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Do Investment Banks' Relationships with Investors Impact Pricing? The Case of Convertible Bond Issues

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This study examines the role of repeat interactions between placement agents (investment banks) and investors in the initial pricing of convertible bonds. Under the assumption that attracting repeat investors can reduce search frictions in primary issue markets, we test the hypothesis that banks' relationships with investors actually allow more favorable pricing for issuing firms (in contrast to the "favoritism" hypothesis, under which banks use underpricing to reward favored clients). In the empirical analysis we also allow for a potentially important alternative channel through which search frictions might impact initial pricing: expected after-market liquidity. Using a sample of 601 Rule 144A issues for the years 1997–2007, we document robust negative relationships between at-issue discounts and both types of frictions. Our findings suggest that search frictions play a meaningful role in initial convertible bond pricing and, specifically, that intermediaries can add substantial value through repeated interactions with investors.

Key words: corporate finance; securities issuance; convertible bonds; underpricing
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1. Introduction

Do relationships between placement agents (investment banks) and investors impact the initial pricing of convertible bonds (CBs)? Despite a vast literature on initial offering discounts, important questions about the initial pricing of intermediated securities remain.[1] This paper examines the role of repeat interactions between placement agents and investors in the initial pricing of CBs. We analyze an extensive sample of Rule 144A CB issues, in which we observe investor-level data across a large number issues. Observing the repeated interactions between placement agents and investors allows us to test the hypothesis that prior relationships reduce search and contracting frictions in primary issue markets. We find a robust, negative relationship between at-issue CB discounts and banks' prior interactions with investors. With all other variables at their mean values, a deal with only 25% repeat investors will tend to be priced at a 10.7% discount relative to fundamental value, whereas a deal with 75% repeat investors will be priced at about a 7.1% discount. Given the mean deal size of $278 million, this difference translates to a potential savings of $10.2 million for the issuer.

The market for Rule 144A CBs provides a particularly useful laboratory for examining the extent to which contracting frictions explain variation in the underpricing of intermediated securities. This is because many of the explanations for underpricing proposed for equity securities—both initial public offerings (IPOs) and seasoned equity offerings (SEOs)—are less relevant in this market, yet CBs are considerably underpriced. In fact, we estimate that our sample of bonds are priced at a 7.6% discount relative to fundamental value. These issuers already have publicly traded stock, implying a lesser role for asymmetric information and uncertainty about fundamental value relative to the case of equity IPOs. The reduced role of information asymmetry means that traditional bookbuilding theories, such as Benveniste and Spindt (1989), in which underwriters compensate repeat investors for revealing their private information, become less important (although we control for information asymmetry in all empirical analysis). In addition, CBs are less informationally sensitive

[1] Ritter and Welch (2002), Ljungqvist (2007), and Eckbo et al. (2007) provide excellent surveys.

than both seasoned and initial equity because of their hybrid structures and seniority to equity claims. Because CBs have downside protection and many investors hedge the equity risk, the possibility that offering discounts are compensation for monitoring incentives is also less likely relative to the case of straight equity.[2] Finally, individual investors do not participate in the 144A CB market because regulation restricts participation to qualified institutional buyers (QIBs).[3] The absence of individual investors in both the primary and secondary 144A markets reduces the potential impact of biases that individuals might exhibit and may also reduce information asymmetries among investors. These factors allow us to come closer to isolating the roles of search frictions in initial pricing.

The model of Duffie et al. (2007) relates search-and-bargaining frictions to prices in over-the-counter markets and suggests greater liquidity discounts when counterparties are harder to find, sellers have less bargaining power, and there are fewer qualified owners. In the context of the CB market, we propose that repeat investors, defined as those who have participated in prior Rule 144A issues by the same placement agent, may reduce bargaining complexities, resulting in higher prices and lower offering discounts for issuing firms. We expect repeat investors to reduce bargaining complexities through their familiarity and experience contracting with the placement agent, compared to unknown investors. A second channel through which search frictions likely influence the offering discount is the ability to find buyers in the secondary market should an investor wish to trade the bond. Given the recent findings of Ellul and Pagano (2006) and Gupta et al. (2008) that expected secondary market liquidity improves initial pricing, we also examine the potential role of secondary market liquidity in all regressions.

In contrast to the search frictions hypothesis, according to the "conflict of interest" or "favoritism" hypothesis, placement agents use their discretion to direct larger allocations of underpriced securities to their relationship investors. Under the "bookbuilding" hypothesis, at-issue discounts provide fair compensation to repeat investors for revealing their private value-relevant information during the offering process. Both the bookbuilding and favoritism hypotheses predict a positive association between repeat investors and underpricing, an opposite prediction from that of the "search cost" hypothesis.

To our knowledge, only two large-sample studies in the extant literature relate investor-placement agent relationships to allocations and pricing of security offerings. Both of those studies focus on the equity IPO market and use mutual fund holding reports (SEC form 13-F) in the quarter following the IPO to measure institutional allocations in equity IPOs. Reuter (2006) relates these holdings to fees and commissions paid by funds to the IPO underwriters. He reports that business relationships with underwriters lead to greater and more favorable IPO allocations. Reuter (2006) presents a test of the importance of interactions across multiple business segments, whereas our study examines the importance of interactions within a single market. Binay et al. (2007) study the determinants of relationships and link them to IPO underpricing, measuring relationships as repeat interactions between investors and banks. Consistent with the favoritism hypothesis, Binay et al. (2007) find greater participation in underpriced IPOs for regular investors, especially during 1999–2000. Our analysis is complementary to both of these studies. Because other determinants of underpricing are less pronounced within the Rule 144A CB market, we can better isolate the role of search frictions. Moreover, our study circumvents the reliance on quarterly mutual fund holding reports, arguably leading to more direct observation of initial allocations.[4] Additionally, both papers include 1999–2000, a period marked by highly unusual growth in IPOs. The CB market, in contrast, remained more stable, implying that this study characterizes more normal times.

Several studies outside of the securities issuance context investigate the role of relationships in financial markets. For example, Diamond (1991) shows that repeated interactions improve outcomes in bank loan provision. In a general contracting setting, Boot et al. (1993) show that reputation can increase flexibility and allow discretion in contracting. Pagano and Röell (1992) and Benveniste et al. (1992) show that reputation can decrease the adverse effects of information asymmetries in trading and liquidity provision. Like our work, although in the context of trading and liquidity provision, Battalio et al. (2007) empirically test the hypothesis that reputation can be beneficial in mitigating the impact of adverse selection in financial markets.

We provide new results to the literature on the initial pricing of intermediated securities and of CBs in particular. We find that investment banks can add value through their relationships with investors. This

[2] Choi et al. (2010) and Mitchell et al. (2007) discuss CB arbitrage strategies. Meidan (2006) examines the role of monitoring in the private investment in public equity (PIPE) setting.

[3] Qualified institutional buyers must have at least $100 million in assets.

[4] Because the stock market is liquid and trading volumes are high following IPOs, quarterly filings may be noisy proxies for initial allocations.

effect is economically and statistically significant and is robust to alternative approaches to calculating the discount. This finding contrasts with the favoritism hypothesis, under which bankers use underpricing to reward repeat investors. Second, we find that at-issue CB discounts are related negatively to proxies for after-market liquidity, consistent with prior findings in the literature. The third key finding is that fees paid by the issuer are lower when search costs and contracting frictions are reduced via repeat interactions. This finding regarding the impact of search frictions on fees is important because it suggests that the decreases in at-issue discounts that we observe are not simply offset by other costs. Thus, when search frictions are reduced, we observe a reduction in the total costs to the issuer. Overall, our findings suggest that the benefits (to the issuer) of investment bank and investor relationships generally outweigh potential conflict of interest costs associated with investor favoritism.

The balance of the paper is organized as follows: Section 2 provides a brief description of the 144A new issue market for CBs, §3 presents the data and framework for empirical analysis, §4 discusses the empirical results, and §5 concludes.

2. The Rule 144A CB Market

Although less widely studied than equity, CBs are an important source of financing for firms. Gomes and Phillips (2012) report that during 1995–2003, convertible debt accounted for 9.0% of the dollar value of all new issuance, whereas equity (both SEOs and IPOs) accounted for 6.5%. The 144A market has become an important source of CB financing (see Gomes and Phillips 2012). A benefit to issuers of SEC Rule 144A is the increased speed at which issuers may raise capital. This flexibility allows firms to take advantage of favorable market conditions and to respond quickly to investment opportunities. Rule 144A does, however, restrict participation and trading to QIBs. All else equal, the market for Rule 144A bonds is less liquid than public markets because participation is restricted to QIBs and transactions take place over the counter. Rule 144A bonds sometimes have registration rights stipulating penalties should the issuer fail to exchange the 144A bonds for otherwise identical registered bonds (which trade without restriction) within an agreed-upon time frame. However, even when bonds do not include registration rights, most issuers register the bonds. In fact, Huang and Ramírez (2010) report that 88% of Rule 144A convertible issuers register the bonds, with 80% registering within three months of issuance.[5]

The process for placing 144A CBs is similar to public equity placements, but it occurs at a vastly accelerated pace, often spanning just a couple of days. The placement process is similar to bookbuilding in that a bank's sales force approaches investors with potential offerings and solicits indications of interest (however, as noted in the introduction, the role of information asymmetry is much less pronounced). Simultaneously, the bank's debt capital desk provides pricing recommendations for the bonds based on current market conditions. Finally, the bank's syndicate desk merges the indications of interest collected from the sales force with the price recommendations from the debt capital desk to determine the final offering terms.

The specifics of the process may vary based on the characteristics of the issuing firm. Our discussions with practitioners reveal that for small firms (market capitalization of less than \$500 million), investment banks may engage in a practice called "wall crossing," in which they approach a small group of investors with a potential offering and solicit feedback on whether the deal looks attractive. The investors listen to the firm's story, run deal terms through their pricing models,[6] and submit indications of interest.[7] The firms that we study had a mean market capitalization of \$3.01 billion and a 25th percentile capitalization of \$626 million. For very large firms like these, the information revelation that occurs via the wall crossing process is likely to be less relevant. The issuer is more likely to approach multiple banks to gather information regarding what type of pricing each CB desk anticipates it can obtain. Because banks vary in their distribution abilities and expertise, pricing varies across banks.

3. Empirical Framework

3.1. CB Pricing

The first step in the analysis involves calculating at-issue discounts. In contrast to the secondary market for equity IPOs and SEOs, trading of newly issued Rule 144A CBs takes place infrequently and in the over-the-counter market. Given this market structure, measuring offering discounts based on post-issuance returns is not possible. To quantify pricing in the new issues market, we compute the discount of the offering price relative to the theoretical bond value. This measure is defined as $Discount_i = 1 - P_i^{\text{issue}}/P_i^{\text{model}}$, where P_i^{model} is the theoretical bond price (described below) and P_i^{issue} denotes the issue price of

[5] Fenn (2000) reports that issuers register greater than 97% of high-yield 144A bonds. Livingston and Zhou (2002) report that 98% of high-yield bonds include registration rights.

[6] During our sample period, practitioners used binomial pricing models, similar to the ones used in this paper.

[7] To participate in these negotiations, the investor has to agree to halt trading in the equity of the issuing firm.

the ith bond in the sample. When $1 - P_i^{\text{issue}}/P_i^{\text{model}}$ is greater than zero, the interpretation is that the bond is underpriced.

CBs are hybrid instruments because they have both bond-like features (coupon payments and return of par value if the bond reaches maturity) and equity-like features (the option to convert the bonds into a specified number of shares of the issuer's stock). A suitable valuation model must incorporate the underlying stock price dynamics as well as interest rates and default likelihood. The model must be sufficiently stylized to allow for implementation across the full sample but must also produce sufficient precision to avoid large estimation error. CBs have numerous embedded American-style option features, and discrete-time binomial models are a natural choice for valuation.[8] We consider two CB pricing models to estimate the theoretical bond price. Each model includes an equity binomial tree with default risk.[9] The first model, which we refer to as the "base model," is used in Choi et al. (2010) and Henderson (2006). The base model assumes the default likelihood is constant over time and across all stock prices. Additionally, the base model assumes that the term structure of risk-free rates is flat. The second model, referred to as the "generalized model," is a version of the model developed by Das and Sundaram (2007). The generalized model allows for time-varying default rates and calibrates the default term structure to current market prices. Additionally, the generalized model incorporates the full term structure of risk-free interest rates where the forward rates are implied by Treasury bond prices. Although the base model makes more restrictive assumptions (a constant default probability through time and across all stock prices and a flat term structure of interest rates), it has the advantage of requiring the estimation of fewer parameters.

3.1.1. Base Pricing Model. The first step in the pricing procedure involves construction of the stock price tree. The model assumes that the issuer's stock price follows a geometric Brownian motion process with constant drift and volatility, a constant hazard rate of default λ, and recovery rate R. The binomial trees consist of 50 time steps per year ($dt = 1/50$). At each time step, the stock price S may move up (to $u \times S$) or down (to $d \times S$), where the size of the stock price change is a function of the stock's return volatility: $u = \exp\sqrt{(\sigma^2 - \lambda)\,dt}$, $d = 1/u$.

The return volatility for each issuer's stock, σ, is the standard deviation of daily historical stock returns during trading days −160 through −20 days prior to issuance.[10] The default intensity, λ, is inferred from credit spreads at the time of the offering. Specifically, the implied default intensity is $\lambda = (r_c - r_f)/(1 - R)$, where r_c is the yield on straight bonds with the same credit rating as the issue, r_f is the risk-free yield, and R is the fraction of par expected to be recovered in the event of default.[11]

The probabilities of the up and down steps, p_u and p_d, respectively, are computed as $p_u = (e^{(r-c)\,dt} - de^{-\lambda\,dt})/(u - d)$, $p_d = (ue^{-\lambda\,dt} - e^{(r-c)\,dt})/(u - d)$, where the parameter c is the continuously compounded dividend rate, estimated as the trailing 12-month dividend rate on the issuer's stock converted from discrete distributions to a continuous rate.

Construction of the CB tree follows from the stock tree. Starting at the terminal node, corresponding to the final maturity date of the bond, the price of the bond is set equal to the maximum of the conversion value or the par value of the bond. Specifically, the expiration date T value of the ith CB in the sample is $P_{i,t} = \max[PAR, CR_i \times S_{i,T}]$, where CR_i is the conversion ratio representing the number of shares of the issuer's stock into which the bond converts, and $S_{i,T}$ designates the issuer's stock price at terminal node T.

The prior nodes on the tree are populated by working backward through the tree. Starting with the time-step immediately prior to expiration and working backward, the value of the bond at each time t and node j is the maximum of the discounted expected payoff and the conversion value. Specifically,

$$P_{j,t} = \max\big[e^{-r_f\,dt}\big(p_u \times P_{t+1}^u + p_d \times P_{t+1}^d + (1 - p_u - p_d) \times R \times PAR\big), CR_i \times S_{j,t}\big]. \quad (1)$$

[8] Typical options embedded in CBs include the issuer's right to call the bonds at specified prices prior to maturity, the bondholders' right to force the issuer to repurchase the bond at specified prices prior to maturity, and the bondholders' right to convert the bonds to a specified number of shares of the issuer's stock.

[9] Ingersoll (1977) uses a contingent claims approach to valuing convertibles in which the bond represents contingent claims on the firm as a whole. The benefit of this approach is that it endogenously accounts for default risk. The challenge in our setting is that we would need to model the value of the entire firm, including all liabilities that are senior to the convertible. We therefore choose to value the bond based on the stock price tree.

[10] We use historical volatility rather than option-implied volatility for three reasons. First, many issuers do not have exchange-traded options, which would lead to a significant reduction in the sample size. Second, most traded options have short maturities, whereas the average CB in our sample has 13.8 years to maturity when issued. Third, selecting the appropriate option from the available strike prices and times-to-expiration is not straightforward, given the complex features of CBs' embedded option features. As a robustness check, we recalculate the *Discount* based on the implied volatility and find that it is highly correlated with the *Discount* using the historical volatility input for the subsample of firms with traded options.

[11] Constant recovery rates is a standard assumption over our sample period. See Bandreddi et al. (2007) and Das and Hanouna (2009) for discussions of recovery rates.

To account for the embedded option features, we collect call and put schedules from Securities Data Corporation (SDC) and Bloomberg and assume optimal exercise policies.

3.1.2. Generalized Pricing Model. In addition to the base model, we estimate a second, more generalized pricing model. The generalized model is an adaptation of the Das and Sundaram (2007) model for pricing hybrid securities that incorporates the full term structures of interest rates and default likelihoods. The model specifies the default process as endogenous to the equity price process, which follows a jump-to-default process.

The pricing procedure begins by building the stock tree. Similar to the base model, each year consists of 50 time steps. The stock price at time t, S_t, evolves over the next time step by taking one of three possible values such that S_{t+h} equals uS_t with probability $q(t-\lambda_t)$, dS_t with probability $(1-q)(t-\lambda_t)$, and 0 with probability λ_t.

The magnitude of an up step is $u = e^{\sigma\sqrt{dt}}$ and the magnitude of a down step is $d = 1/u$. The stock price process is an extension of the Cox et al. (1979) model and allows the stock price to jump to default, where it is absorbed. Denote f as the risk-free rate of interest during each period. The probability of an up step, conditional on no default, is $q = ((1/(1-\lambda))e^{(f-c)\times dt} - d)/(u-d)$. The model allows the default probability (λ) to change over time and across stock prices. This makes intuitive sense because default seems more likely at low stock prices compared to higher stock prices, all else equal. The model assumes a specific default function in time, where $\lambda_{i,t}$ is the probability of default at stock price i and time t and $\eta_{i,j}$ is the corresponding default intensity, where $\lambda_{i,j} = 1 - e^{-\eta_{i,j}\times dt}$ and $\eta_{i,j} = e^{\alpha+\gamma\times dt} S_t^{-\beta}$.

Implementing the model requires, in addition to the stock price volatility σ, estimation of the parameters α and γ, which modulate the default intensity through time, and β, which modulates the intensity across stock prices. To calibrate these parameters, we use the yields on indices for bonds of the same credit rating as sample bond i. Specifically, we use the yields on 1-, 5-, 10-, and 30-year corporate debt indexes (published by Moody's and collected from Bloomberg) to calibrate the market-implied expected default compared to the yields on Treasury bonds of identical maturities. To calibrate the default function, the procedure selects the parameters $\{\alpha, \gamma, \beta\}$ to minimize mean-squared errors between prices on a par bond obtained using the corporate debt index yield and the yield on a risk-free Treasury bond.

After calibrating the default function, construction of the stock price tree is identical to the procedure in the base model. From the stock price tree, the CB price tree is also identical to the base model, with one exception. The discount rate, f, in the generalized model is the periodic forward rate implied by Treasury bond prices (instead of a flat term structure, as in the base model).

3.2. Data and Summary Statistics

The initial sample of 144A CB offerings comes from Sagient's Placement Tracker database for the years 1997–2007.[12] The data include placement agent and investor name; the name and holdings amount of each investor; and a description of the investor type (e.g., mutual fund, hedge fund, pension fund, etc.). To reduce potential double-counting of investors, when the investor and advisor have common names, we replace the investor name with the advisor's name.[13] There are 1,176 unique 144A CB issues in the database.

To obtain issue characteristics, we match the Sagient bonds with CB offerings in the SDC New Issues database based on ticker, name, and closing date. When we are unable to obtain a match in the SDC database, we match with bond issue data from Bloomberg. We exclude from the sample all exchangeable and mandatory issues; issues with floating conversion prices or coupon rates; and any issues that are missing important terms, such as the coupon rate or conversion ratio.[14] After filtering, we obtain discount estimates for 848 bonds. We further require data on all explanatory variables of interest, including the prior relationship measures, leaving a final sample of 601 issues from a broad cross-section of industries.[15] There are 43 unique placement agents and 3,529 unique investor names in the final sample.

The Placement Tracker data have been used in recent studies of private investments in public equity

[12] The Placement Tracker data begin in 1995. We begin the sample in 1997 because one of the variables of interest requires measurement of repeat interactions between investors and placement agents during the preceding 24 months, requiring a two-year observation window prior to the earliest cross-sectional observation. We have repeated the analysis using both 36-month and 60-month windows to define relationships. Results are qualitatively similar.

[13] When a given investor is part of a family of investment funds, we aggregate up to the family level. We repeat all analysis using two additional definitions: (1) keep all investors separate and (2) aggregate all investors based on their advisors and define relationships with placement agents based on their advisors. All of the main results carry through.

[14] We excluded 2 bonds with "floating" coupon rates, 9 bonds with "reset" coupon rates, and 34 bonds with the coupon data field blank.

[15] There are a number of deals with missing fee information in Sagient. When fee data are missing, we use hand-collected data and define fees as 1 minus the ratio of net proceeds (as reported in the statement of cash flows) to gross proceeds. If we rely on the Sagient data alone, the final sample falls to 533 observations; however, the main results are qualitatively similar.

(PIPEs). These papers have examined the impact of investor type on future equity price performance (Brophy et al. 2009) and the pricing of PIPEs (Meidan 2006) but do not include CBs, mainly because of the unobservable nature of the "fundamental prices." We circumvent this problem by estimating a theoretical at-issue price. Huang et al. (2008) also use the Sagient data and, like this paper, measure repeat interactions. They investigate whether banks with large networks help issuers attract investors in PIPE offerings but do not examine the relationship between networks and pricing.

Table 1 presents summary statistics for the variables used in the analysis. The first and most important observation from the table is that CBs are issued at substantial discounts. The mean (median) discount

Table 1 Sample Statistics

Panel A: Descriptive statistics

Variable name	Mean	Median	Minimum	Maximum	Standard deviation
Discount, BaseModel	0.076	0.059	−0.243	0.690	0.144
Discount, GeneralizedModel	0.097	0.084	−0.245	0.691	0.153
GrossProceeds (millions $)	278.866	175.000	30.000	2,821.209	282.398
Fee	0.029	0.030	0.004	0.083	0.008
NumInvestors	56.556	45.000	1.000	272.000	39.617
RepeatInvestors	0.675	0.746	0.000	1.000	0.252
InvestorExperience	0.164	0.160	0.000	0.524	0.073
Strength	0.183	0.182	0.000	0.455	0.066
HHI	0.126	0.083	0.016	1.000	0.126
MarketShare	0.113	0.076	0.001	0.585	0.104
BondRating	5.356	6.000	3.000	7.000	1.067
Unrated	0.636	1.000	0.000	1.000	0.482
UnclassifiedInvestors	0.282	0.250	0.000	1.000	0.182
NonHedgeFund	0.634	0.640	0.000	1.000	0.167
Maturity	13.837	9.997	1.644	30.425	8.468
NumAnalysts	14.865	12.000	0.000	65.000	10.734
DebtRatio	0.256	0.218	0.000	1.353	0.245
MarketCap (billions $)	3.014	1.176	0.006	160.854	8.009

Panel B: Sample firms' industry representation

Sector	Sample observations
Basic materials	10
Communications	100
Consumer cyclical	67
Consumer noncyclical	167
Diversified	5
Energy	34
Financial	43
Industrial	63
Technology	109
Utilities	3

Notes. This table presents summary statistics for the sample of convertible bonds. The initial sample comprises all convertible bond issues under Rule 144A as identified by Sagient Research's Placement Tracker Database. The sample period begins in 1997 and ends in 2007. There are 601 observations. Panel A presents descriptive statistics. Panel B reports industries of the issuers in the sample. *Discount, BaseModel* and *Discount, GeneralizedModel* are the percentage discounts of the offering price below the fundamental value from the pricing models. The following variables are from Placement Tracker: *GrossProceeds* are the issue proceeds, inclusive of fees; *Fee* is the fee paid to the placement agent as a fraction of proceeds; *NumInvestors* is the number of investors in each deal; *RepeatInvestors* is defined as the fraction of investors that purchased another convertible bond from the same placement agent in the preceding 24 months; *InvestorExperience* measures the fraction of previous 144A convertible bond deal flow, excluding any deals by bond i's placement agent, purchased by investors in issue i over the past 24 months; *Strength* is defined as the average participation of investors in issue i in all 144A convertible bond issues by bond i's placement agent during the past 24 months; *HHI* measures buyer power and is defined as the sum of squared fractions of the total proceeds purchased by each investor; *MarketShare* is the placement agent's market share in the 144A convertible bond market over the previous 24 months. *BondRating* is based on S&P ratings and takes numeric values from 1 (AAA) to 9 (C). Bond ratings are from Mergent Fixed Income Securities Database. *UnclassifiedInvestors* is defined as the fraction of proceeds in issue i purchased by investors who are unidentified in the Sagient database. *NonHedgeFund* is defined as the fraction of proceeds purchased by investors not classified as hedge funds by Sagient. *Maturity* is the time-to-maturity (in years) of bond i at the time of its issue. *NumAnalysts* is the number of stock analysts in IBES producing annual earnings forecasts for the convertible bond issuer. *DebtRatio* is the COMPUSTAT book value of debt from the year preceding the offering divided by *MarketCap*. *MarketCap* comes from the Center for Research in Securities Prices (CRSP) and is the product of shares outstanding and share price. Panel B presents the number of observations per industry sector.

relative to fundamental value is 7.6% (5.9%) under the base model and 9.7% (8.4%) under the generalized model. These magnitudes are similar to those reported in prior studies of CB discounts (e.g., Henderson 2006, Chan and Chen 2007) and less than the magnitudes of the discounts reported in private placements of equity (e.g., 20%, reported in Hertzel and Smith 1993; 14% in Brophy et al. 2009 and Huson et al. 2011). Although our evidence suggests that CBs are substantially underpriced on average, the variable exhibits significant variation, with an interquartile range of −1.1% to 14.4% for the base model and −1.4% to 18.6% for the generalized model. Similar variation is seen in the first day returns of IPOs (Ritter 2010).

Referring to Table 1, gross proceeds (issue size) tend to be substantial, with a sample mean (median) of \$278.9 million (\$175 million). The mean (median) fee paid to the placement agent is 2.9% (3.0%) of the issue, with an interquartile range of 2.5% to 3.2%. Unlike IPOs, which have very little variation in gross spreads (see Chen and Ritter 2000), we observe substantial fee variation in our sample. This provides an opportunity to analyze the question of what drives fees.

In choosing a relationship measure, we take a very simple approach: we define *RepeatInvestors* as the fraction of investors in a particular issue that have purchased a new 144A issue by the same placement agent in the past 24 months, relative to all investors in the issue. With the exception of a handful of studies that use proprietary IPO data over short time horizons (e.g., Cornelli and Goldreich 2001, Aggarwal et al. 2002, Aggarwal 2003), the lack of information on investor allocation has posed a major empirical challenge to answering the questions posed in this paper, even in the voluminous IPO literature. The investor identity data disclosed in the 144A CB filings provide an opportunity, using a large sample, to examine the importance of relationships and investor allocation.

We use *RepeatInvestors* and *NumInvestors* (the number of investors in the issue) as proxies for the ease of search for initial investors in the issue and after-market liquidity in the bond markets, respectively. The average issue has 56.6 investors; of those, 67.5% are related to the placement agent in that they have participated in at least one of the placement agent's issues in the last 24 months.[16]

InvestorExperience measures the fraction of all CB deal flow over the past 24 months purchased by issue *i*'s investors, excluding deals placed by issue *i*'s placement agent. Distinct from the prior interactions with deal *i*'s placement agent, *InvestorExperience* provides a general measure of the sophistication of the investors in a given bond issue and is included in the empirical analysis to distinguish the role of relationships versus experience in pricing. On average, investors have purchased 16.4% of all of the prior deal flow of other placement agents.

The median bond in our sample is unrated. Of the rated bonds, the average rating is just below investment grade. The mean rating of 5.36 corresponds to a bond with S&P rating BB, which is expected because CBs are a popular source of financing for firms of lower credit worthiness. In fact, the highest rated bond in our sample has an S&P rating of A. CCC is the lowest rating of the rated bonds in the sample. In regression analysis, we control for bond rating by including five dummy variables: *RateBBB*, which corresponds to an S&P rating of BBB; *RateBB*; *RateB*; *RateCCC*; and *Unrated*, a dummy equal to 1 for unrated bonds.

We observe substantial variation across the types of investors. Of the investors identified by type in the sample, 51.8% of the proceeds are purchased by hedge funds.[17] The second and third largest purchasers are broker-dealers (22.8% of the proceeds) and mutual funds (18.6% of the proceeds), respectively. The remaining identified investors are insurance/pension funds, corporations, banks, venture capital and private equity funds, charitable/educational investors, and family trusts.

The variable *MarketShare* measures the placement agent's market share of prior 144A CB issues over the 24 months preceding the bond offering. The mean (median) *MarketShare* is 11.3% (7.6%), with a standard deviation of 10.4%, indicating the sample includes rich variation in the placement agents' deal flow prior to an offering.

Note that we observe only those investors in 144A issues who choose to be named. They must do so if they plan to sell the bond to public investors at some point in the future. The mean (median) fraction of issues bought by unnamed investors is 28.8% (25.0%) in our sample. We exclude unnamed investors when counting the number of investors to facilitate clearer interpretation of the after-market liquidity proxy because the objective is to construct a measure of investors that plausibly intend to trade the bond. We do not expect the unnamed investor group to create bias in the estimated relationship between the

[16] We expect that the marginal investor is an unrelated investor (in all bond issues with less than 100% repeat investors) and that this investor is the one that impacts pricing. In robustness analysis, we introduce an alternative relationship measure intended to capture the intensity of the prior relationships (*Strength*), which has a mean of 0.183, median of 0.182 and interquartile range of 0.143 to 0.217. See the discussion of Table 4.

[17] This is somewhat lower than values reported in previous papers (Mitchell et al. 2007, Choi et al. 2010). The difference may be because 28% of the bonds are purchased by investors with missing investor type information in the Sagient database (these are labeled "Unknown" in the database).

repeated interaction measure and discounts because we do not have reason to believe that named investors are more or less likely to be related to the placement agent than are unidentified ones. We do, however, include the fraction of unnamed investors as a control variable in all extended regression specifications.

We control for asymmetric information in all regressions by including an analyst following measure, *NumAnalysts*, as a proxy for (low) asymmetric information. We measure analyst following as the natural logarithm of the number of analysts submitting annual earnings per share forecasts in the International Brokers' Estimate System (IBES). The firms in the sample tend to have high analyst coverage, with a mean analyst following of 14.9.

3.3. Empirical Specification

The main empirical specification is as follows:

$$Discount_{i,t} = \alpha + \beta_1 RepeatInvestors_{i,t} + \beta_2 NumInvestors_{i,t} + \beta_3' X_{i,t} + \epsilon_{i,t}. \quad (2)$$

Discount measures the issue price relative to fundamental value as discussed in §3.1. Recall that when this variable is positive, the interpretation is that the bond is underpriced. *RepeatInvestors*, defined as the fraction of investors that have purchased a new 144A issue from issue *i*'s placement agent during the past two years, is the proxy for the ease of locating and contracting with initial investors. If attracting familiar investors reduces search costs and contracting frictions, then issuers may avoid relying upon aggressive bond pricing, in which case we expect to observe higher bond prices relative to fundamental value ($\beta_1 < 0$).[18] Alternatively, if investor favoritism and conflict of interest dominate, then this variable will be related positively to the discount ($\beta_1 > 0$). The coefficient on *RepeatInvestors* allows us to distinguish the dominant effect of favoritism versus contracting frictions.

The (log) number of investors in the issue, *NumInvestors*, is the main proxy for after-market liquidity. We assume *NumInvestors* is proportional to the number of potential investors in the secondary market.[19] The expected relationship between liquidity risk and asset prices has been an important focus of the microstructure and asset pricing literature since Amihud and Mendelson (1986). However, only recently have after-market liquidity and liquidity risk received attention in the literature examining the prices of new issues of securities (i.e., primary market pricing). Ellul and Pagano (2006) are the first to develop and test a model in which after-market liquidity and liquidity risk reduce IPO underpricing. They find evidence consistent with improved pricing when after-market liquidity is expected to be high. Similarly, Gupta et al. (2008) find that expected secondary market liquidity impacts the pricing of syndicated loans such that higher expected liquidity reduces spreads paid by firms.[20] Given the findings in Ellul and Pagano (2006) and Gupta et al. (2008), we expect β_2, the estimated coefficient for *NumInvestors*, to be negative. This hypothesis is also consistent with the model of Duffie et al. (2007) where more potential investors lead to higher prices. Liquidity may be an important determinant of pricing in the 144A market for already issued securities (Chaplinsky and Ramchand 2004). Although this evidence is based on seasoned securities and also includes straight bonds, it highlights the potential importance of after-market liquidity in 144A bond markets.

We include the control vector X in the baseline empirical model. The variables comprising X are (natural log) issue size (*GrossProceeds*), bond rating dummies; underwriter fees (*Fee*), underwriter market share (*MarketShare*), number of equity analysts covering the firm (*NumAnalysts*), and market capitalization of the issuer (*MarketCap*). These control variables are based on the substantial empirical literature.

GrossProceeds and *NumAnalysts* control for information asymmetry at the issue and firm level, respectively. These are based on theoretical models of asymmetric information in issuance (e.g., Rock 1986, Benveniste and Spindt 1989). As noted in the introduction, we expect CB markets to be less subject to asymmetric information problems than are IPO and SEO markets; however, we control for information asymmetry so that the interpretation of the search frictions variables is clear. We include bond ratings controls given findings in Chan and Chen (2007) that ratings explain at-issue discounts.[21] Relative to A-rated bonds (the intercept), if bond ratings capture renegotiation risk and this risk is reflected in bond discounts, as argued by Chan and Chen (2007), we expect all coefficients on the ratings dummies

[18] We expect the marginal investor, regardless of size, to impact pricing. The *RepeatInvestors* measure is based on the number of repeat investors relative to all investors in the deal. In untabulated analysis, we instead define this variable as the fraction of proceeds purchased by repeat investors. The main results are qualitatively similar.

[19] Prior to registration, Rule 144A restricts trading of the bonds to QIBs. Additionally, because the bonds trade over the counter and contain complex features, the number of potential investors is reasonably linked to the number of investors already owning the bonds and familiar with the deal-specific terms.

[20] Wittenberg-Moerman (2008) also examines the syndicated loan market but focuses on the determinants of secondary market liquidity (bid-ask spreads) rather than primary market pricing.

[21] Cai et al. (2007) report statistically significant straight bond underpricing, especially in issues for which rating is low and information asymmetry is high.

to be positive. We also expect the magnitudes of the coefficients to increase as credit rating decreases. We include *Fee* to examine the hypothesis that investment banking fees reflect bankers' efforts to decrease bond discounts. If this is the case, then we would expect lower fees in bonds that have higher discounts. We include *MarketShare*, the placement agent's share of all 144A CB proceeds over the past 24 months, to capture the potential underwriter certification effect (as in Carter and Manaster 1990 and Megginson and Weiss 1991). Investors may perceive a placement agent with a larger market share (and better reputation) as certification of the quality of the issue. Finally, we include *MarketCap* as a proxy for issuer bargaining power. We expect that firms with substantial market capitalization will have significant future financing needs and their issues will receive more attention from placement agents, resulting in lower discounts.

4. Results

4.1. What Factors Drive Variation in CB Discounts?

Table 2 presents results of regressions in which *Discount*, calculated using the base model, is the dependent variable. All regressions contain year fixed effects and standard errors are double clustered by placement agent and issuer. Model 1 of Table 2 shows the benchmark regression from Equation (2), in which the search frictions variables, issue controls, and firm controls are the explanatory variables. Clearly both of the proposed search friction proxies matter. That is, we observe negative and significant coefficients on *RepeatInvestors* (the proxy for the ease with which the placement agent attracts investors) and *NumInvestors* (the proxy for after-market liquidity). Recall that the mean CB discount relative to fundamental value is 7.6%. All else equal, the results suggest that a one standard deviation increase in the fraction of repeat investors results in a decrease in the at-issue discount relative to fundamental value of 1.9% (i.e., at its mean, a reduction from 7.6% to 5.7%). For the average issue ($278 million), this translates to a savings of $5.3 million for the issuer. A one standard deviation increase in the number of investors from its mean results in a decrease in the at-issue discount of 1.2% (i.e., reduction from 7.6% to 6.4%). These findings suggest that search frictions play a meaningful role in bond pricing and that intermediaries add value through their repeated interactions with investors. This result is in contrast to the favoritism hypothesis in which banks use at-issue discounts to reward favored clients.[22]

The only control variables that are significant in Model 1 are *MarketCap* and *MarketShare*. The estimated coefficient on *MarketCap* is negative and significant, suggesting that larger, more visible firms are able to issue convertible debt at more favorable pricing. The positive and significant estimated coefficient on *MarketShare* is somewhat more surprising, given prior findings in the IPO literature (e.g., Ljungqvist and Wilhelm 2002) that placement agent market shares are negatively associated with underpricing. At face value, the coefficient on *MarketShare* in Model 1 suggests that even though firms will receive more favorable pricing if they hire investment banks with larger networks, the effect of the bank's market share partially mitigates this positive effect. This would be expected if high market share banks exercise market power. However, as will be discussed later, the result is not robust.

Model 2 of Table 2 extends the benchmark empirical model to include three additional controls for investor characteristics.[23] We include *UnclassifiedInvestors*, the fraction of proceeds bought by investors who are not identified in the Sagient data, as a control variable. These are investors who do not intend to sell their positions right away because only named investors can sell their holdings in the public market following registration. Based on the idea that hedge funds tend to have shorter investment horizons, we also include *NonHedgeFunds*, the fraction of total proceeds bought by investors who are not classified as hedge funds, to control for differences between short-term and long-term named investors. Finally, we include *InvestorExperience*, defined as the fraction of all CB deal flow over the past 24 months, excluding that placed by issue i's placement agent, purchased by issue i's investors. *InvestorExperience* captures the importance of experienced investors within bond issue i and is included because an alternative interpretation of the negative relation between *RepeatInvestors* and deal pricing is that *RepeatInvestors* captures investor sophistication rather than prior relationships between investors and placement agents. The expected sign on *InvestorExperience* is ambiguous. On one hand, issuing CBs to investors who already have experience purchasing these securities (from any placement agent) may reduce the contracting complexities that would exist for investors who are new to the 144A CB market. On the other

[22] A positive relationship between *RepeatInvestors* and *Discount* would also be consistent with traditional bookbuilding theories and the evidence of partial adjustment in IPO price revisions documented in Hanley (1993) and Ljungqvist and Wilhelm (2002); however, as noted in the introduction, such theories are less relevant in the case of CB issues by already public firms. Much of the otherwise private information that investors would have about demand is likely to be reflected in the equity market.

[23] We thank an anonymous referee for encouraging this line of analysis.

Table 2 What Drives Convertible Bond Discounts?

Regression results: Determinants of offering discount (base model)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Intercept	0.310	(0.76)	0.469	(1.00)	0.121	(0.23)	−0.063	(−0.12)
RepeatInvestors	−0.070**	(−2.10)	−0.073**	(−2.16)	−0.077**	(−2.15)	−0.073**	(−1.99)
NumInvestors	−0.023*	(−1.90)	−0.027**	(−2.22)	−0.024**	(−2.14)	−0.021*	(−1.79)
GrossProceeds	0.007	(0.28)	0.000	(0.01)	0.001	(0.04)	0.011	(0.42)
RateBBB	0.053	(1.40)	0.056	(1.55)	0.049	(1.33)	0.071***	(2.87)
RateBB	−0.050	(−0.82)	−0.049	(−0.82)	−0.057	(−0.93)	−0.020	(−0.41)
RateB	−0.083	(−1.33)	−0.083	(−1.36)	−0.090	(−1.45)	−0.039	(−0.79)
RateCCC	−0.053	(−0.81)	−0.053	(−0.82)	−0.061	(−0.90)	0.010	(0.18)
Unrated	−0.039	(−0.62)	−0.039	(−0.63)	−0.046	(−0.73)	0.001	(0.02)
Fee	1.352	(1.43)	1.247	(1.34)	1.209	(1.30)	2.142**	(2.20)
MarketShare	0.094*	(1.93)	0.096**	(2.06)	0.081*	(1.80)	0.043	(0.84)
log NumAnalysts	−0.019	(−1.56)	−0.020	(−1.60)	−0.019	(−1.53)	−0.009	(−0.79)
log MarketCap	−0.027**	(−2.35)	−0.027**	(−2.32)	−0.027**	(−2.21)	−0.042***	(−2.71)
UnclassifiedInvestors			0.035	(0.85)	0.042	(1.00)	0.047	(0.76)
NonHedgeFunds			−0.034	(−0.86)	−0.040	(−0.99)	−0.049	(−1.14)
InvestorExperience			0.142	(1.00)	0.130	(0.86)	0.174	(1.14)
KZIndex					−0.001	(−0.91)	0.000	(0.39)
BAAtoAAASpread					0.031	(0.64)	0.022	(0.39)
10-*yearTreasury*					0.048**	(1.99)	0.043**	(2.02)
IPOUnderpricing					−0.001	(−1.33)	−0.001*	(−1.82)
IPOGrossVolume					0.001	(0.72)	0.001	(0.74)
EWCumRet					0.018	(0.19)	0.042	(0.50)
Maturity							0.006***	(4.70)
HHI							0.017	(0.17)
DebtRatio							−0.009	(−0.45)
N	601		601		601		601	
Adjusted R^2	0.191		0.189		0.196		0.270	

Notes. This table presents regression results for the following OLS regression:

$$Discount_{i,t}^{\text{base model}} = \alpha + \beta_1\, RepeatInvestors_{i,t} + \beta_2\, NumInvestors_{i,t} + \beta_3' X_{i,t} + \epsilon_{i,t},$$

where $Discount_{i,t}^{\text{base model}}$ is the percentage discount of the offering price below the fundamental value from the base model; *RepeatInvestors* is the fraction of the investors in bond i that also purchased a 144A bond from the placement agent in the preceding 24 calendar months; *NumInvestors* is the (log) number of investors in the bond. The control variables in vector $X_{i,t}$ are all defined in Table 1 with the exception of the following variables. *Rate BBB* corresponds to S&P bond rating of BBB+, BBB, and BBB−. The same applies to the other ratings categories. The highest rated bond in the sample is A (the intercept). *KZIndex* captures the extent to which firms are financially constrained and is measured using the method of Almeida et al. (2004). *BAAtoAAASpread* comes from Moody's and is the difference between the yields on BAA and AAA rated corporate bonds during the month preceding the issue. *10-yearTreasury* is defined as the yield on constant maturity U.S. Treasury bonds during the month preceding the bond issue. *IPOUnderpricing* is the average underpricing of initial public offerings in the month preceding the bond issue, *IPOGrossVolume* is dollar volume of initial public offerings in the month preceding the bond issue. Both *IPOUnderpricing* and *IPOGrossVolume* come from http://bear.warrington.ufl.edu/ritter. *EWCumRet* is the cumulative return of the CRSP equally weighted index, measured over the 30 days preceding the bond issue. There are four model specifications. Model 1 is the benchmark model, which includes the search frictions variables along with issue and firm characteristics controls as explanatory variables. Model 2 extends the benchmark model, adding additional controls for investor characteristics. Model 3 adds variables that have been found to explain private equity discounts. Model 4 adds *Maturity*, *HHI*, and *DebtRatio* to the X vector. All standard errors are double clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

hand, sophisticated investors may be more successful in their demands for favorable pricing. Although not statistically significant, the estimated coefficient on this variable, as shown in Model 2 of Table 2 is consistent with the latter interpretation. The results shown in Table 2 also suggest the proxies for investor horizon do not influence pricing. The estimated coefficient on *NonHedgeFunds* is negative, as expected, but it is not statistically significant. The estimated coefficient on *UnclassifiedInvestors* is positive and also insignificant. Importantly, the magnitudes and significance of the estimated coefficients on the search frictions variables remain after including these additional control variables.

Outside the IPO and SEO settings, there is evidence of substantial discounts in PIPEs, beginning with Hertzel and Smith (1993). In recent work, Huson et al. (2011) document an important role for capital market conditions in the initial pricing of PIPEs. Following the PIPE literature, Model 3 of Table 2 further extends the benchmark model to include variables that capture market conditions and the extent to which firms are financially constrained. Huson et al. (2011) find that discounts are higher when recent market returns have been high, recent IPO underpricing has been high, recent IPO dollar volume is low, 10-year Treasury rates are high, and BAA–AAA spreads are high. We include all five of these market conditions variables in the Model 3 specification. We also include the *KZIndex*, a proxy for firms' financial constraints, given evidence in Huson et al. (2011) of higher discounts for financially constrained firms. Of these variables, the 10-year Treasury rate is the only one that is significant and suggests that at-issue discounts are greater when long-term Treasury yields are high. In addition to the tight credit market conditions interpretation of this positive relationship in Huson et al. (2011), cash-constrained firms may be more willing to issue convertibles when the coupons that they expect to pay on a straight debt issue are high. This is consistent with the debt-sweetener hypothesis of Billingsley and Smith (1996).

An alternative interpretation for the negative and significant coefficient on the number of investors measure (*NumInvestors*) in Models 1–3 is that this variable proxies for investor interest in the deal rather than for secondary market liquidity. In extended regressions, we add *Maturity*, the years-to-maturity of the bond issue, as an additional proxy for after-market liquidity. The basic idea is that as the maturity of the issue becomes longer, short-horizon investors will become concerned about their ability to sell the bond in the aftermarket and will require higher discounts. For example, Amihud and Mendelson (1991) find that the yields on shorter maturity treasuries are substantially smaller than on less liquid long-maturity treasuries. The results are in Model 4 of Table 2. We find that debt maturity is positively and significantly related to *Discount*. That is, longer maturity bonds are priced lower relative to fundamental value. The significant coefficient on *NumInvestors* remains and suggests that *Maturity* captures a different dimension of expected secondary market liquidity. The *Maturity* results provide additional support for a strong positive role for after-market liquidity in bond pricing.[24]

In addition to adding the *Maturity* measure to the analysis, Model 4 also includes investor buyer power, *HHI*, and controls for firm leverage with *DebtRatio*. The *HHI* measure captures the concentration of investor allocation within an issue. If buyer power influences pricing, we expect that issues in which buyer power is high (high *HHI*) will have higher discounts. We include *DebtRatio* because issuers that already have large amounts of debt outstanding may be forced to issue CBs at less favorable terms. We find that both of these measures are insignificant after controlling for prior relationships and the number of investors in the deal.

The signs and significance of the other variables in Model 4 are the same as in Models 1–3, with the exception of *RateBBB*, *Fee*, and *IPOUnderpricing*, which all become significant after adding the additional covariates. The positive and significant coefficient on *RateBBB* is striking because it is larger than those on the other ratings dummies, suggesting that investors require the highest discounts for BBB bonds. This result is consistent with market segmentation in which investors, such as pension funds and insurance companies, are restricted to holding investment grade bonds. For these investors, purchasing a BBB-rated bond, which is only one notch above high-yield, means that they may have to dispose of the bond if the rating drops. It is plausible that these investors demand compensation for taking a ratings downgrade risk. The coefficient on *Fee* is positive and significant, which is contrary to the hypothesis that banking fees reflect bankers' efforts to decrease bond discounts but is consistent with the idea that fees are higher for harder-to-place issues.[25] The negative and significant estimated coefficient on *IPOUnderpricing* suggests substitutability between equity and convertible debt, in which firms move to convertible debt markets when equity investors demand substantial discounts. As noted above, the positive, significant coefficient on *MarketShare* observed in Models 1–3 is not robust. The estimated coefficient on placement agent *MarketShare* becomes insignificant in the extended specification. Importantly, the significant and negative coefficients on both *RepeatInvestor* and *NumInvestors* remain.

Taken together, the results in Models 1–4 show robust relationships between at-issue discounts and search frictions. The estimated coefficients on both *RepeatInvestors* and *NumInvestors* are similar both in magnitude and statistical significance across all four models. Because the analysis relies heavily on the model-based prices, we repeat the Table 2 analysis but instead measure the *Discount* using the prices from the generalized model. Because of the added data requirements and calibration procedure of the generalized model, the sample size is reduced from 601 to 575.

[24] As noted in §2, registration rights might impact expected after-market liquidity. In untabulated analysis, under the assumption that actual registration is a good proxy for expected registration, we create a new variable equal to the (log) number of days between closing and filing date as well as a dummy equal to 1 if we do not observe a filing for the issue. We rerun the regressions in Model 4 and find positive (as we would expect) but insignificant coefficients on both variables.

[25] This assumes that fees are exogenous, an assumption that we will relax in later analysis, given potential concerns that fees and prices are set simultaneously.

Table 3 The Generalized Pricing Model: What Drives Convertible Bond Discounts?

Regression results: Determinants of offering discount

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Intercept	0.576	(1.32)	0.853*	(1.68)	0.623	(1.17)	0.362	(0.73)
RepeatInvestors	−0.074**	(−2.47)	−0.080**	(−2.52)	−0.089***	(−2.77)	−0.091***	(−2.58)
NumInvestors	−0.026*	(−1.69)	−0.028**	(−2.29)	−0.027**	(−2.37)	−0.020	(−1.63)
GrossProceeds	−0.016	(−0.63)	−0.031	(−1.03)	−0.030	(−1.06)	−0.017	(−0.68)
RateBBB	0.090*	(1.79)	0.094**	(1.98)	0.089*	(1.94)	0.118***	(3.81)
RateBB	0.010	(0.13)	0.011	(0.15)	0.005	(0.07)	0.050	(0.88)
RateB	0.010	(0.14)	0.012	(0.16)	0.010	(0.14)	0.070	(1.37)
RateCCC	0.014	(0.20)	0.016	(0.24)	0.017	(0.25)	0.101**	(2.18)
Unrated	0.028	(0.43)	0.030	(0.47)	0.027	(0.42)	0.08*	(1.69)
Fee	0.799	(0.63)	0.640	(0.50)	0.624	(0.50)	1.59	(1.18)
MarketShare	0.131***	(2.83)	0.133***	(2.89)	0.132***	(2.71)	0.107**	(1.99)
log *NumAnalysts*	−0.023**	(−1.96)	−0.024**	(−2.06)	−0.024**	(−2.09)	−0.012	(−1.09)
log *MarketCap*	−0.013	(−1.09)	−0.012	(−0.91)	−0.011	(−0.88)	−0.028**	(−2.20)
UnclassifiedInvestors			0.085**	(1.99)	0.090**	(2.02)	0.089*	(1.76)
NonHedgeFunds			−0.053	(−1.07)	−0.051	(−0.97)	−0.066	(−1.28)
InvestorExperience			0.223	(1.54)	0.220	(1.43)	0.232	(1.61)
KZIndex					−0.000	(−0.33)	0.001	(0.80)
BAAtoAAASpread					0.047	(0.88)	0.036	(0.69)
10-*yearTreasury*					0.033	(1.31)	0.028	(1.33)
IPOUnderpricing					−0.000	(−0.64)	−0.001	(−0.96)
IPOGrossVolume					0.000	(0.14)	0.000	(0.09)
EWCumRet					−0.152	(−1.28)	−0.115	(−1.01)
Maturity							0.006***	(3.98)
HHI							0.039	(0.45)
DebtRatio							−0.023	(−0.86)
N	575		575		575		575	
Adjusted R^2	0.165		0.167		0.169		0.247	

Notes. This table presents regression results for the following OLS regression:

$$Discount_{i,t}^{\text{generalized model}} = \alpha + \beta_1\, RepeatInvestors_{i,t} + \beta_2\, NumInvestors_{i,t} + \beta_3' X_{i,t} + \epsilon_{i,t},$$

where $Discount_{i,t}^{\text{generalized model}}$ is the percentage discount of the offering price below the fundamental value from the generalized model; *RepeatInvestors* is the fraction of the investors in bond i that also purchased a 144A bond from the placement agent in the preceding 24 calendar months; *NumInvestors* is the number of investors in the bond. The control variables in vector X are all defined in Tables 1 and 2. There are four specifications. Model 1 is the benchmark model, which includes the search friction variables along with issue and firm characteristics controls as explanatory variables. Model 2 extends the benchmark model, adding additional controls for investor characteristics. Model 3 adds variables that have been found to explain private equity discounts. Model 4 adds *Maturity*, *HHI*, and *DebtRatio* to the X vector. All standard errors are clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 presents regression results repeating the analysis in Table 2, but where the discount measure is based on prices from the generalized model. The results are qualitatively similar to those in Table 2 and provide strong evidence that the main results are not driven by model choice.[26] The most important observation from the table is that high values of *RepeatInvestors* and *NumInvestors* are associated with significantly lower at-issue discounts. For example, the results from Model 4 imply that a one standard deviation increase in *RepeatInvestors* results in a decrease in the at-issue discount of 2.3% (relative to its mean of 9.7%). A one standard deviation increase in *NumInvestors* from its mean results in a decrease in the discount of 0.46%.[27] Given the consistency of the main results across all four models in both Tables 2 and 3, all subsequent analysis will focus on the extended specification (Model 4).

[26] As an additional check of the *Discount* proxies, for all issues in which we were able to obtain quote data in Datastream within one week of 365 calendar days post issuance, we calculated abnormal bond returns. We then calculated the correlations between after-market returns and the *Discount* to test whether bonds that are priced lower relative to fundamental value actually experience higher subsequent returns (i.e., price convergence toward fundamental value). The correlations over the one year horizon are 0.198 under the base model and 0.180 under the generalized model and are statistically significant. This provides market-based validation for the model based pricing measures and should provide additional confidence in the interpretation of the main analysis.

[27] The standard deviations of *NumInvesors* and *RepeatInvestors* for the 575 observations in the generalized model subsample are 39.39 and 0.252, respectively.

4.2. Strength of Placement Agent–Investor Relationships

The baseline analyses in Tables 2 and 3 use a very simple, intuitive measure to define placement agent–investor relationships. To capture the intensity of the relationship between placement agents and their investors, we examine an alternative definition of past interactions.

We introduce *Strength*, which captures the average participation of investors in issue *i* in all 144A CB issues by *i*'s placement agent during the past 24 months.[28] We compute *Strength* as

$$Strength = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{\text{number of prior issues by placement agent in which investor participated}}{\text{total prior deals by placement agent}}, \quad (3)$$

where N is the number of investors in the bond issue. *Strength* has a mean of 0.186, median of 0.183, and inter-quartile range of 0.15 to 0.22. In Table 4 we repeat the main analysis using both the base and generalized pricing models but replace *RepeatInvestors* with the *Strength* measure. We find that stronger relationships are associated with higher bond prices (lower *Discount*). The estimated coefficients on *Strength* range from 0.174 to 0.196, with economic magnitudes that are similar to the coefficients on *RepeatInvestors* in Tables 2 and 3. For example, the results in Table 4 using the base model imply that a one standard deviation increase in the average strength of the relationship between investors and the placement agent decreases the at-issue discount by 1.15%. Similar to the main results, Table 4 suggests that when a placement agent attracts her most important investors from her "rolodex," aggressive discounting becomes less critical for successful placement of the offering.[29]

The *Strength* variable is introduced to capture relationship intensity. However, given that both the *Strength* and *RepeatInvestors* measures are defined for interactions during the past 24 months, neither variable perfectly captures the extent to which longer-horizon relationships might facilitate learning. In untabulated analysis, we examined the impact of relationship length by introducing an alternative relationship measure, defined as the percentage of proceeds purchased by investors that have had a relationship with the placement agent for at least X years, where $X \in \{1, 2, 3, 5\}$. Similar to the main results, we observe negative and significant coefficients on the new *Length* variable under the three- and five-year definitions (coefficients are marginally significant when we define *Length* over the

Table 4 The Role of Relationship Strength in Offering Discounts

Determinants of discount with relationship strength

	Base model prices		Generalized model prices	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Intercept	−0.055	(−0.11)	0.368	(0.74)
NumInvestors	−0.027**	(−2.50)	−0.026*	(−1.85)
Strength	−0.174*	(−1.90)	−0.196**	(−2.16)
GrossProceeds	0.013	(0.50)	−0.015	(−0.57)
RateBBB	0.074***	(3.14)	0.121***	(3.84)
RateBB	−0.013	(−0.27)	0.058	(1.01)
RateB	−0.034	(−0.67)	0.075	(1.42)
RateCCC	0.013	(0.24)	0.105**	(2.19)
Unrated	0.006	(0.12)	0.090*	(1.77)
Fee	2.267**	(2.37)	1.734	(1.31)
MarketShare	−0.050	(−1.31)	−0.011	(−0.28)
log *NumAnalysts*	−0.010	(−0.94)	−0.014	(−1.27)
log *MarketCap*	−0.043***	(−2.92)	−0.029**	(−2.26)
UnclassifiedInvestors	0.048	(0.74)	0.088	(1.61)
NonHedgeFunds	−0.043	(−1.05)	−0.058	(−1.18)
InvestorExperience	0.189	(1.24)	0.242	(1.64)
KZIndex	0.000	(0.65)	0.001	(1.05)
BAAtoAAASpread	0.024	(0.43)	0.039	(0.74)
10-*yearTreasury*	0.040*	(1.79)	0.025	(1.12)
IPOUnderpricing	−0.001*	(−1.71)	−0.001	(−0.84)
IPOGrossVolume	0.001	(0.93)	0.000	(0.33)
EWCumRet	0.033	(0.39)	−0.125	(−1.11)
Maturity	0.006***	(4.76)	0.006***	(4.05)
HHI	0.002	(0.02)	0.022	(0.24)
DebtRatio	−0.006	(−0.28)	−0.020	(−0.72)
N	601		575	
Adjusted R^2	0.266		0.243	

Notes. This table presents regression results for the following OLS regressions:

$$Discount_{i,t} = \alpha + \beta_1\, NumInvestors_{i,t} + \beta_2\, Strength_{i,t} + \beta_3' X_{i,t} + \epsilon_{i,t},$$

where $Discount_{i,t}$ is the percentage discount of the offering price to the fundamental value from the pricing model and *Strength* is defined as the average participation of investors in issue *i* in all 144A convertible bond issues by bond *i*'s placement agent during the past 24 months. All other variables are defined in Tables 1 and 2 and are based on the extended regressions (Model 4) shown in Tables 2 and 3. The table presents results of two regressions. In the first regression, the *Discount* measure comes from the base model and in the second regression from the generalized model. All standard errors are double clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[28] Although in a very different setting from ours, Davis and Kim (2007) also study relationship intensity measures.

[29] Our sample includes some bonds issued by firms for which the placement agent has previously placed a 144A CB (there are 71 such cases in the Sagient data). One might be concerned that when a placement agent has already placed a bond by given firm, it is easier to attract the same investors to the issue and the discount is therefore lower (because the investors have experience with a similar bond placed by the same placement agent, not because of relationships). To rule out this possibility, in untabulated analysis, we excluded the 71 repeat issues from the analysis. The estimated coefficients on *RepeatInvestors* and *Strength* using both pricing models are qualitatively similar to those shown in Tables 2 and 3.

shorter horizons). More importantly, the magnitudes of the estimated coefficients monotonically increase as we increase the years over which we estimate length of the relationship. This suggests that our results are driven, at least in part, by the learning that takes place in longer-horizon relationships.

4.3. Further Interpretation: The Roles of Affiliated Investors and Investor Experience at the Sector Level

4.3.1. Affiliated Investors. Affiliated investors allow for further examination of the role of contracting frictions in pricing. As in the case with *RepeatInvestors*, there are competing hypotheses regarding the behavior of placement agents' allocations to their affiliated investors. According to the favoritism hypothesis, placement agents allocate favorably priced issues to affiliated investors in order to increase their performance. In the case of IPOs, Ritter and Zhang (2007) find evidence consistent with the favoritism hypothesis. Alternatively, under the search frictions hypothesis, banks may encourage their affiliated investors to purchase issues that are difficult to place. Consistent with this hypothesis (and also with bookbuilding, which is less relevant in our setting), Reuter (2006) finds very little evidence of differences between IPO allocations to affiliated and nonaffiliated investors, but affiliated investors earn slightly lower first day returns, which is inconsistent with "favoritism."

To examine the role of investor affiliation, we introduce *AffiliatedInvestors*, defined as the fraction of proceeds purchased by investors who are affiliated with the investment bank. To connect investors with placement agents, we rely on common name matching. The mean (median) fraction of proceeds sold to affiliated investors in our sample of 601 bond issues is 2.49% (0.00%).

Table 5 presents regression results where the main analysis is extended to include *AffiliatedInvestors*. The table includes *Discount* measured under both the base and generalized pricing models. Although not significant, the negative signs on the *AffiliatedInvestors* coefficients in both of the regressions suggest that affiliated investors, like repeat investors, help reduce contracting costs. This finding is consistent with the search frictions hypothesis and inconsistent with the favoritism hypothesis.

4.3.2. Investor Experience and Contracting Complexity. The *InvestorExperience* measure also provides insight into the role of relationships. Beginning with Model 3 in Table 2, all regressions control for *InvestorExperience* to ensure that any observed relationship between *RepeatInvestors* and the *Discount* is due to prior interactions between the placement agent and the investor, as opposed to proxying for placing bonds in the hands of sophisticated investors. In most specifications, the estimated coefficients on this variable are positive, suggesting that sophisticated investors demand higher discounts. However, the coefficients are marginally significant at best. To clarify the role of sophisticated investors, we adopt a narrower definition of experience. Rather than measure the fraction of all other deal flow by other placement agents, we focus only on same sector deal flow. The basic idea is that investors who have recently bought a CB by an issuer in the same sector will be very well informed, which can either reduce contracting complexity or increase investor bargaining power.[30]

Results are in Table 5. The estimated coefficient on *InvestorExperience* becomes larger in magnitude and is statistically significant in both specifications. The finer definition of *InvestorExperience* confirms the interpretation that investor sophistication and relationships between investors and placement agents play very different roles in the initial pricing of CBs.

4.4. Potential Endogeneity of Fees

The estimated coefficients on *Fee* in Tables 2–5 are positive and statistically significant under the base pricing model, and positive but often insignificant under the generalized model. Under the base model, the estimated coefficient on *Fee* of approximately 2.1 implies that, all else equal, a one standard deviation increase in fees increases the *Discount* by 1.7%. Although economically significant, the analysis assumes that fees are exogenous. If obtaining favorable pricing for issuers requires effort, investment banks may set fees and determine bond pricing simultaneously. In this case, an alternative interpretation of our main findings would be that the nature of the contract between issuers and banks changes and the observed reductions in at-issue discounts are offset by higher fees. To account for the potential endogeneity of fees, we use the two-stage least squares procedure to estimate the following system of equations:

$$\begin{aligned} Discount_{i,t} = {} & \beta_0 + \beta_1 Fee_{i,t} + \beta_2 RepeatInvestors_{i,t} \\ & + \beta_3 NumInvestors_{i,t} + \beta_4' X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

$$\begin{aligned} Fee_{i,t} = {} & \gamma_0 + \gamma_1 Discount_{i,t} + \gamma_2 SEOSpread_{i,t} \\ & + \gamma_3 NoSEO_{i,t} + \gamma_4 RepeatInvestors_{i,t} \\ & + \gamma_5' X_{i,t} + \upsilon_{i,t}. \end{aligned} \tag{5}$$

We introduce two new variables, *SEOSpread* and *NoSEO* in the *Fee* equation as the identifying variables for fees. *SEOSpread* is the mean gross spread charged by the same placement agent in seasoned equity offerings during the issue year. We expect that

[30] We thank a referee for suggesting the potential importance of same sector experience.

Table 5 Additional Measures of Contracting Frictions and Experience

Regression results: Determinants of offering discount with affiliated investors

	Base pricing model				Generalized pricing model			
	Affiliated investors		Sector experience		Affiliated investors		Sector experience	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Intercept	−0.191	(−0.37)	−0.032	(−0.07)	0.243	(0.50)	0.393	(0.81)
RepeatInvestors	−0.065*	(−1.78)	−0.072**	(−1.97)	−0.083**	(−2.26)	−0.090**	(−2.56)
NumberInvestors	−0.025**	(−2.22)	−0.022*	(−1.85)	−0.023*	(−1.93)	−0.020	(−1.56)
AffiliatedInvestors	−0.112	(−1.39)			−0.038	(−0.39)		
GrossProceeds	0.019	(0.74)	0.009	(0.37)	−0.009	(−0.36)	−0.019	(−0.77)
RateBBB	0.070***	(2.92)	0.071***	(2.70)	0.118***	(3.76)	0.117***	(3.65)
RateBB	−0.021	(−0.43)	−0.019	(−0.39)	0.049	(0.86)	0.051	(0.90)
RateB	−0.039	(−0.79)	−0.038	(−0.78)	0.069	(1.33)	0.071	(1.40)
RateCCC	0.007	(0.13)	0.011	(0.21)	0.098**	(2.07)	0.103**	(2.19)
Unrated	0.001	(0.02)	0.002	(0.04)	0.083	(1.64)	0.085*	(1.72)
Fee	2.141**	(2.31)	2.132**	(2.21)	1.515	(1.14)	1.565	(1.19)
MarketShare	0.034	(0.64)	0.044	(0.85)	0.099*	(1.78)	0.107**	(1.98)
log *NumAnalysts*	−0.008	(−0.76)	−0.009	(−0.75)	−0.012	(−1.08)	−0.012	(−1.03)
log *MarketCap*	−0.045***	(−3.00)	−0.042***	(−2.71)	−0.031**	(−2.47)	−0.028**	(−2.16)
UnclassifiedInvestors	0.048	(0.76)	0.050	(0.80)	0.095*	(1.81)	0.091*	(1.76)
NonHedgeFunds	−0.049	(−1.12)	−0.047	(−1.12)	−0.071	(−1.35)	−0.064	(−1.29)
InvestorExperience	0.133	(0.89)	0.197**	(2.11)	0.190	(1.32)	0.246*	(1.87)
KZIndex	0.000	(0.11)	0.000	(0.43)	0.001	(0.68)	0.001	(0.82)
BAAtoAAASpread	0.023	(0.40)	0.022	(0.38)	0.035	(0.70)	0.034	(0.68)
10-*yearTreasury*	0.045**	(2.11)	0.044**	(2.05)	0.030	(1.41)	0.029	(1.37)
IPOUnderpricing	−0.001*	(−1.80)	−0.001*	(−1.88)	−0.001	(−0.97)	−0.001	(−1.02)
IPOGrossVolume	0.001	(0.74)	0.001	(0.71)	0.000	(0.02)	0.000	(0.03)
EWCumRet	0.044	(0.53)	0.042	(0.50)	−0.112	(−0.99)	−0.113	(−0.99)
Maturity	0.006***	(4.65)	0.006***	(4.68)	0.006***	(3.96)	0.006***	(3.95)
HHI	−0.030	(−0.28)	0.019	(0.19)	−0.008	(−0.10)	−0.042	(−0.50)
DebtRatio	−0.005	(−0.25)	−0.010	(−0.52)	−0.021	(−0.76)	−0.025	(−0.92)
N	601		601		575		575	
Adjusted R^2	0.266		0.271		0.237		0.249	

Notes. This table presents regression results for the following OLS regression:

$$Discount_{i,t} = \alpha + \beta_1\, RepeatInvestors_{i,t} + \beta_2\, NumInvestors_{i,t} + \beta_3\, AffiliatedInvestors + \beta_4' X_{i,t} + \epsilon_{i,t},$$

where $Discount_{i,t}$ is the percentage discount of the offering price below the fundamental value from the pricing model; *RepeatInvestors* is the fraction of the investors in bond i that also purchased a 144A bond from the placement agent in the preceding 24 calendar months; *NumInvestors* is the number of investors in the bond. *AffiliatedInvestors* is the fraction of bond i placed with investors affiliated with the deal's placement agent. Regression results labeled "Sector experience" include an alternative definition of *InvestorExperience*: The fraction of same sector deal flow over the previous 24 months purchased by investors in the ith deal. The control variables in vector $X_{i,t}$ are defined in Tables 1 and 2 and are based on the extended regressions (Model 4) shown in Tables 2 and 3. The table presents results where *Discount* is based on prices from both the base model and the generalized model. All standard errors are double clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

cross-sectionally, placement agent fees in the CB market will exhibit variation similar to the variation in fees charged by the same placement agents in the SEO market. Because some placement agents do not participate in the SEO market, we also include a dummy variable equal to 1 if the placement agent's firm did not place an SEO during the issue year.[31] We expect that placement agents who do not participate in multiple issue markets will have higher fixed costs in the CB market (e.g., no potential for sharing costs with activities in SEOs). Importantly, we also expect the exclusion restriction to be satisfied. That is, we do not expect a given placement agent's activities in the separate SEO market to have a direct effect on CB pricing. The specification for the *Discount* equation is identical to the regressions in Tables 2–5. The identifying variables in the *Discount* equation are the secondary market liquidity proxies. These variables are excluded from the *Fee* equation because the ability to trade the bond in secondary markets should not be of direct concern to placement agents, except through the impact on the *Discount*. The variables in the *X* vector are identical in both the *Fee* and *Discount* equations. The exogeneity assumption for the variables in *X* is less of a concern because these variables reflect

[31] Placement agents were hand-matched by firm name and year with the SDC New Issues database.

lagged firm characteristics, issue characteristics, and overall market conditions, which are all unlikely to be negotiated along with bond pricing.

Table 6 presents results of the simultaneous equation model. The *Discount* results in panel A are similar to the main findings in the Table 2 extended regressions. The most important observation from panel A of Table 6 is that in all four specifications, all search frictions proxies (*NumInvestors*, *RepeatInvestors*, *Strength*, and *Maturity*) remain significantly related, both economically and statistically, to the *Discount*. Also important is that *Fee* loses significance in the *Discount* equation once we control for endogeneity. *MarketShare* remains insignificant. These results suggest that issue, firm, and market conditions are more important determinants of the initial pricing of CBs than are the fees charged by placement agents. All signs of the other coefficients are consistent with the main analysis in Table 2.

Panel B of Table 6 presents the *Fee* equation results. The estimated coefficients on both *SEO Spread* and *NoSEO* are positive (as expected) and significant, suggesting that the system is well identified. We observe higher fees for placement agents who also charge higher fees in the SEO market or who are not currently participating in the SEO market. We also observe that *RepeatInvestors* negatively impact fees but *Strength* does not. This is consistent with the interpretation that contracting with prior investors is easier but that the benefit of past relationships on reducing fees does not depend on the intensity/frequency of prior interactions. The finding that relationships (*RepeatInvestors*) decrease fees is consistent with a reduction of search costs through having a large rolodex that is, at least in part, transferred to firms. Finally, we find a significant negative relationship between at-issue discounts and fees. That is, we observe higher percentage fees when bonds are priced favorably for issuers. This finding is consistent with banks charging higher fees as compensation for obtaining higher prices for the bonds.

Overall, the results in Tables 2–6 provide strong evidence that reducing search frictions improves pricing and reduces fees paid to placement agents in the market for privately placed CBs. The finding that *RepeatInvestors* is associated with higher bond prices is contrary to the investor favoritism hypothesis but consistent with models of search costs.

Table 6 Simultaneous Equations Model: Fee and Discount

	Base pricing model				Generalized pricing model			
	Repeat investors		Investor strength		Repeat investors		Investor strength	
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
	Panel A: Dependent variable: *OfferDiscount*							
Intercept	−0.308	(−0.48)	−0.471	(−0.83)	0.177	(0.26)	0.020	(0.03)
Fee	4.786	(0.61)	6.850	(0.90)	3.484	(0.52)	5.356	(0.81)
RepeatInvestors	−0.067*	(−1.90)			−0.087**	(−2.38)		
NumInvestors	−0.021*	(−1.84)	−0.027**	(−2.50)	−0.020	(−1.63)	−0.027*	(−1.86)
Strength			−0.171*	(−1.81)			−0.193**	(−2.12)
GrossProceeds	0.017	(0.72)	0.023	(1.07)	−0.012	(−0.44)	−0.005	(−0.20)
RateBBB	0.074***	(3.31)	0.078***	(3.62)	0.120***	(4.05)	0.124***	(4.21)
RateBB	−0.022	(−0.42)	−0.018	(−0.33)	0.048	(0.84)	0.055	(0.93)
RateB	−0.041	(−0.78)	−0.038	(−0.70)	0.068	(1.33)	0.072	(1.36)
RateCCC	0.011	(0.21)	0.015	(0.27)	0.102**	(2.14)	0.107**	(2.18)
Unrated	−0.001	(−0.02)	0.002	(0.04)	0.083	(1.62)	0.087*	(1.66)
MarketShare	0.051	(0.79)	−0.022	(−0.38)	0.112*	(1.94)	0.011	(0.21)
log *NumAnalysts*	−0.007	(−0.66)	−0.007	(−0.68)	−0.011	(−0.96)	−0.012	(−1.01)
log *MarketCap*	−0.035	(−1.08)	−0.031	(−0.97)	−0.023	(−0.94)	−0.019	(−0.82)
UnclassifiedInvestors	0.052	(0.81)	0.058	(0.87)	0.094**	(1.96)	0.099*	(1.89)
NonHedgeFunds	−0.044	(−0.86)	−0.034	(−0.71)	−0.064	(−1.14)	−0.055	(−1.01)
InvestorExperience	0.144	(0.93)	0.139	(0.91)	0.210	(1.49)	0.201	(1.45)
KZIndex	0.000	(0.27)	0.000	(0.39)	0.001	(0.70)	0.001	(0.85)
BAAtoAAASpread	0.032	(0.61)	0.041	(0.75)	0.042	(0.67)	0.051	(0.81)
10-*yearTreasury*	0.042*	(1.91)	0.039*	(1.71)	0.028	(1.27)	0.025	(1.08)
IPOUnderpricing	−0.001*	(−1.83)	−0.001*	(−1.66)	−0.001	(−0.85)	−0.001	(−0.70)
IPOGrossVolume	0.001	(0.61)	0.001	(0.71)	0.000	(0.01)	0.000	(0.14)
EWCumRet	0.042	(0.50)	0.032	(0.37)	−0.113	(−1.03)	−0.123	(−1.14)
Maturity	0.006***	(7.60)	0.006***	(6.98)	0.007***	(4.69)	0.007***	(4.62)
HHI	−0.011	(−0.08)	−0.049	(−0.37)	0.016	(0.14)	−0.024	(−0.18)
DebtRatio	−0.012	(−0.58)	−0.012	(−0.60)	−0.026	(−0.96)	−0.025	(−0.95)
N	601		601		575		575	
Adjusted R^2	0.262		0.260		0.244		0.240	

Table 6 (Continued)

	Base pricing model				Generalized pricing model			
	Repeat investors		Investor strength		Repeat investors		Investor strength	
	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)
	Panel B: Dependent variable: *PlacementAgentFee*							
Intercept	0.083***	(5.22)	0.081***	(4.55)	0.094***	(4.12)	0.092***	(4.20)
Discount	−0.020**	(−2.40)	−0.020**	(−2.37)	−0.018**	(−2.13)	−0.018**	(−2.13)
RepeatInvestors	−0.003**	(−2.04)			−0.003**	(−2.13)		
Strength			−0.002	(−0.53)			−0.003	(−0.71)
SEOSpread	0.115**	(2.35)	0.121**	(2.37)	0.122**	(2.38)	0.129**	(2.40)
NoSEO	0.006***	(2.59)	0.007***	(2.71)	0.007**	(2.50)	0.007**	(2.61)
GrossProceeds	−0.002**	(−2.33)	−0.002**	(−2.01)	−0.003**	(−2.40)	−0.003**	(−2.21)
RateBBB	0.001	(0.31)	0.001	(0.40)	0.001	(0.62)	0.001	(0.70)
RateBB	0.000	(0.30)	0.001	(0.49)	0.002	(1.03)	0.002	(1.19)
RateB	0.001	(0.37)	0.001	(0.52)	0.002*	(1.86)	0.002**	(2.01)
RateCCC	0.000	(0.15)	0.000	(0.21)	0.002	(1.17)	0.002	(1.21)
Unrated	0.001	(0.92)	0.001	(1.11)	0.002*	(1.79)	0.003*	(1.92)
MarketShare	−0.003	(−0.67)	−0.007*	(−1.84)	−0.001	(−0.37)	−0.006*	(−1.70)
log *NumAnalysts*	−0.001	(−1.27)	−0.001	(−1.34)	−0.001	(−1.03)	−0.001	(−1.10)
log *MarketCap*	−0.004***	(−7.47)	−0.004***	(−7.36)	−0.003***	(−7.34)	−0.003***	(−7.24)
UnclassifiedInvestors	−0.001	(−0.49)	−0.002	(−0.65)	−0.001	(−0.45)	−0.002	(−0.59)
NonHedgeFunds	−0.003	(−1.26)	−0.003	(−1.21)	−0.002	(−0.90)	−0.002	(−0.85)
InvestorExperience	0.015**	(2.54)	0.014**	(2.44)	0.017**	(2.37)	0.016**	(2.29)
KZIndex	0.000	(0.56)	0.000	(0.74)	0.000	(0.57)	0.000	(0.75)
BAAtoAAASpread	−0.003	(−0.98)	−0.003	(−0.92)	−0.002	(−0.75)	−0.002	(−0.68)
10-*yearTreasury*	0.002**	(1.99)	0.001*	(1.85)	0.001	(1.39)	0.001	(1.29)
IPOUnderpricing	−0.000	(−1.32)	−0.000	(−1.25)	−0.000	(−1.17)	−0.000	(−1.06)
IPOGrossVolume	0.000	(1.34)	0.000	(1.57)	0.000	(1.05)	0.000	(1.25)
EWCumRet	0.001	(0.35)	0.001	(0.40)	−0.003	(−0.77)	−0.003	(−0.76)
HHI	0.014**	(2.25)	0.014**	(2.27)	0.014**	(2.44)	0.015**	(2.45)
DebtRatio	0.001	(0.79)	0.001	(0.88)	0.001	(0.66)	0.001	(0.75)
N	601		601		575		575	
Adjusted R^2	0.429		0.428		0.434		0.433	

Notes. This table presents two-stage least squares estimation results for the following simultaneously determined system of equations:

$$Discount_{i,t} = \beta_0 + \beta_1 Fee_{i,t} + \beta_2 RepeatInvestors + \beta_3 NumInvestors_{i,t} + \beta_4' X_{i,t} + \epsilon_{i,t},$$

$$Fee_{i,t} = \gamma_0 + \gamma_1 Discount_{i,t} + \gamma_2 SEOSpread_{i,t} + \gamma_3 NoSEO + \gamma_4 RepeatInvestors_{i,t} + \gamma_5' X_{i,t} + \upsilon_{i,t}.$$

Both *Discount* and *Fee* are treated as endogenous variables. All variables are defined in Tables 1, 2, and 4 with the exception of *SEOSpread* and *NoSEO*. *SEOSpread* is the average gross spread charged by placement agent *i* in seasoned equity issues (as reported in Thomson's SDC database) during the issue year *t*. *NoSEO* is a dummy variable equal to 1 if the placement agent did not place seasoned equity during the year of issue. All standard errors are double clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5. Mechanisms Driving the *Repeat Investors* Result: Demand-Side Interpretation

The findings in Tables 2–6 suggest that relationships enhance banks' ability to attract investors, thereby allowing them to place bonds at higher prices. However, an alternative explanation is that both *RepeatInvestors* and *NumInvestors* proxy for investor demand. Mitchell et al. (2007) document patterns of widespread redemptions among CB arbitrage hedge funds during 2005, which led to forced liquidations of CB positions. They describe a similar phenomenon during 1998 surrounding the Long Term Capital Management crisis. To control explicitly for changes in demand and to disentangle our main results from the demand-side interpretation, we use CB arbitrage hedge fund flows (*Flows*). The *Flows* variable also allows us to examine a potential mechanism through which repeated interactions impact pricing: under the contracting frictions hypothesis, the bank's rolodex becomes more important when demand conditions are unfavorable (when *Flows* are low or negative).

Table 7 contains results of regressions in which we add *Flows* and *Repeat* × *Flows* (the interaction between *Flows* and *RepeatInvestors*) to the empirical specification. There are three important observations from the table. First, *RepeatInvestors* remains significant, after explicitly controlling for the demand-based mechanism. Second, demand has an independent pricing effect: we observe a negative and significant coefficient on hedge fund flows, suggesting lower bond

Table 7 Demand-Side Channel: Hedge Fund Flows

Regression results: Determinants of offering discount with affiliated investors

	Base pricing model				Generalized pricing model			
	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)	Coefficient	(t-statistic)
Intercept	−0.020	(−0.04)	−0.051	(−0.10)	0.395	(0.50)	0.379	(0.76)
Flows	−1.45**	(−2.02)	−0.838	(−1.26)	−1.157**	(−2.33)	−1.157**	(−2.19)
RepeatInvestors	−0.098*	(−1.92)			−0.106***	(−3.21)		
RepeatInvestors × *Flows*	1.653**	(2.15)			1.032	(1.37)		
Strength			−0.252**	(−2.19)			−0.266**	(−2.32)
Strength × *Flows*			4.010	(1.45)			3.404	(1.27)
NumInvestors	−0.022***	(−2.67)	−0.029***	(−2.65)	−0.021*	(−1.71)	−0.029**	(−2.00)
GrossProceeds	0.012	(0.45)	0.014	(0.56)	−0.017	(−0.68)	−0.014	(−0.55)
RateBBB	0.072*	(1.94)	0.077**	(2.13)	0.118***	(3.20)	0.124***	(3.45)
RateBB	−0.018	(−0.32)	−0.013	(−0.23)	0.049	(0.82)	0.056	(0.94)
RateB	−0.038	(−0.67)	−0.033	(−0.57)	0.070	(1.28)	0.075	(1.37)
RateCCC	0.011	(0.18)	0.013	(0.20)	0.098*	(1.94)	0.100**	(1.97)
Unrated	0.002	(0.03)	0.007	(0.11)	0.083	(1.55)	0.089	(1.64)
Fee	2.118**	(2.17)	2.258**	(2.40)	1.480	(1.09)	1.647	(1.25)
MarketShare	0.037	(0.66)	−0.048	(−1.24)	0.097*	(1.78)	−0.015	(−0.36)
log *NumAnalysts*	−0.009	(−0.83)	−0.011	(−1.05)	−0.013	(−1.13)	−0.015	(−1.39)
log *MarketCap*	−0.041**	(−2.62)	−0.043***	(−2.89)	−0.027**	(−2.04)	−0.028**	(−2.09)
UnclassifiedInvestors	0.030	(0.49)	0.042	(0.66)	0.074	(1.42)	0.080	(1.48)
NonHedgeFunds	−0.048	(−1.11)	−0.045	(−1.11)	−0.064	(−1.25)	−0.060	(−1.20)
InvestorExperience	0.160	(1.05)	0.194	(1.28)	0.231	(1.58)	0.256*	(1.72)
KZIndex	0.000	(0.02)	0.000	(0.52)	0.001	(0.63)	0.001	(0.95)
BAAtoAAASpread	0.017	(0.32)	0.027	(0.52)	0.044	(0.81)	0.054	(0.99)
10-*yearTreasury*	0.041*	(1.91)	0.041*	(1.89)	0.032	(1.56)	0.031	(1.47)
IPOUnderpricing	−0.001**	(−2.04)	−0.001*	(−1.71)	−0.001	(−1.25)	−0.001	(−1.08)
IPOGrossVolume	0.001	(0.78)	0.001	(0.89)	−0.000	(−0.05)	0.000	(0.14)
EWCumRet	0.049	(0.56)	0.034	(0.39)	−0.112	(−0.99)	−0.126	(−1.14)
Maturity	0.006***	(4.71)	0.006***	(4.68)	0.006***	(3.87)	0.006***	(3.94)
HHI	0.026	(0.27)	0.005	(0.05)	0.054	(0.59)	0.031	(0.33)
DebtRatio	−0.009	(−0.56)	−0.006	(−0.36)	−0.023	(−0.91)	−0.019	(−0.76)
N	601		601		575		575	
Adjusted R^2	0.316		0.312		0.296		0.293	

Notes. This table presents regression results for the following OLS regression:

$$Discount_{i,t} = \alpha + \beta_1 \, Flows_{i,t} + \beta_2 \, RepeatInvestors_{i,t} + \beta_3 \, RepeatInvestors \times Flow + \beta_4 \, NumInvestors + \beta_5' X_{i,t} + \epsilon_{i,t},$$

where $Discount_{i,t}$ is the percentage discount of the offering price below the fundamental value from the pricing model. Convertible bond hedge fund flow (*Flows*) is defined as the one-month lagged percentage flows. This variable is based on the combined TASS and CISDM/MAR databases as described in Choi et al. (2010). *RepeatInvestors* is the fraction of the investors in bond *i* that also purchased a 144A bond from the placement agent in the preceding 24 calendar months. *NumInvestors* is the number of investors in the bond. *Repeat* × *Flow* is the interaction between *RepeatInvestors* and *Flow*. *Strength* is defined as the average participation of investors in issue *i* in all 144A convertible bond issues by bond *i*'s placement agent during the past 24 months. *Strength* × *Flow* is the interaction between *Strength* and *Flow*. The control variables in vector $X_{i,t}$ are defined in Tables 1 and 2 and are based on the extended regressions (Model 4) shown in Tables 2 and 3. The table presents results where *Discount* is based on prices from both the base model and the generalized model. All standard errors are double clustered by placement agent and issuer, and all regressions include year fixed effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

discounts when demand conditions are favorable. Third, and most striking, the impact of *RepeatInvestors* on pricing is greater following periods of low investor demand (the positive coefficient on the interaction suggests that repeat investors further reduce discounts when flows are lower). This is consistent with the idea that the bank's rolodex is more beneficial when demand is tight.

In addition to the significant interaction effect with market demand conditions, one might also expect that the contracting frictions mechanism will be exacerbated for firms with high asymmetric information (i.e., a stronger impact of *RepeatInvestors* on the *Discount* when information asymmetry about the firm is high). In fact, one interpretation of the *RepeatInvestors* result could be that bond discounts result from information asymmetry and that repeat buyers demand smaller discounts if they trust that the investment bank is not selling them overpriced bonds. However, we do not find evidence of this at the firm level.

In untabulated analysis, we interacted *RepeatInvestors* with the proxy for asymmetric information *NumAnalyst* and found the coefficient on the interaction to be statistically insignificant. Thus, asymmetric information does not appear to be driving the results.[32] Market conditions play a larger role than do firm-specific asymmetric information in the extent to which the placement agents' relationships impact pricing.

5. Conclusions

Our primary findings demonstrate the previously undocumented and important role of search frictions in the initial pricing of CBs. We find that repeat interactions between placement agents and investors can reduce discounts. We document robust, negative relationships between at-issue discounts of CBs and both investors' prior participation in bond issues by the investment bank and proxies for after-market liquidity. These effects are economically and statistically significant and are robust to alternative approaches to calculating the at-issue discount and to the inclusion of a large variety of control variables, including using CB hedge fund flows to control explicitly for investor demand. Our evidence does not support the favoritism hypothesis, in which bankers reward favored investors with larger allocations of more underpriced issues. The results are consistent with the hypothesis that the reduction in contracting frictions that, in the Rule 144A CB market, occurs via repeated interactions between investors and placement agents dominates any impact that favoritism might have on prices. In addition to the direct impact of repeated interactions on pricing, we also find evidence of a second channel through which search frictions impact pricing: expected secondary market liquidity. Allowing for endogenously determined fees, we find lower investment banking fees when bonds are placed with repeat investors. The finding that fees are lower when search frictions are reduced helps us rule out the possibility we are simply observing a change in the nature of the inestment banking contract. That is, the reductions in at-issue discounts that we observe are not being offset by higher fees. Taken together, these findings suggest that search frictions play a meaningful role in CB pricing and that intermediaries can add substantial value through their repeated interactions with investors.

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[32] The asymmetric information proxy is not itself significant in the cross-section.

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