Over-the-Counter Market Frictions and Yield Spread Changes*

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Abstract

We empirically study how intermediation frictions in over-the-counter (OTC) markets affect asset prices. Using transactions data on U.S. corporate bonds, we find that inventory, search, and bargaining frictions capture 10 percentage points in the variation of yield spread changes beyond standard pricing factors. This result implies that these OTC market frictions account for one-third of the explained variation in yield spread changes. We show that the intermediation premium of dealers reflects the intensity of OTC market frictions. Overall, our results confirm the asset pricing implications of leading theories of intermediation frictions in OTC markets.

JEL Classification: G10, G12, G20

Keywords: U.S. corporate bond market, over-the-counter market, yield spread change, empirical asset pricing, dealer market

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1 Introduction

According to frictionless no-arbitrage theory, changes in corporate yield spreads occur because of innovations in firm-specific and macroeconomic fundamentals. This paradigm has been challenged by empirical studies showing that yield spread changes are difficult to explain. Using conventional pricing factors, Collin-Dufresne, Goldstein, and Martin (2001, CDGM thereafter) show that a large set of firm-specific and macroeconomic variables captures only 25% in the variation of yield spread changes. They also find that a significant proportion of the unexplained variation is due to a single common factor. U.S. corporate bonds trade in an over-the-counter (OTC) market where several dealers intermediate between customers through their inventories. Transactions are non-anonymous and occur on a bilateral basis; thus, the terms of the trade are determined by search and bargaining. Consequently, the theoretical literature rationalizes the deviations of asset prices from fundamentals through OTC market frictions. Specifically, Randall (2015) builds on the seminal work of Stoll (1978), showing that asset valuations in negotiated OTC markets reflect compensation for dealers' exposure to inventory risk, that is, the risk of the prices of bonds in inventories moving against them. Duffie, Gârleanu, and Pedersen (2005, 2007, DGP thereafter) show that search and bargaining frictions impact asset valuations. In this paper, we empirically investigate the asset pricing implications of intermediation frictions in OTC markets. We show that inventory, search, and bargaining frictions capture 10 percentage points in the variation of yield spread changes beyond the CDGM factors. This result implies that these OTC market frictions account for around one-third of the explained variation in yield spread changes.

To establish our findings, we employ detailed transaction data on the prices and volumes of U.S. corporate bonds available at the individual dealer level. We use the Trade Reporting and Compliance Engine (TRACE) database containing dealer information, implying that we can assign every transaction to a particular dealer. Our final data set captures 90% of the average total yearly trading volume, which is attributable to 73 dealers over the sample period from the beginning of 2003 to the end of 2013. Our transactions data reveal similar structural properties compared to the quote-based data of CDGM. That is, once we implement the test of CDGM, we find that the explanatory power of monthly yield spread changes implied by firm-specific and macroeconomic variables is low, with an adjusted R^2 value ranging between

16% and 37%. We also find that the residuals are highly cross-correlated and that the first principal component captures 58% of the remaining variation.

After having established the CDGM benchmark result, we start examining the ability of intermediation frictions in explaining yield spread changes. We guide our analysis by the asset pricing implications of the theory of intermediation in OTC markets. DGP, Vayanos and Wang (2007), and Weill (2008) show theoretically that intermediation frictions between dealers and customers matter for asset prices. A common implication of the theory is that market-wide frictions are captured by dealers' intermediation premium, that is, the average differential in sell and buy prices at which dealers intermediate between customers relative to the inter-dealer price. A high intermediation premium is symptomatic of high frictions and, hence, associated with lower asset valuations. Thus, theory predicts that an increase in the intermediation premium must be positively reflected in yield spread changes if market-wide frictions between dealers and customers matter systematically for asset valuations. We confirm this prediction, showing that dealers' intermediation premium captures seven percentage points in the common variation of yield spread changes.

Grossman and Miller (1988) argue that asset valuations are more sensitive to dealers' buy side compared to their sell side because they act as liquidity providers and offer intertemporal immediacy to customers. We test this notion by decomposing the intermediation premium into two (potentially unequal) components, i.e. the markdown and markup premiums. The markdown (markup) premium captures dealers' buying (selling) premium, that is, the price differential at which dealers buy from (sell to) customers relative to the inter-dealer price. The decomposition allows examining whether the intermediation premium is priced through the buy or sell side of dealers. We find that both markdowns and markups are positively reflected in yield spread changes by capturing in total eight percentage points in the common variation. However, the tests reveal that around two-thirds of the pricing impact come from the markdown, that is, dealers' buy side. In other words, this finding supports the notion that dealers act, on average, as liquidity providers.

Although these tests show that the intermediation premium is reflected in yield spreads, they do not provide insights into the type of friction that is priced. Generally, intermediation frictions are hard to measure, which renders their empirical investigation just as challenging. However, our data set offers the possibility of constructing theoretically motivated proxies that reflect the intensity of systematic inventory, search, and bargaining frictions in the corporate bond market. Therefore, we proceed by constructing measures of OTC market frictions and subsequently examine their pricing impact separately within the framework of CDGM.

First, we focus on the role of dealer inventory. The theory of Randall (2015) highlights that asset valuations differ from fundamentals because of the dealers' compensation for exposure to inventory risk. The model predicts that an increase in the level of aggregate dealer inventory lowers asset valuations and vice versa. We confirm this prediction, showing that market-wide inventory is a systematic price factor and that an increase thereof leads to a widening of yield spreads. Overall, market-wide inventory captures five percentage points in the common variation of yield spread changes.

Second, we examine the impact of search frictions on yield spread changes. Specifically, DGP and Lagos and Rocheteau (2009) show that asset valuations increase if search frictions relax, implying that counterparties are easier to find. We construct three measures of search frictions, that is, the average dealer coverage for a standardized bond notional, the underlying network structure of the inter-dealer market as for Li and Schürhoff (2014), as well as dealers' average matching ability in trades. We show that, when search frictions relax, that is, dealer coverage rises, more direct connections emerge in the inter-dealer market, or dealers' matching ability increases, then yield spreads narrow systematically. These findings confirm the predictions of the theory of intermediation in OTC markets, that is, asset valuations increase when counterparties are easier to find. The portion of systematic variation explained by search frictions amounts to four percentage points.

Third, we turn to the role of bargaining. DGP show that asset valuations are lower if dealers extract higher intermediation rents as their bargaining power increases relative to customers. We construct two bargaining factors based on the competitiveness of the dealer market and customers' trade size distributions to capture the bargaining power of dealers relative to customers. Dealers' bargaining power increases as the inter-market becomes less competitive and decreases in the portion of large trades, which is associated with an elevated presence of customers with better bargaining power (e.g. Randall, 2015). The tests confirm the theoretical predictions and reveal that yield spreads widen systematically when dealers' bargaining power increases relative to their customers and vice versa. In total, bargaining frictions capture four percentage points in the systematic variation of yield spread changes.

Finally, we employ all three groups of frictions jointly in the CDGM framework and find that their additional explanatory power is close to 10 percentage points. Thus, the joint explanatory power is slightly lower than the sum of 13 percentage points of the individual incremental adjusted R^2 values. This result supports theoretical discussions of DGP and Lagos, Rocheteau, and Weill (2011) that OTC frictions and their pricing are interrelated.

To rationalize our findings by the theory of intermediation in OTC markets, we illustrate that inventory, search, and bargaining frictions are priced in yield spread changes because they determine dealers' intermediation premium. That is, we show that time-varying OTC market frictions drive the variation in the intermediation premium in terms of both its level and its decomposition into markdown and markup premiums. Specifically, the intermediation premium increases with market-wide inventory (confirming that dealers act on average as liquidity providers) and dealers' bargaining power relative to their customers. While we generally find that a relaxation of search frictions leads to a smaller intermediation premium, the underlying economic impact is less pronounced compared with those of inventory and bargaining. Furthermore, we show that market-wide inventory is the only friction that determines the composition of dealers' intermediation premium. In particular, the markup declines while the markdown rises when market-wide inventory increases and vice versa. This result confirms the prediction of Randall (2015), in that the intermediation premium reflects the compensation of dealers for accepting additional inventory.

After having established the systematic nature of inventory, search, and bargaining frictions, we focus our analysis on dealers' individual pricing policies. Consistent with a wealth effect, as for Kyle and Xiong (2001), we document that idiosyncratic shocks to dealer wealth (measured by stock returns) provide additional information for yield spread changes within dealer inventories, beyond systematic shocks. In particular, we document that the yield spreads of intermediated bonds widen if the dealer experiences a negative wealth shock. Furthermore, we show that differences in dealer characteristics in terms of inventory management, search ability, and bargaining power explain the dispersion in the prices of the same bond on the same day across inventories. While cross-sectional variation in dealer inventory levels does not explain price dispersion, we find that dealers that mainly execute matched trades or that utilize the inter-dealer market to a larger extent have lower markdowns and markups, respectively. Central dealers charge higher markdowns and markups, indicating that they are willing to provide immediacy to customers through their inventories.

In summary, we provide novel insights into the systematic drivers of yield spread changes by elaborating on the asset pricing implications of intermediation frictions in OTC markets.

Literature. At its core, this paper contributes to the empirical literature on identifying the common drivers of yield spread changes. Duffee (1998) examines the relation between corporate yield spread changes and changes in the Treasury yield. Elton, Gruber, Agrawal, and Mann (2001) focus on the risk premium of corporate bonds, while Chen, Lesmond, and Wei (2007) study the role of liquidity in the form of zero-return days. All three studies document the low explanatory power of yield spread changes. Bao, Pan, and Wang (2011) and Friewald, Jankowitsch, and Subrahmanyam (2012) obtain similar results by employing various liquidity measures, such as the Roll (1984) and Amihud (2002) measures. Lin, Wang, and Wu (2011), De Jong and Driessen (2012), Acharya, Amihud, and Bharath (2013), and Bongaerts, de Jong, and Driessen (2017) examine bond returns instead of yield spread changes, showing that liquidity and liquidity risk matter in pricing bonds.

Further, our paper is also related to studies that empirically analyze liquidity and market making in the U.S. corporate bond market. Contributions that examine transaction costs include those of Schultz (2001), Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), and Dick-Nielsen, Feldhütter, and Lando (2012). More recently, several studies investigate dealer behavior and post-crisis implications (see, e.g., Adrian, Boyarchenko, and Shachar, 2017, for a detailed discussion on regulations). Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017) examine trading costs and dealers' capital commitment, arguing that, post-crisis, dealers commit less capital to inventory. Focusing on similar aspects, albeit using different methodologies, Trebbi and Xiao (2015), Dick-Nielsen and Rossi (2016), Bao, O'Hara, and Zhou (2017), Anderson and Stulz (2017), Goldstein and Hotchkiss (2017), and Schultz (2017) examine the time-varying liquidity provision of dealers, showing that, post-crisis, liquidity is more sensitive to dealer behavior.

Our empirical approach is guided by the theory of intermediation in OTC markets. Specifically, DGP, Vayanos and Wang (2007), Weill (2007), Lagos and Rocheteau (2009), Lagos, Rocheteau, and Weill (2011), Feldhütter (2012), and Randall (2015) theoretically elaborate on how inventory, search, or bargaining frictions affect prices and liquidity. We contribute to the literature by explicitly examining the empirical asset pricing implications associated with intermediation frictions in OTC markets.

2 Data

We rely on several data sources to study the impact of OTC market frictions on yield spread changes. We obtain transaction data on the U.S. corporate bond market between January 2003 and December 2013 from TRACE, which is maintained by the Financial Industry Regulatory Authority (FINRA). Every transaction in the U.S. corporate bond market that is conducted by a designated dealer must be reported to TRACE. Thus, the data comprise transaction prices and volumes, trade direction, and the exact date and time of the trade. While, for inter-dealer trades, we know the coded identities of both parties involved in the transaction, for customer–dealer trades, we know only that the trade was with a customer and do not have information about the customer's identity. We only consider secondary market transactions because primary market transactions had not been reported before 2010. We account for reporting errors using standard filtering procedures commonly used for TRACE transaction data (e.g., Friewald, Jankowitsch, and Subrahmanyam, 2012; Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2017).[1] We also account for *give-up* and *locked-in* trades to correctly assign each transaction to the actual dealers behind the trade.[2]

We then merge our transaction data with bond-specific information (i.e., offering amount, offering date, amount outstanding, coupon rate, maturity, and credit rating), which we obtain from the Mergent Fixed Income Securities Database. Following the literature related to corporate bonds, we focus only on corporate debentures with either zero or fixed coupons. We exclude bonds that are convertible, puttable, asset backed, exchangeable, privately placed, perpetual, preferred securities, secured lease obligations, and quoted in a foreign currency. We also remove bonds from the sample that were issued by financial firms (SIC code 6000 to 6999) or utility firms (SIC codes 4900 and 4999) firms, have issue sizes under $10 million, and maturities shorter than one year.

Several hundreds of dealers have been active in the U.S. corporate bond market. To keep the empirical analysis manageable, we consider only the most active dealers that have traded

[1]These include (i) same-day trade corrections and cancellations and (ii) trade reversals, which refer to corrections and cancellations conducted after the trading day.

[2]In a give-up trade, one party reports on behalf of another party, who has reporting responsibility. In a locked-in trade, one party is responsible for reporting both sides of the trade in a single report, thus satisfying the reporting requirements on both sides. Such a locked-in trade can refer to either a transaction between the reporting party and its correspondent (single locked-in trade) or a transaction between two correspondents (two-sided locked-in trade).

for at least three consecutive years during our sample period and, taken together, cover 90% of the average total yearly trading volume. In doing so, we identify 73 dealers that have conducted about 29 million reported transactions in nearly 15,000 bonds.

For the analysis of the determinants of yield spread changes, we compute the yield spread as the difference between the corporate bond yield and the yield of a risk-free bond with the same cash flow structure as the corporate bond. We use the U.S. Treasury yield curve estimates obtained from the Federal Reserve Board as our risk-free benchmark.

We follow CDGM and obtain market- and firm-specific variables that, according to structural models, determine yield spread changes. In particular, we obtain market variables such as the Standard & Poor's S&P 500 index from the Center for Research in Security Prices (CRSP), the volatility index (VIX) from the Chicago Board Options Exchange, and the 10-year Treasury constant maturity rate from the Federal Reserve Bank of St. Louis. As a systematic proxy for the probability or magnitude of a downward jump in firm value, we construct a measure based on at- and out-of-the money put options and at- and in-the-money call options with maturities of less than one year traded on S&P 500 futures. We obtain option-implied volatilities from OptionMetrics. For the exact procedure of estimating the jump component, we refer to CDGM. We use market leverage as a proxy for a firm's creditworthiness. We define market leverage as book debt over the sum of book debt and the market value of equity, where book debt is given by the sum of the Compustat item "Long-Term Debt - Total" (DLTT) and "Debt in Current Liabilities - Total" (DLC). To account for (varying) time lags between a firm's fiscal year-end and information becoming publicly available, we apply a conservative lag of six months before we update a firm's debt-related information. The market value of equity is the number of common shares outstanding times the share price, both obtained from the CRSP. We merge TRACE with CRSP/Compustat data using the first six digits of a bond's CUSIP number, which is commonly referred to as the base. The merged data sample consists of 95,520 end-of-month yield spread observations in 4,980 bonds issued by 871 firms.

To analyze the wealth effect, we need to unmask the dealer identities in TRACE to link transaction data to dealer stock price data. We do so using transaction data obtained from the National Association of Insurance Commissioners (NAIC) between January 2003 and December 2013. The data provide information on all transactions conducted by insurance companies. In particular, the data comprise the identity of the issue, the transaction date and price, the par value traded, and the direction of the trade, that is, whether the trade was an insurance company buying from or selling to a dealer. Importantly, the data also provide the identities of the insurance company and the dealer between whom each trade is completed. Using these data, we are able to reliably identify 50 dealers, 31 of which trade publicly in the United States.

Table 1 provides descriptive statistics of the core trading data that we use in our empirical analysis. The average bond in our sample has an issue size of $481 million, a coupon rate of 7.29%, a time to maturity of about three years, and a credit rating of 12, which corresponds to BB on the S&P credit rating scale. While, generally, the U.S. corporate bond market is relatively active with, on average, 10,000 trades per day and a daily trading volume of nearly $9 billion, only about 1,800 bonds are traded per day. Given that approximately 9,000 bonds are outstanding during our sample period, trading is relatively sparse in each bond. We find that the average bond trades four times a day, with an interdecile range of two to eight trades. The average daily trading volume in a bond is $5 million, where a bond is typically traded only by two dealers a day, with an interdecile range between one and four.

Since our data allow us to link each transaction to a particular dealer, we can provide summary statistics for the dealers' trading activities. On average, per day, a dealer is engaged in 174 transactions, with a total trading volume of $143 million in 87 bonds. There is considerable dispersion across bonds in terms of the number of trades and trading volume. For example, the least active 10% of dealers in our sample transact 24 trades, while the most active 10% of dealers conduct approximately 466 trades per day. The average dealer transacts roughly 90 trades and a volume of $56 million each day in the inter-dealer market. Specifically, 50% of all daily trades and 40% of the daily trading volume for a given dealer happen to be inter-dealer trades, suggesting an active inter-dealer market. Dealers often do not take on overnight inventory risk. That is, they simply match buy and sell orders, so that the net position is zero at the end of the trading day. The average number of daily matched trades and volume are 64 and $53 million, respectively. Put differently, the average dealer matches almost 40% of all daily trades and trading volumes. The inter-dealer market has a core–periphery structure, that is, a set of dealers that are centrally located and well connected with each other while others are located more on the periphery with potentially looser connections with each other than the core dealers. This structure is evident in Figure 1, which displays the inter-dealer network considering the 73 most active dealers.

Each vertex represents a trading relationship that is weighted by the average yearly trading volume between a pair of dealers to reflect the strength of the trading relationship. That is, dealers that are placed closer together have stronger relationships than more distant dealers. Consistent with the graph, we find that the less-connected 10% of dealers (presumably the peripheral dealers) trade with four other dealers while the most connected 10% of dealers (presumably core dealers) trade with 19 dealers. We also find interesting patterns when it comes to dealers' specialization in trading different bonds. For example, the average dealer trades bonds assigned to six industries, as classified by the first digit of the SIC code. However, 10% of the cross section of dealers are more specialized, in that they only trade bonds from four industries, while 10% of the most diversified dealers trade bonds from seven different industries. Similarly, we find that dealers specialize in trading different bond sizes and credit ratings. For example, the interdecile range for the credit rating across dealers is from eight (BBB+) to 15 (B), which suggests that some dealers specialize in intermediating investment-grade bonds, while other focus their business on high-yield bonds. In contrast, the cross-sectional dispersion in terms of time to maturity and bond size is less pronounced, with the average amount outstanding being $888 million and the average maturity being 3.3 years.

FIGURE 1 ABOUT HERE

3 CDGM and yield spread changes

In this section, we first examine the determinants of yield spread changes by employing the test of CDGM. We then use the results as a benchmark for our subsequent analyses, where we examine the impact of intermediation frictions in affecting the common variation of yield spread changes.

To accomplish this, we estimate the yield spread $YS_{j,t}$ of bond j at time t based on the average of all transaction prices on the last trading day in a month. We follow CDGM by employing the same firm and macroeconomic variables that, according to structural models à la Black and Scholes (1973) and Merton (1974), determine yield spread changes. In particular, we consider changes in a firm's underlying leverage ratio ($\Delta lev_{j,t}$), changes in the 10-year Treasury rate (Δrf_t), changes in the slope of the yield curve ($\Delta slope_t$), changes in market volatility (ΔVIX_t), returns on the S&P 500 index (r_t^m), and changes in a jump component ($\Delta jump_t$) that reflects the magnitude and probability of a large negative jump in firm value. As CDGM, we also include the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$, which captures any potential nonlinear effects due to convexity. We define the vector of factors by

$$\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]. \tag{1}$$

In a first step, we implement the test of CDGM, that is, we estimate the following regression model for each bond j with yield spread $YS_{j,t}$:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \epsilon_{j,t}. \tag{2}$$

We only consider bonds that have at least 20 observations of yield spread changes, which generates a sample of $1,024$ bonds.[3] To mimic the test of CDGM, we assign each bond to a leverage group based on the firm's average leverage ratio over the bond's lifetime. The groups are defined as below 15%, 15–25%, 25–35%, 35–45%, 45–55%, and more than 55%. This grouping creates a relatively homogeneous distribution of bonds across cohorts, ranging from 85 bonds in the 45–55% group up to 269 bonds in the 15–25% group. We present the average coefficient and its statistical significance for each cohort in Panel A of Table 2. The signs of the coefficients are economically meaningful, that is, yield spreads increase with leverage, the slope of the term structure, and volatility and decrease with the risk-free rate and the market return. However, as for CDGM, the explanatory power is relatively poor, with an adjusted R^2 value ranging between 16% and 37%.

Table 2 about here

We follow CDGM and carry out principal component analysis (PCA) on the residuals to capture the properties of the remaining variation. In each month, we assign bonds to one of 15 bins that are determined by five leverage groups—below 15%, 15–25%, 25–35%, 35–45%, and more than 45%—as well as by three maturity groups—below five years, five to eight years, and more than eight years. We find that the first principal component (PC_1) accounts for around 58% of the remaining variation, while the second component (PC_2) accounts for

[3]It is worth noting that we use actual transaction prices, while CDGM rely on quotes in their sample of 688 bonds. Their sample shrinks to 29 bonds if they restrict the analysis to only transaction prices.

only 7%. Albeit less pronounced than for CDGM, who document a PC_1 of 75% in their sample, we also find that most of the remaining variation comes from PC_1.

To further investigate the dynamics of the yield spread changes, we again follow CDGM and group bonds by their average credit rating instead of the leverage ratio. Hence, we split bonds into the seven main credit rating classes (AAA, AA, A, BBB, BB, B, and CCC/C) and rerun specification (2) for each bond j.[4] The groupings based on credit ratings lead to a less balanced assignment of bonds in terms of the number of observations, that is, it ranges from 15 for CCC/C to 336 for BBB. Panel B of Table 2 presents the estimation results, which are similar to the leverage results in terms of the economic signs of the factors. The adjusted R^2 values range between 9% and 50%. We undertake the same PCA and again find a PC_1 of around 58%, while PC_2 captures only about 7%.

Overall, the structural properties of yield spread changes in our sample are similar to those of CDGM. The findings are indicative of a missing systematic factor that is not firm specific.

4 OTC market frictions and yield spread changes

In this section, we start investigating the ability of intermediation frictions in OTC markets to explain yield spread changes. The theoretical insights of DGP, Vayanos and Wang (2007), and Weill (2008) highlight that frictions between dealers and customers matter for asset prices. An implication of these theories is that market-wide frictions are captured by dealers' intermediation premium, IP. This measures the premium earned by dealers from intermediating in the market. A high intermediation premium is symptomatic of elevated intermediation frictions and, thus, of lower asset valuations.

We can directly infer the intermediation premium from the underlying transaction data. The intermediation premium consists of the dealers' selling premium (the markup, $MU > 0$) and buying premium (the markdown, $MD > 0$), respectively. The markup is the premium at which dealers sell to customers relative to the inter-dealer price, while the markdown is the discount at which dealers buy from customers relative to the inter-dealer price. Hence,

[4] In the rating classifications, CDGM use the firm's stock return instead of its leverage ratio as an explanatory variable. In accordance with their findings, we also find that the power of the tests as well as their economic insights remain unchanged when using the stock return instead of leverage. Therefore, we stick to the original set of factors and employ the firm's leverage in all our tests.

we estimate the selling and buying premiums as follows: For each bond j, we determine a daily markup by taking the differential between the average dealer sell and the average inter-dealer price, that is, the market-wide dealer valuation of bond j on that day. We normalize this number by the inter-dealer price and obtain the monthly measure MU_t by averaging across all observations in a month. We do so similarly to obtain the buying premium, MD_t.

Panel A of Figure 2 provides the time series of MU and MD. On average, MU is close to 30 basis points (bps) while MD is around 20 bps. This result implies that, generally, investors' sell prices are more attractive than the prices at which they can buy. This provides a first indication that dealers act as liquidity providers and are willing to provide immediacy through their inventories (Demsetz, 1968; Grossman and Miller, 1988). The gap between MU and MD declines during the financial crisis but subsequently widens again.

Figure 2 about here

In estimating MD and MU, we decompose dealers' intermediation premium into the sum of two (unequal) components, that is, we have

$$IP_t = MD_t + MU_t. \tag{3}$$

A direct theoretical implication is that, if intermediation frictions between dealers and customers matter systematically for asset valuations, an increase in the dealer intermediation premium must lead to a widening of yield spreads. We test this notion and augment the CDGM baseline specification by ΔIP, that is, we run the following regression for each bond j:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \gamma_j \Delta IP_t + \epsilon_{j,t}. \tag{4}$$

We show the results based on the leverage groups in Panel A of Table 3. The loadings of IP are positive and highly statistically significant for all cohorts, with t-statistics ranging between seven and 12. Moreover, the coefficient of IP is monotonically increasing in the credit risk of the bonds, that is, the yield spreads of high-leverage groups react more strongly to changes in IP compared to those of low-leverage groups. This finding confirms the theoretical insight of DGP where the pricing impact of intermediation frictions is more pronounced among riskier assets. Hence, our results generally confirm the notion that IP captures the intensity of intermediation frictions. The robust significance of IP translates into an increase in the adjusted R^2 values by up to six percentage points relative to the CDGM baseline specification. In Panel B, we report the results based on the rating classifications, where we observe similar patterns. The coefficient of IP is significantly positive and increases in credit risk. Again, PCA reveals the systematic nature of the intermediation premium: PC_1 decreases by seven percentage points, from 58% to 51%. It is interesting to note that, while CDGM do not find that measures of liquidity explain yield spread changes, we find that dealers' intermediation premium captures an economically significant part of their systematic variation.

Table 3 about here

In differentiating between MD and MU, we can test whether intermediation frictions are reflected in yield spreads largely through dealers' buying or selling premium, respectively. We investigate the pricing implications by estimating the following regression model:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{F_{j,t}} + \gamma_{j,1}\Delta MU_t + \gamma_{j,2}\Delta MD_t + \epsilon_{j,t}. \tag{5}$$

We present the average coefficient and corresponding t-statistic for each leverage group in Panel A of Table 4. The variables MU and MD both exhibit positive coefficients but differ in terms of statistical significance and economic pricing impact. In particular, MU is significant in five out of six cohorts, with t-statistics ranging between 1.4 and 4.4, while MD is highly significant in all cohorts, with t-statistics ranging between 4.3 and 11.1. The loadings of MD monotonically increase in credit risk and are around twice as large compared to those of MU. The fact that both measures have approximately the same variation implies that MD accounts for two-thirds of the total pricing impact of the intermediation premium and, correspondingly, MU accounts for only one-third. In Panel B, we present the results based on the rating classifications and arrive at similar conclusions. Specifically, the pricing impact of MD is around twice as large compared to that of MU, confirming that the intermediation premium is reflected in yield spreads largely through the buy side of dealers. In other words, this finding confirms the idea of Grossman and Miller (1988), in that asset valuations are more affected by the dealers' buying premium, since dealers act as liquidity providers by offering intertemporal immediacy to customers.

Table 4 about here

In employing MD and MU together, the adjusted R^2 values increase in all cohorts by at least one percentage point relative to specification (4), where we use only IP. The increases are larger for credit riskier bonds, which is indicative that these bonds are especially sensitive to variations in dealers' buying premium. The increase in explanatory power is reflected in PC_1 as well, which drops to 50%, compared to the 58% of the CDGM benchmark.

Although these tests show that dealers' intermediation premium is systematically reflected in yield spread changes, they say nothing about the type of friction that is priced. Therefore, to uncover the drivers of the intermediation premium, we guide our subsequent analysis by the theory of intermediation frictions in OTC markets. The common theoretical implication is that dealers' intermediation premium is determined by inventory, search, and bargaining frictions such that

$$IP_t = MD_t + MU_t := f\left(\textbf{inventory},\ \textbf{search},\ \textbf{bargaining}\right), \tag{6}$$

where f is a function that maps these frictions into the premium(s). Specifically, Randall (2015) shows that, in negotiated OTC markets, IP reflects the required compensation for dealers to accept inventory. That is, the aggregate dealer inventory determines whether IP largely reflects dealers' willingness to accept additional inventory ($MU > MD$) or to downsize inventory ($MU < MD$). In particular, the model predicts that an increase in the aggregate dealer inventory elevates MD relative to MU and vice versa when inventory decreases. As far as search and bargaining frictions are concerned, DGP show that IP diminishes when search frictions relax, implying that counterparties are easier to find. Moreover, they show that, when the bargaining power of dealers increases relative to that of their customers, dealers extract higher intermediation rents, which leads to an elevated IP.

In what follows, we examine the underlying asset pricing implications by investigating the ability of inventory, search, and bargaining frictions to explain yield spread changes. We construct theoretically motivated factors that proxy for the intensity of systematic inventory, search, and bargaining frictions. In the first step, we analyze the frictions separately within the framework of CDGM, thereby allowing us to examine their relative importance. In the next step, we consider their joint impact on yield spread changes. Finally, to rationalize our findings by the theory of intermediation in OTC markets, we show that the frictions are priced factors because they determine dealers' intermediation premium. That is, we document that time-varying inventory, search, and bargaining frictions drive the variation of IP in terms of both its level and its de composition into MD and MU premiums.

4.1 Inventory frictions

Randall (2015) shows theoretically that asset valuations in negotiated OTC markets reflect compensation for dealers' exposure to inventory risk. In particular, the model implies that the level of aggregate dealer inventory and asset valuations are inversely related, that is, an increase in inventory lowers valuations and vice versa. In other words, changes in dealer inventory should be positively related to yield spread changes.

Given that our data allow us to assign every single transaction to a particular dealer, we can reconstruct the bond inventory positions of dealers over time. We start with the construction of the inventory series at the individual dealer–bond level (which we use in a subsequent analysis). In particular, let $I_{ij,t}$ denote the nominal level of the dollar inventory of dealer i in bond j at time t. Further, let $q_{ij,t}$ denote the corresponding signed transaction volume, which is positive (negative) when the dealer is buying (selling) the bond. The inventory $I_{ij,t}$ at time t is then defined as

$$I_{ij,t} = I_{ij,0} + \sum_{s=1}^{t} q_{ij,s}, \tag{7}$$

where $I_{ij,0}$ refers to the initial bond inventory, which is unobservable in our data. We first construct a time series of dealer i's inventory in each bond j. We then aggregate the inventory series $I_{ij,t}$ across all bonds and dealers to obtain the market-wide inventory I_t at time t:

$$I_t = \sum_{i} I_{ij,t}. \tag{8}$$

As indicated above, we do not have information on the initial inventory $I_{ij,0}$. However, we note that this does not constitute a restriction, since we use changes in dealer inventories, which are independent of the initial inventory, by construction. We define the vector of market-wide inventory factors as

$$\boldsymbol{\Delta I_t} := \left[\Delta out_t,\ \Delta I_t\right], \tag{9}$$

which includes the aggregate amount outstanding, out_t, to control for any inventory changes caused by newly issued bonds and bonds that are called or mature during the sample period. In Panel B of Figure 2, we plot the dynamics of market-wide inventory, I_t, adjusted by the aggregate amount outstanding, out_t. We plot the cumulative sum of the residuals of the regression $\Delta I_t = \alpha + \beta \Delta out_t + \epsilon_t$. We observe that market-wide inventory steadily increases until the beginning of 2008 and then, with the onset of the financial crisis, dealers start to unload inventory roughly to the level of the pre-crisis period.

We examine the impact of inventory in affecting yield spread changes by augmenting the CDGM baseline specification by the market-wide inventory factors, $\boldsymbol{\Delta I}$, and run the following regression for each bond j:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \boldsymbol{\Delta I_t} + \epsilon_{j,t}. \tag{10}$$

We report the regression results for the leverage (credit rating) cohorts in Panel A (B) of Table 5. The coefficients of Δout are only marginally negatively significant in some of the groups, indicative that, on average, issuances are demand driven. The results for the leverage classification show that the coefficients of ΔI are positive and highly significant for all groups, with t-statistics ranging between 2.1 and 6.5. The overall picture reveals that the loadings on inventory increase almost perfectly monotonically in credit risk, that is, from a value of around seven for low-leverage firms up to 71 for high-leverage firms. Thus, the pricing impact of inventory is around 10 times higher for the credit riskiest bonds compared to the lowest.

Across rating classifications, we find that the coefficient of ΔI is again positive and highly significant in all the cohorts, except for that with the highest ratings (AAA), where it is insignificant. The loadings of the coefficients increase monotonically from one rating class to the next. Hence, these findings provide strong support for the asset pricing implications of inventory models; that is, bond valuations are systematically lower when market-wide inventory increases and vice versa. Furthermore, the patterns of the loadings on market-wide inventory reveal that the inventory premium increases with credit risk.

Table 5 about here

The significance of market-wide inventory translates into large improvements in the explanatory power of yield spread changes. Across all cohorts, the adjusted R^2 values increase by one to nine percentage points. The improvement is more pronounced among the low-credit risk groups compared to the high-credit risk groups. We find that PC_1 drops to 53%, compared to the CDGM benchmark of 58%.

Overall, our findings confirm that the market-wide dealer inventory is a systematic price factor that explains five percentage points in the common variation of yield spread changes.

4.2 Search frictions

From a theoretical standpoint, search frictions are considered one of the major sources of potential illiquidity discounts in the corporate bond market. Specifically, DGP, Vayanos and Wang (2007), and Weill (2008) model the implications of search frictions for asset prices and show that asset valuations drop when search frictions intensify, that is, when finding counterparties becomes more difficult.

Due to the unobservability of search frictions, their measurement is challenging. In the subsequent analysis, we exploit the information available in our data and construct three factors that will reflect the intensity of systematic search frictions. First, we construct a monthly measure of market-wide dealer coverage by determining, for each bond j, the number of dealers trading the bond during a given month. We then standardize this number by the current amount outstanding of the bond at the end of the month to make the measure independent of bond size. Market-wide dealer coverage, $dcov_t$, is then simply the average across all bonds. The measure can be considered an empirical analog of the theoretical notion of Weill (2008) that dealers' asset tradability is indicative of smaller search frictions. We plot the time series of dealer coverage for a standardized notional of \$10 million in Panel C of Figure 2. We observe considerable variation in dealer coverage over our sample period. On average, 0.25 dealer trades a standardized notional of \$10 million. The measure gradually increases until the onset of the financial crisis to a temporary high close to 0.28, potentially due to the increased transparency in the U.S. corporate bond market. Following the outbreak of the financial crisis, dealer coverage dropped to about 0.2, reflecting the general reluctance of dealers to provide immediacy during that period. It subsequently recovers to the pre-crisis level but then again decreases to about 0.2, which could be driven by the enormous aggregate amount of new issuances.

For the second measure, we follow Li and Schürhoff (2014) and Di Maggio, Kermani, and

Song (2016) and compute a graph-level centrality measure, $centrality_t$, of the inter-dealer trading network. It is based on the eigenvector centrality and weighted by the monthly trading volume between dealers to reflect the strength of the relationship between a pair of dealers. We normalize the measure to make it bounded between zero and one. Intuitively, one can think of a value close to one as indicating many direct connections between dealers, while a lower value indicates fewer connections. Hence, a higher centrality measure means lower implied search frictions. We plot the time series of $centrality_t$ in Panel C of Figure 2, where we see that the time series is fairly stable across time, that is, the average value is close to 0.8.

As a third measure for search frictions, we compute dealers' intensity in meeting counterparties in the inter-dealer market. The measure is the empirical counterpart to the matching intensity parameter of DGP. Specifically, we compute the fraction of matched trades within a month to the number of overall trades during the month. We define matched trades as a set of trades that result in a zero net inventory position for the dealer at the end of the trading day. We refer to this measure as $match_t$ and plot its time series in Panel C of Figure 2. The plot shows that the matching intensity increases from slightly above 0.2 at the beginning of the sample period to about 0.4 toward the end.

We now focus on the asset pricing implications of market-wide search frictions and define the vector of search factors by

$$\boldsymbol{\Delta S_t} := [\Delta dcov_t,\ \Delta centrality_t,\ \Delta match_t]\,. \tag{11}$$

We conjecture that bond valuations increase with $\boldsymbol{S}$ because search frictions relax . This means that dealers (and customers) will find counterparties more easily. Thus, we expect a negative relation between changes in the search factors and yield spread changes. We test this conjecture by running the following regression for each bond j:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \boldsymbol{\Delta S_{j,t}} + \epsilon_{j,t}. \tag{12}$$

Table 6 presents the results (Panel A for leverage groups and Panel B for ratings). Overall, the loadings on the search factors have the predicted sign, that is, they are negatively related to yield spread changes. In the leverage classification, *dcov* and *centrality* are statistically significant in four of six cohorts and *match* is statistically significant in five out of six cohorts.

Although not as clear-cut as in the case of inventory, the loadings increase in absolute terms with the riskiness of the bonds. Hence, this result suggests that the search premium increases in the bonds' underlying credit risk. Among the rating cohorts, we find that the loadings are significantly negative in five out of seven groups.

Table 6 about here

Using PCA, we find that PC_1 decreases to 54%, indicating that search factors account for around four percentage points in the systematic variation of yield spread changes.

In summary, the findings show that a relaxation of search frictions is significantly negatively related to yield spread changes, consistent with the asset pricing implications of intermediation in OTC markets. Interestingly, we document that the explanatory power of search factors is somewhat lower than for market-wide inventory factors.

4.3 Bargaining frictions

Trading in the corporate bond market takes place on a bilateral basis. This implies that, when two counterparties meet, they know their identities and bargain over price and quantity. DGP show that asset valuations are lower when the bargaining power of dealers increases relative to that of their customers, since dealers extract higher intermediation rents. Therefore, we expect yield spreads to widen with dealers' bargaining power relative to that of their customers.

Measuring the bargaining power of dealers and customers is challenging because it is, per se, unobservable. We construct theoretically motivated bargaining factors based on the competitiveness of the dealer market and customers' trade size distributions. We assess the competitiveness of the dealer market by estimating the market share for each dealer i in each month in terms of the total trading volume during the month. We then take the maximum market share across all dealers and obtain a monthly measure, which we refer to as dealer market power, $power_t$.

A larger measure means a less competitive dealer market, which suggests a shift of bargaining power from customers toward dealers, as implied by DGP. We plot the time series of our measure in Panel D of Figure 2, where we observe an average market power of 0.09 during the sample period. This result means that the market share of the most active dealer is nine percentage points, on average. We also observe that, after the implementation of

TRACE in mid-2002, the dealer market becomes more competitive. Market power peaks at a value of 0.11 with the onset of the financial crisis, after which it drops to about 0.08. The measure then returns approximately to the pre-crisis level toward the end of the sample period.

We follow the literature and also estimate a measure that captures the trade size distribution. Several studies document that larger transactions are associated with smaller transaction costs (e.g., Edwards, Harris, and Piwowar, 2007). This phenomenon is theoretically reconciled through the idea that larger transactions are associated with customers with better bargaining power (Randall, 2015); for example, large institutional investors instead of small retail investors. Therefore, we estimate for each month the fraction of transactions exceeding \$1 million in trading volume to the overall number of trades during the month and refer to this measure as $mega_t$. With an increasing fraction of mega trades, the intensity of investors with greater bargaining power increases. We plot the time series of the measure in Panel D of Figure 2 and find that it is close to 0.25 in the pre-crisis period, while it is around 0.15 in the post-crisis period.

In the next step, we examine the pricing impact of systematic changes in the bargaining power of dealers relative to that of customers within the CDGM setup; that is, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \boldsymbol{\Delta B_t} + \epsilon_{j,t}, \tag{13}$$

where

$$\boldsymbol{\Delta B_t} := [\Delta power_t,\ \Delta mega_t] \tag{14}$$

is the vector of bargaining factors. The results in Table 7 show that both factors convey important information for yield spread changes. Specifically, within the leverage classification (Panel A), market power is positive and highly statistically significant in all cohorts, with t-statistics ranging between 3.5 and 6.2. This result implies that, when dealers' bargaining power increases, yield spreads widen systematically, consistent with the implications of DGP. The loadings of the coefficient also increase in leverage, indicative that bargaining frictions matter particularly for the pricing of riskier bonds. The pricing impact is almost five times as large for high-credit risk bonds compared to low-credit-risk bonds. The fraction of mega trades exhibits a negative coefficient and is significant in the first four cohorts (t-statistics ranging from 3.2 to 4.2). Along those cohorts, the loadings of the coefficient also increase in absolute terms, indicating that the pricing impact of investors' bargaining power increases with credit risk as well. Panel B provides the results for the rating groups, for which we find overall the same conclusions; that is, *power* is positive with a loading that is monotonically increasing, while *mega* is negatively significant in four out of seven groups.

The clear economic patterns of the factor loadings improve the adjusted R^2 values, which increase steadily across all leverage and ratings groups by up to four percentage points. This finding is reflected in a PCA, where we find that PC_1 drops to 54%.

Table 7 about here

The results show that systematic changes in the bargaining power of dealers relative to that of customers explain about four percentage points in the common variation of yield spread changes. The findings confirm the asset pricing implications of bargaining frictions; that is, valuations are lower if dealers' bargaining power increases relative to that of customers.

4.4 Joint impact of inventory, search, and bargaining frictions

The previous asset pricing tests show that inventory, search, and bargaining frictions are systematic price factors. The frictions differ only marginally in terms of their economic impact. That is, we find that dealer inventory accounts for five percentage points, while search and bargaining frictions account for four percentage points in the common variation of yield spread changes. In other words, if these three factors are independent of each other, then we expect them to jointly capture close to 13 percentage points in the variation of yield spread changes. From a theoretical standpoint, the pricing of these frictions depends on their prevalence. For example, Lagos, Rocheteau, and Weill (2011) show that dealers demand higher compensation for exposure to inventory risk if OTC frictions are more severe. To investigate the joint pricing impact, we estimate the model for each bond j:

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_{j,1}} \cdot \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{j,2}} \cdot \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{j,3}} \cdot \boldsymbol{\Delta B_t} + \epsilon_{j,t}. \tag{15}$$

We show the results in Table 8 (Panel A for leverage, Panel B for credit rating). All factor loadings exhibit their theoretically suggested signs. In particular, an increase in market-wide inventory systematically widens yield spreads. The factor loadings are different from zero in all cohorts and increase with leverage. The search factors load negatively on yield spread changes. However, in contrast to the individual pricing tests, the factor loadings are less significant. For example, the loading on the measure *match* is significantly negative in only two groups. The loadings on dealers' market power are significantly positive in all groups and monotonically increase with leverage. As far as the measure *mega* is concerned, loadings are negatively related to yield spread changes and are different from zero in three cohorts. We obtain similar insights based on rating cohorts.

Table 8 about here

Although the economic relations between the factors and yield spread changes remain unaffected compared to the individual pricing test, employing all factors jointly changes their significance. In particular, while the statistical significance of inventory and bargaining factors remains similar, that of the search factors diminishes slightly. Thus, this finding suggests that the pricing of inventory, search, and bargaining frictions depends on their interaction. We further investigate this notion in a PCA. We thus find that PC_1 diminishes to a level of around 48% compared to 58% of the CDGM benchmark result. Thus, inventory, search, and bargaining frictions capture 10 percentage points in the variation of yield spread changes. This result also shows that the overall increase in explanatory power does not perfectly reflect the sum of the incremental increases of the individual tests of 13 percentage points, confirming theoretical insights that OTC factors are endogenously related.

Overall, the improvement in the explanatory power of yield spread changes arising from inventory, search, and bargaining frictions is comparable to the eight percentage points that we obtain through the components of the intermediation premium, that is, the markdown and markup premiums. Therefore, as implied by the theory of intermediation in OTC markets, this result provides a first indication that systematic inventory, search, and bargaining frictions are priced factors because they determine dealers' intermediation premium. In the next section, we show that this is indeed the case.

4.5 Time variation of the intermediation premium

According to the theory of intermediation in OTC markets, systematic inventory, search, and bargaining frictions are priced in yield spread changes because they determine the intermediation premium. This result implies that time-varying OTC market frictions should be related to the variation in the intermediation premium.

Theory predicts that inventory, search, and bargaining frictions affect the intermediation premium differently. Randall (2015) argues that the intermediation premium reflects either the dealers' buying premium (the markdown MD) or the selling premium (the markup MU), depending on whether dealers are more willing to accept or offload inventory. Specifically, the model predicts that an increase in market-wide inventory raises MD relative to MU and vice versa when inventory decreases. Put differently, if market-wide inventory increases, the compensation to dealers for accepting additional inventory rises as well. DGP show that, when search frictions or dealers' bargaining power relative to customers diminishes, the intermediation premium falls because both MD and MU decrease. We examine the underlying mechanism through variants of the following time series specification:

$$\Delta IP_t = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{\Delta F_t} + \boldsymbol{\gamma_1} \cdot \Delta \boldsymbol{I_t} + \boldsymbol{\gamma_2} \cdot \Delta \boldsymbol{S_t} + \boldsymbol{\gamma_3} \cdot \Delta \boldsymbol{B_t} + \epsilon_t. \tag{16}$$

Hence, we regress changes in the intermediation premium on the changes of CDGM factors and our inventory, search, and bargaining factors.[5] We report the results in Panel A of Table 9. Among the CDGM factors, we find that changes in the risk-free rate, the slope of the term structure, as well as the VIX are significantly related to ΔIP. This result reflects the theoretical insight of Stoll (1978), in that the intermediation premium increases in aggregate risk aversion and/or uncertainty about fundamentals. Furthermore, the CDGM factors capture 29% in the time series variation of ΔIP. Among the OTC market frictions, innovations in inventory and bargaining factors exhibit a stronger impact on ΔIP compared to the search factors. The coefficient of market-wide inventory is positive, reflecting the previous insight that, on average, dealers act as liquidity providers. Furthermore, an increase in dealers' bargaining power relative to that of customers increases IP and vice versa. While the search factors exhibit the expected (negative) sign, only dealer coverage is marginally significant. Overall, in addition to the CDGM factors, the OTC factors capture 13% in the time variation of ΔIP.

Table 9 about here

[5]For this analysis, we construct a market-wide leverage measure, Δlev_t, that captures the change in the average leverage ratio of the underlying firms.

We now focus on whether market-wide inventory determines the composition of IP in terms of MD and MU, as implied by theory, that is, whether an increase in market-wide inventory leads to a decrease in the markup relative to the markdown. We test this notion through variants of the time series regression

$$\Delta(MU_t/IP_t) = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{\Delta F_t} + \boldsymbol{\gamma_1} \cdot \Delta \boldsymbol{I_t} + \boldsymbol{\gamma_2} \cdot \Delta \boldsymbol{S_t} + \boldsymbol{\gamma_3} \cdot \Delta \boldsymbol{B_t} + \epsilon_t, \tag{17}$$

where the dependent variable is the change in the fraction of the markup relative to the intermediation premium. We show the results in Panel B of Table 9, where we see that, among the CDGM factors, only the risk-free rate is different from zero and the factors explain 14% of the variation in the compositional changes of IP. Among the OTC variables, only the inventory factors are statistically different from zero, with the expected sign. In particular, we find that, when market-wide inventory increases, MU decreases relative to MD, implying that IP reflects the markdown more, that is, the compensation of dealers for accepting further inventory. Focusing on explanatory power, we find that our OTC factors capture 10 percentage points in the time series variation of the composition of IP.

5 Market-wide versus individual dealer inventories

In this section, we provide further analyses by discussing the role of the wealth of dealers in yield spread changes. Moreover, we examine whether dealers' intermediation styles explain the daily dispersion in the prices of the same bond across different inventories.

5.1 Idiosyncratic wealth shocks and yield spread changes

In the asset pricing tests so far, we have discussed the impact of systematic inventory, search, and bargaining frictions on yield spread changes. However, it could be that idiosyncratic shocks to individual dealers provide additional information for yield spread changes. For example, Kyle and Xiong (2001) elaborate on the impact of contagion in the form of a wealth effect on asset prices. They show that asset prices could be correlated, even though their fundamentals are independent, given that intermediaries have a wealth constraint. That is, a wealth shock can result in a common decline in the prices of intermediated but otherwise uncorrelated assets. This effect arises due to the consolidated liquidation of positions as a result of a binding wealth constraint. Brunnermeier and Pedersen (2009) provide similar asset price implications by linking the funding liquidity of intermediaries to the underlying market liquidity of assets.

In the subsequent test, we provide evidence that idiosyncratic wealth shocks indeed affect the common variation of yield spreads within dealer inventories. Specifically, we proxy for wealth shocks by dealers' stock returns. We are able to unmask and link 31 of the 73 dealers to stock price data, following the procedure outlined in Section 2. We first assign bonds to cohorts given the firm's underlying leverage. We then run a panel regression for each cohort and dealer i with at least 50 observations of monthly yield spread changes $\Delta YS_{ij,t}$; that is, we estimate the model

$$\Delta YS_{ij,t} = \alpha_i + \boldsymbol{\beta_i} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_{i,1}} \cdot \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}} \cdot \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}} \cdot \boldsymbol{\Delta B_t} + \delta_i r_t^i + \epsilon_{ij,t}, \tag{18}$$

where r_t^i is the stock return of dealer i. Through this specification, we test whether idiosyncratic wealth shocks matter for yield spread changes within dealer inventories, beyond systematic shocks. In the presence of a wealth effect, we expect $\delta_i < 0$; that is, the prices of bonds intermediated by the same dealer increase when the dealers' funding conditions improve, leading to a tightening of yield spreads.

Table 10 about here

For each leverage cohort, we report in Table 10 the average coefficient across dealers and the associated t-statistics. The loadings of the CDGM and OTC factors exhibit identical patterns compared to the previous tests. Furthermore, the results show that the coefficient of dealers' stock returns is negative in all groups (except for one) and differs from zero in three out of six cohorts, with t-statistics between 2.7 and 14.5. The loadings on dealers' stock returns tend to increase in the credit risk of bonds, suggesting that idiosyncratic wealth shocks exhibit a greater impact on the pricing of high-yield bonds. On average, a one standard deviation shock to dealers' stock returns leads to a change in the yield spread of about 25 bps. Overall, our results confirm that dealers' funding conditions matter for yield spread changes in a way that is consistent with a wealth effect, as for Kyle and Xiong (2001).

5.2 The same bond in different inventories

One of the key features of the corporate bond market is price dispersion, that is, the same bond can be traded at the same time at different prices. In this section, we examine whether cross-sectional differences in dealers' intermediation styles explain the dispersion in prices of the same bond on the same day across inventories. Specifically, we are interested in understanding whether cross-sectional differences in inventory levels, the positions of dealers in the network, or dealers' intermediation technologies affect the dispersion of prices across dealer inventories. To address these questions, we estimate a markdown and a markup, respectively, for each dealer i in each bond j on trading day s. Then, we run the panel regression

$$price_{ij,s} = \alpha_i + \alpha_{j\times s} + \boldsymbol{\beta} \cdot \boldsymbol{X_{i,s}} + \epsilon_{ij,s}, \tag{19}$$

where *price* refers to either the markup or the markdown, respectively. The measure $\boldsymbol{X_{i,s}}$ is a vector of dealer characteristics comprising the inventory level, $I_{i,s} = \sum_j I_{ij,s} - \bar{I}_i$. That is, we demean the inventory series of each dealer to correct for the unknown initial inventory level. Further, $\boldsymbol{X_{i,s}}$ includes eigenvector centrality, $centrality_{i,s}$; the fraction of mega trades (i.e., the number of trades with trade volume exceeding \$1 million), $mega_{i,s}$; the fraction of inter-dealer trades, $intr.dlr_{i,s}$; and the dealer and dealer–bond-specific trading volumes, $vol_{i,s}$ and $vol_{ij,s}$, respectively. Furthermore, α_i refers to a dealer fixed effect and $\alpha_{j\times s}$ is a bond–day fixed effect. Hence, through this specification, we test whether the dispersion in prices of bonds across dealers on trading day s is driven by cross-sectional variation in dealer characteristics.

The results for the markup (markdown) are provided in Panel A (B) of Table 11. The level of dealer inventory is not related to differences in either markdowns or markups. Central dealers charge higher markdowns and markups, indicating that they provide immediacy to customers through their inventories. The dispersion in prices is lower for dealers that primarily match trades and which are more active in the inter-dealer market. Moreover, the price dispersion is lower when dealers trade with customers with better bargaining power, with the effect being more pronounced for the markup.

Table 11 about here

Overall, the analysis shows that dealers' intermediation styles affect the dispersion in prices of the same bond across different inventories.

6 Conclusion

Empirical studies show that the variation in yield spread changes is difficult to explain, thereby leaving their economic determinants rather poorly understood. In this paper, we examine whether intermediation frictions that arise specifically in the corporate bond market, given its OTC structure, contribute to an understanding of the drivers of yield spread changes. In particular, we investigate the asset pricing implications of the theory of intermediation in OTC markets. We show that inventory, search, and bargaining frictions account for around 10 percentage points in the variation of yield spread changes beyond standard pricing factors. The pricing of credit riskier bonds is more sensitive to OTC market frictions. Generally, our findings confirm the asset pricing implications of leading theories of intermediation in OTC markets.

We provide additional insights into the determinants of yield spread changes by showing that the time variation in dealers' wealth helps to explain the common variation of yield spread changes of bonds within dealer inventory. Hence, this result highlights the role of dealers funding conditions for liquidity provisioning. Furthermore, we show that dealers' intermediation styles explain the different prices for the same bond across inventories. Specifically, we find that the bonds of dealers that execute more matched trades or that trade more frequently in the inter-dealer market have lower price dispersion. Central dealers offer worse prices to customers compared with peripheral dealers, suggesting that they are more willing to provide immediacy through their inventories.

In summary, we provide novel insights into the systematic drivers of yield spread changes by elaborating on the asset pricing implications of intermediation frictions in OTC markets. Specifically, we document that inventory, search, and bargaining frictions account for one-third of the explained variation in yield spread changes.

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Figures and Tables

Table 1: Descriptive statistics. This table reports summary statistics of the data used in our empirical analysis. We report the mean; standard deviation; 10%, 50%, and 90% quantiles of bond characteristics; and daily trading activity variables at the market, bond, and dealer levels. The bond characteristics are the offering amount, the coupon rate, the time to maturity, and the credit rating, where we assign integer numbers to the credit ratings (i.e., AAA = 1, AA+ = 2, ... , D = 22). As trading activity variables, we report the number of trades and the trading volume at the market, bond, and dealer level. We also report the total number of bonds traded in the market, the number of dealers trading a given bond, and the number of bonds traded by a given dealer. At the dealer level, we further report the number of inter-dealer trades, the inter-dealer trading volume, the number of matched trades, and the matched trading volume. A matched trade is a trade that belongs to a set of transactions of a dealer in a bond that results in a zero net inventory position at the end of the trading day. For the matched trading volume, we report the total trading volume of just one side of the transaction. We further report the number of counterparties a dealer trades with during a day; the different bond industries traded, as defined by the first digit of the SIC code; as well as the credit rating, size, and time to maturity of the traded bonds. The sample comprises the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

	Mean	SD	Q10	Q50	Q90
Bond characteristics					
Offering amount [$ mln]	481.37	470.45	150.00	344.96	1000.00
Coupon rate [%]	7.29	2.46	4.12	7.25	10.50
Time-to-maturity [years]	3.09	3.85	0.16	1.64	8.15
Credit rating	11.67	4.54	6.00	11.49	17.00
Market trading activity					
Trades	10307.85	4382.52	5737.20	8629.50	16403.90
Trading volume [$ mln]	8785.11	3022.08	5193.74	8940.80	12477.89
Bonds	1839.15	530.10	1351.00	1655.00	2579.90
Bond trading activity					
Trades	4.14	4.27	1.71	2.90	7.56
Trading volume [$ mln]	5.12	6.09	1.07	3.65	10.05
Dealers	2.10	1.35	1.10	1.68	3.56
Dealer trading activity					
Trades	174.02	195.27	24.02	108.99	466.23
Trading volume [$ mln]	143.30	176.08	25.65	57.86	468.06
Bonds	86.92	93.78	11.08	40.69	210.37
Inter-dealer trades	89.77	101.77	9.25	48.46	238.54
Inter-dealer trading volume [$ mln]	55.89	65.71	8.33	22.41	156.06
Matched trades	63.71	102.41	6.42	28.21	129.08
Matched trading volume [$ mln]	53.06	62.70	11.02	27.88	117.19
Counterparties traded with	21.73	15.49	5.44	18.56	42.36
Traded bond industries	5.75	1.14	4.17	5.87	7.09
Traded credit ratings	10.89	2.49	7.95	10.40	14.51
Traded bond sizes [$ mln]	888.10	182.18	617.27	910.60	1122.99
Traded maturities [years]	3.33	0.91	2.23	3.24	4.48

Table 2: Determinants of yield spread changes in the Collin-Dufresne, Goldstein, and Martin (2001) framework. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on heteroscedasticity- and autocorrelation-consistent (HAC) standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.01**	0.01	0.02*	0.02**	0.01	0.11***
	(2.01)	(1.12)	(1.94)	(2.17)	(0.72)	(4.28)
$\Delta lev_{j,t}$	0.02**	0.01*	0.01**	0.02***	0.04***	0.12***
	(2.08)	(1.69)	(2.12)	(3.54)	(6.32)	(6.45)
Δrf_t	−0.14***	−0.23***	−0.23***	−0.42***	−0.41***	−0.14
	(−2.99)	(−4.82)	(−3.34)	(−4.17)	(−2.86)	(−0.88)
$(\Delta rf_t)^2$	−0.00	0.10	0.04	0.31	0.44	−0.27
	(−0.01)	(1.05)	(0.20)	(1.52)	(1.62)	(−0.68)
$\Delta slope_t$	0.12*	0.12**	0.28***	0.35***	0.37**	0.38*
	(1.88)	(1.97)	(3.03)	(2.63)	(2.59)	(1.68)
ΔVIX_t	0.01***	0.01**	0.01**	0.01**	0.03***	−0.01
	(3.83)	(2.58)	(2.13)	(2.48)	(2.84)	(−0.53)
r_t^m	−0.01***	−0.02***	−0.03***	−0.04***	−0.03***	−0.13***
	(−3.55)	(−5.74)	(−7.64)	(−5.73)	(−3.75)	(−4.92)
$\Delta jump_t$	0.00	0.00	0.01***	0.00	0.02***	0.01*
	(0.36)	(0.45)	(2.75)	(1.65)	(3.29)	(1.90)
Adj. R^2	0.16	0.18	0.25	0.30	0.31	0.37
Bonds	219	269	179	155	85	117

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	0.02***	0.01	0.02***	0.00	0.06***	0.06**	0.23***
	(6.22)	(1.61)	(3.94)	(0.45)	(2.95)	(2.15)	(5.76)
$\Delta lev_{j,t}$	0.05	−0.00	0.00	0.02***	0.05***	0.09***	0.27***
	(1.44)	(−0.59)	(0.98)	(4.22)	(5.43)	(9.35)	(6.00)
Δrf_t	−0.01	−0.10**	−0.17***	−0.35***	−0.23	−0.20	−1.14***
	(−0.06)	(−2.54)	(−3.37)	(−6.10)	(−1.45)	(−1.33)	(−8.75)
$(\Delta rf_t)^2$	−0.01	0.07	−0.02	0.18	−0.04	0.02	2.06**
	(−0.14)	(0.96)	(−0.27)	(1.40)	(−0.14)	(0.04)	(2.32)
$\Delta slope_t$	−0.16	0.14*	0.14**	0.23***	0.39**	0.41*	1.07
	(−1.71)	(1.71)	(2.43)	(3.11)	(2.28)	(1.83)	(1.46)
ΔVIX_t	0.01*	0.01*	0.01***	0.01**	0.02**	0.01	−0.09
	(1.85)	(1.83)	(3.73)	(2.13)	(2.48)	(1.32)	(−1.45)
r_t^m	−0.00	−0.01**	−0.01***	−0.03***	−0.05***	−0.08***	−0.32**
	(−0.39)	(−2.46)	(−6.47)	(−7.04)	(−5.74)	(−5.31)	(−2.71)
$\Delta jump_t$	0.00	0.00	0.00*	0.00**	0.01	0.01*	0.04*
	(1.41)	(0.18)	(1.76)	(2.32)	(1.49)	(1.83)	(2.07)
Adj. R^2	0.09	0.10	0.17	0.25	0.33	0.38	0.50
Bonds	22	91	333	336	118	109	15

Table 3: Intermediation premium and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \gamma_j \Delta IP_t + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The variable IP_t is the intermediation premium earned by dealers for intermediating between customers relative to the inter-dealer price. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.03***	0.03***	0.05***	0.06***	0.06***	0.18***
	(5.56)	(4.82)	(5.07)	(5.51)	(2.80)	(5.90)
$\Delta lev_{j,t}$	0.02**	0.01	0.01**	0.02***	0.04***	0.12***
	(2.33)	(1.47)	(2.12)	(3.84)	(6.04)	(5.82)
Δrf_t	−0.09*	−0.16***	−0.13*	−0.29***	−0.21	−0.03
	(−1.90)	(−3.55)	(−1.96)	(−2.93)	(−1.55)	(−0.20)
$(\Delta rf_t)^2$	−0.18*	−0.13	−0.30*	−0.14	−0.03	−1.12***
	(−1.97)	(−1.28)	(−1.89)	(−0.66)	(−0.13)	(−2.92)
$\Delta slope_t$	0.04	0.02	0.10	0.17	0.13	0.16
	(0.66)	(0.35)	(1.21)	(1.26)	(0.86)	(0.68)
ΔVIX_t	0.01***	0.00*	0.01*	0.01**	0.03***	−0.01
	(3.27)	(1.89)	(1.69)	(2.29)	(2.84)	(−0.45)
r_t^m	−0.01**	−0.01***	−0.02***	−0.03***	−0.02**	−0.11***
	(−2.40)	(−4.60)	(−5.46)	(−4.49)	(−2.26)	(−4.39)
$\Delta jump_t$	0.00	0.00	0.01***	0.01*	0.02***	0.01***
	(0.15)	(0.40)	(2.94)	(1.75)	(3.60)	(2.63)
ΔIP_t	2.19***	2.98***	4.32***	5.37***	5.97***	9.30***
	(8.46)	(10.87)	(12.02)	(10.96)	(6.76)	(7.25)
Adj. R^2	0.20	0.23	0.31	0.36	0.34	0.40
Bonds	219	269	179	155	85	117

Table 3 continues on next page

Table 3 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	0.03***	0.03***	0.04***	0.04***	0.10***	0.11***	0.37***
	(5.34)	(4.59)	(7.84)	(5.90)	(5.17)	(4.63)	(5.61)
$\Delta lev_{j,t}$	0.07*	−0.01	0.01	0.02***	0.05***	0.09***	0.29***
	(1.80)	(−0.77)	(1.33)	(3.74)	(5.28)	(9.94)	(5.74)
Δrf_t	0.01	−0.06	−0.09*	−0.26***	−0.12	−0.02	−0.84
	(0.08)	(−1.50)	(−1.76)	(−4.74)	(−0.73)	(−0.17)	(−1.42)
$(\Delta rf_t)^2$	−0.05	−0.12*	−0.24***	−0.18	−0.63**	−0.61*	0.64
	(−0.37)	(−1.89)	(−3.03)	(−1.42)	(−2.36)	(−1.79)	(0.46)
$\Delta slope_t$	−0.19	0.11	0.01	0.09	0.21	0.16	0.46
	(−1.67)	(1.18)	(0.20)	(1.26)	(1.24)	(0.74)	(0.49)
ΔVIX_t	0.01	0.00*	0.01***	0.01**	0.02**	0.01	−0.08
	(1.59)	(1.81)	(2.68)	(2.56)	(2.51)	(1.04)	(−1.26)
r_t^m	−0.00	−0.01*	−0.01***	−0.02***	−0.04***	−0.07***	−0.27**
	(−0.04)	(−1.76)	(−5.47)	(−5.42)	(−4.50)	(−4.64)	(−2.38)
$\Delta jump_t$	0.00	0.00	0.00	0.00***	0.01**	0.01***	0.02
	(1.26)	(0.14)	(1.45)	(2.63)	(2.03)	(3.39)	(0.89)
ΔIP_t	0.87	2.40***	2.52***	4.43***	6.82***	8.04***	15.59***
	(0.87)	(8.51)	(10.60)	(14.52)	(10.70)	(6.95)	(5.55)
Adj. R^2	0.13	0.15	0.22	0.31	0.38	0.42	0.54
Bonds	22	91	333	336	118	109	15

Table 4: Markdown/markup premium and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \gamma_{j,1}\Delta MU_t + \gamma_{j,2}\Delta MD_t + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$, the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The variable MU_t refers to the markup premium (i.e., the premium at which dealers sell to customers relative to the inter-dealer price) and MD_t refers to the markdown premium (i.e., the discount at which dealers buy from customers relative to the inter-dealer price). We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.02***	0.03***	0.04***	0.06***	0.06***	0.18***
	(4.93)	(4.07)	(4.55)	(5.62)	(2.82)	(4.68)
$\Delta lev_{j,t}$	0.02**	0.01**	0.01**	0.02***	0.04***	0.12***
	(2.24)	(2.19)	(2.08)	(4.02)	(6.50)	(5.33)
Δrf_t	−0.11**	−0.14***	−0.14*	−0.28***	−0.20	0.26
	(−2.39)	(−3.20)	(−1.91)	(−2.70)	(−1.16)	(1.21)
$(\Delta rf_t)^2$	−0.18**	−0.11	−0.30*	−0.13	−0.06	−1.22***
	(−1.97)	(−1.01)	(−1.76)	(−0.64)	(−0.25)	(−3.70)
$\Delta slope_t$	0.07	0.01	0.13	0.22	0.14	0.13
	(1.02)	(0.22)	(1.47)	(1.60)	(0.75)	(0.45)
ΔVIX_t	0.01***	0.00**	0.01*	0.01*	0.03***	−0.01
	(3.33)	(2.20)	(1.74)	(1.93)	(2.93)	(−0.57)
r_t^m	−0.01**	−0.01***	−0.02***	−0.03***	−0.02**	−0.12***
	(−1.98)	(−3.60)	(−5.35)	(−4.34)	(−2.38)	(−4.06)
$\Delta jump_t$	0.00	0.00	0.01***	0.00	0.02***	0.02**
	(0.30)	(0.55)	(2.64)	(1.35)	(3.58)	(2.31)
ΔMU_t	1.57***	1.88***	1.48**	3.12***	4.31***	3.34
	(4.26)	(4.41)	(2.29)	(3.78)	(3.26)	(1.40)
ΔMD_t	2.70***	3.74***	6.66***	7.29***	7.54***	15.05***
	(5.42)	(6.22)	(11.22)	(8.95)	(4.28)	(5.19)
Adj. R^2	0.21	0.24	0.32	0.37	0.36	0.42
Bonds	219	269	179	155	85	117

Table 4 continues on next page

Table 4 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	0.03***	0.02***	0.03***	0.03***	0.10***	0.12***	0.42***
	(17.01)	(2.84)	(7.38)	(5.22)	(4.93)	(4.93)	(3.11)
$\Delta lev_{j,t}$	0.07	−0.01	0.01*	0.02***	0.05***	0.09***	0.31***
	(1.65)	(−1.40)	(1.76)	(4.64)	(6.13)	(8.43)	(5.36)
Δrf_t	0.00	−0.10*	−0.09*	−0.26***	−0.03	0.11	0.05
	(0.04)	(−1.72)	(−1.71)	(−4.20)	(−0.23)	(0.57)	(0.11)
$(\Delta rf_t)^2$	−0.12	−0.10	−0.23**	−0.12	−0.67**	−0.75**	−0.14
	(−0.99)	(−1.43)	(−2.51)	(−0.94)	(−2.40)	(−2.26)	(−0.12)
$\Delta slope_t$	−0.18*	0.11	0.04	0.09	0.20	0.15	0.73
	(−1.79)	(1.06)	(0.69)	(1.32)	(1.23)	(0.59)	(0.90)
ΔVIX_t	0.01	0.01**	0.01***	0.01**	0.02**	0.01	−0.08
	(1.50)	(2.17)	(2.78)	(2.48)	(2.44)	(0.90)	(−1.27)
r_t^m	−0.00	−0.00	−0.01***	−0.02***	−0.04***	−0.07***	−0.31*
	(−0.31)	(−0.81)	(−5.33)	(−4.89)	(−4.35)	(−4.63)	(−2.11)
$\Delta jump_t$	0.00	0.00	0.00*	0.01***	0.01**	0.01***	0.04
	(1.11)	(0.25)	(1.86)	(2.69)	(2.10)	(2.71)	(1.48)
ΔMU_t	0.62	1.38**	1.01***	3.30***	2.65**	3.92*	1.98
	(1.12)	(2.31)	(3.28)	(7.62)	(2.37)	(1.85)	(0.21)
ΔMD_t	0.85	3.04***	3.76***	5.37***	10.56***	11.65***	30.29***
	(0.55)	(3.67)	(8.20)	(9.09)	(7.75)	(5.48)	(3.60)
Adj. R^2	0.15	0.17	0.23	0.32	0.41	0.43	0.56
Bonds	22	91	333	336	118	109	15

Table 5: Inventory frictions and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \Delta \boldsymbol{I_t} + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\Delta \boldsymbol{I_t} := [\Delta out_t,\ \Delta I_t]$ refers to the changes in the market-wide inventory factors, where out_t is the aggregate amount outstanding and I_t is the market-wide dealer inventory. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.02	0.02	0.05**	0.05**	0.06*	0.15***
	(1.44)	(1.44)	(2.16)	(2.34)	(1.83)	(3.03)
$\Delta lev_{j,t}$	0.02**	0.01**	0.02***	0.02***	0.05***	0.13***
	(2.41)	(2.52)	(2.74)	(3.22)	(6.82)	(5.98)
Δrf_t	−0.17**	−0.33***	−0.36***	−0.55***	−0.49***	−0.28
	(−2.57)	(−5.32)	(−3.97)	(−5.29)	(−3.34)	(−1.30)
$(\Delta rf_t)^2$	0.04	0.17	0.24	0.54**	0.55*	−0.05
	(0.38)	(1.45)	(1.04)	(2.35)	(1.81)	(−0.11)
$\Delta slope_t$	0.22***	0.25***	0.42***	0.51***	0.54***	0.39*
	(2.65)	(3.16)	(3.93)	(3.44)	(3.79)	(1.76)
ΔVIX_t	0.01***	0.00*	0.01	0.01	0.02**	−0.02
	(2.60)	(1.82)	(1.64)	(1.35)	(2.42)	(−1.07)
r_t^m	−0.01***	−0.02***	−0.03***	−0.04***	−0.03***	−0.13***
	(−4.23)	(−5.94)	(−7.88)	(−5.39)	(−3.68)	(−5.01)
$\Delta jump_t$	0.00	0.00	0.01***	0.00	0.01***	0.01
	(0.67)	(0.31)	(2.64)	(1.55)	(2.98)	(1.55)
Δout_t	−0.36	−0.69	−2.52***	−3.37***	−2.21*	−3.54
	(−0.88)	(−1.41)	(−3.03)	(−3.33)	(−1.80)	(−1.13)
ΔI_t	6.95**	14.65***	25.84***	28.12***	20.44**	70.76***
	(2.12)	(5.62)	(6.54)	(4.73)	(2.34)	(4.43)
Adj. R^2	0.21	0.22	0.29	0.33	0.33	0.39
Bonds	219	269	179	155	85	117

Table 5 continues on next page

Table 5 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	−0.01	0.02	0.03***	0.03**	0.05	0.10**	0.39***
	(−0.48)	(1.48)	(3.20)	(2.10)	(1.52)	(2.15)	(4.40)
$\Delta lev_{j,t}$	0.05*	0.00	0.01	0.02***	0.06***	0.10***	0.30***
	(2.00)	(0.08)	(1.26)	(4.90)	(6.36)	(9.05)	(5.59)
Δrf_t	−0.03	−0.13**	−0.24***	−0.44***	−0.47***	−0.30*	−1.47***
	(−0.37)	(−2.29)	(−3.42)	(−6.63)	(−2.88)	(−1.75)	(−3.74)
$(\Delta rf_t)^2$	−0.08	0.15**	0.08	0.24	0.47	0.17	2.15
	(−0.40)	(2.02)	(0.63)	(1.56)	(1.42)	(0.40)	(1.54)
$\Delta slope_t$	0.12	0.19**	0.24***	0.37***	0.61***	0.46*	1.08**
	(0.70)	(2.03)	(3.05)	(4.25)	(3.19)	(1.94)	(2.17)
ΔVIX_t	0.00	0.01	0.01***	0.00	0.01*	0.01	−0.10
	(0.58)	(1.58)	(2.92)	(0.66)	(1.88)	(0.80)	(−1.37)
r_t^m	−0.01	−0.01**	−0.02***	−0.03***	−0.05***	−0.08***	−0.32**
	(−1.66)	(−2.15)	(−7.00)	(−6.61)	(−5.35)	(−5.44)	(−2.90)
$\Delta jump_t$	0.00	0.00	0.00	0.00**	0.00	0.01	0.04
	(1.05)	(0.75)	(1.52)	(2.38)	(0.66)	(1.61)	(1.67)
Δout_t	1.11	−0.92	−0.88**	−1.79***	−3.24**	−4.07**	−4.04
	(1.07)	(−1.36)	(−2.17)	(−3.01)	(−2.19)	(−2.03)	(−0.23)
ΔI_t	−8.72	11.10**	14.29***	21.72***	34.20***	51.35***	130.19***
	(−0.62)	(2.37)	(5.15)	(5.48)	(3.22)	(4.12)	(3.89)
Adj. R^2	0.18	0.16	0.22	0.28	0.37	0.40	0.49
Bonds	22	91	333	336	118	109	15

Table 6: Search frictions and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \boldsymbol{\Delta S_t} + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\boldsymbol{\Delta S_t} := [\Delta dcov_t,\ \Delta centrality_t,\ \Delta match_t]$ refers to the changes in the market-wide search factors, where $dcov_t$ is the average value of the number of dealers trading a given bond during a month per unit of the bond's current amount outstanding, $centrality_t$ is a graph-level eigenvector centrality measure of the inter-dealer network, and $match_t$ is the matching intensity, which refers to the number of matched trades relative to all trades in a month. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15 - 25\%$	$25 - 35\%$	$35 - 45\%$	$45 - 55\%$	$> 55\%$
Intercept	0.01	0.01	0.01	0.02*	0.01	0.10***
	(1.50)	(0.93)	(1.40)	(1.78)	(0.50)	(3.79)
$\Delta lev_{j,t}$	0.01	0.01	0.01*	0.02***	0.04***	0.12***
	(1.52)	(1.39)	(1.94)	(4.14)	(5.52)	(5.27)
Δrf_t	−0.20***	−0.24***	−0.32***	−0.44***	−0.35***	−0.08
	(−2.88)	(−4.53)	(−3.47)	(−4.40)	(−3.09)	(−0.39)
$(\Delta rf_t)^2$	0.07	0.18*	0.14	0.29	0.49*	−0.35
	(0.68)	(1.78)	(0.76)	(1.34)	(1.74)	(−0.73)
$\Delta slope_t$	0.18**	0.13*	0.36***	0.34**	0.24*	0.20
	(2.15)	(1.92)	(3.30)	(2.60)	(1.70)	(0.72)
ΔVIX_t	0.01***	0.01**	0.01	0.01**	0.02**	−0.02
	(3.34)	(2.02)	(1.58)	(2.20)	(2.36)	(−1.00)
r_t^m	−0.01***	−0.02***	−0.03***	−0.04***	−0.04***	−0.13***
	(−3.99)	(−6.06)	(−8.35)	(−5.73)	(−3.93)	(−5.13)
$\Delta jump_t$	−0.00	0.00	0.00*	0.01	0.01**	0.01*
	(−0.27)	(1.09)	(1.87)	(1.65)	(2.45)	(1.91)
$\Delta dcov_t$	−0.67	−1.99***	−0.12	−1.88**	−3.86***	−3.19**
	(−1.52)	(−3.86)	(−0.19)	(−2.31)	(−3.19)	(−2.29)
$\Delta centrality_t$	−1.39***	−0.77***	−0.48	−1.59***	−1.78**	−0.70
	(−4.96)	(−3.23)	(−1.19)	(−3.79)	(−2.35)	(−0.48)
$\Delta match_t$	−1.93***	−2.28***	−3.05***	−2.53**	−4.52**	1.14
	(−3.78)	(−4.18)	(−3.69)	(−2.14)	(−2.01)	(0.50)
Adj. R^2	0.17	0.19	0.25	0.31	0.32	0.37
Bonds	219	269	179	155	85	117

Table 6 continues on next page

Table 6 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	0.02***	0.01	0.02***	−0.00	0.04*	0.07**	0.18***
	(4.09)	(1.42)	(4.14)	(−0.51)	(1.68)	(2.57)	(3.43)
$\Delta lev_{j,t}$	0.05	−0.01	0.00	0.02***	0.05***	0.09***	0.30***
	(1.60)	(−1.04)	(0.59)	(4.07)	(5.21)	(8.03)	(5.49)
Δrf_t	0.00	−0.11**	−0.22***	−0.34***	−0.35***	−0.13	−1.03***
	(0.00)	(−2.28)	(−3.19)	(−5.68)	(−3.03)	(−0.71)	(−4.87)
$(\Delta rf_t)^2$	−0.01	0.13	−0.01	0.29**	0.14	−0.16	2.08**
	(−0.13)	(1.31)	(−0.06)	(2.14)	(0.47)	(−0.40)	(2.76)
$\Delta slope_t$	−0.14	0.11	0.20***	0.21***	0.42***	0.23	1.01
	(−1.42)	(1.16)	(2.69)	(2.66)	(3.16)	(0.78)	(1.46)
ΔVIX_t	0.01	0.01*	0.01***	0.01*	0.01**	0.00	−0.11
	(1.27)	(1.69)	(3.28)	(1.70)	(1.98)	(0.42)	(−1.62)
r_t^m	−0.01	−0.01***	−0.02***	−0.03***	−0.05***	−0.10***	−0.31**
	(−0.51)	(−2.95)	(−7.00)	(−7.42)	(−5.30)	(−5.81)	(−2.80)
$\Delta jump_t$	0.00	0.00	0.00	0.00	0.01**	0.01**	0.07**
	(0.88)	(0.17)	(0.75)	(1.28)	(1.98)	(2.15)	(2.59)
$\Delta dcov_t$	−0.57	−0.86	−0.51	−1.86***	−2.97**	−3.01**	−8.77
	(−1.30)	(−1.06)	(−1.42)	(−3.24)	(−2.39)	(−2.20)	(−1.03)
$\Delta centrality_t$	−1.36**	−1.24***	−1.42***	−1.11***	−0.22	−1.85*	9.21**
	(−2.38)	(−3.05)	(−7.29)	(−3.40)	(−0.43)	(−1.70)	(2.45)
$\Delta match_t$	−0.68	−1.63**	−2.79***	−3.49***	−2.48	1.08	14.19
	(−0.77)	(−2.34)	(−5.57)	(−4.89)	(−1.53)	(0.56)	(1.67)
Adj. R^2	0.09	0.12	0.19	0.26	0.34	0.39	0.51
Bonds	22	91	333	336	118	109	15

Table 7: Bargaining frictions and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_j} \cdot \Delta \boldsymbol{B_t} + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\Delta \boldsymbol{B_t} := [\Delta power_t,\ \Delta mega_t]$ refers to the changes in the market-wide bargaining factors, where $power_t$ is the market share in terms of the monthly trading volume of the most active dealer and $mega_t$ is the fraction of mega trades (i.e., trading volumes greater than $1 million) to the overall number of trades in the market during a month. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage ratio

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.01***	0.01**	0.02**	0.03*	0.03	0.12***
	(2.65)	(2.05)	(2.57)	(1.97)	(1.51)	(4.45)
$\Delta lev_{j,t}$	0.02***	0.01	0.01	0.02***	0.04***	0.12***
	(2.71)	(1.63)	(1.62)	(3.38)	(6.83)	(6.26)
Δrf_t	−0.12**	−0.22***	−0.24***	−0.45***	−0.36**	−0.15
	(−2.50)	(−5.05)	(−3.23)	(−4.95)	(−2.07)	(−1.18)
$(\Delta rf_t)^2$	−0.03	0.10	0.01	0.31	0.40	−0.31
	(−0.36)	(0.90)	(0.08)	(1.36)	(1.54)	(−0.70)
$\Delta slope_t$	0.12**	0.17**	0.37***	0.46***	0.41**	0.46**
	(1.99)	(2.55)	(3.66)	(3.18)	(2.31)	(2.41)
ΔVIX_t	0.01***	0.01***	0.01***	0.02***	0.03***	−0.00
	(3.91)	(3.29)	(2.75)	(2.96)	(2.75)	(−0.09)
r_t^m	−0.01***	−0.02***	−0.03***	−0.04***	−0.03***	−0.12***
	(−3.09)	(−6.71)	(−7.30)	(−5.14)	(−3.52)	(−4.94)
$\Delta jump_t$	0.00	0.00	0.00**	0.00	0.02***	0.02**
	(0.19)	(0.27)	(2.04)	(1.42)	(3.48)	(2.26)
$\Delta power_t$	3.09***	5.96***	7.90***	10.97***	11.36***	16.13***
	(3.48)	(5.51)	(6.21)	(6.10)	(4.58)	(4.44)
$\Delta mega_t$	−1.14***	−1.49***	−1.80***	−2.55***	−1.60	−1.95
	(−3.43)	(−4.06)	(−3.15)	(−4.22)	(−1.52)	(−1.27)
Adj. R^2	0.19	0.22	0.29	0.34	0.33	0.39
Bonds	219	269	179	155	85	117

Table 7 continues on next page

Table 7 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	0.03***	0.02***	0.02***	0.01	0.06***	0.08**	0.18***
	(9.51)	(2.97)	(4.79)	(1.23)	(2.97)	(2.36)	(4.44)
$\Delta lev_{j,t}$	0.04	0.01	0.00	0.02***	0.05***	0.09***	0.27***
	(1.03)	(1.17)	(0.77)	(4.22)	(4.40)	(9.91)	(5.55)
Δrf_t	0.04	−0.08*	−0.17***	−0.33***	−0.29*	−0.24*	−0.96***
	(0.39)	(−1.82)	(−3.23)	(−5.80)	(−1.85)	(−1.98)	(−6.30)
$(\Delta rf_t)^2$	−0.09	0.02	−0.04	0.15	0.08	−0.09	2.20*
	(−1.29)	(0.29)	(−0.48)	(1.10)	(0.26)	(−0.21)	(2.09)
$\Delta slope_t$	−0.18*	0.17*	0.17***	0.27***	0.56***	0.57***	0.57
	(−1.75)	(1.88)	(2.86)	(3.68)	(3.08)	(2.74)	(0.98)
ΔVIX_t	0.01	0.01**	0.01***	0.01***	0.02***	0.02	−0.07
	(1.58)	(2.00)	(3.84)	(3.25)	(2.86)	(1.53)	(−1.20)
r_t^m	−0.00	−0.01***	−0.02***	−0.03***	−0.05***	−0.08***	−0.29**
	(−0.60)	(−2.78)	(−6.50)	(−6.79)	(−5.51)	(−4.72)	(−2.30)
$\Delta jump_t$	0.00	−0.00	0.00*	0.00*	0.01	0.01**	0.06**
	(0.29)	(−0.34)	(1.85)	(1.79)	(1.21)	(2.51)	(2.27)
$\Delta power_t$	1.50	3.33***	4.11***	7.48***	17.45***	16.49***	11.47*
	(0.64)	(3.26)	(4.12)	(6.52)	(8.32)	(4.00)	(1.97)
$\Delta mega_t$	−0.06	−1.05**	−1.41***	−2.23***	−1.16	−2.84**	1.97
	(−0.15)	(−2.11)	(−4.95)	(−5.20)	(−1.22)	(−2.24)	(0.22)
Adj. R^2	0.11	0.15	0.21	0.29	0.37	0.40	0.48
Bonds	22	91	333	336	118	109	15

Table 8: OTC market frictions and yield spread changes. For each industrial bond j with at least 20 monthly observations of yield spread changes, $\Delta YS_{j,t}$, we estimate the model

$$\Delta YS_{j,t} = \alpha_j + \boldsymbol{\beta_j} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_{j,1}} \cdot \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{j,2}} \cdot \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{j,3}} \cdot \boldsymbol{\Delta B_t} + \epsilon_{j,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\boldsymbol{\Delta I_t} := [\Delta out_t,\ \Delta I_t]$ refers to the changes in the market-wide inventory factors, where out_t is the aggregate amount outstanding and I_t is the market-wide dealer inventory. The vector $\boldsymbol{\Delta S_t} := [\Delta dcov_t,\ \Delta centrality_t,\ \Delta match_t]$ refers to the changes in the market-wide search factors, where $dcov_t$ is the average value of the number of dealers trading a given bond during a month per unit of its current amount outstanding, $centrality_t$ is a graph-level eigenvalue centrality measure of the inter-dealer network, and $match_t$ is the matching intensity, which refers to the number of matched trades relative to all trades in a month. The vector $\boldsymbol{\Delta B_t} := [\Delta power_t,\ \Delta mega_t]$ refers to changes in the market-wide bargaining factors where $power_t$ is the market share in terms of the monthly trading volume of the most active dealer and $mega_t$ is the fraction of mega trades (i.e., trading volumes greater than $1 million) to the overall number of trades in the market during a month. We assign each bond to a cohort based on the firm's average leverage ratio (credit rating) and report in Panel A (B) the average coefficients across bonds and the associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Leverage

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.01	0.01	0.02	0.04*	0.05	0.12*
	(0.73)	(0.99)	(0.96)	(1.72)	(1.29)	(1.66)
$\Delta lev_{j,t}$	0.01	0.01**	0.01	0.03***	0.05***	0.14***
	(1.50)	(2.17)	(1.50)	(4.11)	(6.33)	(3.79)
Δrf_t	−0.16**	−0.29***	−0.36***	−0.58***	−0.34***	−0.35
	(−2.37)	(−5.15)	(−3.71)	(−5.36)	(−3.46)	(−1.35)
$(\Delta rf_t)^2$	0.14	0.21	0.23	0.57**	0.58	−0.03
	(1.35)	(1.63)	(0.86)	(2.09)	(1.51)	(−0.05)
$\Delta slope_t$	0.22***	0.24***	0.48***	0.48***	0.35**	0.46
	(2.65)	(2.77)	(4.08)	(3.08)	(2.29)	(1.57)
ΔVIX_t	0.01***	0.00**	0.01**	0.01	0.02**	−0.01
	(3.49)	(2.01)	(2.03)	(1.31)	(2.07)	(−0.68)
r_t^m	−0.01***	−0.02***	−0.03***	−0.04***	−0.03***	−0.11***
	(−4.13)	(−6.78)	(−8.19)	(−4.99)	(−3.39)	(−6.14)
$\Delta jump_t$	−0.00	0.00	0.00	0.00	0.02***	0.03*
	(−0.26)	(1.01)	(1.20)	(1.23)	(2.87)	(1.96)
Δout_t	−0.31	−0.22	−1.39	−3.98***	−1.79	−5.25
	(−0.68)	(−0.42)	(−1.57)	(−2.88)	(−1.51)	(−1.38)
ΔI_t	6.85**	12.97***	22.93***	28.80***	19.60**	71.23***
	(2.21)	(4.76)	(5.04)	(4.71)	(2.48)	(3.36)
$\Delta dcov_t$	−0.33	−2.28***	−0.76	−2.56***	−4.80***	−5.96***
	(−0.67)	(−4.50)	(−1.10)	(−2.92)	(−3.68)	(−2.90)
$\Delta centrality_t$	−1.22***	−0.94***	−0.54	−1.93***	−1.95***	−0.09
	(−4.27)	(−3.66)	(−1.46)	(−3.65)	(−3.88)	(−0.05)
$\Delta match_t$	−1.21**	−1.85***	−1.56	−1.34	−2.27	5.47**
	(−2.16)	(−3.06)	(−1.60)	(−1.04)	(−0.99)	(2.15)
$\Delta power_t$	3.06***	5.69***	6.79***	11.48***	9.58***	15.95***
	(2.97)	(4.65)	(4.47)	(7.79)	(4.16)	(3.48)
$\Delta mega_t$	−1.01***	−0.61	−1.87***	−1.08**	−0.95	−1.03
	(−2.65)	(−1.64)	(−3.41)	(−2.25)	(−0.96)	(−0.60)
Adj. R^2	0.24	0.26	0.32	0.36	0.34	0.42
Bonds	219	269	179	155	85	117

Table 8 continues on next page

Table 8 continued

B: Credit rating

	AAA	AA	A	BBB	BB	B	CCC/C
Intercept	−0.01	0.02	0.03**	0.02	0.03	0.08	0.43**
	(−0.36)	(1.11)	(2.43)	(0.78)	(0.88)	(0.96)	(2.39)
$\Delta lev_{j,t}$	0.04	0.00	0.00	0.02***	0.05***	0.10***	0.39***
	(1.33)	(0.02)	(0.38)	(4.00)	(5.24)	(8.94)	(3.41)
Δrf_t	0.04	−0.09*	−0.22***	−0.39***	−0.57***	−0.29	−1.81***
	(0.25)	(−1.68)	(−2.79)	(−6.79)	(−3.71)	(−1.60)	(−3.35)
$(\Delta rf_t)^2$	−0.09	0.20*	0.09	0.31*	0.67*	0.03	2.02
	(−0.46)	(1.80)	(0.70)	(1.80)	(1.67)	(0.05)	(1.49)
$\Delta slope_t$	0.03	0.13	0.22***	0.36***	0.71***	0.50*	0.73*
	(0.15)	(1.39)	(2.70)	(4.25)	(3.77)	(1.90)	(1.96)
ΔVIX_t	0.00	0.01*	0.01***	0.00	0.01	0.00	−0.04
	(0.64)	(1.93)	(3.61)	(1.47)	(1.65)	(0.21)	(−1.13)
r_t^m	−0.01	−0.01***	−0.02***	−0.03***	−0.05***	−0.09***	−0.19***
	(−1.51)	(−2.94)	(−6.87)	(−6.57)	(−4.90)	(−4.81)	(−4.44)
$\Delta jump_t$	0.00	−0.00	0.00	0.00	0.01	0.01*	0.14**
	(0.54)	(−0.06)	(0.87)	(1.32)	(1.17)	(1.90)	(2.24)
Δout_t	1.10	−0.91	−0.30	−1.42**	−3.50*	−2.22	−31.22
	(1.03)	(−1.06)	(−0.76)	(−2.09)	(−1.98)	(−1.10)	(−1.35)
ΔI_t	−6.76	10.26**	11.35***	22.18***	34.90***	44.44***	171.98***
	(−0.52)	(2.07)	(4.07)	(4.74)	(2.94)	(2.83)	(5.76)
$\Delta dcov_t$	−0.64	−0.64	−0.44	−2.31***	−4.73***	−4.10**	−21.87*
	(−1.67)	(−0.80)	(−1.23)	(−3.35)	(−4.22)	(−2.22)	(−2.13)
$\Delta centrality_t$	−0.89***	−1.09***	−1.34***	−1.27***	−0.78	−1.37	9.49
	(−3.79)	(−2.92)	(−5.21)	(−4.09)	(−1.18)	(−0.99)	(1.36)
$\Delta match_t$	−1.42	−0.63	−1.69***	−2.30***	−1.21	3.77	23.37***
	(−1.52)	(−0.78)	(−3.66)	(−3.30)	(−0.66)	(1.48)	(3.36)
$\Delta power_t$	1.61	3.59***	4.27***	6.52***	15.91***	14.10***	32.51*
	(0.89)	(3.37)	(4.33)	(4.98)	(6.59)	(3.19)	(2.14)
$\Delta mega_t$	−0.35	−1.00*	−1.08***	−1.27***	−0.95	−2.11	9.24
	(−0.73)	(−1.92)	(−4.14)	(−3.68)	(−1.02)	(−1.51)	(1.01)
Adj. R^2	0.21	0.19	0.26	0.31	0.41	0.41	0.50
Bonds	22	91	333	336	118	109	15

Table 9: Time variation of dealers' intermediation premium. This table presents the results of the monthly drivers of the time variation in the intermediation premium, IP, which is the premium earned by dealers for intermediating between customers relative to the inter-dealer price. In Panel A, we run the regression

$$\Delta IP_t = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{\Delta F_t} + \boldsymbol{\gamma_1} \cdot \Delta \boldsymbol{I_t} + \boldsymbol{\gamma_2} \cdot \Delta \boldsymbol{S_t} + \boldsymbol{\gamma_3} \cdot \Delta \boldsymbol{B_t} + \epsilon_t,$$

where the vector $\boldsymbol{\Delta F_t} := \left[\Delta lev_t^m,\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the market-wide average of the firm's leverage ratios, Δlev_t^m; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\boldsymbol{\Delta I_t} := [\Delta out_t,\ \Delta I_t]$ refers to the changes in the market-wide inventory factors, where out_t is the aggregate amount outstanding and I_t the market-wide dealer inventory. The vector $\boldsymbol{\Delta S_t} := [\Delta dcov_t,\ \Delta centrality_t,\ \Delta match_t]$ refers to the changes in the market-wide search factors, where $dcov_t$ is the average value of the number of dealers trading a given bond during a month per unit of its current amount outstanding, $centrality_t$ is a graph-level eigenvalue centrality measure of the inter-dealer network, and $match_t$ is the matching intensity, which refers to the number of matched trades relative to all trades in a month. The vector $\boldsymbol{\Delta B_t} := [\Delta power_t,\ \Delta mega_t]$ refers to the changes in the market-wide bargaining factors, where $power_t$ is the market share in terms of the monthly trading volume of the most active dealer and $mega_t$ is the fraction of mega trades (i.e., trading volumes greater than \$1 million) to the overall number of trades in the market during a month. In Panel B, we run the regression

$$\Delta(MU_t/IP_t) = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{\Delta F_t} + \boldsymbol{\gamma_1} \cdot \Delta \boldsymbol{I_t} + \boldsymbol{\gamma_2} \cdot \Delta \boldsymbol{S_t} + \boldsymbol{\gamma_3} \cdot \Delta \boldsymbol{B_t} + \epsilon_t,$$

where MU_t is the market-wide markup, that is, the premium at which dealers sell to customers relative to the inter-dealer price. We report the coefficients and associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Intermediation premium

	Model 1	Model 2	Model 3	Model 4	Model 5
Δlev_t^m	−0.001				0.001
	(−0.153)				(0.290)
Δrf_t	−0.033***				−0.031**
	(−2.866)				(−2.273)
$(\Delta rf_t)^2$	0.035**				0.033**
	(2.106)				(2.062)
$\Delta slope_t$	0.062**				0.057*
	(2.378)				(1.847)
ΔVIX_t	0.003*				0.004*
	(1.792)				(1.825)
r_t^m	−0.001				0.000
	(−0.426)				(0.011)
$\Delta jump_t$	0.000				0.001
	(0.650)				(1.212)
Δout_t		−0.498***			−0.340***
		(−3.386)			(−2.970)
ΔI_t		2.588*			2.800***
		(1.713)			(3.047)
$\Delta dcov_t$			−0.449**		−0.155
			(−2.349)		(−0.627)
$\Delta centrality_t$			0.178		−0.035
			(1.490)		(−0.348)
$\Delta match_t$			−0.089		−0.053
			(−0.256)		(−0.165)
$\Delta power_t$				0.919***	0.937***
				(2.818)	(3.215)
$\Delta mega_t$				−0.459***	−0.399***
				(−5.644)	(−3.165)
Adj. R^2	0.292	0.050	0.016	0.099	0.424
Num. obs.	131	131	131	131	131

Table 9 continues on next page

Table 9 continued

B: Composition of the intermediation premium

	Model 1	Model 2	Model 3	Model 4	Model 5
Δlev_t^m	0.224				0.099
	(1.309)				(0.737)
Δrf_t	3.496***				4.079***
	(4.087)				(3.263)
$(\Delta rf_t)^2$	0.693				0.144
	(0.346)				(0.068)
$\Delta slope_t$	−0.771				−0.613
	(−0.811)				(−0.485)
ΔVIX_t	−0.088				−0.066
	(−1.519)				(−1.249)
r_t^m	0.072				0.062
	(1.041)				(0.964)
$\Delta jump_t$	0.007				−0.020
	(0.095)				(−0.341)
Δout_t		16.514*			18.856*
		(1.951)			(1.837)
ΔI_t		−273.035***			−369.456***
		(−3.787)			(−4.176)
$\Delta dcov_t$			14.075		17.412
			(1.022)		(1.467)
$\Delta centrality_t$			−10.365		0.962
			(−1.078)		(0.102)
$\Delta match_t$			6.309		0.684
			(0.329)		(0.032)
$\Delta power_t$				−41.048	−16.901
				(−1.541)	(−0.585)
$\Delta mega_t$				8.566	3.123
				(1.424)	(0.410)
Adj. R^2	0.144	0.060	−0.007	0.009	0.237
Num. obs.	131	131	131	131	131

Table 10: Idiosyncratic wealth shocks and yield spread changes. We first assign each industrial bond j to a cohort based on its underlying average leverage ratio. Given the monthly yield spread changes, $\Delta YS_{ij,t}$, we then estimate for each cohort and dealer i the model

$$\Delta YS_{ij,t} = \alpha_i + \boldsymbol{\beta_i} \cdot \boldsymbol{\Delta F_{j,t}} + \boldsymbol{\gamma_{i,1}} \cdot \Delta \boldsymbol{I_t} + \boldsymbol{\gamma_{i,2}} \cdot \Delta \boldsymbol{S_t} + \boldsymbol{\gamma_{i,3}} \cdot \Delta \boldsymbol{B_t} + \delta_i r_t^i + \epsilon_{ij,t},$$

where the vector $\boldsymbol{\Delta F_{j,t}} := \left[\Delta lev_{j,t},\ \Delta rf_t,\ (\Delta rf_t)^2,\ \Delta slope_t,\ \Delta VIX_t,\ r_t^m,\ \Delta jump_t\right]$ refers to the structural model variables of Collin-Dufresne, Goldstein, and Martin (2001). These are the change in the firm's leverage ratio, $\Delta lev_{j,t}$; the change in the 10-year Treasury rate, Δrf_t; the squared change in the 10-year Treasury rate, $(\Delta rf_t)^2$; the change in the slope of the yield curve, $\Delta slope_t$; the change in the market volatility, ΔVIX_t; the return on the S&P 500 index, r_t^m; and the change in a jump component, $\Delta jump_t$. The vector $\boldsymbol{\Delta I_t} := [\Delta out_t,\ \Delta I_t]$ refers to the changes in the market-wide inventory factors, where out_t is the aggregate amount outstanding and I_t the market-wide dealer inventory. The vector $\boldsymbol{\Delta S_t} := [\Delta dcov_t,\ \Delta centrality_t,\ \Delta match_t]$ refers to the changes in the market-wide search factors, where $dcov_t$ is the average value of the number of dealers trading a given bond during a month per unit of its current amount outstanding, $centrality_t$ is a graph-level eigenvalue centrality measure of the inter-dealer network, and $match_t$ is the matching intensity, which refers to the number of matched trades relative to all trades in a month. The vector $\boldsymbol{\Delta B_t} := [\Delta power_t,\ \Delta mega_t]$ refers to the changes in the market-wide bargaining factors, where $power_t$ is the market share in terms of the monthly trading volume of the most active dealer and $mega_t$ is the fraction of mega trades (i.e., trading volumes greater than $1 million) to the overall number of trades in the market during a month. Finally, the variable r_t^i refers to the stock return of dealer i. For each cohort, we report average coefficients across dealers and their associated t-statistics based on HAC standard errors, using Newey and West (1987), with an optimal truncation lag chosen as suggested by Andrews (1991). The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

	$< 15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$45-55\%$	$> 55\%$
Intercept	0.02*	0.01	0.02	−0.00	0.04**	0.06***
	(1.78)	(1.36)	(1.43)	(−0.09)	(2.67)	(3.51)
$\Delta lev_{j,t}$	0.01***	0.01*	0.02***	0.06***	0.04***	0.11***
	(4.98)	(1.79)	(3.51)	(9.00)	(4.40)	(12.04)
Δrf_t	−0.24**	−0.26**	−0.17	−0.22**	−0.43***	−0.69***
	(−2.82)	(−2.31)	(−1.48)	(−2.68)	(−4.32)	(−8.76)
$(\Delta rf_t)^2$	0.23**	0.24	−0.03	0.62*	0.15	0.85**
	(2.61)	(1.60)	(−0.31)	(1.76)	(0.48)	(2.44)
$\Delta slope_t$	0.39**	0.21**	0.15***	0.42***	0.35***	0.08
	(2.47)	(2.69)	(4.01)	(9.66)	(6.07)	(0.48)
ΔVIX_t	0.01***	0.01***	0.02***	0.02***	0.01***	0.00
	(3.21)	(6.68)	(6.78)	(2.98)	(2.96)	(0.11)
r_t^m	−0.02***	−0.01***	−0.02***	−0.01	−0.04***	−0.07**
	(−4.62)	(−3.16)	(−2.97)	(−1.37)	(−25.44)	(−2.45)
$\Delta jump_t$	0.01***	0.00	0.00	0.00	−0.02*	−0.01
	(2.96)	(1.10)	(0.60)	(0.90)	(−2.09)	(−0.43)
Δout_t	−0.00	−0.00***	−0.00***	−0.00*	−0.00	0.00
	(−0.08)	(−3.23)	(−3.10)	(−1.98)	(−1.36)	(0.28)
ΔI_t	14.05***	20.05***	25.38***	25.79***	19.27**	56.10***
	(4.40)	(11.25)	(8.68)	(6.82)	(2.50)	(4.65)
$\Delta dcov_t$	−1.19**	0.32	0.72	0.12	−1.09*	−6.15
	(−2.56)	(0.36)	(1.43)	(0.11)	(−2.00)	(−1.34)
$\Delta centrality_t$	−0.37	−0.95***	−0.78***	0.30	−0.63	1.38
	(−1.69)	(−3.26)	(−2.93)	(0.34)	(−0.77)	(0.94)
$\Delta match_t$	0.42	0.30	0.06	2.78	−0.67	6.58
	(0.63)	(0.23)	(0.03)	(1.45)	(−0.59)	(1.12)
$\Delta power_t$	1.24	4.97***	8.31***	7.39*	7.92	7.66**
	(1.02)	(26.92)	(6.02)	(1.98)	(1.32)	(2.78)
$\Delta mega_t$	0.68*	−1.33***	−2.88***	−3.22***	−0.23	−6.81**
	(1.79)	(−4.75)	(−7.55)	(−5.40)	(−0.38)	(−2.34)
r_t^i	−0.07	−0.27**	−0.24	−0.19***	−0.45***	0.74
	(−0.33)	(−2.72)	(−1.63)	(−3.56)	(−14.54)	(1.70)
Adj. R^2	0.17	0.18	0.27	0.27	0.29	0.31
Dealer	21	20	20	17	16	18

Table 11: The same bond at different prices across inventories. We estimate the model

$$price_{ij,s} = \alpha_i + \alpha_{j\times s} + \boldsymbol{\beta} \cdot \boldsymbol{X_{i,s}} + \epsilon_{ij,s},$$

where $price_{ij,s}$ refers to the markup (markdown) in Panel A (B) of dealer i and bond j, observed on trading day s. The vector $\boldsymbol{X_{i,s}}$ refers to dealer characteristics comprising the demeaned inventory level, $I_{i,s}$; the eigenvector centrality, $centrality_{i,s}$; the fraction of mega trades (i.e., the number of trades with trade volume exceeding \$1 million), $mega_{i,s}$; the fraction of inter-dealer trades, $intr.dlr_{i,s}$; and the trading volumes, $vol_{i,s}$ and $vol_{ij,s}$, respectively. Furthermore, α_i is a dealer fixed effect and $\alpha_{j\times s}$ is a bond–day fixed effect. We report coefficient estimates and associated t-statistics based on double-clustered standard errors at the bond and dealer levels. The sample is based on the U.S. transaction data of corporate bonds obtained from TRACE and provided by FINRA for the period January 2003 to December 2013.

A: Markup

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$I_{i,s}$	12.299					8.212
	(1.012)					(0.794)
$centrality_{i,s}$		−0.343***				0.446***
		(−6.564)				(5.185)
$mega_{i,s}$			−0.988***			−0.943***
			(−6.171)			(−7.540)
$match_{i,s}$				−0.314***		−0.051
				(−3.221)		(−0.870)
$int.dlr_{i,s}$					−0.641***	−0.655***
					(−5.290)	(−5.661)
$vol_{i,s}$	−0.224***	−0.000	0.029	−0.385***	−0.369***	−0.449***
	(−4.067)	(−0.010)	(0.600)	(−4.761)	(−5.338)	(−4.862)
$vol_{ij,s}$	−2.692	−2.245	−0.147	−2.051	−2.121	−0.165
	(−1.498)	(−1.303)	(−0.103)	(−1.248)	(−1.303)	(−0.116)
Adj. R^2	0.024	0.027	0.038	0.031	0.042	0.054
Num. obs.	935339	935339	935339	935339	935339	935339

B: Markdown

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$I_{i,s}$	−16.051**					−12.406
	(−2.082)					(−1.456)
$centrality_{i,s}$		0.049				0.185***
		(1.053)				(4.986)
$mega_{i,s}$			−0.006			0.098
			(−0.064)			(1.235)
$match_{i,s}$				−0.225***		−0.249***
				(−6.557)		(−6.709)
$int.dlr_{i,s}$					−0.107*	−0.072
					(−1.763)	(−1.037)
$vol_{i,s}$	0.123***	0.087***	0.121***	0.001	0.094**	−0.168***
	(3.265)	(3.781)	(5.580)	(0.029)	(2.429)	(−4.674)
$vol_{ij,s}$	−3.273**	−3.354***	−3.275***	−2.843**	−3.199**	−3.201***
	(−2.553)	(−2.635)	(−2.644)	(−2.255)	(−2.523)	(−2.590)
Adj. R^2	0.008	0.008	0.008	0.012	0.008	0.013
Num. obs.	935339	935339	935339	935339	935339	935339

Figure 1: Core–periphery structure of inter-dealer network. This figure shows the network structure of the 73 most active dealers in the U.S. corporate bond market that, taken together, trade at least 90% of the average total yearly trading volume. We require each dealer to be active in the market for at least three consecutive years. Each node in the figure represents a dealer and each vertex a trading relationship that is weighted by the average yearly trading volume between a pair of dealers.

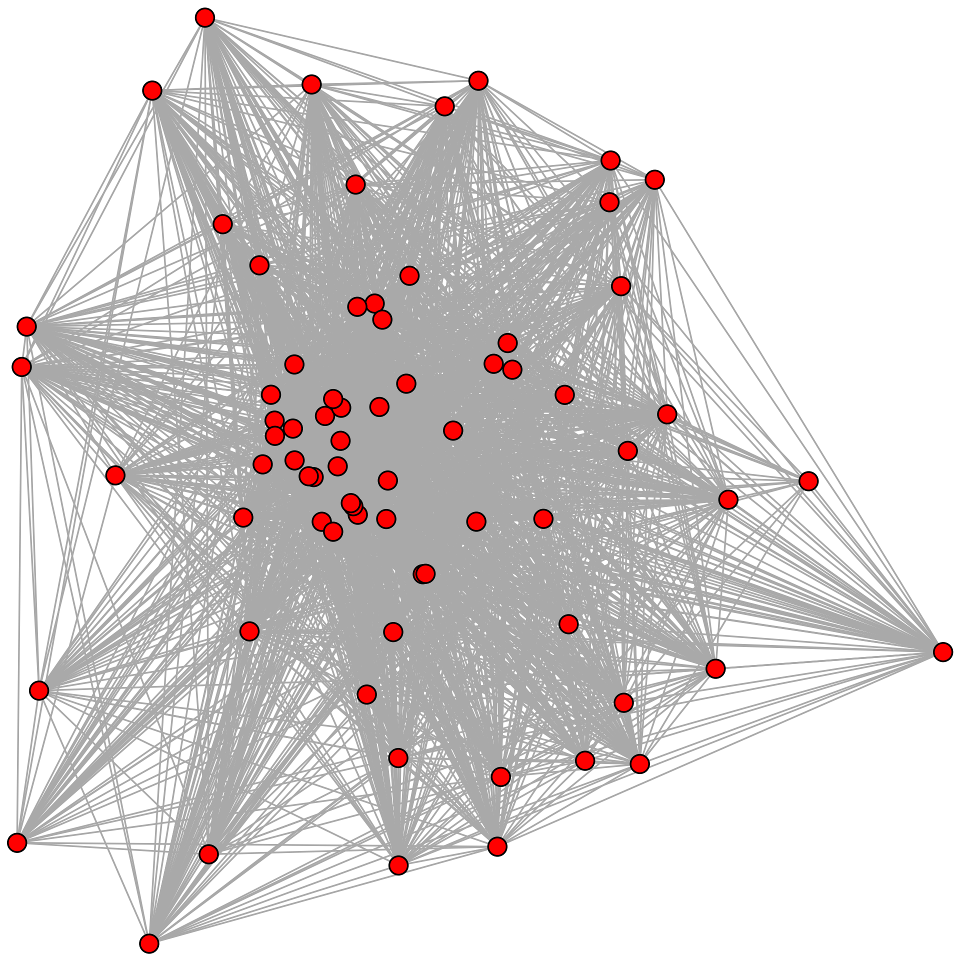

Figure 2: Dealers' intermediation premium and proxies for OTC market frictions. We plot the time series of the composition of dealers' intermediation premium (the markup and markdown premiums) in Panel A, the aggregate inventory in Panel B, search proxies (dealer coverage, eigenvector centrality, and matching intensity) in Panel C, and proxies for bargaining power (market power and fraction of mega trades) in Panel D. The markup (markdown) MU_t (MD_t) is the premium (discount) at which dealers sell to (buy from) customers relative to the inter-dealer price. The aggregate inventory, I_t, is the cumulative sum of the residual of the regression $\Delta I_t = \alpha + \beta \Delta out_t + \epsilon_t$, where out_t refers to the aggregate amount outstanding of bonds. Dealer coverage, $dcov_t$, is the average value of the number of dealers trading a given bond during a month per unit of its current amount outstanding. The variable $centrality_t$ is a graph-level eigenvector centrality measure of the inter-dealer network. Market power, $power_t$ is the market share in terms of the monthly trading volume of the most active dealer. The matching intensity, $match_t$ is the number of matched trades relative to all trades in a month. Finally, $mega_t$ is the fraction of mega trades (i.e., trading volumes greater than \$1 million) to the overall number of trades in the market during a month. The sample is based on the U.S. transaction data of corporate bonds from TRACE, provided by FINRA for the time period January 2003 to December 2013.