Over-the-Counter Market Frictions and Yield Spread Changes

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ABSTRACT

We empirically study whether systematic over-the-counter (OTC) market frictions drive the large unexplained common factor in yield spread changes. Using transaction data on U.S. corporate bonds, we find that marketwide inventory, search, and bargaining frictions explain 23.4% of the variation of the common component. Systematic OTC frictions thus substantially improve the explanatory power of yield spread changes and account for one-third of their total explained variation. Search and bargaining frictions combined explain more in the common dynamics of yield spread changes as inventory frictions. Our findings support the implications of leading theories of intermediation frictions in OTC markets.

JEL Classification: G10; G12; G20

Keywords: Corporate bond market, over-the-counter market, yield spread changes, intermediation frictions, dealer market

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 factors, Collin-Dufresne, Goldstein, and Martin (2001, CDGM henceforth) show that a large set of firm-specific and macroeconomic variables performs poorly in explaining the variation of yield spread changes over time. A substantial 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 manage bond inventories to provide liquidity to customers. Transactions are non-anonymous and occur on a bilateral basis; thus, the terms of the trade are determined by search and bargaining frictions. Consequently, the theoretical literature starting with Duffie, Gârleanu, and Pedersen (2005, 2007, DGP henceforth) rationalizes deviations of prices from fundamentals through OTC market frictions. In this paper, we empirically investigate the ability of time-varying OTC frictions to explain the remaining common component of yield spread changes. We find that systematic inventory, search, and bargaining frictions explain 23.4% of the variation of the common component and account for one-third of the total explained variation of yield spread changes.

To establish our findings, we employ detailed transaction data on the prices and volumes of U.S. corporate bonds. We use the Trade Reporting and Compliance Engine (TRACE) database containing dealer information so that we can assign every transaction to a particular dealer. The final data set captures all trades executed by more than 2,600 dealers over the sample period, from the beginning of 2003 to the end of 2013. Our transaction data reveal similar properties compared to the quote- and price-based data of CDGM. That is, once we implement the CDGM baseline regression model on our sample of 974 bonds, we find that the explanatory power of monthly yield spread changes is low, with a mean adjusted R^2 value of 21.7%. Using principal component analysis (PCA), we also find that the residuals are highly cross-correlated and exhibit a large common component. That is, the first principal component captures 48.4% of the unexplained variation.

After having established the CDGM benchmark result, we investigate whether the common component of yield spread changes is related to systematic OTC frictions. Several studies find that proxies of transaction costs relate positively and systematically to yield spread changes (e.g., Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007; Bao, Pan, and Wang, 2011). However, while transaction costs are symptomatic of intermediation frictions, the previous literature does not provide insights into the type of friction that affects yield spread changes. Intermediation frictions are hard to measure, which renders their empirical investigation just as challenging. We fill this gap and exploit the granularity of our data set to construct proxies for the intensity of systematic inventory, search, and bargaining frictions in the corporate bond market.

First, we focus on the role of systematic inventory frictions. Theories based on the works of Stoll (1978) and Ho and Stoll (1981, 1983) relate asset prices to dealer inventories. These theories predict that an increase in the level of aggregate dealer inventory lowers prices (increases yield spreads) and vice versa. We use aggregate order flow to proxy for changes in marketwide inventory. More advanced theories of liquidity provision by financially constrained intermediaries further imply that increases in dealers' time-varying risk aversion and in their funding costs of holding inventory, respectively, lower asset prices (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Nagel, 2012). To measure dealers' risk aversion, we utilize the fact that dealers can avoid inventory risk by prearranging trades between sellers and buyers and conjecture that more prearranged trades imply more risk-averse dealers. We use the TED spread to proxy for dealers' funding costs. In yield spread regressions we find that all measures are significant, exhibit the predicted sign, and reduce the common unexplained variation across bonds. Specifically, we find that marketwide inventory frictions jointly explain 13.9% of the variation of the common component.

Second, we examine the impact of systematic search frictions on yield spread changes. The broad implication of the random search framework of DGP and Lagos and Rocheteau

(2009) is that asset valuations increase when search frictions relax and thus counterparties are easier to find. However, Di Maggio, Kermani, and Song (2016) provide empirical evidence that dealers do not randomly search but form trading networks to mitigate search frictions, consistent with models of network formation (e.g., Neklyudov, 2014; Chang and Zhang, 2016; Wang, 2016). Our first search proxy is therefore a measure of the overall connectivity between dealers, which we define as the graph-level eigencentrality of the interdealer network. As expected, we find that yield spreads narrow when dealers are more closely connected, implying that bonds are easier to locate and search frictions are lower.

Further, recent theory on intermediation chains in OTC markets (e.g., Hugonnier, Lester, and Weill, 2016; Shen, Wei, and Yan, 2016; Neklyudov and Sambalaibat, 2017) suggests that the intensity of search frictions is reflected in the properties of intermediation chains. Therefore, we identify intermediation chains by tracing bonds through the interdealer network once they have been sold by customers and before they disappear into clients' portfolios. We allow for split intermediation chains, which generalize the chains introduced by Hollifield, Neklyudov, and Spatt (2017) and Li and Schürhoff (2018) in that there are multiple sales to dealers along the chain. We first focus on the chain length, that is, the number of dealers involved in the chain. We find that longer chains are associated with smaller yield spreads. This result is consistent with, for example, the models of Shen, Wei, and Yan (2016) and Neklyudov and Sambalaibat (2017), where lower search costs lead to an endogenously larger intermediary sector with more competitive allocations and, thus, longer chains.

Moreover, the theory of intermediation chains models search frictions as for DGP through the meeting rate between sellers and buyers. In any intermediation chain an initial volume is disseminated to a number of final customers. Therefore, we use the chains as a laboratory to posit conclusions about meeting rates. That is, we investigate the required number of sales to customers to complete the chain. We allow for heterogeneity and examine chains with large and small initial volumes separately. We find that more sales in large-volume chains result in smaller yield spreads. This result suggests that when dealers split up large initial volumes, search frictions are low and meeting rates are high, as dealers can rely on a large client base. Contrary, for small-volume chains we find that more sales lead to a widening of yield spreads. This finding indicates that when dealers disseminate a relatively small volume to many customers, the meeting rate is low and search frictions are high. Overall, systematic search frictions capture 6.3% of the variation of the common component.

Third, we turn to the role of systematic bargaining frictions. The prediction implied by the search and bargaining framework of DGP is that yield spreads increase if dealers extract higher intermediation rents when their bargaining power increases relative to customers, and vice versa. Hence, we construct two systematic measures for both customer bargaining power and dealer bargaining power. Specifically, in the framework of DGP the bargaining power of customers increases in their outside options to trade, which we measure by the number of trading relationships customers have with their dealers. Furthermore, we use the marketwide fraction of block trades, which are associated with the elevated presence of customers with better bargaining power (see, e.g., Randall, 2015).

With respect to dealers' bargaining power, we compute a Herfindahl–Hirschman concentration measure based on dealers' transaction volumes with customers. A higher measure indicates a less competitive dealer market, implying that dealers have more bargaining power relative to customers. Further, the model of Lagos, Rocheteau, and Weill (2011) suggests that dealers' bargaining power increases when certain investors receive a shock to their demand for holding bonds. Similarly as does Feldhütter (2012), we therefore exploit the notion that dealers' bargaining power increases when bonds are downgraded to junk status, because either regulation (Ellul, Jotikasthira, and Lundblad, 2011) or investor mandates (Chen et al., 2014) force some investors to sell their holdings. Tests confirm the theoretical predictions: that is, yield spreads widen when dealers' bargaining power increases relative to their customers. In total, systematic bargaining frictions explain 15.4% of the variation of the common component.

Finally, we investigate the impact of all three types of frictions jointly in our tests.

Overall, systematic OTC frictions explain 23.4% of the time-series variation of the common component of the CDGM model. Generally, when jointly considering two types of frictions, we find their explanatory power is smaller compared to the sum of the adjusted R^2 values of the individual frictions. Hence, as implied by theory, this observation suggests that the impact of different OTC frictions on yield spread changes cannot be considered to be independent. We find that search and bargaining frictions combined capture 18.0% of the variation of the common component and thus more than the obtained value of 13.9% of inventory frictions. Generally, in yield spread regressions the statistical significance and signs of the coefficients of systematic OTC frictions remain very robust. Compared to the CDGM model, we obtain incremental mean and median adjusted R^2 values of 9.0 and 14.4 percentage points. These figures show that OTC market frictions account for around one-third of the total explained variation of yield spread changes.

In additional tests we show that our results are not driven by the crisis period. We also demonstrate that the information in our measures for OTC frictions is not subsumed by other factors that are usual candidates in asset pricing studies. That is, our results are robust to including the five factors of Fama and French (2015), the illiquidity factor of Pastor and Stambaugh (2003), and the intermediary capital risk factor of He, Kelly, and Manela (2017). We find that asymmetric information is not a major determinant of OTC frictions, as predicted by alternative theories of intermediation frictions (Glode and Opp, 2016; Babus and Kondor, 2018). Specifically, our results are unaffected when including the factor of the probability of information-based trading of Easley, Hvidkjaer, and O'Hara (2002). Moreover, our results are robust to several alternative definitions of the CDGM variables. To sum up, we provide novel insights into the common drivers of yield spread changes over time.

In examining the ability of systematic OTC frictions to explain yield spread changes, our paper differs from other studies that analyze the dynamics of yield spreads. In particular, Duffee (1998) examines the relation between corporate yield spread changes and changes in Treasury yield. Elton et al. (2001) focus on the risk premium of corporate bonds, while Longstaff, Mithal, and Neis (2005) show that the non-default component of yield spreads is related to bond-specific as well as macroeconomic measures of liquidity. Further, Chen, Lesmond, and Wei (2007) study the role of liquidity in the form of zero-return days while Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012) investigate various liquidity proxies, such as the measures of Roll (1984) and Amihud (2002), respectively. 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 or liquidity risk matters in pricing bonds.

Further, our paper differs from studies that analyze transaction costs and market making in the corporate bond market. Schultz (2001) provides a first analysis of transaction costs, while Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007) study the impact of post-trade transparency due to the introduction of TRACE on transaction costs. More recently, several studies investigate market making and post-crisis implications (Adrian, Boyarchenko, and Shachar, 2017, provide detailed discussions). Bessembinder et al. (2017) examine trading costs and dealers' capital commitment, arguing that, post-crisis, dealers commit less capital to inventory management. Focusing on similar aspects, albeit using different methodologies, Trebbi and Xiao (2015), Schultz (2017), Bao, O'Hara, and Zhou (2017), Anderson and Stulz (2017), Goldstein and Hotchkiss (2017), and Dick-Nielsen and Rossi (2018) examine the time-varying liquidity provision of dealers, showing that, post-crisis, liquidity is more sensitive to dealer behavior.

The rest of the article is structured as follows. Section I describes the data and Section II presents our base case analysis, following CDGM. Section III introduces our measures of systematic OTC market frictions. Section IV presents the main results by explaining yield spread changes through our measures of OTC frictions. Section V concludes the paper.

I. Data Description

We rely on several data sources to study the impact of systematic 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 each trade. While, for interdealer trades, we know the coded identities of both parties involved in the transaction, for customer–dealer trades, we know only that the trade is with a customer and do not have information about the customer's identity. We focus our analysis on secondary market transactions because primary market transactions were not reported to TRACE 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 et al., 2017).[1] We also correct 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 restrict our sample to corporate debentures and exclude bonds that have variable coupons, are convertible, putable, asset backed, exchangeable, privately placed,

[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).

perpetual, preferred securities, secured lease obligations, unrated, or quoted in a foreign currency. We also remove bonds from the sample that were issued by financial firms (Standard Industrial Classification, or SIC, codes 6000–6999) or utility firms (SIC codes 4900–4999) and bonds that have issue sizes under $10 million or a time-to-maturity of more than 30 years or less than one month. The merged data sample comprises approximately 44 million intraday transactions in 14,300 bonds issued by 3,700 issuers that have been conducted by 2,600 dealers during the entire sample period. In addition, we obtain the corporate bond transaction data of insurance companies, mutual funds, and pension funds from Thomson Reuters eMAXX. In particular, the data provide information on the identities of the managing firms and the brokers with which they trade. We merge all data sources and use this sample to compute our proxies for systematic OTC frictions.

Table I provides summary statistics for our data sample. Panel A shows the number of observations, mean, standard deviation, and 5%, 50%, and 95% quantiles of several bond characteristics. The average bond size in the sample is about $900 million, with an interquintile range between $250 million and $2 billion. The average bond is 4.1 years old and has a remaining time to maturity of 8.5 years. The average coupon rate is 6.5% and shows considerable variation across the sample, which is also reflected in the credit rating. The interquintile range of the credit rating is between four (AA-) and 16 (B-). Overall, the summary statistics suggest that our sample comprises a wide cross section of corporate bonds. In Panel B, we provide descriptive statistics of the daily trading activity in the U.S. corporate bond market. On average, we observe nearly twice as many daily customer trades (7,643) as interdealer trades (4,071). Customer trades are also much larger than interdealer trades ($831,000 versus $387,000). Both exhibit considerable dispersion across the sample. Dealers, on average, buy larger quantities from customers ($995,000) compared to what they sell to customers ($714,000). Correspondingly, the number of dealer buys is lower than the number of dealer sales (3,209 versus 4,477).

Table I about here

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 to estimate 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 Compustat items 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 when the information becomes 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 CUSIP base.

The main variable in our empirical analysis is the yield spread. We compute the corporate bond yield from the average end-of-month transaction price and define 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. Next, we compute the changes and returns, respectively, from months t to $t + 1$ of all the variables. Following CDGM, we only consider bonds for which we have at least 25 observations of monthly yield spread changes. The merged data sample consists of 105,810 observations of end-of-month yield spreads that result in 45,350 observations of yield spread changes of 974 bonds issued by 237 firms. We show descriptive statistics of the end-of-month yield spread in Panel A of Table I. The average yield spread is 3.0%, with a standard deviation of 2.8%.

II. CDGM Model and Yield Spread Changes

CDGM show that there is a large unexplained common component in yield spread changes. However, their analysis is primarily based on dealer quotes instead of actual transaction prices. This potentially impairs their conclusion regarding the magnitude of the latent factor. The reason is that dealer quotes may be stale, that is, they are not updated regularly or are based on matrix pricing. Consequently, we employ CDGM's base-case regression analysis, using transaction prices to examine to what extent yield spreads are driven by a single latent factor.[3] We then use the results as a benchmark for our subsequent analyses, where we examine the impact of time-varying systematic OTC frictions on the dynamics of yield spread changes.

We follow CDGM and use the same firm-specific and macroeconomic variables that, according to structural models à la Black and Scholes (1973) and Merton (1974), drive yield spread changes. In particular, we consider changes in a firm's underlying leverage ratio (ΔLEV), changes in the 10-year Treasury rate (ΔRF), as well as the squared change in the 10-year Treasury rate, $(\Delta RF)^2$, which captures any potential nonlinear effects due to convexity. Furthermore, we consider changes in the slope of the yield curve ($\Delta SLOPE$), changes in market volatility (ΔVIX), returns on the S&P 500 index (RM), and changes in a jump component ($\Delta JUMP$) that reflect the magnitude and probability of a large negative jump in firm value. We define the vector of CDGM variables of bond i at time t as

$$\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\ \Delta RF_t,\ (\Delta RF_t)^2,\ \Delta SLOPE_t,\ \Delta VIX_t,\ RM_t,\ \Delta JUMP_t\right]. \tag{1}$$

[3] In a sub-analysis, CDGM also restrict their sample to transaction prices only but are then left with merely 29 bonds for their analysis.

In a first step, we estimate the following regression model for each bond i with yield spread changes $\Delta YS_{i,t}$:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \epsilon_{i,t} \tag{2}$$

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 the six cohorts, ranging from 84 bonds in the 45%–55% group up to 256 bonds in the 15%–25% group. We present the average coefficients and their statistical significance for each cohort in Table II. The associated t-statistics are calculated from the cross-sectional variation over the coefficient estimates within a cohort. Thus, for each cohort we divide the average coefficient by the standard deviation of the coefficient estimates and scale by the square root of the number of bonds in the cohort. To facilitate the presentation of the results, we also present the average coefficients and their statistical significance in a regression where we use all 974 bonds. 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 low, with mean adjusted R^2 values ranging between 14.6% and 32.9% (overall mean value is 21.7%). We also report the median adjusted R^2 values, which reveal a quantitatively similar pattern. The overall median value is 20.1%.

Table II about here

We follow CDGM and carry out a PCA on the residuals to capture the properties of the unexplained variation. Each month, we assign bonds to one out of 18 bins that are determined by the six leverage groups (as defined above) as well as by three maturity groups; under five years, five to eight years, and more than eight years. We show the results of the PCA in Table III. The total unexplained variance is 167 basis points. We find that the first principal component, PC1, accounts for a substantial magnitude of 48.4% of the total unexplained variance, while the second component, PC2, accounts for only 9.5%. Albeit less pronounced than for CDGM, who find a PC1 value of 75% in their sample, we also document that a single common factor captures most of the remaining variation. More importantly, the loadings of each bin on the PC1 are all positive, ranging between 0.09 and 0.48. This result suggests that a latent factor drives the yield spreads of all bonds jointly and in the same direction.[4] Given the trading environment of the U.S. corporate bond market, we conjecture that systematic OTC frictions are obvious candidates to be associated with the single common component. Specifically, theory postulates that trading frictions should be positively related to yield spreads. We underpin this conjecture by employing systematic measures of OTC frictions in the subsequent tests.

Table III about here

III. Systematic OTC Market Frictions

In this section, we establish our measures that proxy for the intensity of systematic inventory, search, and bargaining frictions in the corporate bond market. Subsequently, we use these measures to investigate the ability of intermediation frictions in OTC markets to explain the variation of yield spread changes.

A. Inventory Frictions

Theories of inventory risk management (Stoll, 1978; Amihud and Mendelson, 1980; Ho and Stoll, 1981, 1983; Grossman and Miller, 1988) relate asset prices to dealer inventories. These theories imply that dealers exert price pressure to mean-revert inventory and thus manage their risk. More advanced theories, such as those of Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Nagel (2012), also show that dealers' time-varying risk aversion and their funding costs of holding inventory matter for asset prices. The general predictions of these models are that yield spreads increase in dealers' inventory, their risk aversion, and their inventory holding costs, respectively.

[4]Within maturity cohorts, we find that the loadings are increasing with leverage. CDGM obtain a qualitatively similar result, albeit less pronounced. Our results suggest that the latent factor is more relevant for more risky bonds.

While inventory theories have been rigorously tested in the equity market, a thorough analysis in the corporate bond market has been missing so far.[5] There are important differences between the two markets. In contrast to equity markets, trading in the corporate bond market is decentralized and occurs on a bilateral basis where the counterparties know each other. Consequently, inventory frictions may not be considered independently from other frictions when describing the dynamics of yield spread changes. Furthermore, trade can be delayed by search as dealers have to find counterparties (Duffie, 2010). This suggests that inventory management is potentially of greater concern to bond dealers compared with liquidity provision in the equity market.

To test the predictions of inventory theories, we control for the riskiness of the assets and proxy for the aggregate dealer inventory, the risk aversion of dealers, and the funding costs to hold inventory, respectively. The riskiness of the assets in our setup is captured by the CDGM variables. To construct a series for aggregate end-of-month dealer inventory, *inv*, we compute the cumulative marketwide order flow, which has positive (negative) increments when dealers buy from (sell to) customers.[6] Furthermore, we follow Longstaff, Mithal, and

[5] Several contributions examine the implications of the theory of dealer inventory management in stock markets. Hansch, Naik, and Viswanathan (1998) study the inventory dynamics of specialists on the London Stock Exchange. Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004) analyze the relation between aggregate order imbalances, market liquidity, and stock returns, respectively, on the New York Stock Exchange (NYSE). Naik and Yadav (2003) examine the relation between individual stock positions and dealers' total inventories. Hendershott and Seasholes (2007) study the joint dynamics of inventories and prices of individual market makers for a small sample of specialists on the NYSE. Comerton-Forde et al. (2010) study the role of financing constraints for market liquidity by examining the trading revenues of specialists' inventory positions on the NYSE. Hendershott and Menkveld (2014) estimate inventory reversion rates for NYSE stocks and quantify the price pressure of specialists induced by extreme inventories.

[6] The Federal Reserve Bank of New York reports aggregate primary dealer statistics on inventories. There are important differences between our aggregate dealer inventory measure and that of the Federal Reserve. First, the Federal Reserve's inventory statistics are solely based on primary dealers. Typically about 20 to 30 dealers are designated as primary dealers, on average, per year, whereas our sample comprises about

Neis (2005) and employ the aggregate amount outstanding, *amt.out*, which controls for the unobserved order flow in our data that is due to newly issued bonds and bonds that are called or retired during the sample period. Next, we estimate dealer risk aversion by exploiting a feature of the corporate bond market. Bessembinder et al. (2017) and Schultz (2017) point out that, upon receiving a sell order from a client, dealers can choose between adding the bond to the inventory (principal trade) or asking the seller to wait until the dealer finds a matching buy order (prearranged trade). In a prearranged trade, the dealer assumes no risk, because the bond is not in the dealer's inventory. Hence, more prearranged trades are indicative that dealers are more risk averse to holding inventory. Each month, we compute the marketwide fraction of prearranged trades, *match.trd*. We follow Schultz (2017) and define a matched trade as a trade that occurs within one minute. We require at least one customer trade in the transaction. Finally, we follow Garleanu and Pedersen (2011) and use the TED spread, *ted*, as a measure of dealer funding costs. Typically, inventory is short-term financed through the interbank market and the TED spread captures the health of the intermediary sector. To reiterate, theory predicts that all inventory-related proxies are positively related to yield spreads.

B. Search Frictions

Search frictions are considered a major impediment to efficient trade in the corporate bond market. The more difficult a bond is to locate, the more search effort must be spent to trade the asset. The incurred cost eventually results in a price that is lower than the asset's fundamental value. Search frictions are inherently difficult to observe and can only be inferred ex post from trading activity. We exploit the information in our transaction data

2,600 dealers over the entire sample period. Second, up until April 2013, the Federal Reserve reported an aggregate dealer inventory measure that also included holdings in commercial paper and mortgage-backed securities. The disaggregated data made available after April 2013 indicate that mortgage-backed securities account for a substantial part, over 50%, of dealers' holdings.

and construct proxies for the intensity of systematic search frictions.

The theories of DGP and Lagos and Rocheteau (2009) provide insights into why prices deviate from fundamentals in the face of search frictions. A key feature of these models is that dealers have access to a frictionless interdealer market where they can offload inventory at competitive prices. Consequently, interdealer links are random and not persistent and dealer networks or intermediation chains do not arise. However, consistent with models of network formation (e.g., Neklyudov, 2014; Chang and Zhang, 2016; Wang, 2016), empirical evidence shows that OTC markets typically exhibit a core–periphery structure. That is, there are a few well-connected core dealers at the center of the network and several hundreds of less active dealers on the periphery. While Di Maggio, Kermani, and Song (2016) provide empirical evidence that the core–periphery network structure of the U.S. corporate bond market is persistent, whether the overall degree of connectedness between dealers remains stable over time is less clear, since new dealers can enter the market while others leave.[7] Consequently, new trading relationships between dealers emerge while existing linkages can strengthen, weaken, or even disappear and thereby affect the ease with which a bond can be sought and traded. In other words, a better-connected interdealer market is synonymous with lower search frictions.

Further, we use intermediation chains to infer the intensity of search frictions. In doing so, we trace bonds through the interdealer network once they have been sold by customers and before they are reabsorbed into clients' portfolios. Intermediation chains basically allow us to disentangle search-induced effects from inventory effects, since the net cumulative order flow remains unaffected. Recent theoretical contributions investigate the properties of these intermediation chains and their relations to prices and transaction costs. Specifically, the most common modeled metric is the length of intermediation chains, that is, the number of dealers involved in the chain. For example, in the model of Hugonnier, Lester, and Weill

[7] Hollifield, Neklyudov, and Spatt (2017) and Li and Schürhoff (2018) identify core–periphery structures in the U.S. structured product market and U.S. municipal bond market, respectively.

(2016), agents have heterogeneous and time-varying asset valuations, which endogenously leads them to trade through intermediation chains. Formally there is no distinction between dealers and customers, however, agents with intermediate asset valuations are designated as intermediaries, while those with extreme valuations are labeled as customers. They show that in equilibrium a higher meeting intensity between agents coincides with lower levels of misallocation. In turn, this relation gives rise for the role of intermediation in facilitating trade and thus, lengthens the intermediation chain.

Shen, Wei, and Yan (2016) extend the model of Hugonnier, Lester, and Weill (2016) and endogenize the size of the intermediary sector by incorporating fixed costs of search. The occurrence of search costs implies that not all agents stay in the market continuously. Those that stay are dealers, while the others act as customers. In equilibrium, lower search costs imply longer intermediation chains. This effect arises because lower search costs imply that more agents find it profitable to be dealers, leading to a larger intermediary sector and thus longer intermediation chains. Neklyudov and Sambalaibat (2017) arrive at a similar conclusion; that is, they show that a larger dealer market increases the length of intermediation chains. They argue that multiple dealers are more efficient at producing matches, thus lowering search frictions.

Generally, a key ingredient in models of intermediation chains is the meeting intensity between sellers and buyers. Intermediation chains provide a laboratory to posit conclusions about meeting rates, because any intermediation chain disseminates an initial volume to a number of final customers. Therefore, this property allows us to investigate the required number of sales to customers to complete the chain. Empirical regularities in how search frictions affect the number of sales to customers in a chain have not yet been studied comprehensively. Moreover, along the final customer domain, the existing theoretical literature on intermediation chains provides little guidance, as most models assume non-divisible assets and do not formally distinguish between dealers and customers. An exception is Colliard and Demange (2018), however, their model does not provide predictions on the number of sales to customers. The key empirical question is whether more sales to customers imply a high or a low meeting rate. To address this point, we explore the relation between yield spreads and the required number of sales to customers to complete a chain of a given initial volume.

Following the previous discussion, we employ four proxies for systematic search frictions. First, we use an overall measure of connectedness between dealers by computing the graph-level eigencentrality, *centr*, based on dealers' trading relationships. We consider a pair of dealers to have a trading relationship if they trade at least 50 times during a given month. The eigenvector centrality of a dealer measures the strength of the connectedness to other dealers. The measure increases the better connected, in turn, these other dealers are in the network. We normalize the graph-level eigencentrality measures to be bounded between zero and one by dividing the measure by its theoretical graph-level maximum. To obtain our three other measures of systematic search frictions, we first describe the algorithm to determine intermediation chains. We start with a definition of dealer round trips and subsequently explain how we connect round trips together to form intermediation chains.

Dealer round trips. We define dealer round trips (i.e., inventory cycles) as a sequence of buy transactions followed by a sequence of sell transactions by the same dealer in the same bond that exactly offset each other. Thus, the inventory levels at the start and at the end of the round trip are the same. We exclude round trips from our sample with more than one dealer buy trade because they are difficult to connect with other round trips.[8] We further exclude round trips from our sample that last for more than seven days, because dealers could hold these bonds not for liquidity provision but, rather, for speculative purposes. In doing so, we identify close to 10.7 million round trips in around 14,000 bonds.

[8]Essentially, round trips with more than one dealer buy would result in recombining intermediation chains.

Intermediation chains. We link round trips together to obtain intermediation chains. We allow for split chains, that is, there can be multiple sales to different dealers along the chain. Thus, the concept of a split intermediation chain is a more generalized version compared to intermediation chains used in previous studies.[9] Therefore, we also make a methodological contribution that permits further insights into intermediation patterns in the corporate bond market. Any type of intermediation chain is triggered by one or more sales of customers to a dealer and ends only once the initial volume has completely left the interdealer market. Figure 1 shows the conceptual differences between a non-split intermediation chain (Panel A) and a split intermediation chain (Panel B), respectively. The non-split intermediation chain in Panel A consists of three round trips. Dealer D1 buys $10,000 in bonds from customer C1 at a price of 95.125. Dealer D1 then immediately sells the bond to D2, who passes on the bond a few days later to D3, who then sells to customer C2. Panel B shows an example of a split intermediation chain that also consists of three round trips by three dealers. However, unlike in Panel A, four customers are involved and there is a split after dealer D1, who passes the bond on to customer C2 and dealers D2 and D3.

Figure 1 about here

We identify 2.8 million intermediation chains in nearly 14,000 bonds, about one-third of which are complete, that is, for which we can fully trace the acquired bonds through the interdealer network before they disappear again in clients' portfolios.[10] We restrict our

[9]For example, the intermediation chains of Hollifield, Neklyudov, and Spatt (2017) and Li and Schürhoff (2018) in the structured product market and the municipal bond market, respectively, do not feature dealer splits along the chain.

[10]The fraction of incomplete chains is significantly larger in the corporate bond market compared to intermediation chains constructed in the municipal bond market (Li and Schürhoff, 2018, document that around 20% of chains are incomplete) and the structured product market (Hollifield, Neklyudov, and Spatt, 2017, document that around 15% of chains are incomplete), respectively. The identification of intermediation chains in the corporate bond market is more challenging because the trading activity of individual corporate bonds is less sparsely spaced in time compared to municipal bond and structured product markets, respectively.

sample of intermediation chains to completed chains with at most eight dealers. Finally, we exclude all chains executed within one minute because these are likely prearranged trades. It is reasonable to assume that the observed search costs in prearranged trades are lower, because dealers wait until an offsetting order arrives to match opposing transactions. Our final sample of intermediation chains consists of 943,578 observations, of which 7,204 are split chains. Hence, the vast majority of completed chains are non-split.

Table IV shows that, generally, for a given chain length (i.e., the number of dealers), the number of sales to customers increases with the initial chain volume. This observation reflects that dealers disseminate larger initial volumes to several investors. Furthermore, a substantial fraction (i.e., 84%) of the chains consists of only one dealer, while, at the same time, these chains exhibit the largest initial volumes. This result shows that dealers first try to sell to customers before they offload bonds into the more competitive interdealer market, where they potentially obtain worse prices. Moreover, the chains are longer the smaller the initial acquired volume. This observation indicates that it is less attractive for dealers to incur search costs for the smallest quantities, implying that the dealers, instead, prefer to sell these in the interdealer market.

Table IV about here

We exploit the properties of these intermediation chains to provide more accurate proxies of the intensity of systematic search frictions. We define the chain length, *chain.len*, as the average number of dealers involved in the chain. Furthermore, we allow for heterogeneity in the initial chain volume and compute the number of sales to customers for two different types of chains: we define large-volume chains with initial volumes greater or equal to $1 million and small-volume chains with initial volumes less or equal to $100,000. We then compute for each month the average number of sales to customers for large-volume chains, *lvc.sales*, and small-volume chains, *svc.sales*.

C. Bargaining Frictions

Trading in the corporate bond market takes place on a bilateral basis. This implies that, when dealers and customers meet, they know their identities and bargain over the terms of the trade. DGP show that asset valuations are lower when the bargaining power of dealers increases relative to that of their customers, since dealers extract higher rents. Thus, models on bargaining predict that yield spreads widen with dealers' bargaining power relative to that of their customers.

Measuring bargaining power is, per se, challenging because it is unobservable. We exploit the granularity of our data to construct two systematic measures that proxy for the bargaining power of customers and two for the bargaining power of dealers. We start with the bargaining power of customers. The framework of DGP implies that the bargaining power of customers increases in their outside options to trade. To proxy for customers' outside options, we determine the number of trading relationships customers have with dealers. We consider clients to have a stable trading relationship if they trade at least 25 times with a dealer during a month. We then average the number of trading relationships across all clients and denote this measure *outside.opt*. Further, we follow the literature and use the properties of customers' trade size distributions. Edwards, Harris, and Piwowar (2007) document that larger transactions result in better prices. This phenomenon is theoretically reconciled through the idea that larger transactions are associated with customers with better bargaining power, that are typically institutional and less likely to be retail investors (see, e.g., Randall, 2015). We thus determine the fraction of block trades, *block.trd*, by computing the number of transactions exceeding $10 million in customer trading volume relative to all customer trades in a given month.

With respect to dealer bargaining power, we compute a measure for the competitiveness of the dealer market. Clearly, in more concentrated dealer markets, dealers have relatively more bargaining power toward their customers. Hence, for each month and bond, we determine a dealer's market share based on the log customer trading volume. We then compute a Herfindahl–Hirschman index (HHI) from the dealers' market shares and normalize the measure to have it bounded between zero and one. Finally, in each month we average HHI across all bonds to obtain our measure of concentration, *dlr.conc*.

Next we rely on the model of Lagos, Rocheteau, and Weill (2011), which highlights that dealers' bargaining power increases when certain investors receive a shock to their demand to hold bonds. Hence, we exploit the fact that credit ratings play a pivotal role in the investment practices of several types of investors.[11] For example, the mandates of insurance firms and pension funds mostly restrict them from investing in speculative-grade issues. Ellul, Jotikasthira, and Lundblad (2011) show that these institutions are forced to sell their holdings upon a downgrade to junk status, which puts them in a less favorable position when negotiating the terms of the trade. Consequently, we determine the number of rating downgrades from investment grade to junk status per month, $ig2junk$, as an alternative proxy for dealer bargaining power.

Again, based on the theoretical predictions, we expect yield spreads to decrease in the bargaining power of customers (*outside.opt*, *block.trd*) and to increase in that of dealers (*dlr.conc*, $ig2junk$).

D. Time-Series Dynamics of Systematic OTC Market Frictions

To get a sense of the time-series patterns of systematic OTC frictions we plot our measures in Figure 2. Generally, we find that most of our proxies exhibit considerable time-series variation. We obtain the time-series for the aggregate inventory level, *inv*, by calculating the cumulative marketwide order flow. Inventory decreases in the beginning of the sample period, then it stabilizes with some fluctuations before it increases again towards the end of

[11]For example, Chen et al. (2014) study how credit rating classifications affect investment practices. They show that quasi-exogenous changes in rating-based bond index compositions affect yield spreads due to investor mandates.

the sample.[12] The fraction of prearranged trades, *match.trd*, steadily grows and peaks at a value of 0.37 around the outbreak of the financial crisis, broadly in line with the estimates of Schultz (2017). The pattern suggests increasing risk aversion before the onset of the crisis. However, the detection of prearranged trades from the data is difficult, because offsetting trades are not always reported with the exact same time stamp. Thus, given a certain cutoff in defining prearranged trades, the measure could also partly reflect dealers' matching intensity.

Some proxies peak in the midst of the financial crisis (e.g., *match.trd*, *ted*, *centr*, and *svc.sales*), suggesting OTC frictions are more severe in times of market stress. While the number of sales to customers in small-volume chains, *svc.sales*, increases during the crisis, the corresponding variable for large-volume chains, *lvc.sales*, shows no particular pattern. This result indicates that search frictions are differently reflected in large- and small-volume chains. Intermediation chains lengthen over time, consistent with the findings for other OTC markets (see Shen, Wei, and Yan, 2016, for detailed discussions).

Further, among the bargaining proxies, *outside.opt* and *dlr.conc* exhibit a clear regime shift at the beginning of 2009. Both measures depend on the number of active dealers in the market, which sharply grows in 2009 from about 300 to 400. Consequently, *dlr.conc* decreases from the pre-crisis to the post-crisis period, from a value of around 0.13 to 0.08, indicative of a more competitive dealer market. Conversely, the variable *outside.opt* increases over the

[12]Note that the cumulative marketwide order flow provides an inaccurate picture of the time-series dynamics of the inventory level, given that we do not observe the initial dealer inventory positions at the beginning of our sample period as well as at new bond issuances. Typically a fraction of a newly issued bond is not directly placed to investors but is distributed through dealers' inventories in the secondary market. In Figure IA.1 in the Internet Appendix we provide a more realistic time-series plot of the dynamics of the marketwide inventory level. That is, we account for changes in the amount outstanding by running the regression, $\Delta inv_t = \alpha + \beta \Delta amt.out_t + u_t$, and then plot the cumulative residuals. The figure shows that inventory increases up until the onset of the financial crisis and then drops below the pre-crisis level before increasing again towards the end of the sample period.

same period, from a value of around 18 to 25. Overall, these patterns indicate a shift in bargaining power from dealers to customers over time.

Figure 2 about here

IV. Systematic OTC Frictions and Yield Spread Changes

In this section, we use our measures of inventory, search, and bargaining frictions to investigate the ability of systematic OTC frictions to explain the variation of yield spread changes. First, we analyze the effect of each proxy separately within the framework of CDGM. In the next step, we consider their joint impact on yield spread changes by augmenting the CDGM model with all our measures of OTC frictions.

We start our analysis by reporting the unconditional correlations between the changes in yield spreads and our proxies, as well as among the proxies in Table V. When comparing our measures within and across the three groups of OTC frictions, we find that, generally, the absolute correlation coefficients are relatively low. While this was to be expected across groups, the low correlation within groups is more surprising. The highest pairwise correlation of 0.47 within groups by far is between inventory, *inv*, and amount outstanding, *amt.out*, and that across groups of 0.45 is between matched trades, *match.trd*, and chain length, *chain.len*, respectively. Thus, these results suggest that each measure reflects a slightly different aspect of the corresponding OTC friction. This prompts the use of all our proxies in the further empirical analysis. Table V also reports the standard deviations of all our variables to ease the interpretation of the economic impact of our proxies in the subsequent regression analyses.

Table V about here

A. Inventory Frictions and Yield Spread Changes

We examine the impact of systematic inventory frictions on yield spread changes by augmenting the CDGM baseline specification by the marketwide inventory measures:

$$\boldsymbol{\Delta I_t} := [\Delta inv_t,\ \Delta amt.out_t,\ \Delta match.trd_t,\ \Delta ted_t] \tag{3}$$

We run the time-series regression for each bond i,

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'}\boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_i'}\boldsymbol{\Delta I_t} + \epsilon_{i,t}, \tag{4}$$

and report the average coefficients across bonds, their statistical significance, and the explanatory power in Panel A of Table VI. Column (1) reiterates the results of the CDGM baseline model. When testing the effect of the inventory frictions separately in Columns (2) to (5), we find that they all have their predicted signs and are statistically significant, with t-statistics ranging from 3.5 to 10.2. That is, yield spreads widen with either an increase in the aggregate dealer inventory, *inv*; the amount outstanding, *amt.out*; dealers' risk aversion, *match.trd*; or dealers' funding costs, *ted*. The underlying mechanism is such that, when dealers face higher costs in holding inventories, they will charge investors a higher intermediation premium, which eventually results in lower prices and thus larger yield spreads. In a joint test of all inventory proxies in Column (6), we find that the coefficients remain statistically significant with their predicted signs, suggesting again that they each measure a different aspect of inventory friction. Thus, our results clearly confirm the predictions made by inventory models.

We find that each of our inventory proxies, on average, increases the adjusted R^2 value between 1.5 and 2.6 percentage points, with the change in the aggregate inventory exhibiting the highest incremental mean adjusted R^2 value compared with the CDGM baseline specification. Employing all variables together increases the mean and median adjusted R^2 values by 6.0 and 7.9 percentage points, respectively. Note that this is a sizable fraction, given that we explain changes in yield spreads and not their levels.

Table VI about here

While we find that, on average, inventory frictions increase the explanatory power of yield spread changes, our results do not yet tell us whether the marketwide proxies affect all bonds systematically and with comparable magnitudes. In a first step, we thus again undertake a PCA on the residuals of Equation (4) and report the properties of the remaining variation in

Panel B of Table VI. We find that inventory frictions decrease the proportion of unexplained variance associated with the common component, PC1, by 8.1 percentage points, that is, from 48.4% in the CDGM benchmark to a value of 40.3%. Further, inventory frictions reduce the total unexplained variance by 38 basis points to a value of 129 basis points.

To test for the significance of the unexplained variance reduction we run simple time-series regression of PC1 on our inventory friction variables.[13] We report the R^2 values as well as the F-statistics and corresponding p-values of a Wald-test in Panel C. Overall, we find that inventory frictions are indeed significantly related to the common component. That is, using all friction measures we obtain an adjusted R^2 value of 13.9% with an F-statistic of 6.1 (significant at 1%-level). Further, to assess the relative importance within the group of inventory frictions, we run the regression using each individual friction measure separately. In these one-factor models the R^2 value reflects the relative reduction in PC1 implied by a given friction. We find that the change in the aggregate dealer inventory represents the friction that explains PC1 the most, that is, the R^2 value is 7.8% (significant at 1%-level).

Overall, our findings show that systematic inventory frictions explain a substantial proportion of the common component of yield spread changes. Moreover, the signs of the individual coefficients obtained in the yield spread regressions confirm the implications of theories related to inventory frictions.

B. Search Frictions and Yield Spread Changes

In this section, we focus on the impact of systematic search frictions on yield spread changes and define the vector of search measures:

$$\boldsymbol{\Delta S_t} := [\Delta centr_t,\ \Delta chain.len_t,\ \Delta lvc.sales_t,\ \Delta svc.sales_t] \tag{5}$$

[13]We end up with 129 instead of 131 monthly observations, because for two months we cannot assign bonds to each of the 18 bins due to missing observations.

To examine their importance, we run the following regression for each bond i:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'\Delta F_{i,t}} + \boldsymbol{\gamma_i'\Delta S_t} + \epsilon_{i,t} \tag{6}$$

Panel A in Table VII provides the results, where we first test our proxies individually in Columns (2) to (5). All our proxies are statistically significant, with absolute t-statistics ranging between 3.2 and 10.9. As expected, eigenvector centrality, *centr*, is negatively related to yield spread changes, implying that yield spreads narrow when dealers are overall better connected and form closer trading relationships. The length of the intermediation chains, *chain.len*, exhibits a negative sign, showing that yield spreads decrease when chains are longer. This result is consistent with the models of Hugonnier, Lester, and Weill (2016), Shen, Wei, and Yan (2016) and Neklyudov and Sambalaibat (2017), where longer chains coincide with lower levels of misallocation and with an endogenously larger intermediary sector, respectively. The number of sales to customers in large-volume chains, *lvc.sales*, is negatively related to yield spread changes. This finding suggests that when dealers split up relatively large initial volumes, meeting rates are high and search frictions are low as dealers can rely on a large customer base. Moreover, we find that sales to customers in small-volume chains, *svc.sales*, are positively related to yield spread changes, indicating that, when dealers need to approach many customers to disseminate rather small initial volumes, the meeting rate is low and search frictions are high. When the search proxies are considered together, they increase the average (median) adjusted R^2 value by 2.7 (4.9) percentage points.

Table VII about here

In Panel B of Table VII, we provide the results of the corresponding PCA. We find that our search proxies reduce the remaining value of PC1 from the CDGM model by 3.9 percentage points and the total unexplained variance by 28 basis points. The figures of the time-series regression in Panel C further show that our search proxies jointly explain 6.3% (significant at 5%-level) of the variation of PC1. However, while we employ a battery of search friction measures, it appears that *lvc.sales* is the single most important among our search measures, capturing 7.9% (significant at 1%-level) of the variation of the common component. Overall, our analysis indeed provides evidence that search frictions drive the common variation of yield spread changes.

C. Bargaining Frictions and Yield Spread Changes

To examine the impact of systematic bargaining frictions on yield spread changes, we define the vector of bargaining measures:

$$\boldsymbol{\Delta B_t} := [\Delta outside.opt_t,\ \Delta block.trd_t,\ \Delta dlr.conc_t,\ \Delta ig2junk_t] \tag{7}$$

Then we estimate for each bond i the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'\Delta F_{i,t}} + \boldsymbol{\gamma_i'\Delta B_t} + \epsilon_{i,t} \tag{8}$$

We report the results in Panel A of Table VIII, where we first analyze the effect of the bargaining proxies individually in Columns (2) to (5). All measures exhibit their theoretically predicted signs and are significant, with absolute t-statistics ranging from 4.7 to 14.6. That is, yield spreads decrease in the proxies of customer bargaining power (*outside.opt*, *block.trd*) and increase in the proxies of dealer bargaining power (*dlr.conc*, *ig2junk*). When we test all measures jointly in Column (6), they keep their signs and significance. The results reveal that bargaining frictions improve the explanatory power in terms of the mean and median adjusted R^2 values by 2.9 and 6.1 percentage points, respectively.

Table VIII about here

In Panel B of Table VIII, we carry out the PCA and report the properties of the remaining variation. We find that bargaining frictions decrease the proportion of unexplained variance associated with PC1 by 9.5 percentage points. Again, to test for the significance in the unexplained variance reduction, we run time-series regressions of PC1 on our measures of bargaining frictions and report R^2 values, F-statistics and p-values in Panel C. We find that the bargaining proxies jointly explain 15.4% (significant at 1%-level) of the variation of the common component. The two most important measures are block trades, *block.trd*, and dealer concentration, *dlr.conc*, with R^2 values of 10.0% and 8.3%, respectively (both are significant at 1%-level).

In sum, the tests show that bargaining frictions capture a considerable fraction of the variation of the common component. Further, the signs of the coefficients obtained in the yield spread regressions confirm the theoretical implications. That is, yield spreads decrease in the bargaining power of customers and increase in that of dealers.

D. Joint Impact of Inventory, Search, and Bargaining Frictions

The previous tests show that time-series variation of systematic inventory, search, and bargaining frictions affect the common component of yield spread changes. The frictions differ in terms of the fractions they capture in the remaining systematic component of the CDGM model. That is, we find that inventory frictions explain 13.9%, search frictions 6.3%, and bargaining frictions 15.4%, respectively.

From a theoretical standpoint, the impact of these frictions on yield spreads depends on their severity and degree of interaction. For example, DGP and Lagos and Rocheteau (2007) show that the pricing impact of search frictions depends on dealers' bargaining power and vice versa. Lagos, Rocheteau, and Weill (2011) argue that dealers demand higher compensation for providing liquidity through their inventory if both search and bargaining frictions are more severe. Similarly, in the model of Üslü (2016), higher search frictions make dealers effectively more averse to holding inventory because the possibility of risk sharing in the interdealer market becomes limited. Further, Randall (2015) argues that it is important to condition on dealer bargaining power in examining the pricing impact of inventory frictions in the corporate bond market. Normally, larger trades tend to receive better prices, irrespective of the potential inventory cost they generate. This effect arises because larger orders come from institutional investors that have greater bargaining power.

To investigate the joint pricing impact of inventory, search, and bargaining frictions, we estimate different subsets of the following regression model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'}\boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_{i,1}'}\boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}'}\boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}'}\boldsymbol{\Delta B_t} + \epsilon_{i,t} \tag{9}$$

We show the results in Table IX. Generally, when two types of frictions are considered, their joint explanatory power is lower than the sum of the incremental adjusted R^2 values of each one, as reported in Columns (2) to (4). Similarly, the joint effect in explaining the common component is less than the sum of the individual effects. As suggested by theory, these results indicate that the pricing impact of different types of frictions cannot be considered to be completely independent. For example, compared to the individual model of inventory frictions, the marginal effect of dealer risk aversion (*match.trd*) on yield spreads increases considerably once we control for search frictions. As discussed above, this provides qualitative evidence that dealers' risk aversion and search frictions are indeed interrelated.

Table IX about here

Somewhat surprisingly, when we test the joint effect of all measures in Column (5) in Table IX, only three of our proxies (*amt.out*, *outside.opt*, and *ig2junk*) become insignificant. All the other proxies keep their signs and significance. The incremental explanatory power of the full model compared with the baseline specification of CDGM is substantial. The mean (median) adjusted R^2 value improves by 9.0 (14.4) percentage points. Put differently, this result implies that OTC market frictions account for around one-third of the total explained variation of yield spread changes.

While we have shown that the coefficients of our proxies are, generally, statistically significant and relatively stable across different model specifications, their economic importance also merits discussion. To do so, we rely on the full model and analyze the implied yield spread change for a one standard deviation change in a particular friction measure. For example, among the inventory frictions, *inv* has a pricing impact of close to five basis points, while those of *match.trd* and *ted* are around seven basis points. Among the search and bargaining frictions, the variable *centr* has an economic impact of five basis points, while *chain.len*, *lvc.sales*, and *block.trd* each have an impact of around four basis points. The economic pricing impacts obtained are quite substantial, considering that the standard deviation of monthly average yield spread changes is 31 basis points.

Further, to better understand by how much our proxies reduce the common component of the CDGM model, we again undertake a PCA and present the results in Panel B. The results are quite striking as we find that our proxies for OTC frictions reduce the value of PC1 by 18.6 percentage points, that is, from a value of 48.4% to 29.8%. This magnitude is also reflected in the change of the total unexplained variance, which decreases from a value of 167 basis points to 92 basis points.

To test for the significance of the unexplained variance reduction we perform time-series regressions of PC1 on our measures of OTC frictions and present the results in Panel C. We find that all our friction measures jointly explain 23.4% (significant at 1%-level) of the time-series variation of the common component. Search and bargaining frictions combined explain 18.0% (significant at 1%-level) and thus, more than the 13.9% of inventory frictions (see Panel C in Table VI).

Overall, our results show that a substantial proportion of the latent factor uncovered by CDGM is indeed related to time-varying systematic OTC frictions.

E. Additional Evidence and Robustness

In this section, we demonstrate that the results are not driven by the crisis period and that our measures of OTC market frictions convey additional information for yield spread changes beyond other factors that are usual candidates in asset pricing studies. Further, we show that the results are invariant to alternative definitions of the CDGM variables.

E.1. Excluding the Crisis Period

In the subsequent analysis, we show that the overall nature of our results is not driven by the crisis period. To do so, we follow Dick-Nielsen, Feldhütter, and Lando (2012), Friewald, Jankowitsch, and Subrahmanyam (2012), and Bao, O'Hara, and Zhou (2017) in defining the period between July 2007 to April 2009 as the crisis period. We exclude observations from this period and rerun the full regression model in Equation (9). Note that exclusion of the crisis period shrinks the sample to 864 bonds and 107 monthly observations. We report the results in Table X. When considering each friction type separately, all measures of OTC market frictions keep their signs and remain statistically significant, apart from *chain.len*, which becomes marginally insignificant. The increase in explanatory power remains basically the same. That is, OTC frictions increase the mean adjusted R^2 value by 8.3 percentage points, from 17.1% to 25.4%. Similarly, the median adjusted R^2 value increases by 12.6 percentage points, from 14.8% to 27.4%. In Panel B, we report the results of the PCA. We find that the remaining common variation of the CDGM model is reduced by 15.7 percentage points, that is, from 39.5% to 23.8%.

Further, Panel C provides the results of a time-series regression of the common component on our OTC friction proxies. Using all friction variables jointly we explain 13.7% (significant at the 1%-level) of the variation of PC1. When considering each friction type separately in the regression specifications, we find that inventory proxies capture 12.2% and bargaining proxies capture 9.1%, respectively (both significant at the 1% level) while search proxies become insignificant.

Table X about here

E.2. Other Potential Drivers of Yield Spread Changes

Factors that successfully explain equity returns should also be informative in describing corporate yield spreads, because bonds and stocks are claims on the same underlying assets. We therefore investigate the marginal impact of the Fama and French (2015) five-factor model (FF5) in explaining yield spread changes by extending Equation (9) with the factors SMB, HML, RMW, and CMA.[14] We report the results in Column (2) of Table IA.I and,

[14]We do not consider the MKT factor in the regression because of potential multicollinearity with S&P 500 returns.

to facilitate comparison, we repeat the model of Equation (9) in Column (1). Although we find that the FF5 factors are all significant, the additional explanatory power is rather weak, with an incremental mean adjusted R^2 value of 0.9 percentage points. Extending the model with the FF5 factors hardly affects the coefficients of our proxies. The only variable that becomes insignificant at the 10%-level is *svc.sales*. Further, the incremental adjusted R^2 value obtained in the time-series regression is negligible.

In a next step, we examine the liquidity factor proposed by Pastor and Stambaugh (2003), PS, which is supposed to capture the price impact of order flow in the equity market. We report the results in Column (3) of Table IA.I. While we find that PS is negative and statistically significant, extending our model of OTC market frictions by PS virtually does not affect the coefficients of our proxies. Thus, we conclude that the informational content of our measures of OTC frictions for yield spread changes is basically unrelated to liquidity risk in the equity market. The incremental adjusted R^2 value in the time-series regression is non-negligible, confirming the findings of Bongaerts, de Jong, and Driessen (2017) that equity liquidity risk affects bond prices systematically.

Recent empirical asset pricing literature (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017) emphasizes the role of financial intermediaries as marginal investors. Their marginal value of wealth should thus be important in pricing assets. We investigate whether the intermediary capital risk factor, ICR, of He, Kelly, and Manela (2017) affects yield spreads. We report the result of the corresponding specification in Column (4) and find that the coefficient of ICR exhibits the expected negative sign; that is, yield spreads narrow when intermediaries have higher capital ratios. The addition of ICR to our model of OTC market frictions does not essentially affect our measures, with one notable exception. Among the inventory frictions, the coefficient of *ted* becomes insignificant, which suggests an interaction between funding costs and dealers' debt capacity. Note that this result was to be expected, given that dealers can more easily raise debt and lower their capital ratios when funding becomes less expensive. Thus, the addition of ICR improves the mean adjusted R^2 value across bonds slightly, by 1.9 percentage points, however, there is basically no change in the explanatory power of the common component.

Finally, we focus on the role of asymmetric information. Babus and Kondor (2018) argue that central dealers are less exposed to adverse selection. Hence, in their model, informational frictions give rise to changes in search frictions over time. In a similar vein, Glode and Opp (2016) provide a theory of intermediation chains based on asymmetric information. To investigate the effect of informational frictions on yield spreads, we follow the methodology of Easley, Hvidkjaer, and O'Hara (2002) and estimate the marketwide probability of information-based trading, PIN. We augment our model of market frictions by PIN and report the results in Column (5) of Table IA.I. The coefficient of PIN is positive, as expected, but turns out to be insignificant. More important, we find that the coefficients of our measures remain virtually unaffected by the addition of PIN. Further, the explanatory power of PC1 remains basically unchanged. Hence, it seems unlikely that informational frictions drive search frictions over time.

Overall, the additional tests confirm that OTC market frictions are major determinants of the dynamics of yield spread changes.

E.3. Alternative Definitions of CDGM Variables

We further demonstrate the robustness of our results in Table IA.II, using alternative definitions of the CDGM variables. First, we replace VIX with the firm's asset volatility, which is, according to structural models, the crucial input. As an approximation of asset volatility, we compute the firm's stock return volatility based on daily returns in a given month. We show the results of the CDGM baseline regression in Column (1) and report the results of the model augmented by OTC market frictions in Column (2). The results remain essentially unaffected in terms of statistical significance, the signs of the OTC friction measures, and explanatory power. In a next step, we replace each firm's leverage ratio by the stock return and show the results in Columns (3) and (4), respectively. Again, the results are basically unaffected. Systematic OTC frictions account for around one-third of the total explained variation of yield spread changes and explain around 23% of the variation of the common component. Replacing both the VIX and the firm's leverage by their corresponding alternative proxies does not influence the results either, as reported in Columns (5) and (6).

V. Conclusions

Existing empirical evidence shows that yield spread changes exhibit a large unexplained common factor, thereby leaving their economic determinants rather poorly understood. In this paper, we examine whether systematic intermediation frictions that arise specifically in the corporate bond market, given its OTC structure, contribute to an understanding of the common component in yield spread changes. We find that systematic inventory, search, and bargaining frictions capture 23.4% of the variation of the common component. Hence, systematic OTC frictions contribute substantially to the explanatory power of yield spread changes and account for around one-third of their total explained variation. Furthermore, our results show that search and bargaining frictions taken together explain more in the common variation of yield spread changes as inventory frictions.

In summary, we provide novel insights into the latent common driver of yield spread changes by elaborating on the role of systematic intermediation frictions in OTC markets.

Table I: Summary Statistics. This table reports summary statistics of the data. We report the number of observations, the mean, the standard deviation, and 5%, 50%, and 95% quantiles of bond characteristics and the yield spread in Panel A and daily trading activity variables in Panel B. The bond characteristics in Panel A comprise the offering amount, the bond age, 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, ...). In Panel B we report the number of daily trades and the trade sizes of interdealer trades, customer trades, dealer buy trades from customers, and dealer sell trades to customers, respectively. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

Panel A: Bond Characteristics and the Yield Spread

Variable	Observations	Mean	Std. dev.	Q05	Q50	Q95
Offering amount [$ millions]	44207081	909.26	807.38	250.00	650.00	2000.00
Age [years]	44207081	4.05	3.96	0.35	2.95	8.95
Time to maturity [years]	44207081	8.50	7.93	1.93	6.25	22.34
Coupon rate [%]	44207081	6.49	1.96	4.12	6.45	8.88
Credit rating	44207081	9.67	4.11	5.00	9.00	16.00
Yield spread [%]	105810	2.98	2.76	0.82	2.01	6.25

Panel B: Trading Activity

Variable	Mean	Std. dev.	Q05	Q50	Q95
Number of Daily Trades					
Interdealer	4071	2428	1544	2821	7513
Customer	7643	3149	4368	7214	11863
Dealer buy from customer	3209	1340	1827	2971	5044
Dealer sale to customer	4477	1924	2438	4184	7214
Trade Sizes in $1,000					
Interdealer	387	1198	5	25	1000
Customer	831	4720	5	40	2250
Dealer buy from customer	995	5426	5	50	3000
Dealer sale to customer	714	4135	5	30	2000

Table II: Determinants of Yield Spread Changes in the Collin-Dufresne, Goldstein, and Martin (2001) Framework. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \epsilon_{i,t}$$

The vector $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\ \Delta RF_t,\ (\Delta RF_t)^2,\ \Delta SLOPE_t,\ \Delta VIX_t,\ RM_t,\ \Delta JUMP_t\right]$ refers to the structural model variables defined in Section II, where ΔLEV is the firm's leverage ratio, ΔRF the change in the 10-year Treasury rate, $(\Delta RF)^2$ the squared change in the 10-year Treasury rate, $\Delta SLOPE$ the change in the slope of the yield curve, ΔVIX the change in the market volatility, RM the return on the S&P 500 index, and $\Delta JUMP$ the change in a jump component. We assign each bond to a cohort based on the firm's average leverage ratio and report the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. We also report the results across all bonds. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	<15%	15%–25%	25%–35%	35%–45%	45%–55%	>55%	All
Intercept	0.091***	0.071***	0.024**	0.023	0.062***	0.131***	0.066***
	(5.226)	(5.186)	(2.346)	(1.477)	(2.740)	(4.162)	(9.074)
$\Delta LEV_{i,t}$	0.057**	0.003	0.019***	0.032***	0.039***	0.107***	0.036***
	(2.290)	(0.419)	(3.065)	(4.530)	(5.695)	(7.927)	(6.065)
ΔRF_t	−0.071	−0.203***	−0.299***	−0.437***	−0.520***	−0.198*	−0.254***
	(−1.180)	(−3.597)	(−4.102)	(−4.920)	(−4.504)	(−1.705)	(−7.978)
$(\Delta RF_t)^2$	−0.373**	−0.198	0.144	0.161	−0.022	−0.245	−0.110
	(−2.219)	(−1.590)	(0.970)	(0.741)	(−0.087)	(−0.693)	(−1.401)
$\Delta SLOPE_t$	0.441***	0.392***	0.350***	0.405***	0.754***	0.373**	0.426***
	(4.843)	(3.992)	(3.613)	(3.076)	(4.174)	(2.087)	(8.753)
ΔVIX_t	0.012***	0.013***	0.015***	0.020***	0.023***	0.005	0.014***
	(2.934)	(3.842)	(4.298)	(4.886)	(2.808)	(0.438)	(6.807)
RM_t	−0.007	−0.014***	−0.024***	−0.027***	−0.037***	−0.099***	−0.028***
	(−1.284)	(−3.550)	(−5.776)	(−4.594)	(−4.328)	(−8.412)	(−10.746)
$\Delta JUMP_t$	0.005	0.003	0.007*	0.008**	0.011*	−0.001	0.005***
	(1.314)	(1.041)	(1.952)	(2.022)	(1.804)	(−0.241)	(3.128)
Mean adj. R^2	0.156	0.146	0.233	0.295	0.271	0.329	0.217
Median adj. R^2	0.143	0.122	0.239	0.336	0.285	0.331	0.201
Observations	9596	11802	8304	6407	3760	5481	45350
Bonds	203	256	179	141	84	111	974

Table III: Principal Component Analysis. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \epsilon_{i,t}$$

The vector $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\, \Delta RF_t,\, (\Delta RF_t)^2,\, \Delta SLOPE_t,\, \Delta VIX_t,\, RM_t,\, \Delta JUMP_t\right]$ refers to the structural model variables defined in Section II, with ΔLEV as the firm's leverage ratio, ΔRF the change in the 10-year Treasury rate, $(\Delta RF)^2$ the squared change in the 10-year Treasury rate, $\Delta SLOPE$ the change in the slope of the yield curve, ΔVIX the change in the market volatility, RM the return on the S&P 500 index, and $\Delta JUMP$ the change in a jump component. We then assign each month's residuals to one of 18 bins defined by three maturity groups (short denotes less than five years, medium denotes five to eight years, long is over eight years) and six leverage groups (low is less than 15%, 2 is 15%–25%, 3 is 25%–35%, 4 is 35%–45%, 5 is 45%–55%, high is greater than 55%) and compute an average residual. We extract the principal components of the covariance matrix of these residuals. For each bin, we report the number of bonds, the number of observations, the loadings, and the proportions of the variance of the residuals explained by the first and second principal components, PC1 and PC2, respectively. We further report the total unexplained variance of the regression in percentage points. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

Maturity	Leverage	Bonds	Observations	PC1	PC2
Short	Low	223	4107	0.109	0.168
Short	2	324	5190	0.135	0.213
Short	3	288	2719	0.174	0.218
Short	4	227	1894	0.246	0.456
Short	5	160	1360	0.325	0.456
Short	High	162	2257	0.478	−0.208
Medium	Low	188	2211	0.101	0.082
Medium	2	264	2919	0.129	0.045
Medium	3	233	1890	0.181	−0.070
Medium	4	225	1576	0.247	0.046
Medium	5	187	1447	0.234	0.129
Medium	High	152	1622	0.351	−0.087
Long	Low	262	3893	0.093	0.014
Long	2	329	3797	0.110	−0.003
Long	3	277	2934	0.129	−0.033
Long	4	264	2140	0.189	−0.024
Long	5	181	1427	0.211	−0.198
Long	High	130	1967	0.358	−0.583
Proportion of variance explained by PC				0.484	0.095
Unexplained variance				1.666	

Table IV: Intermediation Chains. We classify intermediation chains by the number of dealers involved and the number of sales to customers in the chain. We then report, for each group, the number of observations and the acquired chain volume in \$1,000. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

Dealers	Customer Sales	Observations	Chain Volume
1	1	755268	1239.56
1	2	40388	1466.92
1	≥3	8329	811.28
2	1	69650	357.98
2	2	5116	761.00
2	≥3	1308	915.69
3	1	38272	193.98
3	2	3938	443.98
3	≥3	910	640.71
≥4	1	14667	40.95
≥4	2	5071	87.92
≥4	≥3	661	301.37

Table V: Standard Deviations and Correlation Matrix of Changes in Yield Spreads and Proxies of Systematic OTC Market Frictions. This table reports the standard deviation and correlation matrix of the changes in yield spreads (ΔYS), the changes in the proxies of systematic inventory frictions (Δinv, $\Delta amt.out$, $\Delta match.trd$, and Δted) introduced in Section III.A, the changes in the proxies of the systematic search frictions ($\Delta centr$, $\Delta chain.len$, $\Delta lvc.sales$, and $\Delta svc.sales$) introduced in Section III.B, and the changes in the proxies for systematic bargaining frictions ($\Delta outside.opt$, $\Delta block.trd$, $\Delta dlr.conc$, and $\Delta ig2junk$) introduced in Section III.C. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	SD	YS	inv	$amt.out$	$match.trd$	ted	$centr$	$chain.len$	$lvc.sales$	$svc.sales$	$outside.opt$	$block.trd$	$dlr.conc$	$ig2junk$
ΔYS	0.3138	1.00												
Δinv	0.0028	0.05	1.00											
$\Delta amt.out$	0.0109	0.01	0.47	1.00										
$\Delta match.trd$	0.0130	0.04	−0.17	−0.29	1.00									
Δted	0.2762	0.10	0.02	−0.06	−0.24	1.00								
$\Delta centr$	0.0367	−0.02	−0.13	−0.14	−0.05	0.24	1.00							
$\Delta chain.len$	0.0357	−0.10	−0.06	−0.14	0.45	−0.27	−0.05	1.00						
$\Delta lvc.sales$	0.0169	−0.04	−0.30	−0.10	0.15	−0.13	−0.06	0.04	1.00					
$\Delta svc.sales$	0.0185	0.04	−0.17	−0.17	0.07	0.08	−0.05	−0.01	0.07	1.00				
$\Delta outside.opt$	1.1470	−0.09	−0.20	−0.08	−0.06	−0.03	−0.04	0.11	−0.01	−0.08	1.00			
$\Delta block.trd$	0.0034	−0.09	0.01	0.12	−0.16	−0.19	−0.16	−0.01	0.10	0.01	0.16	1.00		
$\Delta dlr.conc$	0.0101	0.11	0.02	0.01	0.09	0.13	0.17	−0.04	−0.17	0.17	−0.24	−0.26	1.00	
$\Delta ig2junk$	8.1178	0.01	0.05	0.03	0.06	0.16	0.05	−0.05	−0.10	0.04	0.03	0.05	−0.01	1.00

Table VI: Inventory Frictions and Yield Spread Changes. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the model

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_i'} \boldsymbol{\Delta I_t} + \epsilon_{i,t},$$

where $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\ \Delta RF_t,\ (\Delta RF_t)^2,\ \Delta SLOPE_t,\ \Delta VIX_t,\ RM_t,\ \Delta JUMP_t\right]$ is the vector of the structural model variables defined in Section II. The vector $\boldsymbol{\Delta I_t} := [\Delta inv_t,\ \Delta amt.out_t,\ \Delta match.trd_t,\ \Delta ted_t]$ refers to the proxies for systematic inventory frictions introduced in Section III.A. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\text{PC1}_t = \alpha + \boldsymbol{\gamma'} \boldsymbol{\Delta I_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Bond Regressions						
Intercept	0.066***	0.060***	0.026***	0.057***	0.071***	0.029***
	(9.074)	(7.567)	(3.084)	(7.956)	(9.883)	(3.414)
$\Delta LEV_{i,t}$	0.036***	0.036***	0.035***	0.035***	0.038***	0.036***
	(6.065)	(5.965)	(5.673)	(6.040)	(6.453)	(5.940)
ΔRF_t	−0.254***	−0.324***	−0.292***	−0.252***	−0.271***	−0.328***
	(−7.978)	(−9.882)	(−8.622)	(−7.848)	(−8.063)	(−9.268)
$(\Delta RF_t)^2$	−0.110	−0.002	−0.114	0.004	−0.183**	0.037
	(−1.401)	(−0.030)	(−1.401)	(0.054)	(−2.291)	(0.416)
$\Delta SLOPE_t$	0.426***	0.473***	0.509***	0.411***	0.504***	0.537***
	(8.753)	(9.663)	(10.339)	(8.436)	(9.922)	(10.316)
ΔVIX_t	0.014***	0.011***	0.014***	0.015***	0.013***	0.010***
	(6.807)	(5.170)	(6.708)	(7.069)	(6.086)	(4.445)
RM_t	−0.028***	−0.029***	−0.028***	−0.027***	−0.028***	−0.029***
	(−10.746)	(−11.165)	(−10.752)	(−10.301)	(−10.765)	(−10.939)
$\Delta JUMP_t$	0.005***	0.005***	0.004**	0.005***	0.007***	0.007***
	(3.128)	(3.206)	(2.394)	(3.083)	(4.118)	(3.854)
Δinv_t		24.099***				20.849***
		(10.244)				(9.120)
$\Delta amt.out_t$			3.260***			3.019***
			(3.512)			(3.126)
$\Delta match.trd_t$				1.811***		3.489***
				(3.630)		(6.581)
Δted_t					0.524***	0.486***
					(9.466)	(8.514)
Mean adj. R^2	0.217	0.243	0.237	0.232	0.237	0.277
Median adj. R^2	0.201	0.233	0.224	0.218	0.227	0.280
Observations	45350	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974	974
Panel B: Principal Component Analysis						
PC1	0.484	0.448	0.464	0.478	0.472	0.403
PC2	0.096	0.101	0.100	0.094	0.103	0.115
Unexpl. var.	1.666	1.579	1.634	1.586	1.512	1.289

Panel C: Time-Series Regression of PC1 on Inventory Frictions

	Δinv	$\Delta amt.out$	$\Delta match.trd$	Δted	ΔI
Adj. R^2					0.139
R^2	0.078	0.009	0.011	0.046	0.166
F-statistic	10.782	1.167	1.400	6.167	6.149
p-value	0.001	0.282	0.239	0.014	0.000
Observations	129	129	129	129	129

Table VII: Search Frictions and Yield Spread Changes. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the model

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_i'} \boldsymbol{\Delta S_t} + \epsilon_{i,t},$$

where $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\ \Delta RF_t,\ (\Delta RF_t)^2,\ \Delta SLOPE_t,\ \Delta VIX_t,\ RM_t,\ \Delta JUMP_t\right]$ is the vector of the structural model variables defined in Section II. The vector $\boldsymbol{\Delta S_t} := [\Delta centr_t,\ \Delta chain.len_t,\ \Delta lvc.sales_t,\ \Delta svc.sales_t]$ refers to the proxies for systematic search frictions introduced in Section III.B. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\text{PC1}_t = \alpha + \boldsymbol{\gamma'} \boldsymbol{\Delta S_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Bond Regressions						
Intercept	0.066***	0.067***	0.069***	0.064***	0.067***	0.067***
	(9.074)	(9.091)	(9.313)	(8.634)	(8.971)	(8.708)
$\Delta LEV_{i,t}$	0.036***	0.037***	0.034***	0.036***	0.037***	0.035***
	(6.065)	(5.816)	(5.781)	(5.811)	(5.908)	(5.170)
ΔRF_t	−0.254***	−0.250***	−0.218***	−0.267***	−0.240***	−0.222***
	(−7.978)	(−7.846)	(−6.920)	(−8.149)	(−7.319)	(−6.720)
$(\Delta RF_t)^2$	−0.110	−0.105	−0.159**	−0.092	−0.084	−0.086
	(−1.401)	(−1.299)	(−2.040)	(−1.146)	(−1.025)	(−1.021)
$\Delta SLOPE_t$	0.426***	0.419***	0.418***	0.530***	0.414***	0.500***
	(8.753)	(8.597)	(8.541)	(10.557)	(8.321)	(9.610)
ΔVIX_t	0.014***	0.014***	0.014***	0.015***	0.013***	0.014***
	(6.807)	(6.488)	(6.858)	(7.331)	(6.022)	(5.613)
RM_t	−0.028***	−0.027***	−0.027***	−0.026***	−0.029***	−0.025***
	(−10.746)	(−10.288)	(−10.441)	(−9.936)	(−10.572)	(−9.015)
$\Delta JUMP_t$	0.005***	0.004**	0.004**	0.006***	0.006***	0.005***
	(3.128)	(2.552)	(2.241)	(3.609)	(3.465)	(2.754)
$\Delta centr_t$		−0.899***				−1.167***
		(−5.639)				(−6.853)
$\Delta chain.len_t$			−0.961***			−0.619**
			(−3.685)			(−2.066)
$\Delta lvc.sales_t$				−3.317***		−3.272***
				(−10.881)		(−9.751)
$\Delta svc.sales_t$					0.796***	1.145***
					(3.185)	(4.262)
Mean adj. R^2	0.217	0.220	0.228	0.228	0.219	0.244
Median adj. R^2	0.201	0.209	0.217	0.214	0.206	0.250
Observations	45350	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974	974
Panel B: Principal Component Analysis						
PC1	0.484	0.476	0.488	0.457	0.479	0.445
PC2	0.096	0.099	0.093	0.100	0.094	0.101
Unexpl. var.	1.666	1.576	1.612	1.554	1.622	1.384

Panel C: Time-Series Regression of PC1 on Search Frictions

		$\Delta centr$	$\Delta chain.len$	$\Delta lvc.sales$	$\Delta svc.sales$	ΔS
Adj. R^2						0.063
R^2		0.000	0.017	0.079	0.000	0.092
F-statistic		0.052	2.210	10.939	0.051	3.148
p-value		0.820	0.140	0.001	0.822	0.017
Observations		129	129	129	129	129

Table VIII: Bargaining Frictions and Yield Spread Changes. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the model

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_i'} \boldsymbol{\Delta B_t} + \epsilon_{i,t},$$

where $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\ \Delta RF_t,\ (\Delta RF_t)^2,\ \Delta SLOPE_t,\ \Delta VIX_t,\ RM_t,\ \Delta JUMP_t\right]$ is the vector of the structural model variables defined in Section II. The vector $\boldsymbol{\Delta B_t} := [\Delta outside.opt_t,\ \Delta block.trd_t,\ \Delta dlr.conc_t,\ \Delta ig2junk_t]$ refers to the proxies for systematic bargaining frictions introduced in Section III.C. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\mathrm{PC1}_t = \alpha + \boldsymbol{\gamma'} \boldsymbol{\Delta B_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Bond Regressions						
Intercept	0.066***	0.064***	0.068***	0.067***	0.068***	0.070***
	(9.074)	(8.782)	(8.741)	(9.436)	(9.252)	(9.064)
$\Delta LEV_{i,t}$	0.036***	0.035***	0.039***	0.035***	0.036***	0.035***
	(6.065)	(5.498)	(6.510)	(5.797)	(5.665)	(5.347)
ΔRF_t	−0.254***	−0.231***	−0.246***	−0.223***	−0.242***	−0.189***
	(−7.978)	(−7.318)	(−7.438)	(−7.086)	(−7.323)	(−5.482)
$(\Delta RF_t)^2$	−0.110	−0.100	−0.190**	−0.099	−0.156**	−0.200**
	(−1.401)	(−1.250)	(−2.380)	(−1.288)	(−2.023)	(−2.566)
$\Delta SLOPE_t$	0.426***	0.421***	0.508***	0.368***	0.415***	0.437***
	(8.753)	(8.568)	(9.824)	(7.646)	(8.471)	(8.446)
ΔVIX_t	0.014***	0.014***	0.014***	0.014***	0.014***	0.013***
	(6.807)	(6.707)	(6.673)	(6.625)	(6.624)	(6.043)
RM_t	−0.028***	−0.027***	−0.027***	−0.026***	−0.028***	−0.026***
	(−10.746)	(−10.502)	(−9.936)	(−10.012)	(−10.601)	(−9.470)
$\Delta JUMP_t$	0.005***	0.005***	0.007***	0.009***	0.005***	0.009***
	(3.128)	(3.149)	(4.310)	(4.999)	(3.066)	(4.946)
$\Delta outside.opt_t$		−0.035***				−0.021***
		(−7.413)				(−4.407)
$\Delta block.trd_t$			−19.528***			−16.136***
			(−10.657)			(−8.582)
$\Delta dlr.conc_t$				7.163***		5.806***
				(14.607)		(10.039)
$\Delta ig2junk_t$					0.003***	0.004***
					(4.662)	(5.416)
Mean adj. R^2	0.217	0.226	0.232	0.228	0.221	0.246
Median adj. R^2	0.201	0.206	0.227	0.224	0.204	0.262
Observations	45350	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974	974
Panel B: Principal Component Analysis						
PC1	0.484	0.460	0.439	0.449	0.475	0.389
PC2	0.096	0.099	0.111	0.101	0.100	0.123
Unexpl. var.	1.666	1.604	1.566	1.589	1.625	1.436

Panel C: Time-Series Regression of PC1 on Bargaining Frictions

	$\Delta outside.opt$	$\Delta block.trd$	$\Delta dlr.conc$	$\Delta ig2junk$	ΔB
Adj. R^2					0.154
R^2	0.051	0.100	0.083	0.007	0.180
F-statistic	6.868	14.120	11.531	0.881	6.816
p-value	0.010	0.000	0.001	0.350	0.000
Observations	129	129	129	129	129

Table IX: OTC Market Frictions and Yield Spread Changes. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_{i,1}'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}'} \boldsymbol{\Delta B_t} + \epsilon_{i,t}$$

The vector $\boldsymbol{\Delta F_{i,t}}$ refers to the structural model variables defined in Section II. The vector $\boldsymbol{\Delta I_t} := [\Delta inv_t,\ \Delta amt.out_t,\ \Delta match.trd_t,\ \Delta ted_t]$ refers to the proxies for systematic inventory frictions introduced in Section III.A, the vector $\boldsymbol{\Delta S_t} := [\Delta centr_t,\ \Delta chain.len_t,\ \Delta lvc.sales_t,\ \Delta svc.sales_t]$ refers to the proxies for systematic search frictions introduced in Section III.B, and the vector $\boldsymbol{\Delta B_t} := [\Delta outside.opt_t,\ \Delta block.trd_t,\ \Delta dlr.conc_t,\ \Delta ig2junk_t]$ refers to the proxies for systematic bargaining proxies introduced in Section III.C. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\mathrm{PC1}_t = \alpha + \boldsymbol{\gamma_1'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_2'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_3'} \boldsymbol{\Delta B_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)
Panel A: Individual Bond Regressions					
Intercept	0.066***	0.034***	0.046***	0.069***	0.048***
	(9.074)	(3.578)	(4.613)	(8.314)	(4.421)
Δinv_t		17.764***	21.825***		16.218***
		(6.978)	(8.028)		(5.656)
$\Delta amt.out_t$		2.395*	2.586**		1.355
		(1.890)	(2.485)		(0.982)
$\Delta match.trd_t$		5.169***	2.146***		4.949***
		(7.296)	(3.638)		(5.721)
Δted_t		0.412***	0.350***		0.254***
		(5.663)	(5.489)		(3.135)
$\Delta centr_t$		−0.765***		−1.519***	−1.382***
		(−4.074)		(−7.722)	(−6.269)
$\Delta chain.len_t$		−0.908**		−0.356	−1.051**
		(−2.227)		(−1.116)	(−2.479)
$\Delta lvc.sales_t$		−2.138***		−2.820***	−2.347***
		(−5.859)		(−7.602)	(−5.237)
$\Delta svc.sales_t$		1.552***		0.752**	1.236***
		(5.321)		(2.290)	(3.374)
$\Delta outside.opt_t$			−0.005	−0.021***	−0.000
			(−0.798)	(−4.064)	(−0.054)
$\Delta block.trd_t$			−12.387***	−17.174***	−12.200***
			(−6.398)	(−8.357)	(−5.502)
$\Delta dlr.conc_t$			5.266***	3.805***	2.260***
			(8.592)	(5.860)	(2.815)
$\Delta ig2junk_t$			0.000	0.002**	−0.001
			(0.426)	(2.471)	(−1.533)
CDGM variables	Yes	Yes	Yes	Yes	Yes
Mean adj. R2	0.217	0.292	0.293	0.271	0.307
Median adj. R2	0.201	0.312	0.311	0.288	0.345
Observations	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974
Panel B: Principal Component Analysis					
PC1	0.484	0.378	0.326	0.358	0.298
PC2	0.096	0.129	0.134	0.135	0.130
Unexpl. var.	1.666	1.086	1.107	1.185	0.922

Panel C: Time-Series Regression of PC1 on OTC Frictions

	$\Delta I + \Delta S$	$\Delta I + \Delta B$	$\Delta S + \Delta B$	$\Delta I + \Delta S + \Delta B$
Adj. R^2	0.176	0.226	0.180	0.234
R^2	0.227	0.275	0.231	0.306
F-statistic	4.414	5.685	4.515	4.261
p-value	0.000	0.000	0.000	0.000
Observations	129	129	129	129

Table X: OTC Market Frictions and Yield Spread Changes, Excluding the Crisis Period. Excluding the crisis period (July 2007 to April 2009), for each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the model

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_{i,1}'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}'} \boldsymbol{\Delta B_t} + \epsilon_{i,t},$$

where the vector $\boldsymbol{\Delta F_{i,t}}$ refers to the structural model variables defined in Section II. The vector $\boldsymbol{\Delta I_t} := [\Delta inv_t, \Delta amt.out_t, \Delta match.trd_t, \Delta ted_t]$ refers to the proxies for systematic inventory frictions introduced in Section III.A, the vector $\boldsymbol{\Delta S_t} := [\Delta centr_t, \Delta chain.len_t, \Delta lvc.sales_t, \Delta svc.sales_t]$ to the proxies for systematic search frictions introduced in Section III.B, and the vector $\boldsymbol{\Delta B_t} := [\Delta outside.opt_t, \Delta block.trd_t, \Delta dlr.conc_t, \Delta ig2junk_t]$ to the proxies for systematic bargaining proxies introduced in Section III.C. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\text{PC1}_t = \alpha + \boldsymbol{\gamma_1'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_2'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_3'} \boldsymbol{\Delta B_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

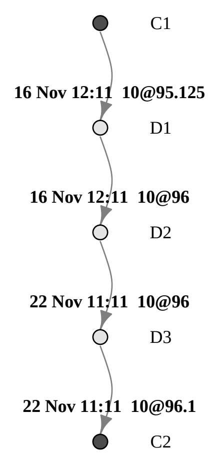
	(1)	(2)	(3)	(4)	(5)
Panel A: Individual Bond Regressions					
Intercept	0.060***	0.035***	0.064***	0.060***	0.054***
	(7.499)	(3.787)	(7.453)	(7.201)	(4.805)
Δinv_t		12.545***			13.727***
		(5.718)			(4.763)
$\Delta amt.out_t$		3.345***			1.510
		(2.901)			(0.966)
$\Delta match.trd_t$		2.319***			4.352***
		(3.938)			(4.447)
Δted_t		0.617***			0.347***
		(9.302)			(3.636)
$\Delta centr_t$			−0.701***		−0.778***
			(−3.762)		(−2.926)
$\Delta chain.len_t$			−0.357		−0.776
			(−1.059)		(−1.643)
$\Delta lvc.sales_t$			−1.769***		−1.012**
			(−5.097)		(−2.045)
$\Delta svc.sales_t$			0.858***		1.040***
			(3.025)		(2.776)
$\Delta outside.opt_t$				−0.011**	0.006
				(−2.239)	(0.741)
$\Delta block.trd_t$				−4.436**	−3.277
				(−2.184)	(−1.337)
$\Delta dlr.conc_t$				6.243***	2.791***
				(9.560)	(2.882)
$\Delta ig2junk_t$				0.006***	0.001
				(8.025)	(1.386)
CDGM variables	Yes	Yes	Yes	Yes	Yes
Mean adj. R^2	0.171	0.227	0.193	0.204	0.254
Median adj. R^2	0.148	0.222	0.182	0.191	0.274
Observations	36514	36514	36514	36514	36514
Bonds	864	864	864	864	864
Panel B: Principal Component Analysis					
PC1	0.395	0.326	0.358	0.330	0.238
PC2	0.110	0.141	0.116	0.135	0.158
Unexpl. var.	1.153	1.020	1.013	1.034	0.722

Panel C: Time-Series Regression of PC1 on OTC Frictions

	ΔI	ΔS	ΔB	$\Delta I + \Delta S + \Delta B$
Adj. R^2	0.122	0.009	0.091	0.137
R^2	0.155	0.047	0.126	0.235
F-statistic	4.693	1.251	3.667	2.404
p-value	0.002	0.294	0.008	0.009
Observations	107	107	107	107

Figure 1: Intermediation Chains. This figure provides two examples of intermediation chains. Panel A shows a non-split intermediation chain and Panel B a split intermediation chain. Each node either represents a customer (denoted by C) or a dealer (denoted by D). Arrows indicate a bond transaction for which we report the date and time, the transacted volume in $1,000, and the transaction price.

Panel A: Non-split intermediation chain



Panel B: Split intermediation chain

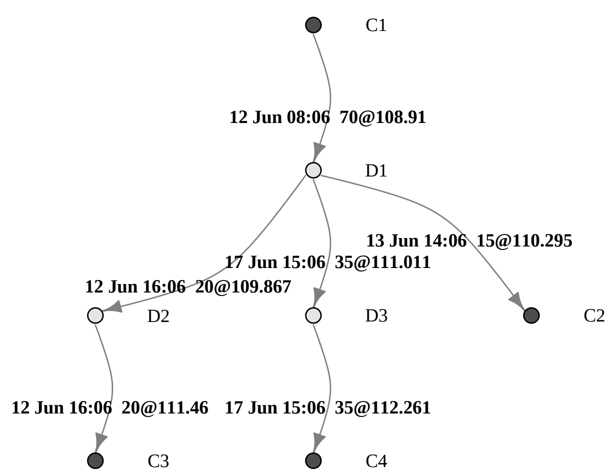
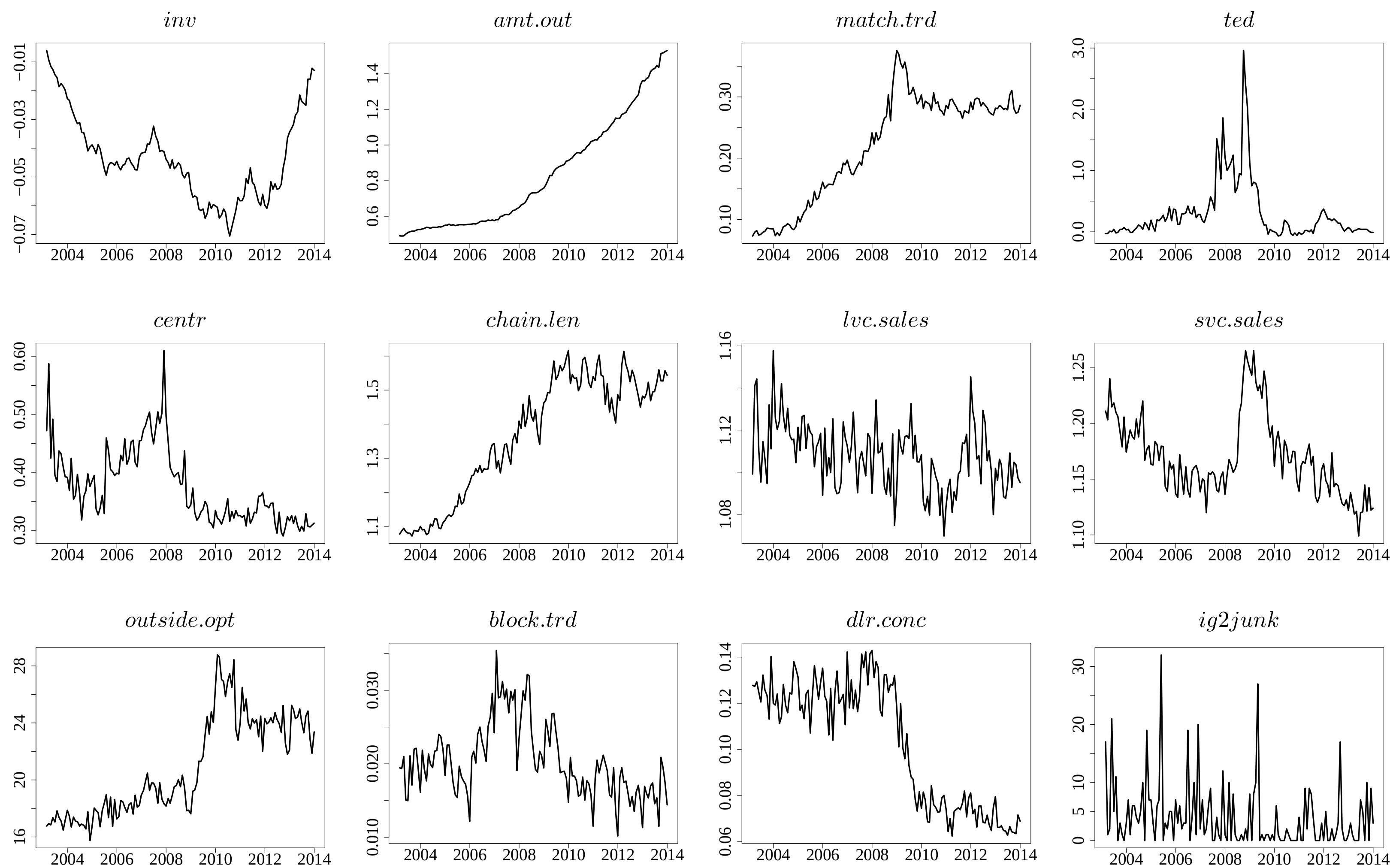


Figure 2: Time-Series Dynamics of Systematic Proxies for OTC Market Frictions. We plot the time series of the cumulative marketwide order flow in $1 trillion, *inv*; the aggregate amount outstanding in $1 trillion, *amt.out*; the fraction of prearranged trades, *match.trd*; the TED spread, *ted*; the graph-level eigencentrality measure, *centr*; the average length of intermediation chains, *chain.len*; the average number of sales to customers of large-volume chains, *lvc.sales*; the average number of sales to customers of small-volume chains, *svc.sales*; the average number of customers' outside options, *outside.opt*; the fraction of block trades, *block.trd*; the dealer concentration, *dlr.conc*; and the number of downgrades from investment grade to speculative grade, *ig2junk*. The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.



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Internet Appendix for

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

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Figure IA.1: Time-Series Dynamics of Dealer Inventory Adjusted for Amount Outstanding. We plot the time-series of the marketwide dealer inventory adjusted for the aggregate amount outstanding, that is, we estimate the following regression model:

$$\Delta inv_t = \alpha + \beta \Delta amt.out_t + u_t$$

Then we compute the cumulative residuals and obtain an adjusted time-series of the dynamics of the level of dealer inventory, $inv_t^* = \sum_{s=0}^{t} u_s$. Inventory is given in \$1 trillion, and the sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

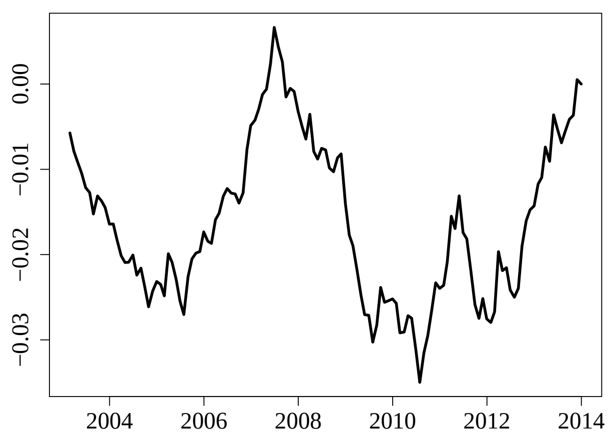

Table IA.I: OTC Market Frictions and other Potential Determinants of Yield Spread Changes. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'}\boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_{i,1}'}\boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}'}\boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}'}\boldsymbol{\Delta B_t} + \boldsymbol{\gamma_{i,4}'}\boldsymbol{\Delta D_t} + \epsilon_{i,t}$$

The vector $\boldsymbol{\Delta F_{i,t}}$ refers to the structural model variables defined in Section II. The vector $\boldsymbol{\Delta I_t} := [\Delta inv_t,\ \Delta amt.out_t,\ \Delta match.trd_t,\ \Delta ted_t]$ refers to the proxies for systematic inventory frictions introduced in Section III.A, the vector $\boldsymbol{\Delta S_t} := [\Delta centr_t,\ \Delta chain.len_t,\ \Delta lvc.sales_t,\ \Delta svc.sales_t]$ refers to the proxies for systematic search frictions introduced in Section III.B, and the vector $\boldsymbol{\Delta B_t} := [\Delta outside.opt_t,\ \Delta block.trd_t,\ \Delta dlr.conc_t,\ \Delta ig2junk_t]$ to the proxies for systematic bargaining proxies introduced in Section III.C. The vector $\boldsymbol{\Delta D_t} := [SMB_t,\ HML_t,\ RMW_t,\ CMA_t,\ PS_t,\ ICR_t,\ \Delta PIN_t]$ refers to other potential determinants of yield spread changes. These include the Fama and French (2015) five factors; the liquidity factor, PS, of Pastor and Stambaugh (2003); the intermediary capital risk factor, ICR, of He, Kelly, and Manela (2017); as well as the factor based on the probability of information-based trading, PIN, of Easley, Hvidkjaer, and O'Hara (2002). Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\text{PC1}_t = \alpha + \boldsymbol{\gamma_1'}\boldsymbol{\Delta I_t} + \boldsymbol{\gamma_2'}\boldsymbol{\Delta S_t} + \boldsymbol{\gamma_3'}\boldsymbol{\Delta B_t} + \boldsymbol{\gamma_4'}\boldsymbol{\Delta D_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)
Panel A: Individual Bond Regressions					
Intercept	0.048***	0.068***	0.058***	0.034***	0.048***
	(4.421)	(5.193)	(5.484)	(3.048)	(4.190)
Δinv_t	16.218***	15.241***	15.870***	10.990***	16.075***
	(5.656)	(4.583)	(5.067)	(3.409)	(5.498)
$\Delta amt.out_t$	1.355	−0.495	1.960	−0.228	1.857
	(0.982)	(−0.288)	(1.454)	(−0.157)	(1.296)
$\Delta match.trd_t$	4.949***	5.355***	4.044***	6.006***	4.607***
	(5.721)	(4.496)	(4.890)	(6.594)	(4.929)
Δted_t	0.254***	0.184*	0.339***	0.138	0.276***
	(3.135)	(1.665)	(3.939)	(1.642)	(3.151)
$\Delta centr_t$	−1.382***	−1.612***	−1.222***	−1.648***	−1.408***
	(−6.269)	(−5.917)	(−5.573)	(−6.933)	(−6.087)
$\Delta chain.len_t$	−1.051**	−1.473***	−0.839**	−1.194***	−0.933**
	(−2.479)	(−2.665)	(−2.180)	(−2.884)	(−2.215)
$\Delta lvc.sales_t$	−2.347***	−1.741***	−2.067***	−2.580***	−2.355***
	(−5.237)	(−3.193)	(−4.261)	(−4.843)	(−4.976)
$\Delta svc.sales_t$	1.236***	0.721	1.199***	1.219***	1.240***
	(3.374)	(1.556)	(3.220)	(3.180)	(2.709)
$\Delta outside.opt_t$	−0.000	−0.001	−0.000	−0.005	−0.002
	(−0.054)	(−0.172)	(−0.012)	(−0.701)	(−0.304)
$\Delta block.trd_t$	−12.200***	−16.322***	−9.947***	−10.861***	−12.138***
	(−5.502)	(−5.628)	(−4.504)	(−4.473)	(−4.555)
$\Delta dlr.conc_t$	2.260***	1.571*	2.204***	1.294	2.596***
	(2.815)	(1.667)	(2.618)	(1.454)	(2.932)
$\Delta ig2junk_t$	−0.001	−0.001	−0.002**	−0.001	−0.001
	(−1.533)	(−1.227)	(−2.252)	(−0.704)	(−1.232)
SMB_t		−0.011***			
		(−3.007)			
HML_t		−0.019***			
		(−3.631)			
RMW_t		−0.014**			
		(−2.132)			
CMA_t		0.015*			
		(1.833)			
PS_t			−0.673***		
			(−3.339)		
ICR_t				−1.352***	
				(−5.457)	
ΔPIN_t					1.361
					(1.006)
CDGM variables	Yes	Yes	Yes	Yes	Yes
Mean adj. R2	0.307	0.316	0.313	0.326	0.317
Median adj. R2	0.345	0.367	0.353	0.371	0.350
Observation	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974
Panel B: Principal Component Analysis					
PC1	0.298	0.280	0.296	0.287	0.291
PC2	0.130	0.136	0.127	0.125	0.135
Unexpl. var.	0.922	0.763	0.837	0.844	0.877
Panel C: Time-Series Regression of PC1 on OTC Frictions and Other Variables					
Adj. R^2	0.234	0.240	0.289	0.232	0.235
R^2	0.306	0.335	0.361	0.310	0.313
F-statistic	4.261	3.524	5.002	3.980	4.025
p-value	0.000	0.000	0.000	0.000	0.000
Observations	129	129	129	129	129

Table IA.II: OTC Market Frictions and Yield Spread Changes, Alternative Variable Specifications. For each industrial bond i with at least 25 monthly observations of yield spread changes, $\Delta YS_{i,t}$, we estimate the following model:

$$\Delta YS_{i,t} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{\Delta F_{i,t}} + \boldsymbol{\gamma_{i,1}'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_{i,2}'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_{i,3}'} \boldsymbol{\Delta B_t} + \epsilon_{i,t}$$

The vector $\boldsymbol{\Delta F_{i,t}} := \left[\Delta LEV_{i,t},\, \Delta R_{i,t},\, \Delta RF_t,\, (\Delta RF_t)^2,\, \Delta SLOPE_t,\, \Delta VIX_t,\, \Delta\sigma_{i,t},\, RM_t,\, \Delta JUMP_t\right]$ is a modified version of the structural model variables defined in Section II. The vector $\boldsymbol{\Delta I_t} := [\Delta inv_t,\, \Delta amt.out_t,\, \Delta match.trd_t,\, \Delta ted_t]$ refers to the proxies for systematic inventory frictions introduced in Section III.A, the vector $\boldsymbol{\Delta S_t} := [\Delta centr_t,\, \Delta chain.len_t,\, \Delta lvc.sales_t,\, \Delta svc.sales_t]$ to the proxies for systematic search frictions introduced in Section III.B, and the vector $\boldsymbol{\Delta B_t} := [\Delta outside.opt_t,\, \Delta block.trd_t,\, \Delta dlr.conc_t,\, \Delta ig2junk_t]$ to the proxies for systematic bargaining proxies introduced in Section III.C. Panel A reports the average coefficients across bonds, the associated t-statistics, the mean and median adjusted R^2 values, and the numbers of observations and bonds in the sample, respectively. The t-statistics are calculated from the cross-sectional variation over the estimates for each coefficient. That is, we divide each reported coefficient value by the standard deviation of the estimates and scale by the square root of the number of bonds. Panel B reports the results of a principal component analysis on the residuals. We assign each month's residuals to one of 18 bins defined by three maturity groups (less than five years, five to eight years, greater than eight years) and six leverage groups (less than 15%, 15%–25%, 25%–35%, 35%–45%, 45%–55%, greater than 55%). For each bin and month we compute an average residual and then extract the principal components of the covariance matrix of these residuals. We report the proportions of variance explained by the first and second principal components, PC1 and PC2, respectively, and the total unexplained variance in percentage points. In Panel C we report the R^2 values, the F-statistics and corresponding p-values of a Wald-test of the following time-series regression model:

$$\text{PC1}_t = \alpha + \boldsymbol{\gamma_1'} \boldsymbol{\Delta I_t} + \boldsymbol{\gamma_2'} \boldsymbol{\Delta S_t} + \boldsymbol{\gamma_3'} \boldsymbol{\Delta B_t} + \epsilon_t$$

The sample is based on U.S. corporate bond transaction data from TRACE for the period 2003–2013.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Bond Regressions						
Intercept	0.082***	0.059***	0.072***	0.052***	0.088***	0.067***
	(9.920)	(5.380)	(8.317)	(3.998)	(10.153)	(5.605)
$\Delta LEV_{i,t}$	0.034***	0.029***				
	(4.703)	(3.055)				
$\Delta R_{i,t}$			−0.008***	−0.009***	−0.008***	−0.009***
			(−7.179)	(−6.851)	(−6.999)	(−6.940)
ΔRF_t	−0.216***	−0.180***	−0.262***	−0.269***	−0.223***	−0.208***
	(−6.065)	(−3.691)	(−7.890)	(−5.955)	(−6.679)	(−4.704)
$(\Delta RF_t)^2$	−0.275***	−0.205*	−0.147*	−0.055	−0.321***	−0.262**
	(−3.225)	(−1.683)	(−1.709)	(−0.461)	(−3.800)	(−2.129)
$\Delta SLOPE_t$	0.384***	0.486***	0.459***	0.670***	0.422***	0.567***
	(7.476)	(6.380)	(8.793)	(8.905)	(7.953)	(7.152)
ΔVIX_t			0.014***	0.008***		
			(6.415)	(2.608)		
$\Delta\sigma_{i,t}$	0.070***	0.025*			0.075***	0.030**
	(8.037)	(1.745)			(8.793)	(1.971)
RM_t	−0.037***	−0.032***	−0.024***	−0.021***	−0.032***	−0.026***
	(−13.526)	(−11.345)	(−8.094)	(−5.846)	(−12.212)	(−10.374)
$\Delta JUMP_t$	0.003*	0.008***	0.005***	0.005**	0.004**	0.008***
	(1.847)	(2.875)	(3.029)	(2.300)	(2.013)	(3.026)
Δinv_t		16.304***		14.459***		14.417***
		(5.154)		(4.495)		(4.652)
$\Delta amt.out_t$		1.853		1.093		1.599
		(1.225)		(0.741)		(1.054)
$\Delta match.trd_t$		4.156***		5.289***		4.359***
		(4.848)		(5.493)		(4.751)
Δted_t		0.279***		0.219**		0.232**
		(3.159)		(2.431)		(2.505)
$\Delta svc.sales_t$		1.298***		1.273***		1.251***
		(3.413)		(3.733)		(3.454)
$\Delta lvc.sales_t$		−1.790***		−2.340***		−1.799***
		(−3.587)		(−4.748)		(−3.620)
$\Delta chain.len_t$		−0.886*		−1.223***		−0.968**
		(−1.941)		(−2.659)		(−2.027)
$\Delta centr_t$		−1.042***		−1.362***		−1.037***
		(−4.188)		(−5.580)		(−4.313)
$\Delta outside.opt_t$		−0.010		0.002		−0.008
		(−1.382)		(0.302)		(−1.119)
$\Delta dlr.conc_t$		2.944***		1.845**		2.481***
		(3.377)		(2.237)		(2.778)
$\Delta block.trd_t$		−11.026***		−12.762***		−11.896***
		(−4.384)		(−5.506)		(−4.858)
$\Delta ig2junk_t$		−0.001		−0.001		0.000
		(−0.760)		(−1.087)		(0.256)
Mean adj. R^2	0.231	0.323	0.226	0.316	0.239	0.331
Median adj. R^2	0.227	0.370	0.211	0.349	0.231	0.376
Observations	45350	45350	45350	45350	45350	45350
Bonds	974	974	974	974	974	974
Panel B: Principal Component Analysis						
PC1	0.465	0.285	0.477	0.293	0.462	0.279
PC2	0.089	0.126	0.098	0.130	0.089	0.130
Unexpl. var.	1.618	0.888	1.626	0.891	1.578	0.860
Panel C: Time-Series Regression of PC1 on OTC Frictions						
Adj. R^2		0.234		0.232		0.230
R^2		0.306		0.304		0.302
F-statistic		4.266		4.224		4.192
p-value		0.000		0.000		0.000
Observations		129		129		129