Market Dominance in Bond and CDS Interdealer Networks*

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Abstract

Using a hand-constructed dataset that matches trading activity of credit dealers across both corporate bond and CDS markets, we investigate the network structure across both markets. Within the bonds and CDS outstanding for a given corporate bond issuer, we find a significant relationship between common dealers having high market share across both markets and the liquidity of that issuer's bonds. Even after controlling for dealer concentration in each market separately, the existence of common cross-market dealers with significant market dominance is associated with higher bond trading costs. This finding is robust to the inclusion of a variety of controls known to impact credit market liquidity. This paper adds to our understanding on the relationship between bond and CDS market activity.

JEL classification: G10, G12, G13, G14.

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1 Introduction

The process of credit risk intermediation and price discovery can occur across many markets and classes of securities. Investors differ both in their tolerance for credit risk exposure and in their private information about a particular credit risk, and can choose in which market to execute a trade. Market makers (dealers) operate across multiple markets and seek to facilitate credit risk transfers and learn from investor order flow. However, some markets (e.g. the market for a distressed or thinly traded bond) may only accommodate a few dealers, leading to differences in the degree of competition and market power across different markets.

With the growth in CDS markets, there is an increasing interest in understanding how these two markets in particular interact and how the trading activity between these two markets is related. Several theoretical papers have addressed various aspects of how the existence of CDS markets impact the market for bonds (e.g., Bolton and Oehmke (2011); Oehmke and Zawadowski (2015)). The empirical research in this area has primarily used data aggregated at an individual issuer- or bond-level (e.g., Blanco, Brennan, and Marsh (2005); Ashcraft and Santos (2009); Nashikkar, Subrahmanyam, and Mahanti (2011); Das, Kalimipalli, and Nayak (2014)). In contrast, this paper is the first to use a novel, granular dataset which matches the activity of individual dealers across both markets. This allows us to gain a more complete view of the overall trading activity of dealers in both credit markets. We use these data to investigate the relationship between dealers with very large market shares in both the bond and CDS markets for a particular issuer and the variation in liquidity across the bond market by issuer.

The interlinkages between trading in bonds and CDS has been analyzed since the inception of CDS trading. The main areas of concern to the academic literature have included i) how investors choose whether to trade in CDS versus bonds and how liquidity is affected by the introduction of CDS, ii) what positive and negative effects the introduction of CDS has on bondholders by facilitating information aggregation, risk management, and liquidity provision, but reducing monitoring incentives and increasing moral hazard, and iii) the potential of CDS to increase contagion across credit intermediaries by concentrating tail risks. This paper contributes to these three strands of the literature by examining the relationship between the costs to trading the bonds of a particular issuer firm and the market shares of common dealers across the bond and CDS markets of that issuer. As Gilchrist and Zakrajšek (2012) show, the excess bond premium implied in credit spreads is predictive of declines in future economic activity, because it reflects lower risk-bearing capacity in the financial sector. By focusing our study on dealer intermediation across two related credit markets—bonds and CDS—we hope to provide new information on the channel through which risk-bearing capacity is shared among these financial institutions.

In our empirical analysis, we match the set of bond dealers with the set of counterparties with positions in the CDS market for the period from January 2010 to December 2015. We aggregate the notional of corporate bond transactions in the secondary market by each dealer at each month for all bonds from a particular issuer and, using this, construct the dealer network at each month for each bond issuer. We then merge this dataset on the dealer's CDS positions on the same reference entity in the same month. This gives us a time series view into the importance of each dealer in both the bond and CDS interdealer network for each issuer firm. We document the characteristics of these related networks and analyze the relationship between the market shares of common dealers across the two markets and bond market liquidity.

We find that within the set of common dealers, the typical credit dealer is more central and connected in CDS markets than in bond markets. The "core-peripheral" network structure is also relatively more pronounced in CDS markets. In our main regression analysis, we find that common cross-market dealer concentration—having just a few dealers who are central in both CDS and bond markets at the same time—is associated with higher transaction costs in bond markets. This result remains robust and statistically significant even after accounting for the dealer concentration in the individual markets. This finding is also robust to the inclusion of a variety of controls capturing issuer characteristics and market conditions known to impact credit market liquidity.

Several papers have investigated the impact of large fractions of common ownership in generating excess correlation between markets and increasing market "fragility" (e.g., Greenwood and Thesmar (2011)). Others have examined the relationship between market concentration or skewed size distributions and aggregate volatility (e.g., Gabaix (2011); Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). Higher market concentrations increase aggregate market volatility by increasing the aggregate impact of idiosyncratic shocks to large dealers. In credit markets, this would mean that higher dealer concentrations would be associated with higher market volatility and hence, higher transaction costs in these markets. Our main findings are consistent with such a channel.

The rest of the paper is organized as follows. The next section presents a review of the relevant literature. Section 3 describes the data and variable definitions used in the empirical analysis. Section 4 gives an empirical overview of the bond and CDS inter-dealer networks and presents descriptive statistics of the market concentrations. Section 5 presents the main regression results analyzing the relationship between credit market liquidity and cross-market dealer concentration. The final section concludes.

2 Literature Review

Das, Kalimipalli, and Nayak (2014); Ashcraft and Santos (2009) look at whether CDS trading has provided a benefit for corporate bond trading and both find the introduction of CDS markets to be largely detrimental, with no reduction in bond spreads or pricing errors. In particular, Das, Kalimipalli, and Nayak (2014) find that corporate bond markets "became less efficient, evidenced no reduction in pricing errors, and experienced no improvement in liquidity."

Information from CDS markets can help explain corporate bond risk premia. Longstaff, Mithal, and Neis (2005) use data from CDS markets to separate out corporate bond spreads to default and non-default related components. They find that the default component accounts for most of the corporate spread across all ratings levels. The size of the non-default component is time-varying and is affected by both firm-specific and macroeconomic factors.

Several papers have looked at the relative pricing between CDS and bonds, and recent work has shown that liquidity across these two markets is a significant factor in the degree of mispricing. Blanco, Brennan, and Marsh (2005) look at pricing and spreads in the early life of the CDS market, and find evidence that CDS and bonds sometimes deviate from the parity relation first put forth by Duffie (1999). Nashikkar, Subrahmanyam, and Mahanti (2011) find that illiquidity in the bond market increases the price of the referencing CDS, due to limits to arbitrage. Moreover, they find that a liquid CDS market improves the relative pricing across bonds and CDS. Recently, Oehmke and Zawadowski (2015) construct a model of the trading relationship between CDS and bonds and show that the introduction of CDS brings both positive and negative effects: bonds are allocated more to long-term investors (the natural holders of these bonds), but CDS that is less costly to trade than bonds will crowd out demand for the underlying bond.

One significant concern from the availability of CDS linked to a bond is the effect this has on bondholder incentives. Bolton and Oehmke (2011) study the empty creditor problem, where a debtholder is protected by CDS insurance which reduces the incentives to monitor that debt and also increases the debtholder's bargaining power in bankruptcy. In a model of debt with and without CDS, their paper shows that lenders buy more CDS protection than is optimal, and this leads to an inefficiently high bankruptcy rate. In contrast, Streitz (2015) finds empirical evidence that when a borrower's CDS is actively traded, bank lenders are less likely to syndicate loans and tend to retain a larger fraction of the loans on their books. Streitz finds no evidence of increased moral hazard, implying lower syndication is likely due to a preference for risk management using CDS markets. On the borrower's side, Subrahmanyam, Tang, and Wang (2014) show that distressed firms are more likely to file for bankruptcy when they have CDS trading on them.

Because investors may choose to trade in both bonds and CDS when CDS is introduced, there is the potential for contagion effects which increase the correlation across these two markets for credit intermediation. Norden and Weber (2009) investigate the co-movement of bonds and CDS from 2000-2002. Their paper finds that CDS is more price-informative than bonds, and CDS is more sensitive to the reference entity's stock returns than bonds are, but both CDS and bond spreads are closely linked. Das, Duffie, Kapadia, and Saita (2007); Duffie, Eckner, Horel, and Saita (2009) present empirical evidence that over time, corporate defaults are significantly clustered, and that a latent factor of "frailty" can explain this clustering. Jorion and Zhang (2007) investigate the nature of this frailty, and find a credit contagion channel from a borrower's bankruptcy announcement to creditors' negative abnormal equity returns and higher CDS spreads.

The interlinkage between bond and CDS markets is crucial to our understanding of systemic risk. Indeed, a broad series of papers, including Beber, Brandt, and Kavajecz (2009); Duffie (2010); Palladini and Portes (2011); Friewald, Jankowitsch, and Subrahmanyam (2012), study the role of credit markets, and the failure of dealers who intermediate these markets, in contributing to systemic crises. For example, Duffie (2010) shows that dealer banks who interact across markets for securities, derivatives, securities lending, and repurchase agreements will naturally create a self-reinforcing isolation of troubled dealers that can precipitate a liquidity crisis and disrupt the network of credit market intermediation.

To characterize these networks within credit markets, we build on the literature of Neklyudov (2015); Hollifield, Neklyudov, and Spatt (2014); Dick-Nielsen, Feldhütter, and Lando (2012); Maggio, Kermani, and Song (2015) that use "small-world" structures (Watts and Strogatz (1998)) where each node represents a dealer. Neklyudov (2015) characterizes the bond market with a core-periphery network structure, and finds that core dealers sell to periphery dealers when not in distress, and buy from the periphery when in distress. Contrary to Babus and Kondor (2013), inventory risk rather than adverse selection drives this empirical finding. To construct the network Neklyudov (2015) looks at trading across all bonds with the same 5-digit CUSIP issuer, since many traders choose to be informed about an issuer, and may trade based on that information across multiple issues.

Hollifield, Neklyudov, and Spatt (2014) look at the role of market power within the interdealer network for bonds. They find that core dealers receive better pricing and trade at lower spreads than weaker, peripheral dealers. This effect increases in 144a securitizations, which have less public information and are less liquid. Maggio, Kermani, and Song (2015) find that central dealer markup charged to peripheral dealers in bonds rises during crisis, and dealers give better trade terms to others with whom they trade more frequently. This suggests that there is a value to the relationships dealers form from trading with each other, and removing a dealer from the network will then harm those dealers who had close trading relationships with the departed dealer.

Dick-Nielsen, Feldhütter, and Lando (2012) look at bond market liquidity during the 2008 financial crisis, across bonds whose lead underwriters became distressed versus those whose who did not, and find that bonds with distressed underwriters suffered worse illiquidity. Lead underwriters have an implicit commitment to support the liquidity of a bond in secondary market trading, and are therefore likely to be central dealers in the network of dealers trading on that issuer[1]. Rather than use a transaction-based measure of liquidty, the authors construct a liquidity premium as the portion of credit spreads not explained by other known factors in a first-stage regression.

Because CDS is a contract offering premiums in exchange for a default-contingent payment, it is naturally associated with tail risks. Therefore it is a particularly interesting market to study the potential for contagion and systemic risk. Zawadowski (2013) models banks who hedge their portfolios in the OTC market but do not hedge their counterparty risk, and show that a systemic run of lenders can occur when just one bank fails. Farboodi (2014) demonstrates a model of endogenous network formation among strategic financial intermediaries, which creates a core-periphery network structure featuring risky "overconnected" banks which face excessive counterparty risk. In Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), a different model of bank credit provision leads to an endogenously formed network that creates excessive lending and is prone to contagious defaults.

Empirical approaches to measuring the systemic risk posed by networks of financial intermediaries vary in their complexity and information requirements. Duffie (2011) proposes a "10-by-10-by-10" approach, where 10 core institutions are each required to

[1] We empirically investigate the network centrality of lead underwriter dealers and find this to be indeed true.

report detailed stress test results for 10 different scenarios, and their 10 largest counterparty exposures in each scenario. Wang (2015) proposes a measure of distress dispersion, estimated using the Z-scores of financial firms, as a measure of systemic risk across an imperfectly observed and endogenously formed network structure. Glasserman and Young (2015) make only minimal assumptions about the network structure of financial institutions using data on the European banking system, but use key firm-level risk measures to provide upper and lower bounds to the effects of network structure on amplifying or dampening contagion. They find that network structure is most critical when firms are highly heterogeneous and interconnected.

3 Data and Variable Definitions

3.1 Bond Transactions

We use a regulatory dataset containing all corporate bond transactions in the over-the-counter secondary market from January 2010 to December 2015 collected by the the Financial Industry Regulatory Authority, Inc. (FINRA) through their Trade Reporting and Compliance Engine (TRACE). This dataset identifies a party to a transaction when it is a bond dealer or an affiliate. Non-dealers in the data are marked only as customers ("C"). This allows us to obtain a granular network view over time of the interdealer bond market.

There are 9,058 distinct bond issuers in our data, where an issuer is identified through the first six digits of the CUSIP identifier of a bond. There are 1,847 distinct dealer subsidiaries trading during this sample period. We match 1,066 distinct dealer subsidiaries to 139 "parent" dealer institutions which trade across both bonds and CDS markets (not necessarily on the same reference entity).

3.2 CDS Positions

We use a regulatory dataset of all CDS positions from January 2010 to December 2015 from the Depository Trust and Clearing Corporation (DTCC), where at least one party to a transaction is a US person or the reference entity of the CDS is a US firm. We collect all single-name positions where one party is a bond dealer or CDS dealer. This excludes index CDS positions, but allows us to directly map a dealer's explicit exposure to a particular reference entity in both bond and CDS markets.

We match CDS contracts to the bond issuers they reference using Markit Reference Entity Database (RED) identifiers which map to bond CUSIPs. There are 4,105 distinct RED IDs in our sample, which map to 3,379 issuer CUSIPs.

Some large non-dealer CDS market participants cannot be matched to their bond market transactions, because the bond transactions dataset identifies all non-dealers only as customers with a "C". However, this does not affect the completeness of our view of the interdealer network constructed from all credit (bond and CDS) dealers.

3.3 Measures of Market Concentration

We use concentration measures based on the Herfindahl index for dealer notional activity in bond and credit networks to characterize the competitive nature of the interdealer network for each issuer at a particular point in time. The main measures used in the empirical analysis is shown in Eqs. 1, 2, and 3. The higher the Herfindahl measure, the higher the concentration of dealers for that issuer. The maximum possible value for all three measures is 1. In the regressions which use a continuous variable for dealer concentration, we use the standardized version of the log of these measures to capture concentration levels. In the main specifications, we use dummy variables to clearly show the characteristics of markets in the highest quintile and lowest quintile concentration.

$Herf\_Common_{i,t}$ measures the market concentration across bond and CDS markets for an issuer by the same dealers. For this measure to be relatively high for a particular issuer, the *same* few dealers must be dominant (have a large market share) in both the bond and CDS markets for that issuer. This captures the dominance of common dealers across bond and CDS markets. Note that, $Herf\_Common_{i,t} \not\equiv Herf\_Bond_{i,t} \times$

$Herf\_CDS_{i,t}$.

$$Herf\_Bond_{i,t} = \Sigma_d (\frac{Bond\_Notional_{d,i,t}}{Total\_Bond\_Notional_{i,t}})^2 \quad (1)$$

$$Herf\_CDS_{i,t} = \Sigma_d (\frac{CDS\_Notional_{d,i,t}}{Total\_CDS\_Notional_{i,t}})^2 \quad (2)$$

$$Herf\_Common_{i,t} = \Sigma_d [\frac{Bond\_Notional_{d,i,t}}{Total\_Bond\_Notional_{i,t}})^2 \cdot (\frac{CDS\_Notional_{d,i,t}}{Total\_CDS\_Notional_{i,t}})^2] \quad (3)$$

where, d is the dealer, i is the issuer, and t is the current month.

3.4 Market Liquidity

We use two measures of bond market liquidity in our empirical analysis. The first is Roll's measure (*TC_Roll*) from Roll (1984), a measure of relative bid-ask spreads, given by the bid-ask bounce.

For the second, we calculate the round-trip transaction cost (*TC_Roundtrip*) using the methodology in Feldhütter (2012). We aggregate all trades per bond with the same volumes that occur within a 15-minute window—this is defined as a round-trip transaction. Twice the difference between the lowest and highest trade price in the round-trip transaction is defined as the the round-trip transaction cost. This measure is then standardized by dividing the cost by the average of the maximum and minimum price in the round-trip transaction. $TC\_Roundtrip_{i,t}$ is the average overall round-trip transaction cost at each month t, for all the bond traded on issuer i.

To account for corrections of erroneous trades, duplicate reporting, or trades which were later withdrawn, we follow the process given in Dick-Nielsen (2009, 2014). To further remove mistaken trade reports in the Finra TRACE dataset, we also use the median and reversal filters of Edwards, Harris, and Piwowar (2007).

3.5 Controls for Bond Issuer Characteristics and Market Conditions

We use an array of control variables in our empirical analysis which are common to the literature and have been shown to affect bond liquidity and dealer market maker activity. These include issuer characteristics from Compustat: leverage, operating income to sales ratio, long term debt to assets ratio, and pre-tax interest rate coverage ratio (Blume, Lim, and MacKinlay, 1998; Dick-Nielsen, Feldhütter, and Lando, 2012); a measure of information asymmetry regarding the issuer: the ratio of dispersion in analysts' quarterly earnings estimates divided by the firm's stock price (Güntay and Hackbarth, 2010); bond characteristics from Mergent FISD: bond age, amount outstanding, coupon rate, time to maturity (Sarig and Warga, 1989; Longstaff, Mithal, and Neis, 2005); and macro controls to capture funding conditions that may affect dealer activity from CBOE and FRED: the VIX, 10 year swap rate (level of the yield curve) and 10 year minus 1 year swap rates (slope of the yield curve) (Duffie and Lando, 2001).

Table 1 shows summary statistics for characteristics of the bond issuers in our data sample.

Table 1: Bond Issuer Characteristics

Variable	N	Mean	Median	Std. Dev.
Op. Income to Sales	19,288	0.216	0.198	0.308
LT Debt to Assets	20,682	0.282	0.248	0.172
Leverage	20,724	3.577	1.807	50.124
Forecast Dispersion	4,264	0.003	0.001	0.036
Bond Notional	29,075	322.832	92.823	841.067
CDS Notional	29,075	10,136.749	6,065.648	13,754.276

4 Credit Interdealer Networks and Concentration

4.1 Network Characteristics

Table 2 presents summary statistics of the weekly time series of eigenvector centrality, degree centrality, and coreness-degree residual. Eigenvector centrality (EVC) measures the importance of a node within a network. The greater the number of node i's connections to other important nodes, the greater the EVC of node i. The degree centrality ("degree") of a node is the number of node connections to or from that node. The coreness of a node is defined as: if node i belongs to the k-core, but not the $k+1$-core, it has a coreness of k. k-core is the maximal subgraph where all nodes have at least degree k. Coreness-degree residual (CDResidual) is the difference between coreness and degree centrality.

Table 2 shows that for the same reference entity, the CDS network is more centralized than the bond network: nodes have an average EVC of 0.448 for CDS compared to 0.180 for bonds. Moreover, the average degree centrality and coreness are also both higher in the CDS networks.

We flag parties that have been an underwriter for any bond by a particular issuer. We are able to match 70 unique underwriters to both markets in our sample, across a large proportion of the bonds in our sample. Table 3 presents the network summary statistics separately for credit dealers who are bond underwriters and those that are not. Bond underwriters are more central and connected in *both* bond and CDS markets for the issuers whose bond they have underwritten.

Table 4 presents the network summary statistics separately for credit dealers who are dealers in CDS markets, and those that are not. The bond dealers who are also dealers in the CDS market are more central in *both* bond and CDS networks.

Table 2: Node Summary Statistics

	Mean	Median	Stdev
EVC_BOND	0.180	0.019	0.295
EVC_CDS	0.448	0.426	0.344
Degree_BOND	6.804	4.000	8.722
Degree_CDS	10.894	12.000	6.881
Coreness_BOND	3.462	3.000	2.752
Coreness_CDS	7.507	8.000	4.183
CDResidual_BOND	3.342	1.000	6.542
CDResidual_CDS	3.388	3.000	3.533

Table 3: Bond Underwriter Centrality in CDS and Bond Markets

Bond Underwriter	EVC_CDS	EVC_Bond	Degree_CDS	Degree_Bond
No	0.308	0.139	8.569	7.879
Yes	0.588	0.235	12.842	13.945

Table 4: CDS Dealer Centrality in CDS and Bond Markets

CDS Dealer	EVC_CDS	EVC_Bond	Degree_CDS	Degree_Bond
No	0.033	0.059	2.769	9.079
Yes	0.501	0.203	11.802	10.764

4.2 Market Concentration

This section presents descriptive statistics to illustrate the characteristics of issuers with varying degrees of dealer concentration in bond and CDS markets, as well as variation in the concentration of common dealers across both. Issuers are sorted into buckets by their concentration quintile at each month. Table 5 and 6 show summary statistics by dealer concentration (as measured by Eqs. 1 and 2) quintile in bond and CDS markets, respectively. Table 7 shows summary statistics by quintile for the cross-market concentration measure for dealers across both bond and CDS markets (Eq. 3). The set of issuers with the lowest concentration is denoted with a 1 and the highest with a 5. For the issuers in each quintile bucket, the three tables show the mean, median, and standard deviation of the concentration measures, bond market dollar notional, CDS market dollar notional, number of dealers, dispersion in equity analyst forecasts, leverage, operating income to sales, and long-term debt to assets. In the regressions in the next section analyzing the relationship between bond market liquidity and dealer concentration, we control for these and other variables capturing issuer characteristics and prevailing credit conditions.

Tables 5, 6, and 7 show that issuers who have high bond market dealer concentration tend to also have high CDS market dealer concentration and that this is due to common dealers being prominent across both these two markets. Issuers with higher concentration in both markets and across both through common cross-market dealers tend to have smaller markets by dollar notional and fewer common credit dealers operating in them. There is no significant trend by quintile for the other issuer characteristics of dispersion in equity analyst forecasts, leverage, operating income to sales, and long-term debt to assets.

Table 5: Summary Statistics by Bond Herfindahl Quintile

	Herf_Bond	Herf_CDS	Herf_Both	Bond Notional	CDS Notional	Num Dealers	Op. Income to Sales	LT Debt to Assets	Leverage	Forecast Dispersion
Mean										
1	0.131	0.118	0.002	630.837	18069.729	15.851	0.223	0.284	2.521	0.002
2	0.193	0.146	0.003	326.841	12277.178	12.181	0.221	0.297	4.313	0.002
3	0.268	0.184	0.008	233.110	9242.458	9.804	0.216	0.285	5.185	0.003
4	0.380	0.236	0.017	189.552	6435.078	7.814	0.211	0.273	3.254	0.005
5	0.641	0.272	0.043	235.663	4720.545	6.595	0.208	0.272	2.696	0.003
Median										
1	0.132	0.111	0.001	381.911	13077.477	15.000	0.231	0.250	1.802	0.001
2	0.191	0.136	0.003	146.788	8452.764	12.000	0.202	0.260	2.003	0.001
3	0.266	0.167	0.005	74.285	5723.196	9.000	0.192	0.244	1.825	0.001
4	0.376	0.213	0.011	38.790	3574.621	7.000	0.190	0.243	1.759	0.001
5	0.609	0.260	0.022	28.272	2325.942	6.000	0.185	0.247	1.689	0.001
Std.Dev.										
1	0.023	0.027	0.001	844.603	17802.833	3.915	0.357	0.162	56.907	0.005
2	0.026	0.045	0.003	830.791	14579.760	3.596	0.336	0.194	59.785	0.006
3	0.034	0.071	0.008	799.405	12678.861	3.631	0.284	0.181	43.055	0.007
4	0.049	0.100	0.021	704.602	9589.318	3.391	0.235	0.160	56.974	0.083
5	0.148	0.107	0.061	932.608	7335.272	2.953	0.307	0.160	23.531	0.009

Figure 1 shows the plots of the mean dealer Herfindahl in CDS markets ($Herf\_CDS$) against the mean dealer Herfindahl in bond markets ($Herf\_Bond$) across issuers and across time, respectively.

Figure 1(a) shows the time average of concentrations in CDS and bond markets across all issuers. While most periods where the average CDS market concentration is relatively low also has relatively lower bond market concentration, there are a significant number of months whether such a relationship does not hold.

Figure 1(b) shows the average concentrations across time by issuer. Issuers with a relatively higher concentration in one credit market tend to have a relatively higher concentration in the other. This is inline with the summary statistics in Tables 5 to 7, which show correlation in the concentrations across the two markets. Figure 1(b) shows that while there are issuers that deviate from this pattern, it holds for most issuers.

Table 6: Summary Statistics by CDS Herfindahl Quintile

	Herf_Bond	Herf_CDS	Herf_Both	Bond Notional	CDS Notional	Num Dealers	Op. Income to Sales	LT Debt to Assets	Leverage	Forecast Dispersion
Mean										
1	0.178	0.105	0.002	891.355	23152.294	16.879	0.235	0.267	4.193	0.002
2	0.235	0.129	0.004	350.792	12321.192	12.695	0.197	0.308	4.602	0.002
3	0.301	0.161	0.007	203.046	8022.547	10.111	0.210	0.297	1.794	0.006
4	0.392	0.215	0.016	119.878	4995.627	7.537	0.211	0.271	4.224	0.003
5	0.508	0.345	0.045	52.966	2288.192	5.035	0.227	0.267	2.864	0.002
Median										
1	0.148	0.103	0.001	449.319	16820.405	16.000	0.230	0.245	1.999	0.001
2	0.198	0.125	0.002	173.506	9606.688	13.000	0.189	0.273	1.966	0.001
3	0.259	0.159	0.005	81.526	6027.514	10.000	0.198	0.253	1.790	0.001
4	0.345	0.214	0.010	39.125	3179.222	7.000	0.192	0.234	1.695	0.001
5	0.463	0.324	0.024	14.780	924.557	5.000	0.195	0.248	1.635	0.001
Std.Dev.										
1	0.100	0.013	0.002	1444.693	21999.927	3.928	0.390	0.134	27.078	0.005
2	0.122	0.016	0.004	645.502	9704.570	2.429	0.286	0.200	71.252	0.007
3	0.151	0.019	0.008	579.607	7474.680	2.256	0.315	0.193	73.920	0.082
4	0.180	0.026	0.018	456.136	6024.136	1.971	0.308	0.164	27.633	0.009
5	0.199	0.085	0.061	218.584	3416.817	1.213	0.180	0.157	16.889	0.004

Table 7: Summary Statistics by Cross-Market Herfindahl Quintile

	Herf_Bond	Herf_CDS	Herf_Both	Bond Notional	CDS Notional	Num Dealers	Op. Income to Sales	LT Debt to Assets	Leverage	Forecast Dispersion
Mean										
1	0.202	0.132	0.001	670.688	19086.113	15.344	0.245	0.254	3.468	0.002
2	0.218	0.144	0.002	392.159	12279.008	12.630	0.214	0.305	2.894	0.002
3	0.288	0.173	0.004	277.739	9031.618	10.387	0.202	0.299	4.947	0.003
4	0.372	0.213	0.011	178.362	6530.788	8.166	0.214	0.284	3.164	0.002
5	0.535	0.293	0.055	97.842	3826.303	5.719	0.203	0.270	3.419	0.006
Median										
1	0.149	0.112	0.001	317.343	12496.636	15.000	0.234	0.226	1.741	0.001
2	0.181	0.128	0.002	182.950	9003.443	13.000	0.198	0.276	1.962	0.001
3	0.247	0.153	0.004	94.223	6330.163	10.000	0.195	0.271	1.921	0.001
4	0.334	0.196	0.010	47.163	4077.440	8.000	0.186	0.249	1.786	0.001
5	0.492	0.279	0.035	20.405	1880.482	5.000	0.185	0.242	1.676	0.001
Std.Dev.										
1	0.152	0.064	0.000	1182.378	21519.208	4.953	0.230	0.145	21.525	0.003
2	0.114	0.061	0.001	809.460	12254.610	3.497	0.251	0.195	78.629	0.006
3	0.135	0.071	0.001	750.926	9911.689	3.299	0.413	0.186	69.975	0.008
4	0.150	0.080	0.004	652.186	7966.497	2.867	0.350	0.168	19.043	0.010
5	0.192	0.095	0.058	548.620	5873.720	1.971	0.260	0.158	21.853	0.081

5 Credit Market Liquidity and Dealer Concentration

This section presents results from analyzing the relationship between the presence of dominant market players on bond liquidity and transaction costs. Eqs. 4 and 5 show the first-pass regression specification, which uses standardized versions of the log of the concentration measures defined in section 3.3. This allows the coefficients to be easily interpreted as the basis point change in bond market transaction costs associated with one standard deviation change in dealer concentration. Our main findings are robust to these transformations in the Herfindahl measures.

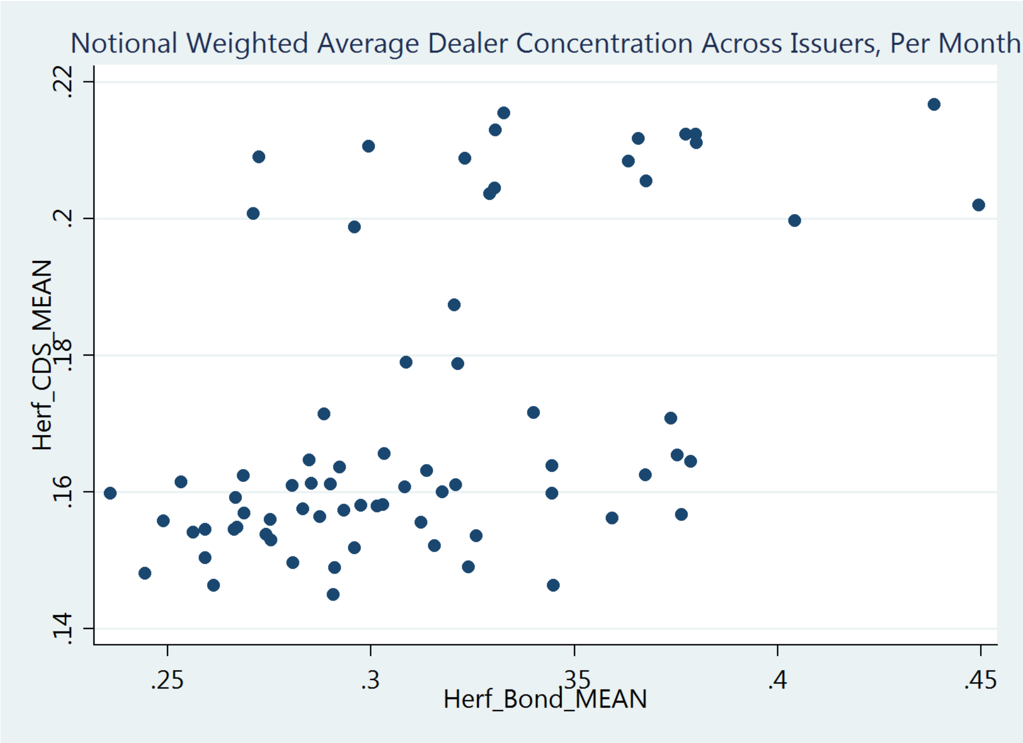
$$\begin{aligned} TC\_Roll_{i,t} =& \beta_1 Herf\_CDS_{i,t-1} + \beta_2 Herf\_Bond_{i,t-1} \\ &+ \beta_3 Herf\_Common_{i,t-1} + \boldsymbol{\gamma} \mathbf{Z_{i,t-1}} + \eta_{i,t}. \end{aligned} \tag{4}$$

$$\begin{aligned} TC\_Rountrip_{i,t} =& \beta_1 Herf\_CDS_{i,t-1} + \beta_2 Herf\_Bond_{i,t-1} \\ &+ \beta_3 Herf\_Common_{i,t-1} + \boldsymbol{\gamma} \mathbf{Z_{i,t-1}} + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

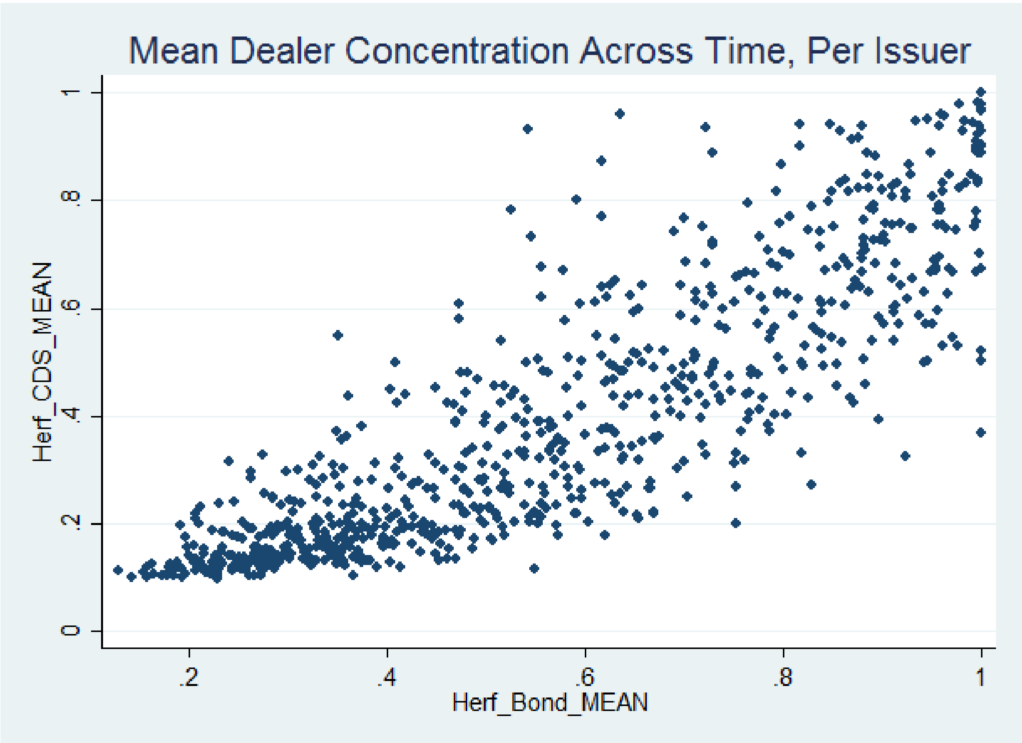
where, i is the issuer, t is the current month, $\mathbf{Z}$ is a set of controls, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ denote regression coefficients.

Regressions 1 through 5 in Table 8 use $TC\_Roll_{i,t}$ as the dependent variable, while regressions 6 through 10 use $TC\_Rountrip_{i,t}$, both in units of basis points. The coefficient on $Herf\_Common$ is positive and strongly significant under all specifications. This indicates that a high market concentration across bond and CDS markets by the same dealers is associated with an increase in transaction costs in bond markets. In these regressions, a one standard deviation increase in $Herf\_Common$ for an issuer is associated in the subsequent month with an increase in TC_Roll between 3.768 and 4.656 basis points and an increase in $TC\_Rountrip$ between 1.983 and 3.159 basis points.

We verify the robustness of this finding by using dummy variables in the regressions to capture the level of dealer concentration instead of the continuous concentration measures. Eq. 6 gives the specification of the regressions that use high/low quintile/tercile dummies instead of continuous Herfindahl measures. In the results shown in this section, high HHI refers to observations in the highest quintile of issuers by concentration



(a) Average concentration by month



(b) Average concentration by issuer

Figure 1: Bond and CDS market concentrations.
This figure plots the mean dealer Herfindahl in CDS markets against the mean dealer Herfindahl in Bond markets across issuers and across time, respectively.
Source: Authors' analysis.

Table 8: Bond Market Liquidity Regressions - Continuous Measure of Dealer Concentration

This table shows results for the panel regressions of monthly bond market liquidity as the dependent variable; regressions 1 through 5 use $TC\_Roll_{i,t}$ and regressions 6 through 10 use $TC\_Rountrip_{i,t}$. The units of these are transaction cost measures are in basis points. The results reported here are over the sample period (72 months) for all issuers in the sample (713). These regressions use the log of the concentration measures from all common dealers in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	$TC\_Roll_{i,t}$					$TC\_Rountrip_{i,t}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Herf_CDS	2.114***		1.864***		0.452	1.367***		0.638		-0.575
	5.670		3.749		0.705	4.964		1.476		-1.304
Herf_Bond		1.599***	0.364		-0.887		1.484***	1.061**		-0.011
		3.681	0.629		-1.510		5.098	2.378		-0.021
Herf_Common				2.927***	3.226***				2.363***	2.767***
				7.163	4.770				6.633	4.712
Observations	27,975	27,975	27,975	27,975	27,975	27,940	27,940	27,940	27,940	27,940
Adjusted R^2	0.031	0.030	0.030	0.031	0.031	0.049	0.049	0.049	0.050	0.050

within a particular month. Low HHI refers to observations in the lowest quintile of issuers by concentration within a particular month. This specification further removes concerns regarding heteroscedasticity, which are already addressed through the use of transformed Herfindahl measures in the previous regressions. This specifications using high/low dummy variables also allow for the analysis of any asymmetric relationships between high versus low dealer concentration issuers and their bond market liquidity. The main findings are robust to using tercile buckets instead of quintiles.

$$\begin{aligned} TC\_Roll_{i,t} =& \beta_1 High\_CDS\_HHI_{i,t-1} + \beta_2 Low\_CDS\_HHI_{i,t-1} \\ &+ \beta_3 High\_Bond\_HHI_{i,t-1} + \beta_4 Low\_Bond\_HHI_{i,t-1} \\ &+ \beta_5 High\_Common\_HHI_{i,t-1} + \beta_6 Low\_Common\_HHI_{i,t-1} \\ &+ \boldsymbol{\gamma} \mathbf{Z_{i,t-1}} + \eta_{i,t}. \end{aligned} \tag{6}$$

where, i is the issuer, t is the current month, $\mathbf{Z}$ is a set of controls, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ denote regression coefficients.

The coefficient on $High\_Common\_HHI$ is positive and significant in all specifications it is included in Table 9. Moreover, the coefficient on Low_Common_HHI is negative and strongly significant in all specifications it is included. This confirms the finding in Table 8 that high market concentration across bond and CDS markets by the same dealers is associated with an increase in transaction costs in bond markets. In these regressions, an issuer being in the highest quintile by $Herf\_Common$ is associated in the subsequent month with an increase in TC_Roll between 3.963 and 5.335 basis points, all else equal. An issuer being in the lowest quintile by $Herf\_Common$ is associated in the subsequent month with a *decrease* in TC_Roll between 5.029 and 5.504 basis points, all else equal.

This finding is also robust to including $High\_CDS\_HHI * High\_Bond\_HHI$ and $Low\_CDS\_HHI * Low\_Bond\_HHI$ as a dependent variable, indicated that the effect from the *same* dealer having high market shares across bond and CDS markets dominates the effect from the issuer having high concentrations in both markets independent of which dealers dominate across markets.

While the coefficients on $High\_CDS\_HHI$ and $High\_Bond\_HHI$ are consistently positive in the all the specifications they are included, the relationship is not significant once $High\_Common\_HHI$ is included in the regressions.

The results in Table 9 and the tables following remain essentially the same when dealers are sorted into *terciles* by their concentration measures, instead of quintiles. The baseline specification results with tercile buckets are shown in the appendix in Table A1.

5.1 Controlling for Issuer Characteristics

Table 10 adds in as controls the total notional of bond transactions and the number of common dealers across bond and CDS markets. These variables are at an issuer-month level. The coefficient on Low_Common_HHI is negative and strongly significant in all specifications it is included. Consistent with the results in Table 9, in this specification an issuer being in the lowest quintile by $Herf\_Common$ is associated in the subsequent month with a *decrease* in TC_Roll between 5.130 and 5.542 basis points.

The panel regression results with the same set of controls that instead use the continuous versions of the standardized concentration measures are shown in the appendix in Table A2. The main results remain the same in this specification.

Table 9: Baseline Bond Market Liquidity and Dealer Concentration Regressions

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 29,267 issuer-month observations. These regressions use highest and lowest quintile of the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	(1)	(2)	(3)	(4)	(5)	(6)
High_CDS_HHI	2.696**		2.308*		0.236	-0.609
	2.112		1.900		0.203	-0.408
Low_CDS_HHI	-3.496***		-2.146***		-0.057	-0.120
	-4.536		-3.100		-0.077	-0.105
High_Bond_HHI		1.047	0.035		-1.495	-2.289*
		0.960	0.035		-1.468	-1.860
Low_Bond_HHI		-4.257***	-2.869***		-0.652	-0.766
		-5.249	-3.677		-0.812	-0.634
High_Common_HHI				4.433***	4.898***	5.030***
				3.878	4.348	4.351
Low_Common_HHI				-6.474***	-6.231***	-6.259***
				-8.936	-8.176	-7.999
High_CDS_HHI*High_Bond_HHI						2.031
						1.003
Low_CDS_HHI*Low_Bond_HHI						0.072
						0.044
Observations	27,975	27,975	27,975	27,975	27,975	27,975
Adjusted R^2	0.030	0.030	0.031	0.032	0.032	0.032

Table 10: Bond Market Liquidity and Dealer Concentration Regressions

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 11,112 issuer-month observations. These regressions use highest and lowest quintile of the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	(1)	(2)	(3)	(4)	(5)	(6)
High_CDS_HHI	0.087		-0.011		-0.577	-1.222
	0.067		-0.009		-0.478	-0.756
Low_CDS_HHI	-2.559***		-2.097**		-1.491	-1.210
	-2.602		-2.269		-1.639	-0.836
High_Bond_HHI		1.090	1.252		0.255	-0.328
		1.038	1.281		0.254	-0.268
Low_Bond_HHI		-3.012***	-2.639***		-0.954	-0.736
		-3.318	-3.229		-1.154	-0.553
High_Common_HHI				4.349***	4.644***	4.747***
				3.742	4.148	4.194
LLow_Common_HHI				-7.985***	-7.477***	-7.447***
				-9.500	-9.233	-8.794
High_CDS_HHI*High_Bond_HHI						1.493
						0.732
Low_CDS_HHI*Low_Bond_HHI						-0.626
						-0.348
Issuer_Bond_Notional	-3.108***	-3.118***	-3.119***	-3.093***	-3.104***	-3.109***
	-13.445	-13.882	-13.277	-14.218	-13.312	-13.087
Num_Dealers	0.687***	0.721***	0.828***	1.059***	1.165***	1.154***
	8.097	9.572	9.209	12.539	12.260	11.558
Observations	27,975	27,975	27,975	27,975	27,975	27,975
Adjusted R^2	0.033	0.033	0.033	0.035	0.035	0.035

In addition to the issuer-level controls included in Table 10, Table 11 adds in additional issuer characteristics as controls: operating income to sales, and long-term debt to assets, leverage, dummies for the pre-tax interest rate coverage ratio, and dispersion in equity analyst forecasts. The finding that an issuer being in the lowest quintile by $Herf\_Common$ is associated in the subsequent month with a *decrease* in TC_Roll remains robust. In these specifications the coefficient on Low_Common_HHI is negative and strongly significant in all specifications it is included.

The panel regression results with the same set of controls that instead use the continuous versions of the standardized concentration measures are shown in the appendix in Table A3. The main results remain the same in this specification.

5.2 Controlling for Funding Conditions

In addition to the issuer characteristics controls included in Table 11, the regressions presented in this section control for variables that capture prevailing funding conditions, which may affect the market maker activity of credit dealers. Table A4 and 12 control for high and low VIX periods (sorted into terciles), and the level and slope of the yield curve (as characterized by the 10-year swap rate and the difference in the 10-year and 1-year swap rates).

In Table A4, the coefficient on $Herf\_Common$ is positive and strongly significant under all specifications. Even after controlling for prevailing funding conditions, a high market concentration across bond and CDS markets by the same dealers is associated with an increase in transaction costs in bond markets. In these regressions, a one standard deviation increase in $Herf\_Common$ for an issuer is associated in the subsequent month with an increase in TC_Roll between 2.603 and 3.416 basis points. The coefficients on the interaction terms $Herf\_Common * High\_VIX$ and $Herf\_Common * Low\_VIX$ indicate that during periods of high VIX, this relationship is more positive and during periods of low VIX, it is smaller.

In Table 12, the finding that an issuer being in the lowest quintile by $Herf\_Common$ is associated in the subsequent month with a *decrease* in TC_Roll remains robust to the

Table 11: Bond Market Liquidity and Dealer Concentration Regressions

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 11,112 issuer-month observations. These regressions use highest and lowest quintile of the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	(1)	(2)	(3)	(4)	(5)	(6)
High_CDS_HHI	-2.007		-2.053		-2.323	-2.769
	-1.189		-1.305		-1.492	-1.358
Low_CDS_HHI	-0.944		-0.296		0.298	-0.559
	-0.962		-0.326		0.329	-0.364
High_Bond_HHI		0.863	1.272		0.542	0.162
		0.657	1.067		0.474	0.113
Low_Bond_HHI		-3.550***	-3.269***		-1.660*	-2.515*
		-3.464	-3.587		-1.808	-1.664
High_Common_HHI				2.647**	3.127***	3.142***
				2.016	2.829	2.763
Low_Common_HHI				-6.871***	-6.193***	-6.331***
				-7.606	-7.256	-6.929
High_CDS_HHI*High_Bond_HHI						1.049
						0.416
Low_CDS_HHI*Low_Bond_HHI						1.900
						0.915
Issuer_Bond_Notional	-2.870***	-2.801***	-2.902***	-2.793***	-2.893***	-2.870***
	-11.097	-10.344	-10.657	-11.308	-10.843	-10.603
Num_Dealers	0.479***	0.693***	0.653***	0.897***	0.901***	0.911***
	3.956	6.454	5.017	8.078	6.640	6.694
OpIncome_Sales	-1.638***	-1.670***	-1.640***	-1.589***	-1.568***	-1.568***
	-3.165	-3.296	-3.179	-3.119	-3.039	-3.037
LTDebt_Assets	-0.317	-0.190	-0.220	-0.270	-0.240	-0.230
	-0.859	-0.520	-0.597	-0.720	-0.641	-0.619
Leverage	0.575	0.555	0.555	0.559	0.547	0.548
	1.295	1.258	1.260	1.264	1.244	1.248
Pretax_Dummy1	-0.274**	-0.279**	-0.279**	-0.279**	-0.281**	-0.282**
	-2.310	-2.301	-2.317	-2.343	-2.354	-2.360
Pretax_Dummy2	-3.479***	-3.448***	-3.460***	-3.372***	-3.380***	-3.379***
	-14.617	-14.670	-14.619	-14.093	-14.178	-14.204
Pretax_Dummy3	-0.467***	-0.454***	-0.462***	-0.433***	-0.440***	-0.436***
	-4.392	-4.307	-4.344	-4.156	-4.177	-4.210
Pretax_Dummy4	0.153***	0.153***	0.157***	0.148***	0.154***	0.154***
	4.599	4.545	4.717	4.249	4.506	4.487
Observations	18,401	18,401	18,401	18,401	18,401	18,401
Adjusted R^2	0.040	0.040	0.040	0.041	0.041	0.041

inclusion of controls for funding conditions that may affect dealer market making activity.

6 What Makes a Dealer Central?

Many hypotheses have been put forth in the literature that seek to explain the origin and evolution of over-the-counter market structure. Previous empirical work has also sought to confirm observed network characteristics, such as the core-periphery structure documented in , , , , however these studies stop short of attempting to rule out alternative hypothesis in favor of one. We characterize these hypotheses according to three categories: path dependence/history, differential risk aversion or risk bearing capacity, and skill.

Path dependence comes from a model where traders face search costs, such as in Duffie, Garleanu, Pedersen, ...

Models developed with a mechanism of differential risk aversion for generating a network can be found in

Differential dealer skill is a potential that has been less studied in the literature, ...

These three alternative hypotheses bear radically different implications for policymakers and the future development of this market. If dealers become and remain central simply because search costs are large and certain dealers had a "first-mover" advantage from being central when the bond was newly issued, that suggests dealers are replaceable and policymakers should worry about alleviating search costs and encouraging centralized exchanges. On the other hand, if dealers become central because they are more risk-loving than other dealers, policymakers should be concerned that central dealers concentrate risk and could be held to tighter standards and supervision than peripheral dealers. However, if dealers are central due to superior skill, this suggests an important benefit to current market structure: our central dealers are those most effective at enforcing price informativeness and intermediating credit risk in the market, and policymakers should seek to support their continued activity, e.g. via emergency liquidity guarantees.

The main contribution of our paper is to present and employ a method of identification between these three competing hypotheses. We do this by constructing a high-frequency,

Table 12: Bond Market Liquidity and Dealer Concentration Regressions

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 11,112 issuer-month observations. These regressions use highest and lowest quintile of the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include issuer fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	(1)	(2)	(3)	(4)	(5)
High_CDS_HHI	0.397		0.985		0.662
	0.275		0.684		0.446
Low_CDS_HHI	-0.746		-1.225		-1.239
	-0.845		-1.390		-1.336
High_Bond_HHI		-1.313	-1.447		-1.938**
		-1.431	-1.560		-2.033
Low_Bond_HHI		0.268	0.364		0.692
		0.280	0.371		0.679
High_Common_HHI				1.834*	2.412**
				1.882	2.307
Low_Common_HHI				-1.480**	-1.682**
				-2.215	-2.197
High_VIX	7.853***	7.603***	7.854***	7.018***	7.546***
	3.297	3.220	3.293	2.970	3.177
High_VIX*High_CDS_HHI	-0.297		-1.550		-2.773
	-0.133		-0.722		-1.158
High_VIX*Low_CDS_HHI	-2.466**		-0.701		-0.483
	-2.105		-0.533		-0.357
High_VIX*High_Bond_HHI		1.940	2.397		1.382
		0.972	1.333		0.717
High_VIX*Low_Bond_HHI		-3.041**	-2.945**		-2.724*
		-2.500	-1.997		-1.754
High_VIX*High_Common_HHI				2.922*	3.127
				1.665	1.569
High_VIX*Low_Common_HHI				-1.742	-0.272
				-1.372	-0.180
10y_Swap	57.585***	57.675***	57.645***	57.625***	57.621***
	6.554	6.555	6.561	6.570	6.574
10y-1y_Swap	-54.382***	-54.422***	-54.445***	-54.478***	-54.517***
	-6.247	-6.243	-6.258	-6.263	-6.279
Issuer Controls	Yes	Yes	Yes	Yes	Yes
Observations	18,401	18,401	18,401	18,401	18,401
Adjusted R^2	0.189	0.189	0.188	0.189	0.189

granular measure of dealer trading profits from market-making across individual CUSIPs and across time, as well as measures of time-varying, CUSIP-specific network centrality for each dealer.

We define dealer market-making profits in several ways. The most coarse measure of dealer profit comes from taking the gross dollars spent selling securities minus the gross dollars spent buying securities across N trades by dealer i in CUSIP j at time period t, as well as their profits and losses on outstanding inventory positions, i.e.

$$DealerProfits_{i,j,t} = \sum_{n=1}^{N} (\mathbb{1}_{sell} * Quantity_n * Price_n - \mathbb{1}_{buy} * Quantity_n * Price_n) + (Inventory_t * Price_t - Inv \tag{7}$$

However, assessing and evaluating dealer profit is not necessarily this straightforward, because dealers can offer customers a tradeoff between price and immediacy. Riskless principal trades (where the dealer does not trade with a customer until they've found an offsetting trade with another counterparty) may be less costly for central dealers, if they face lower search costs than periphery dealers. These kinds of trades would likely have lower time in inventory for the dealer, as well as lower dealer profits. Therefore we identify chains of pre-arranged trades according to several potential filters:

Riskless Principal Trades: A chain of buy and sell orders involving the same dealer, whose quantities completely offset each other and occur within 15 minutes.

"Pure" Riskless Principal Trades: a subset of riskless principal trades, which occur within 1 minute, and involve just one buy order and one sell order

Same-day Trades: A chain of buy and sell orders involving the same dealer, whose quantities completely offset other and occur within the same day. Note that it is possible for a dealer to have additional trades that day which are not offset, and are separate from this trade chain but still considered in our analysis.

"FIFO" Trades: Using the "FIFO" method of trade classification from Li and Schurhoff (2014), we look at chains of trades where the dealer was able to completely offset a position within 40 days.

7 Conclusions

This paper uses a matched dataset of dealers common to both corporate bond and CDS markets to investigate the relationship between the activity of these common dealers and bond market liquidity. The novel, granular dataset used in the empirical analysis allows us to gain a more complete view of the overall credit risk taken by dealers.

We find that common cross-market dealer concentration is associated with higher transaction costs in bond markets. This result remains robust and statistically significant even after accounting for any impact from the dealer concentration in the individual markets. This finding is also robust to the inclusion to controls capturing issuer characteristics and market conditions known to impact credit market liquidity, drawn from the previous literature (Sarig and Warga, 1989; Blume, Lim, and MacKinlay, 1998; Duffie and Lando, 2001; Longstaff, Mithal, and Neis, 2005; Güntay and Hackbarth, 2010).

Dealers who are dominant players in both bond and CDS markets may have a higher information advantage, smaller risk of adverse selection, higher risk-bearing capacity, higher inventory management efficiency, or greater monopoly power. If that is the case, the variation in the extent to which dealers are concentrated in both markets for a particular reference entity should be related to the cost of transacting that issuer's bonds. Moreover, other studies have shown that high concentrations are associated with higher levels of aggregate volatility (e.g., Gabaix (2011); Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)), which would in turn also affect bond market liquidity. The findings in this paper provides insight into which of these mechanisms likely prevail between bond and CDS markets. In future work, we hope to narrow down the channel through which the relationship between common dealer market share and bond market liquidity arises.

A Appendix

Table A1: Bond Market Liquidity Regressions - Dealer Concentration Terciles

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 29,267 issuer-month observations. These regressions use highest and lowest tercile of the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	(1)	(2)	(3)	(4)	(5)	(6)
High_CDS_HHI	1.105		0.878		-1.074	-1.456
	0.794		0.767		-0.991	-1.060
Low_CDS_HHI	-2.996***		-2.991*		-1.040	1.343
	-2.732		-1.681		-0.657	1.363
High_Bond_HHI		1.520*	0.740		-0.860	-1.517
		1.714	0.818		-0.849	-1.359
Low_Bond_HHI		-1.322	0.308		2.487	4.842
		-1.018	0.166		1.155	1.323
High_Common_HHI				4.158***	5.521***	6.056***
				3.394	4.986	6.007
Low_Common_HHI				-3.152***	-4.019***	-3.628***
				-2.863	-2.627	-2.620
High_CDS_HHI*High_Bond_HHI						1.516
						0.770
Low_CDS_HHI*Low_Bond_HHI						-5.144
						-1.488
Observations	27,975	27,975	27,975	27,975	27,975	27,975
Adjusted R^2	0.030	0.030	0.030	0.031	0.031	0.032

Table A2: Bond Market Liquidity Regressions - Continuous Measure of Dealer Concentration

This table shows results for the panel regressions of monthly bond market liquidity as the dependent variable; regressions 1 through 5 use $TC\_Roll_{i,t}$ and regressions 6 through 10 use $TC\_Rountrip_{i,t}$. The units of these are transaction cost measures are in basis points. The results reported here are for all common dealers over the sample period (60 months) for 29,267 issuer-month observations. These regressions use the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	$TC\_Roll_{i,t}$					$TC\_Rountrip_{i,t}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Herf_CDS	0.751		0.442		-0.333	1.820***		0.967*		0.197
	1.155		0.692		-0.481	3.389		1.648		0.339
Herf_Bond		1.043	0.974		-0.092		2.839***	2.688***		1.634***
		1.617	1.503		-0.145		7.009	6.158		3.247
Herf_Common				3.119***	3.212***				3.840***	3.181***
				4.705	4.611				7.690	5.367
Issuer_Bond_Notional	-3.045***	-3.131***	-3.089***	-2.991***	-3.017***	-4.268***	-4.481***	-4.387***	-4.284***	-4.316***
	-13.437	-14.175	-13.522	-13.609	-13.415	-20.145	-22.119	-20.450	-21.371	-20.375
Num_Dealers	0.650***	0.695***	0.750***	0.959***	0.909***	1.478***	1.635***	1.756***	1.727***	1.912***
	5.925	6.098	5.587	7.803	6.380	12.677	17.501	15.300	18.012	16.600
Observations	27,975	27,975	27,975	27,975	27,975	27,940	27,940	27,940	27,940	27,940
Adjusted R^2	0.033	0.033	0.033	0.034	0.034	0.061	0.062	0.062	0.063	0.064

Table A3: Bond Market Liquidity Regressions - Continuous Measure of Dealer Concentration

This table shows results for the panel regressions of monthly bond market liquidity as the dependent variable; regressions 1 through 5 use $TC\_Roll_{i,t}$ and regressions 6 through 10 use $TC\_Rountrip_{i,t}$. The units of these are transaction cost measures are in basis points. The results reported here are for all common dealers over the sample period (60 months) for 11,112 issuer-month observations. These regressions use the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include time fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	$TC\_Roll_{i,t}$					$TC\_Rountrip_{i,t}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	127.163***	124.540***	125.841***	121.769***	123.813***	134.029***	129.844***	130.702***	128.007***	128.260***
	66.120	63.516	52.212	61.389	46.350	78.018	122.048	76.355	111.292	73.841
Herf_CDS	-0.176		-0.707		-1.406**	0.868		-0.467		-1.313*
	-0.229		-1.011		-2.061	1.241		-0.634		-1.789
Herf_BOND		1.469	1.578*		0.546		3.902***	3.974***		2.724***
		1.574	1.708		0.655		8.088	7.831		5.007
Herf_BOTH				2.822***	2.844***				4.401***	3.442***
				3.403	4.389				8.020	5.708
Issuer_Bond_Notional	-2.806***	-2.845***	-2.921***	-2.681***	-2.844***	-4.354***	-4.594***	-4.645***	-4.274***	-4.550***
	-10.848	-10.494	-10.448	-10.730	-10.361	-15.847	-17.073	-16.602	-15.996	-16.336
Num_Dealers	0.459***	0.715***	0.633***	0.860***	0.753***	1.414***	1.907***	1.853***	1.880***	1.997***
	3.082	3.549	2.856	5.002	3.147	11.024	17.500	13.854	18.403	14.703
OpIncome_Sales	-1.669***	-1.664***	-1.646***	-1.650***	-1.613***	-2.211***	-2.166***	-2.155***	-2.155***	-2.114***
	-3.263	-3.306	-3.262	-3.300	-3.228	-5.511	-5.450	-5.447	-5.442	-5.399
LTDebt_Assets	-0.281	-0.123	-0.149	-0.107	-0.125	-1.256***	-0.904**	-0.922**	-1.044***	-0.893**
	-0.771	-0.322	-0.394	-0.286	-0.328	-3.224	-2.291	-2.342	-2.647	-2.268
Leverage	0.577	0.573	0.570	0.566	0.560	-0.014	-0.029	-0.031	-0.034	-0.043
	1.295	1.284	1.281	1.257	1.250	-0.038	-0.080	-0.085	-0.093	-0.118
Pretax_Dummy1	-0.273**	-0.278**	-0.278**	-0.277**	-0.277**	-0.188*	-0.201*	-0.201*	-0.193*	-0.200*
	-2.285	-2.304	-2.302	-2.322	-2.320	-1.782	-1.886	-1.886	-1.848	-1.903
Pretax_Dummy2	-3.477***	-3.453***	-3.465***	-3.387***	-3.405***	-3.755***	-3.716***	-3.724***	-3.636***	-3.652***
	-14.426	-14.169	-14.168	-13.490	-13.562	-17.012	-17.272	-17.106	-16.658	-16.687
Pretax_Dummy3	-0.459***	-0.440***	-0.449***	-0.423***	-0.436***	-0.069	-0.038	-0.044	-0.028	-0.028
	-4.378	-4.109	-4.223	-4.016	-4.116	-0.589	-0.312	-0.364	-0.234	-0.231
Pretax_Dummy4	0.151***	0.154***	0.157***	0.152***	0.158***	0.164***	0.176***	0.177***	0.169***	0.179***
	4.498	4.570	4.676	4.449	4.654	3.617	3.836	3.886	3.625	3.861
Observations	18,401	18,401	18,401	18,401	18,401	18,396	18,396	18,396	18,396	18,396
Adjusted R^2	0.040	0.040	0.040	0.041	0.041	0.098	0.102	0.102	0.102	0.104

Table A4: Bond Market Liquidity Regressions - Continuous Measure of Dealer Concentration

This table shows results for the panel regressions of monthly $TC\_Roll_{i,t}$ as the dependent variable. The units of this transaction cost measures is in basis points. The results reported here are for all common dealers over the sample period (60 months) for 11,112 issuer-month observations. These regressions use the log of the concentration measures in Eqs. 1-3, which are then standardized. All regressions include issuer fixed effects. t-statistics clustered by month are shown below each coefficient estimate.

	$TC\_Roll_{i,t}$					$TC\_Rountrip_{i,t}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	38.621***	37.912***	38.748***	36.770***	38.211***	30.935***	30.064***	30.817***	28.742***	29.939***
	7.480	7.625	7.690	7.326	7.683	6.604	7.198	6.552	7.012	6.425
Herf_CDS	-1.370		-1.473		-1.830	-0.504		-0.499		-1.183
	-0.969		-1.016		-1.252	-0.414		-0.399		-0.953
Herf_Bond		-0.591	-0.150		-0.525		0.246	0.243		-0.455
		-0.780	-0.275		-0.958		0.481	0.449		-0.775
Herf_Common				0.488	1.097*				1.510***	1.973***
				0.662	1.783				2.893	3.305
High_VIX	7.409***	7.311***	7.394***	7.323***	7.371***	7.654***	7.676***	7.664***	7.602***	7.654***
	3.105	3.025	3.076	3.067	3.066	4.787	4.787	4.788	4.786	4.789
High_VIX*Herf_CDS	0.848		1.646		1.631	0.103		-0.346		0.090
	0.975		1.003		0.813	0.148		-0.402		0.089
High_VIX*Herf_Bond		-0.024	-1.123		-1.133		0.430	0.633		1.049
		-0.022	-0.605		-0.678		0.659	0.805		1.144
High_VIX*Herf_Common				0.361	-0.003				-0.174	-1.046
				0.395	-0.002				-0.240	-0.875
10y_Swap	58.266***	57.652***	58.304***	57.524***	58.315***	37.504***	37.264***	37.488***	36.977***	37.500***
	6.467	6.545	6.450	6.517	6.462	10.050	9.737	10.015	9.638	10.001
10y-1y_Swap	-54.965***	-54.399***	-55.023***	-54.275***	-55.051***	-30.896***	-30.668***	-30.863***	-30.412***	-30.889***
	-6.156	-6.218	-6.122	-6.215	-6.144	-8.068	-7.911	-8.045	-7.833	-8.038
Issuer Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,401	18,401	18,401	18,401	18,401	18,396	18,396	18,396	18,396	18,396
Adjusted R^2	0.189	0.189	0.189	0.189	0.189	0.425	0.425	0.425	0.425	0.425

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