where the conditional expectation is maximized over \( \theta \). This procedure is repeated in an iterative manner until convergence is achieved.

Let \( c_i \) represent the index of the bank chosen by firm \( i \).
Let \( \theta = \{ \alpha, \beta, \mu, \gamma, \sigma \} \).

We observe \( c_i \) and \( p_{i,c_i} \), as well as \( x_{i,j} \), \( z_i \). The task is to estimate \( \theta \) according to the maximum likelihood principle. We will do this by an EM-type algorithm, assuming \( p_{-c_i} \) to be the “hidden” data and hence \( \{c_i, p_{c_i}, p_{-c_i}\} \) to be the complete data. Thus we need to establish \( \Pr(c_i, p_{c_i}, p_{-c_i} | \theta) \).
\[
Pr(c, p_c, p_{-c} | \theta) = Pr(c | p_c, p_{-c}, \theta) Pr(p_c, p_{-c} | \theta)
\]

by Bayes rule. According to the logistic choice model

\[
Pr(c | p_c, p_{-c}, \theta) = \frac{e^{d^T \mu + \alpha p_c + \beta x_c}}{\sum_{k=1}^{K} e^{d_k^T \mu + \alpha p_k + \beta x_k}}
\]

(9)

According to the iid normal distribution of \( \delta_k \), we know that each \( p_k \sim N(z^T \gamma_k, \sigma^2) \) independently. Hence

\[
Pr(p_c, p_{-c} | \theta) = \prod_{k=1}^{K} \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{1}{2\sigma^2}(p_k - z^T \gamma_k)^2}
\]

(10)

Hence, we have log likelihood of the complete data (of a single firm) as

\[
\ln Pr(c, p_c, p_{-c} | \theta) = -\frac{1}{2\sigma^2} \sum_{k=1}^{K} (p_k - z^T \gamma_k)^2 - \frac{K}{2} \ln 2\pi \sigma^2 + \ln \frac{e^{d^T \mu + \alpha p_c + \beta x_c}}{\sum_{k=1}^{K} e^{d_k^T \mu + \alpha p_k + \beta x_k}}
\]

(11)

In order to implement the E-step, we need to compute

\[
E_{\theta^{(0)}} (\ln Pr(c, p_c, p_{-c} | \theta) | c, p_c) = \int \ln (Pr(c, p_c, p_{-c} | \theta)) Pr(p_{-c} | c, p_c, \theta^{(0)}) dp_{-c}
\]

\[
= \left( \int \frac{\prod_{k \neq c} e^{-\frac{1}{2\sigma^2}(p_k - z^T \gamma_k^{(0)})^2}}{e^{d_c^T \mu + \alpha c p_c + \beta c x_c} + \sum_{k \neq c} e^{d_k^T \mu + \alpha k p_k + \beta k x_k}} dp_{-c} \right)^{-1} \int \ln (Pr(c, p_c, p_{-c} | \theta)) \left( \frac{\prod_{k \neq c} e^{-\frac{1}{2\sigma^2}(p_k - z^T \gamma_k^{(0)})^2}}{e^{d_c^T \mu + \alpha c p_c + \beta c x_c} + \sum_{k \neq c} e^{d_k^T \mu + \alpha k p_k + \beta k x_k}} \right) dp_{-c}
\]

(12)

Note that the first integral term is irrelevant in the M-step because it is a function only of the old parameters \( \theta^{(0)} \) and therefore is invariant with respect to new \( \theta \). So for the rest of this section I will drop this term from the analysis. What remains inside the second integral term is the product of a log of complete-data likelihood (evaluated at the new \( \theta \)) and the remaining part of the conditional probability \( Pr(p_{-c} | c, p_c, \theta^{(0)}) \), to be evaluated at the old \( \theta \).
These are high-dimensional ($K = 15$) integrals over hybrid distributions consisting of normal and logit components and are computationally non-trivial. Neither numerical integration nor Monte-Carlo EM (where the E-step is replaced by a Monte-Carlo process) is trivial nor immediately promising given the high dimensionality. So instead I use what is commonly referred to as an “EM-type algorithm,” whereby the single most likely value $p_{-c}$ that maximizes the conditional density above (i.e. only $\Pr(c, p_c, p_{-c}|\theta(0))$) is computed and a probability of 1 is placed on this data. In terms of the underlying economic problem, this part can be described as adjusted price imputation, where instead of using unconditionally imputed prices for unobserved prices, I am replacing them with prices that are adjusted so as to maximize the joint likelihood $\Pr(c_i, p_c, p_{-c})$, using estimates of $\theta$ from the previous iteration.

To monitor convergence, we need to evaluate the observed-data likelihood function $L(\theta^{(k)})$ in each ($k$th) iteration. In my model the incomplete-data likelihood function is expressed as

$$\Pr(c, p_c|\theta) = \int \Pr(c, p_c, p_{-c}|\theta) \, dp_{-c}$$

$$= \int \prod_{k=1}^{K} \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{1}{2\sigma^2}(p_k - \beta x_k)^2} \left( \frac{e^{\alpha p_c + \beta x_c}}{\sum_{k=1}^{K} e^{\alpha p_k + \beta x_k}} \right) \, dp_{-c}$$

(13)

As discussed in the previous section, the integrals above are computationally challenging. Laplace’s method provides a useful way of approximating integrals that take the form

$$I(\lambda) = \int_D e^{-\lambda g(x)} f(x) \, dx$$

(14)

where $\lambda$ is a large parameter$^{26}$. I apply this approximation method to evaluate the observed-data likelihood function.

References


$^{26}$See pp. 545-7 in (Judd 1996).


This figure reports the scatterplot of underwriting fees against issue amount (in $ millions). The data consist of 1,536 corporate bond issues, from January, 1993 to August, 1997. The plot follows the industry practice of expressing underwriting fees as % of issue amount.
This figure specifies the nest structure employed in the nested-logit demand model. Coefficient $\lambda$ captures the dissimilarity of alternatives belonging to a particular subset.
Figure 3: Underwriting Mechanism

This figure illustrates the structure of a typical underwriting syndicate. The choice of an underwriter in the demand model corresponds to the choice of a book-runner, or lead-manager, in this figure.
<table>
<thead>
<tr>
<th>Bank issues</th>
<th>All issues</th>
<th>Investment bank issues</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Issue size ($m)</strong></td>
<td>no. (%)</td>
<td>volume ($m)</td>
</tr>
<tr>
<td>&lt;=75</td>
<td>54</td>
<td>24%</td>
</tr>
<tr>
<td>75&lt;</td>
<td>115</td>
<td>52%</td>
</tr>
<tr>
<td>&lt;150</td>
<td>54</td>
<td>24%</td>
</tr>
<tr>
<td>223</td>
<td>100%</td>
<td>$29,192.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Maturity (yr.)</th>
<th>no. (%)</th>
<th>volume ($m)</th>
<th>no. (%)</th>
<th>volume ($m)</th>
<th>no. (%)</th>
<th>volume ($m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;=5</td>
<td>44</td>
<td>20%</td>
<td>$3,490.00</td>
<td>196</td>
<td>15%</td>
<td>$29,395.70</td>
</tr>
<tr>
<td>5&lt;</td>
<td>154</td>
<td>69%</td>
<td>$22,094.50</td>
<td>809</td>
<td>62%</td>
<td>$155,861.80</td>
</tr>
<tr>
<td>15&lt;</td>
<td>25</td>
<td>11%</td>
<td>$3,607.50</td>
<td>308</td>
<td>23%</td>
<td>$65,471.60</td>
</tr>
<tr>
<td>223</td>
<td>100%</td>
<td>$29,192.00</td>
<td>1,313</td>
<td>100%</td>
<td>$250,729.10</td>
<td>1,536</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Credit Rating</th>
<th>no. (%)</th>
<th>volume ($m)</th>
<th>no. (%)</th>
<th>volume ($m)</th>
<th>no. (%)</th>
<th>volume ($m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caa-Ba3</td>
<td>73</td>
<td>33%</td>
<td>$11,181.00</td>
<td>396</td>
<td>30%</td>
<td>$75,866.60</td>
</tr>
<tr>
<td>Baa1-Aaa</td>
<td>190</td>
<td>67%</td>
<td>$17,382.00</td>
<td>1017</td>
<td>77%</td>
<td>$122,124.50</td>
</tr>
</tbody>
</table>

This table classifies out sample based on (1) issue size into small (less than $75 million), medium (between $75 million and $150 million) and large (greater than $150 million) segments, (2) maturity into low (less than 5 years), medium (between 5 and 15 years), and high (greater than 15 years) segments, (3) based on Moody’s credit rating into sub-investment grade—i.e. junk—rated (Caa-Ba3) and investment grade rated (Baa1-Aaa) categories. In addition, within each of these segments, the issues are classified as commercial bank (Section 20 subsidiary) underwritings and investment bank underwritings.
This table classifies our sample based on previous issue experience into first-time issues (by issuers which have not issued a corporate bond in the U.S. market before) and seasoned issues (by issuers which have previous issue experience in the U.S. corporate bond market) segments. In addition, within each of these segments, the issues are classified as commercial bank (Section 20 subsidiary) underwritings and investment bank underwritings.

<table>
<thead>
<tr>
<th>Issuer</th>
<th>no. of issues(%)</th>
<th>Bank issues</th>
<th>no. no. (%)</th>
<th>volume($m)</th>
<th>volume(%)</th>
<th>Investment bank issues</th>
<th>no. no. (%)</th>
<th>volume($m)</th>
<th>volume(%)</th>
<th>All issues</th>
<th>no. no. (%)</th>
<th>volume($m)</th>
<th>volume(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First-time</td>
<td>44%</td>
<td>117 17%</td>
<td>$16,447</td>
<td>13%</td>
<td></td>
<td>562 83%</td>
<td>$107,909</td>
<td>87%</td>
<td></td>
<td>679 100%</td>
<td>$124,356</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Seasoned</td>
<td>56%</td>
<td>106 12%</td>
<td>$12,745</td>
<td>8%</td>
<td></td>
<td>751 88%</td>
<td>$142,820</td>
<td>92%</td>
<td></td>
<td>857 100%</td>
<td>$155,565</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>223 15%</td>
<td>$29,192</td>
<td>10%</td>
<td></td>
<td>1313 85%</td>
<td>$250,729</td>
<td>90%</td>
<td></td>
<td>1536 100%</td>
<td>$279,921</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Sample Tabulation by Previous Issue Experience
This table classifies our sample based on issuer's primary SIC codes into seven 1-digit segments. SIC code 4000's (financial firms) and 6000's (regulated industries) are excluded from our sample following the literature practice. In addition, within each of these segments, the issues are classified as commercial bank (Section 20 subsidiary) underwritings and investment bank underwritings.
This table reports the results of the basic (i.e. no interaction with issuer reputation characteristics) multinomial nested-logit model estimation. The upper-panel labeled “Demand estimates” presents estimates of the demand model; the lower-panel labeled “Price estimates” presents the price imputation results. Of regressors in the price imputation, “function of MATURITY” refers to the variable LMAT as defined in the Appendix, which is the natural log of maturity of bonds in number of years. The variable “fn. of Past Experience” refers to the variable LNBOND as defined in the Appendix, which is the natural log of (number of previous bond issues + 1). MTN variable takes the value of 1 if the issue is under the Medium-Term Notes (MTN) program, or else 0. Unless indicated otherwise, the coefficients are significant at 1% level. * indicates statistical significance of 5% level.

Table 4: Estimation Results (1): Basic Model
Table 5: Estimation Results (2): Junk vs. Non-Junk

<table>
<thead>
<tr>
<th>Demand estimates</th>
<th>Reputation category</th>
<th>Non-junk issuers</th>
<th>Junk bond issuers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variable names</td>
<td>PRICE</td>
<td>LOAN</td>
</tr>
<tr>
<td></td>
<td>Estimates</td>
<td>-2.5989</td>
<td>1.3008</td>
</tr>
<tr>
<td></td>
<td>Standard errors</td>
<td>(0.0969)</td>
<td>(0.0424)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Price estimates</th>
<th>Inclusive Variable names</th>
<th>Value</th>
<th>FIRST-TIME</th>
<th>AMOUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variables</td>
<td>λ</td>
<td>δ1</td>
<td>δ2</td>
</tr>
<tr>
<td></td>
<td>Estimates</td>
<td>1.3388</td>
<td>0.3183</td>
<td>-0.4312</td>
</tr>
<tr>
<td></td>
<td>Standard errors</td>
<td>(0.1375)</td>
<td>(0.1418)</td>
<td>(0.0755)</td>
</tr>
</tbody>
</table>

This table reports the results of the interacted model where product characteristics are interacted with issuer’s reputation characteristics. In this specification, separate coefficients are estimated for junk bond issuers and non-junk bond issuers. Of regressors in the price imputation, “function of MATURITY” refers to the variable LMAT as defined in the Appendix, which is the natural log of maturity of bonds in number of years. The variable “fn. of Past Experience” refers to the variable LNBOND as defined in the Appendix, which is the natural log of (number of previous bond issues + 1). MTN variable takes the value of 1 if the issue if under the Medium-Term Notes (MTN) program, or else 0. Unless indicated otherwise, the coefficients are significant at 1% level. * indicates statistical significance of 5% level.
### Demand estimates

<table>
<thead>
<tr>
<th>Reputation category</th>
<th>Non-first-time issuers</th>
<th>First-time issuers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable names</td>
<td>PRICE</td>
<td>LOAN</td>
</tr>
<tr>
<td>Estimates</td>
<td>-1.4178</td>
<td>0.7347</td>
</tr>
<tr>
<td>Standard errors</td>
<td>(0.0746)</td>
<td>(0.2412)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable names</th>
<th>Inclusive Value FIRST-TIME AMOUNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>λ</td>
</tr>
<tr>
<td>Estimates</td>
<td>1.1934</td>
</tr>
<tr>
<td>Standard errors</td>
<td>(0.1411)</td>
</tr>
</tbody>
</table>

### Price estimates

<table>
<thead>
<tr>
<th>Bank</th>
<th>function of MATURITY</th>
<th>JUNK BOND</th>
<th>ln of Past Experience</th>
<th>MTN (shelf registration)</th>
<th>LOAN (junk only)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank1</td>
<td>0.2031</td>
<td>1.2286</td>
<td>-0.0363</td>
<td>-0.0022</td>
<td>-0.6514</td>
</tr>
<tr>
<td>Bank2</td>
<td>0.1831</td>
<td>2.0053</td>
<td>0.0687</td>
<td>-0.0853</td>
<td>0.1618</td>
</tr>
<tr>
<td>Bank3</td>
<td>0.4366</td>
<td>1.5150</td>
<td>0.0189</td>
<td>-0.1377</td>
<td>0.3338</td>
</tr>
<tr>
<td>Bank4</td>
<td>0.2072</td>
<td>1.8624</td>
<td>-0.0332</td>
<td>-0.2079</td>
<td>-1.5239</td>
</tr>
<tr>
<td>Bank5</td>
<td>0.2795</td>
<td>1.5386</td>
<td>0.0464</td>
<td>-0.0789</td>
<td>-0.0909</td>
</tr>
<tr>
<td>Bank6</td>
<td>0.1780</td>
<td>1.2715</td>
<td>-0.0336</td>
<td>-0.1079</td>
<td></td>
</tr>
<tr>
<td>Bank7</td>
<td>0.1879</td>
<td>1.4420</td>
<td>-0.0121</td>
<td>-0.0516</td>
<td></td>
</tr>
<tr>
<td>Bank8</td>
<td>0.1012</td>
<td>1.4226</td>
<td>-0.0738</td>
<td>-0.1480</td>
<td></td>
</tr>
<tr>
<td>Bank9</td>
<td>0.1860</td>
<td>1.7321</td>
<td>-0.0220</td>
<td>-0.0526</td>
<td></td>
</tr>
<tr>
<td>Bank10</td>
<td>0.1901</td>
<td>1.6364</td>
<td>-0.0215</td>
<td>-0.0902</td>
<td></td>
</tr>
<tr>
<td>Bank11</td>
<td>-0.2063</td>
<td>1.7693</td>
<td>-0.1709</td>
<td>-0.1854</td>
<td></td>
</tr>
<tr>
<td>Bank12</td>
<td>0.2085</td>
<td>1.6496</td>
<td>-0.0286</td>
<td>0.0158</td>
<td></td>
</tr>
<tr>
<td>Bank13</td>
<td>0.1471</td>
<td>1.9942</td>
<td>-0.0124</td>
<td>0.1046</td>
<td></td>
</tr>
<tr>
<td>Bank14</td>
<td>0.2108</td>
<td>1.9848</td>
<td>-0.0342</td>
<td>0.2118</td>
<td></td>
</tr>
<tr>
<td>Bank15</td>
<td>0.2741</td>
<td>1.7539</td>
<td>-0.0249</td>
<td>0.2405</td>
<td></td>
</tr>
<tr>
<td>Bank16</td>
<td>0.2343</td>
<td>1.9515</td>
<td>-0.0058</td>
<td>0.1691</td>
<td></td>
</tr>
</tbody>
</table>

This table reports the results of the interacted model where product characteristics are interacted with issuer’s reputation characteristics. In this specification, separate coefficients are estimated for first-time issuers and seasoned issuers. Of regressors in the price imputation, “function of MATURITY” refers to the variable $\text{LMA T}$ as defined in the Appendix, which is the natural log of maturity of bonds in number of years. The variable “ln of Past Experience” refers to the variable $\text{LNBOND}$ as defined in the Appendix, which is the natural log of (number of previous bond issues + 1). MTN variable takes the value of 1 if the issue if under the Medium-Term Notes (MTN) program, or else 0. Unless indicated otherwise, the coefficients are significant at 1% level. * indicates statistical significance of 5% level.
Table 7: Effect of Increase in Price: Mean Own-Price Elasticities

<table>
<thead>
<tr>
<th>Reputation category</th>
<th>All issuers</th>
<th>Non-junk issuers</th>
<th>Junk bond issuers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>commercial banks</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank1</td>
<td>-1.371</td>
<td>-1.646</td>
<td>-0.746</td>
</tr>
<tr>
<td>Bank2</td>
<td>-2.004</td>
<td>-2.392</td>
<td>-1.124</td>
</tr>
<tr>
<td>Bank3</td>
<td>-1.799</td>
<td>-2.189</td>
<td>-0.915</td>
</tr>
<tr>
<td>Bank4</td>
<td>-1.927</td>
<td>-2.316</td>
<td>-1.042</td>
</tr>
<tr>
<td>Bank5</td>
<td>-1.799</td>
<td>-2.198</td>
<td>-0.891</td>
</tr>
<tr>
<td>Mean</td>
<td>-1.780</td>
<td>-2.148</td>
<td>-0.944</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.245</td>
<td>0.293</td>
<td>0.146</td>
</tr>
<tr>
<td><strong>investment banks</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank6</td>
<td>-1.332</td>
<td>-1.574</td>
<td>-0.782</td>
</tr>
<tr>
<td>Bank7</td>
<td>-1.381</td>
<td>-1.617</td>
<td>-0.847</td>
</tr>
<tr>
<td>Bank8</td>
<td>-1.332</td>
<td>-1.537</td>
<td>-0.866</td>
</tr>
<tr>
<td>Bank9</td>
<td>-1.413</td>
<td>-1.607</td>
<td>-0.972</td>
</tr>
<tr>
<td>Bank10</td>
<td>-1.394</td>
<td>-1.598</td>
<td>-0.932</td>
</tr>
<tr>
<td>Bank11</td>
<td>-1.689</td>
<td>-2.055</td>
<td>-0.858</td>
</tr>
<tr>
<td>Bank12</td>
<td>-1.423</td>
<td>-1.642</td>
<td>-0.925</td>
</tr>
<tr>
<td>Bank13</td>
<td>-1.848</td>
<td>-2.167</td>
<td>-1.124</td>
</tr>
<tr>
<td>Bank14</td>
<td>-1.663</td>
<td>-1.919</td>
<td>-1.082</td>
</tr>
<tr>
<td>Bank15</td>
<td>-1.819</td>
<td>-2.175</td>
<td>-1.009</td>
</tr>
<tr>
<td>Bank16</td>
<td>-1.835</td>
<td>-2.164</td>
<td>-1.086</td>
</tr>
<tr>
<td>Mean</td>
<td>-1.557</td>
<td>-1.823</td>
<td>-0.953</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.214</td>
<td>0.272</td>
<td>0.112</td>
</tr>
</tbody>
</table>

This table reports the mean own-price elasticities of each of the 16 underwriting banks based on the demand estimates obtained in Table 5. For each bank, price elasticities are calculated for the whole sample, and separately for junk bond issuers and non-junk bond issuers.
Table 8: % Change in Own Total Demand from 1% Increase in Price

<table>
<thead>
<tr>
<th>Reputation category</th>
<th>All issuers</th>
<th>Non-junk issuers</th>
<th>Junk bond issuers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>commercial banks</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank1</td>
<td>-1.400</td>
<td>-1.620</td>
<td>-0.726</td>
</tr>
<tr>
<td>Bank2</td>
<td>-1.944</td>
<td>-2.342</td>
<td>-1.119</td>
</tr>
<tr>
<td>Bank3</td>
<td>-1.409</td>
<td>-1.599</td>
<td>-0.910</td>
</tr>
<tr>
<td>Bank4</td>
<td>-1.718</td>
<td>-2.167</td>
<td>-0.874</td>
</tr>
<tr>
<td>Bank5</td>
<td>-1.639</td>
<td>-2.013</td>
<td>-0.882</td>
</tr>
<tr>
<td>Mean</td>
<td>-1.622</td>
<td><strong>-1.948</strong></td>
<td><strong>-0.902</strong></td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.228</td>
<td>0.330</td>
<td>0.141</td>
</tr>
<tr>
<td><strong>investment banks</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank6</td>
<td>-1.359</td>
<td>-1.547</td>
<td>-0.770</td>
</tr>
<tr>
<td>Bank7</td>
<td>-1.421</td>
<td>-1.605</td>
<td>-0.834</td>
</tr>
<tr>
<td>Bank8</td>
<td>-1.363</td>
<td>-1.506</td>
<td>-0.853</td>
</tr>
<tr>
<td>Bank9</td>
<td>-1.467</td>
<td>-1.604</td>
<td>-0.967</td>
</tr>
<tr>
<td>Bank10</td>
<td>-1.427</td>
<td>-1.569</td>
<td>-0.923</td>
</tr>
<tr>
<td>Bank11</td>
<td>-1.170</td>
<td>-1.740</td>
<td>-0.850</td>
</tr>
<tr>
<td>Bank12</td>
<td>-1.458</td>
<td>-1.618</td>
<td>-0.918</td>
</tr>
<tr>
<td>Bank13</td>
<td>-1.887</td>
<td>-2.188</td>
<td>-1.121</td>
</tr>
<tr>
<td>Bank14</td>
<td>-1.687</td>
<td>-1.883</td>
<td>-1.080</td>
</tr>
<tr>
<td>Bank15</td>
<td>-1.765</td>
<td>-2.097</td>
<td>-1.007</td>
</tr>
<tr>
<td>Bank16</td>
<td>-1.820</td>
<td>-2.117</td>
<td>-1.085</td>
</tr>
<tr>
<td>Mean</td>
<td>-1.529</td>
<td><strong>-1.770</strong></td>
<td><strong>-0.946</strong></td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.214</td>
<td>0.256</td>
<td>0.116</td>
</tr>
</tbody>
</table>

This table reports the % change in own demand from 1% increase in own underwriting fees calculated from the demand estimates obtained in Table 5. For each bank, the % change in demand are calculated for the whole sample, and separately for junk bond issuers and non-junk bond issuers.