Information Friction in OTC Interdealer Markets

Benjamin Gardner and Yesol Huh*

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Abstract

In over-the-counter (OTC) securities markets, interdealer markets are an important venue through which dealers can offload positions and share risk amongst themselves. Contrary to the popular conception that search frictions and dealer network matter the most in OTC markets, we find that in the interdealer market for U.S. corporate bonds, information frictions are most relevant. Large dealers face large and informed customers and pay more than small dealers to transact in the interdealer market, despite on average providing liquidity to other dealers. Large dealers tend to trade through interdealer brokers (IDBs) to mitigate information leakage, but interdealer markets are still far from efficient.

*Benjamin Gardner: Yale University, ben.gardner@yale.edu; Yesol Huh: Federal Reserve Board, yesol.huh@frb.gov. Please direct comments and questions to yesol.huh@frb.gov. We thank the participants at the Summer Workshop on Money, Banking, Payments, and Finance for their feedback and suggestions. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the staff, by the Board of Governors, or by the Federal Reserve System.

1 Introduction

In over-the-counter (OTC) securities markets, interdealer markets are an important venue through which dealers can offload positions and share risk with one other. Dealers intermediate customer order flow and offload some of that order flow through the interdealer market. Much of the literature on OTC markets has focused on search frictions and network formation to explain price and trading dynamics (Duffie et al., 2005; Lagos and Rocheteau, 2009; Wang, 2016). Moreover, the empirical literature on OTC interdealer markets has emphasized the core-periphery network in this market as an imperfect mechanism to mitigate search costs.

In this paper, we study which frictions are most relevant in the OTC interdealer markets. We find that in the U.S. corporate bond market, contrary to popular conception, information frictions play a large role. Large dealers face large and informed customers, so they have a more difficult time offloading customer order in the interdealer market—large dealers pay more to transact in the interdealer market despite the fact that they on average provide liquidity in this market. Large dealers tend to trade through interdealer brokers (IDBs) to mitigate information leakage, but interdealer markets are still far from efficient.

We divide dealers into six categories. We generally think of dealers as engaging in similar activities—intermediating customer order flow and offloading some of that order flow in the interdealer market—and differing mostly along the dimensions of size, search costs, or their position in the network. However, three categories—alternative trading systems (ATS), interdealer brokers (IDBs), and client brokers—are "special" types in that these types of dealers are somewhat different from the dealers that are typically discussed in the literature. ATS and IDBs predominantly engage in interdealer trades only. ATS are designated by FINRA and are mostly different types of electronic platforms.[1] IDBs are brokers that match buyers with sellers in the interdealer market and account for 25% of interdealer volume. Client brokers mostly act as agents between customers and other dealers. The other three dealer categories are the "typical" dealers, which we divide into small, medium, and large by customer volume.

The existing literature has mostly compared central dealers and peripheral dealers. Not surprisingly, large dealers are more central, and small dealers are peripheral. Thus, some "centrality" effects studied in the prior literature, such as whether central dealers charge higher bid-ask spreads (Li and Schürhoff, 2019; Hollifield et al., 2016; Di Maggio et al., 2017; Dick-Nielsen et al., 2023), may be driven by dealer balance sheet size or customer volume rather than centrality. Moreover, our results indicate that some of the IDBs account for a large share of interdealer volume and are quite central in the interdealer network. However,

[1] See https://www.finra.org/filing-reporting/otc-transparency/finra-equity-ats-firms-list for the list of ATS.

these IDBs behave quite differently from large dealers. Thus, some of the centrality effects documented in the literature may arise because researchers conflate large dealers with IDBs despite their disparate roles. For instance, the finding that central dealers charge higher bid-ask spreads in the interdealer market (Di Maggio et al., 2017; Dick-Nielsen et al., 2023) is attributable to IDBs, not large dealers, charging higher bid-ask spreads.

We study who provides liquidity to whom and at what prices different categories of dealers trade in the interdealer market. Consistent with Li and Schürhoff (2019), we find that large dealers tend to provide liquidity to smaller dealers. However, we also find that despite providing liquidity on average, large dealers actually pay higher trading costs in the interdealer market compared to medium and small dealers. Additionally, interdealer trading costs have a U-shape in which the largest and the smallest dealers pay higher trading costs than medium sized dealers. We conjecture that for larger dealers (the top 30-40 dealers), information asymmetry matters more, whereas for smaller dealers, search frictions matter more. If so, given that top 30 dealers account for much more of the interdealer volume than small dealers, information asymmetry is the more dominant friction in the U.S. corporate bond interdealer market.

Consistent with this conjecture, we find that large dealers absorb significantly more informed customer order flow. Thus, when they try to offload this order flow in the interdealer market, other dealers are reluctant to trade with them. Therefore, large dealers offload less and face higher trading costs in the interdealer market.[2]

Moreover, large dealers are more likely to trade through IDBs than smaller dealers are. If search frictions were the dominant constraint, we would expect IDBs to predominantly intermediate the trades of small dealers since they face highest search costs. On the other hand, information asymmetry can lead large dealers to use IDBs. Bilateral contact can lead to information leakage even if a trade does not ultimately happen, because trading intent and identity are revealed to the counterparty. If this information leakage is costly, we would expect large dealers to trade through IDBs to keep their identity hidden and minimize information leakage. Furthermore, Glode and Opp (2016) argue that intermediation chains can help mitigate information asymmetry. If information asymmetry between the potential buyer and seller is high, trade may not happen despite the potential gains from trade. Trading through a moderately-informed intermediary can allow the trade to happen, leading to better allocations. Consistent with these channels, large dealers tend to offload larger positions through IDBs and smaller positions bilaterally. Moreover, when large dealers

[2] An alternative but not mutually exclusive explanation for why large dealers offload less is that larger dealers receive more customer order flow and potentially can more easily find offloading interest from customers, which will result in higher profits than offloading in the interdealer market (Üslü, 2019). While this channel likely plays a role, it cannot explain why large dealers pay higher trading costs in the interdealer market.

trade with IDBs, their ultimate counterparty is usually another large dealer with whom they already have a trading relationship. Therefore, IDBs mostly serve to mitigate information frictions rather than search frictions.

Lastly, we measure interdealer market efficiency. If information frictions are important enough, potential gains from trade between large dealers may be forgone. We focus on cases with clearest potential gains from trade, where one large dealer had positive customer order flow and another large dealer had negative customer order flow in the same bond on the same day. We then track whether the two dealers trade with each other to offset their positions in subsequent days, either directly through a bilateral trade or through a chain of trades. We find that such gains from trades are realized only less than 5% of the time through direct bilateral trading between the two large dealers, and up to 23% of the time through a chain of trades, usually involving IDBs. Therefore, IDBs help mitigate information frictions, but interdealer markets are still relatively inefficient.

Our paper is closely related to the literature on OTC search and network. Much of the literature focuses on search frictions and the core-periphery structure of the interdealer network. Li and Schürhoff (2019) and Hollifield et al. (2016) document that dealers form trading networks with a core-periphery structure in OTC markets to mitigate search frictions.[3] Subsequent papers have studied the core-periphery structure of the interdealer segment of OTC markets and in particular have focused on whether customers pay a higher bid-ask spread to central dealers ("centrality premium") or to peripheral dealers ("centrality discount"). In the municipal bond market, Li and Schürhoff (2019) show that core dealers provide liquidity and immediacy to both customers and peripheral dealers and that there is a centrality premium. Di Maggio et al. (2017) and Dick-Nielsen et al. (2023) document a centrality premium in the corporate bond interdealer market. Hollifield et al. (2016) show that there is a centrality discount in securitization markets. On the theory side, difference in search frictions or position in the interdealer network is often assumed to be the main friction that drives trading behavior. Üslü (2019) and Neklyudov (2013) show that in a model in which dealers have heterogeneous search frictions, ones with lower search costs end up as central dealers, and study the implications of the dealer network on trading costs. Colliard et al. (2021) study how dealers' connections affect inventory and prices.

We add to this literature by showing that in the interdealer segment of OTC markets, information frictions matter greatly, and within large and medium dealers, more than search frictions. Given that top 30 dealers account for almost 90% of customer volume and that information frictions matter more for these

[3] Hendershott et al. (2020b) document the importance of clients establishing trading relationships with dealers to mitigate search frictions.

dealers, decreasing information frictions would improve market efficiency more than decreasing interdealer market search frictions. For the small retail trader that trades with a small peripheral dealer, search frictions matter more. Thus, overall, there is a U-shape pattern in the degree of frictions, which is missed by previous literature because they usually assume a linear effect on centrality (Dick-Nielsen et al., 2023).

Our analyses also have a few other implications for the OTC search and network literature. First, because most papers have focused on completed intermediation chains, they do not look at the degree to and the speed of which various dealer types offload their customer order flows, and we fill that gap. We find that small dealers offload a large share of their customer order flow in the interdealer market within a day, which is more consistent with active offloading than a search framework that is used in the literature. Second, the length of intermediation chains is often used as a measure of the degree of search friction (Friewald and Nagler, 2019), but our results indicate that longer intermediation chains likely involve IDBs and may be driven by information frictions rather than search frictions.

We also show that there are in effect two types of dealers with high centrality—large traditional dealers and IDBs. These two types of dealers behave very differently, and simply considering a centrality dimension and putting them in the same category may lead to misleading conclusions. IDBs and the role they play have not been studied much despite the large share of volume they intermediate. An exception is De Roure et al. (2019), which document the extensive use of IDBs in the German sovereign bond interdealer market market. Their focus is on venue choice (exchange, bilateral, IDB) and argue that use of IDBs is driven by dealers' desire to preserve an informational advantage and avoid front running. We document a similar extensive use of IDBs in the U.S. corporate bond market and show how that impacts network measures and risk sharing.

Eisfeldt et al. (2024) argue that imperfect risk sharing among dealers due to frictions in the interdealer market reduce the overall risk-bearing capacity of the dealer sector and has pricing implications. They show that lower risk sharing increases interdealer price dispersion, which is a priced risk factor. Their paper, as well as Eisfeldt et al. (2022), highlight that frictions in the OTC interdealer market matter for overall dealer capacity and bond pricing; however, their paper is silent about the nature of the friction in the interdealer market. Our paper complements theirs by showing that information frictions are crucial.

Our results also have implications for transparency. Since information is contained in customer order flow, disseminating information about customer trades immediately would allow large dealers to more easily offload in interdealer markets but make it harder for them to profit from the information. This is consistent with the results of Lewis and Schwert (2021). Moreover, our results indicate that even with post-trade transparency, the interdealer market, especially between large dealers, is inefficient. This implies that for large dealers, the risk of information leakage and information asymmetry are large compared to their inventory costs.

A number of papers show that there is informed trading in the corporate bond market around default (Han and Zhou, 2014), acquisitions (Kedia and Zhou, 2014), and earnings announcements (Wei and Zhou, 2016). Hendershott et al. (2020a) show that short-sellers in the corporate bond market are informed. The focus of these papers is mostly to show the existence of informed trading and that customer order flow can predict future returns. Pinter et al. (2024) and Czech and Pintér (2022) show that information asymmetry affects customer trading costs and dealer-customer connections. These papers mostly focus on the dealer-customer market and do not study the impact of informed trading in the interdealer market. Babus and Kondor (2018) models information percolation in an interdealer network, where dealers learn about their counterparties' private information by trading. They find that in general, central dealers pay lower trading costs because their counterparties tend to be more connected. We show that dealers' information primarily comes from their customer orders rather than through their trading relationships with other dealers.

2 Data

We use the regulatory TRACE data for the sample period of August 2016 through July 2019. We apply standard cleaning such as cleaning for trade cancellations and corrections and delete trades with non-FINRA affiliates. Because our focus is on interdealer trades, we keep both sides of interdealer trades as well as adding the other side of trade for interdealer trades that are reported only once such as two-sided locked-in trades. We delete convertible bonds, MTNs, and 144A bonds as well as trades that happen in the first 30 days of issuance. Bond characteristics are from FISD Mergent. Similar to Choi et al. (2024), we aggregate the dealer identifiers (MPIDs) up to a high holder level because some dealers have multiple MPIDs or shift use of MPIDs over time. We also delete trades between MPIDs of the same high holder. We keep trades that are reported as principal trades only. Our end data has 11.8 million dealer-customer trades and 18.9 million interdealer trade observations, with most interdealer trades appearing twice, spanning 11,510 cusips and 1,069 dealers.

We also use the Fixed Income Data Feed from ICE Data Pricing & Reference Data to calculate information asymmetry in Section 3.2. The Fixed Income Data Feed contains end-of-day daily prices for most TRACE bonds over the sample period.[4]

[4]Prices are "evaluated prices" by the data vendor (Intercontinental Exchange), which to our best of our knowledge, are calculated from dealer quotes, traded prices, and matrix pricing model.

3 Dealer Types and Information Asymmetry

3.1 Dealer classification

We classify the dealers into six types—ATS, interdealer brokers (IDBs), client brokers, small, medium, and large. For each dealer with more than 2000 trades over the sample period, we calculate the share of the dealer's trades, separately in terms of trade count and volume, that are interdealer trades. Also, for each dealer, we calculate the share of prearranged trades by volume and count.[5] The classification criteria are not mutually exclusive. We assign dealers to groups in the order stated below, but it is unlikely that a dealer falls in multiple categories. We classify the dealers in the following way.

- "ATS": Of the dealers that are identified as ATS by FINRA, those that have more than 75% of their trades in interdealer trades by both volume and trade count basis or more than 90% of their trades by either volume or trade count basis.
- "Interdealer brokers" (IDBs): All dealers that have more than 75% of their trades in interdealer trades by both volume and trade count basis or more than 90% of their trades by either volume or trade count basis that are not classified as ATS.
- "Client brokers" (CBs): Dealers that are not ATS and IDBs, and also either have a prearranged share above 75% in both volume and trade count basis or above 90% in either volume or trade count basis.
- "Small," "Medium," and "Large": Among the remaining dealers, for each year (Aug-Jul year), the top 10 by customer volume are classified as "large," the next 20 are classified as "medium," and the rest are "small".

Table 1 provides summary statistics on dealer group classification. Panel (a) reports the share of customer volume and the share of interdealer volume that each dealer type is involved in. As shown in previous papers, customer trades are concentrated, where the ten largest dealer account for almost 70% of customer volume, and the next 20 dealers (medium dealers) account for another 20%. There are a large number of small dealers that account for fairly little customer volume. This table also shows that there are a number of dealers that account for very little customer volume but a fairly large amount of interdealer volume. IDBs together account for more than 25% of interdealer volume, and ATS account for 8.6%, but both account for

[5] Prearranged trades are identified as trades that remain in the dealers' inventory for less than 15 minutes, and the construction follows Choi et al. (2024).

less than 1% of customer volume. Lastly, there are a large number of client brokers, which mostly act as an agent between customers and dealers.

Table 1: **Summary statistics by dealer type:** Panel (a) presents for each dealer type, the average number of dealers per year, share of interdealer trades in which the dealer type is a party to, share of dealer-customer trades in which the dealer type is a party to, and the share of dealer type's trades that are dealer-customer trades. Panel (b) shows for each dealer type, the share of interdealer or dealer-customer trade volume that are DC-DC, DC-ID, ID-ID, or invt >15min trades. Trade type classifications are from Choi et al. (2024). In Panel (c), we present the centrality measures calculated from interdealer trades. deg, ev, and cl are degree centrality, eignenvector centrality, and closeless measures, respectively. deg_vols and ev_vols are degree centrality and eigenvector centrality using interdealer volume weights. We first calculate each centrality measure at the dealer-year level and present the average centrality measures, weighted by interdealer volume, for each dealer type. Panel (d) presents summary statistics on who trades with whom in the interdealer market. For each dealer type in each row, we present the share of their trade volumes with each counterparty types.

(a) **Dealer group summary stats**

dealer type	# of dealers	% of total ID volume	% of total DC volume	share DC
large	10	32.01%	69.57%	81.65%
medium	20	13.72%	19.42%	74.35%
small	243.3	7.02%	4.22%	55.15%
ATS	10	8.57%	0.35%	7.70%
IDB	40	25.58%	0.66%	5.01%
client broker	545	13.11%	5.79%	47.50%

(b) **Trade type by dealer group**

	interdealer			dealer-customer		
dealer type	DC-ID	ID-ID	invt>15min	DC-DC	DC-ID	invt>15min
large	8.40%	0.67%	90.93%	12.03%	1.70%	86.27%
medium	9.05%	1.70%	89.25%	15.51%	2.98%	81.51%
small	20.15%	11.46%	68.39%	18.03%	16.20%	65.77%
ATS	6.63%	91.74%	1.63%	14.61%	81.85%	3.54%
IDB	2.15%	76.80%	21.05%	7.91%	41.44%	50.64%
client broker	45.34%	39.16%	15.50%	26.63%	50.21%	23.15%

(c) **Dealer group centrality**

dealer type	deg	deg_vols	ev	ev_vols	cl
large	288.563	6.846	0.869	0.469	0.568
medium	225.482	1.848	0.76	0.105	0.542
small	160.911	0.463	0.581	0.026	0.508
ATS	110.383	2.376	0.423	0.114	0.482
IDB	120.198	7.556	0.499	0.503	0.493
client broker	135.6	5.655	0.511	0.258	0.492

(d) **Who trades with whom:**

dealer type	large	medium	small	ATS	IDB	client broker
large	9.18%	6.15%	6.08%	12.89%	49.11%	16.59%
medium	16.68%	7.04%	7.33%	12.49%	32.50%	23.96%
small	29.37%	14.48%	7.81%	8.59%	19.12%	20.63%
ATS	48.95%	22.73%	7.53%		8.31%	12.48%
IDB	61.53%	19.58%	5.70%	2.78%	1.85%	8.57%
client broker	33.67%	24.70%	11.17%	7.25%	15.88%	7.32%

Panel (b) shows the share of trades that are DC-DC, DC-ID, ID-ID, or invt>15min trades. These classifications are from Choi et al. (2024). The DC-DC trade classification denotes a dealer-customer trade offloaded through another dealer-customer trade within 15 minutes; that is, the dealer prearranged offsetting customer trades. DC-ID trades are instances in which customer trades are prearranged with offsetting interdealer trades.[6] Similarly, ID-ID trades are instances of prearranged offsetting interdealer trades. Lastly, invt>15min trades are trades taken into dealers' inventories. Results in Panel (b) indicate that IDBs, which are not restricted to having a high prearranged share, still prearrange almost 80% of their interdealer trades. Thus, these dealers mostly act as brokers between different dealers in interdealer trades rather than absorbing inventory, hence the "interdealer broker" name. ATS, by definition are platforms that dealers trade on, and thus are mostly ID-ID trades. Client brokers, by construction, contain a high share of DC-ID trades. The more "traditional" dealers take a larger share of trades into inventory, but this share also varies with dealer size. Large dealers, compared to medium and small dealers, are more likely to take both customer and interdealer trades into inventory and thereby provide immediacy. This result on dealer size is consistent with Li and Schürhoff (2019).

Panel (c) presents the average centrality measures for each dealer groups. Many papers (Li and Schürhoff, 2019; Hollifield et al., 2016) have documented a core-periphery structure in OTC interdealer markets. Looking at large, medium, and small dealer groups, dealers that are more central in the interdealer market also have more customer trades. It is also notable that IDBs have the highest centrality when volume-weighted centrality measures are used. Most of the literature misses ATS and IDBs that stand to intermediate between dealers. Because IDBs are central, papers that group dealers by centrality measures may group IDBs together with large dealers, which may confound the behavior of these two very different groups of dealers.

Lastly, Panel (d) looks at who trades with whom in the interdealer market. Large dealers trade almost half of their interdealer volume with IDBs, which is quite surprising. If IDBs' main function was to ease

[6] Both the customer trades and the interdealer trades in these pairs are referred to as DC-ID trades.

search frictions, smaller dealers should utilize IDBs significantly more than large dealers do. However, we find the exact opposite—large, medium, and small dealers trade about 49.1%, 32.5%, and 19.1% of their interdealer volume through IDBs, respectively.

3.2 Information Asymmetry

In this subsection, we show that large dealers face the highest information asymmetry from their customers. We first calculate information asymmetry that each dealer faces from their customers at the dealer, year, and rating group (investment grade or high yield) level in the following way. If the dealer received order flow of $v_{i,t}$ from customers for bond i on day t (positive $v_{i,t}$ means that customers bought from the dealer, negative $v_{i,t}$ means that customers sold to the dealer):

$$InfoAsym = \frac{\sum_{v_{i,t}>0} r_{i,[t,t+\tau]} |v_{i,t}|}{\sum_{v_{i,t}>0} |v_{i,t}|} - \frac{\sum_{v_{i,t}<0} r_{i,[t,t+\tau]} |v_{i,t}|}{\sum_{v_{i,t}<0} |v_{i,t}|} \tag{1}$$

where $r_{i,[t,t+\tau]}$ is the market-adjusted return of bond i between end of day t and $t+\tau$ where $\tau = 5$. Dealer and year subscripts are omitted in the equation. We get end-of-day bond prices from the Fixed Income Data Feed. To calculate market-adjusted return, we divide bonds into portfolios by rating (AAAs, AA+ through AA-, A+ through A-, BBB+ through BBB-, BB+ through BB-, B+ through B-, CCC and lower) first. Because AAA and CCC and lower groups have fewer bonds, we divide them into two groups and all other into three groups by time-to-maturity to form portfolios. We form portfolios based on last month's data and then subtract the portfolio return from bond i return. We restrict the sample to bonds in which the price data (from Fixed Income Data Feed) is not stale by deleting bonds in which prices remain exactly same in consecutive days for more than 10% of the sample.

This measure captures how much the prices move against the dealer within τ days after the customer trade. Because this measure doesn't take into account the actual traded price, and therefore the bid-ask spread charged to the customer, a positive measure does not imply that the dealer loses money on the customer trade. It rather says that if the dealer traded with a customer on day t, the price will move against the dealer between end of day t and day $t+\tau$. Our *InfoAsym* measure is similar in concept to the permanent price impact that is often used in the equity market to measure asymmetric information (Glosten and Harris, 1988; Hasbrouck, 1991; Hendershott, Jones, and Menkveld, 2011). In that literature, price changes are decomposed into transitory price impact, which reflect inventory concerns or order processing costs, and permanent price impact, which reflect the information component in trades. The permanent price impact, or the information asymmetry component, is generally measured as the change in quote midpoint (average of best bid and best ask quote) between right before the transaction and 5-30 minutes after the transaction (or a couple transactions after the original trade), multiplied by the trade direction. We cannot use this measure directly in corporate bond markets because there is no market-wide best bid and best ask quotes that are updated continuously or even intraday. Instead of using the quote right before the trade, we use the quote at the end of the day—thus, our measure may be biased towards not finding any evidence of information asymmetry if prices move fast and all the information that is contained in the trade is already incorporated into prices before the end of the day. The speed of transaction and information travel are much slower in corporate bond markets compared to equity markets, so it is suitable to use days instead of minutes. Lastly, we do not calculate *InfoAsym* for ATS and interdealer brokers because these dealers do very little customer trades.

Table 2 presents the summary statistics for *InfoAsym* by dealer group. Large dealers face the highest information asymmetry—on average, after a customer buys a investment grade bond from a large dealer, the market-adjusted price increases by 12.7 bps, compared with after a customer sell. This number is more than double (27.2 bps) for high-yield bonds, which also supports the idea that *InfoAsym* measures information asymmetry. For medium dealers, the average *InfoAsym* is 8.1 bps and 11.96 bps for investment grade and high yield bonds. *InfoAsym* is much lower for small dealers and client brokers.

Table 2: **Information asymmetry summary stat:** The table below presents the mean and median *InfoAsym* measure for each dealer group (excluding ATS and ID broker).

	Investment grade		High yield	
	mean	median	mean	median
large	12.711	13.14	27.171	27.094
medium	8.056	7.52	11.955	14.916
small	-0.251	0.12	-3.134	0.122
client broker	-0.214	-0.1	3.69	4.867

We look at how information asymmetry varies with dealer size and ratings more formally by running the following regression:

$$InfoAsym_{j,k,y} = \alpha + \sum_g \beta_g 1[j \text{ in dlr group } g] + \epsilon_{j,k,y} \tag{2}$$

where $InfoAsym_{j,k,y}$ is the information asymmetry measure for dealer j, ratings group k (either IG or HY), year y. We run the regression separately for investment grade bonds and high-yield bonds. Table 3 presents the results. Large dealers face the most informed customer order flow. For investment grade bonds, their information asymmetry is 4.7 bps higher than medium dealers and 12.9 bps higher than small dealers and client brokers, and these differences are statistically significant. Moreover, such a difference in information asymmetry is larger in high-yield bonds; the difference with medium dealers is 15 bps and 23–30 bps with small dealers and client brokers.

Table 3: **Information asymmetry regression:** The following table presents the results from regression (2). Standard errors are clustered by dealers. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Investment grade		High yield	
	(1)	(2)	(3)	(4)
medium	−4.655***	−4.650***	−15.216***	−15.310***
	(1.155)	(1.169)	(5.119)	(5.104)
small	−12.962***	−12.937***	−30.305***	−30.173***
	(2.069)	(2.061)	(5.328)	(5.324)
client broker	−12.924***	−12.829***	−23.481***	−22.955***
	(1.437)	(1.441)	(5.027)	(5.000)
Constant	12.711***		27.171***	
	(0.557)		(2.806)	
Year f.e.	No	Yes	No	Yes
Observations	1,549	1,549	960	960
R^2	0.003	0.005	0.005	0.009

The Fixed Income Data Feed price data used to calculate the information asymmetry are not necessarily always tradable quotes or traded prices; hence, the information asymmetry measure might be biased in a certain way that affects the results. In Appendix B, we show that results are robust to using traded interdealer prices from TRACE to calculate information asymmetry. We also show in the Internet Appendix that results are robust to using alternative ways to adjust for market movements.

4 Interdealer market

Having established that larger dealers face more informed order flow, we show that information asymmetry affect trading and prices in the interdealer market. We provide further evidence of information asymmetry by looking more closely at interdealer brokers. Lastly, we measure the degree of efficiency in the interdealer market.

4.1 Who offloads to who?

The main function of interdealer markets is for dealers to share risks and offload inventories that stem from customer order flow with other dealers (Ho and Stoll, 1983; Hansch et al., 1998; Viswanathan and Wang, 2004). Li and Schürhoff (2019), using the municipal market data and creating intermediation chains, find that more central dealers provide liquidity to peripheral dealers.

Central dealers providing more liquidity to peripheral dealers is consistent with multiple channels. First, using a search model, Üslü (2019) shows that central dealers have lower aversion to holding inventory because they have more offloading opportunities, and thus endogenously arise as intermediation providers. Relatedly, since large dealers have more customers (by construction) and dealers make higher profits by offloading to customers (Di Maggio et al., 2017), it may be optimal for large dealers to maximize profits by offloading less in the interdealer market, absorbing small dealers' flows, and offloading to customers. Second, under information frictions, when large dealers try to offload, other dealers would be hesitant to take the other side, but would be happy to do so when small dealers try to offload. Last, large dealers may be associated with large dealer banks and have lower funding costs, which can also lead to the same result.

In this section, we look at what share of customer order flow each dealer group offloads through the interdealer market, and to which dealer types that they offload to over what horizon. To the best of our knowledge, we are the first to quantify the degree of inventory offloading in the OTC interdealer market for different types of dealers. Because previous papers have focused on completed intermediation chains, the degree and the speed of risk offloading have not been measured directly. Our results overall, in addition to confirming a few other results that have already been shown, adds the following. First, smallest dealers offload a fairly large amount of customer order flow on the same day to other dealers, pointing to active inventory management and relative ease of offloading, which is inconsistent with low search intensity. In random search models typically used in the literature, one would need small dealers to have a unreasonably high search intensity to get a large amount of same-day offloading. Second, large dealers trade with each other through IDBs, which is consistent with information frictions and inconsistent with search frictions.

We first test, at the dealer type level, which dealer types on aggregate offload customer order flow to which dealer types. To do so, we run the following regression:

$$IDG_{i,g,t} = 0 + \sum_{h \in S} \alpha_h DCG_{i,h,t} + \epsilon_{i,h}, \tag{3}$$

where g and h denote dealer groups. $DCG_{i,g,t}$ is the aggregate signed dealer-customer trade volume for dealer group g on bond i and day t, and $IDG_{i,g,t}$ is the aggregate signed interdealer trade volume for dealer group g on bond i and day t. A positive $DCG_{i,g,t}$ implies that dealer group g on net bought from customers, and a positive $IDG_{i,g,t}$ implies that dealer group g on net bought from other dealers. We set $S = \{large, medium, small, CB \text{ (client broker)}\}$ and consider the same set of dealers for g. We do not include IDBs and ATS because these dealers do not take much aggregate daily net positions in both the dealer-customer and the interdealer segment. We use daily data for the estimations and run the regression separately by dealer group g. Because there is a very large number of observations for which all dependent and independent variables are all zeros, we set the intercept to be zero and omit those observations when estimating the regression.

Table 4 report the regression results, which indicate the following. First, smaller dealers and client brokers offload a larger share of their aggregate daily customer order flow through the interdealer market to other types of dealers. For instance, in high yield bonds (Panel b), small dealers offload 63.5% of their daily aggregate net customer order flow through the interdealer market, and 62% of client brokers do so. In contrast, only 4.6% and 20.6% of large and medium dealers, respectively, offload their daily aggregate net customer order flow to other dealer groups. Even if we delete trades that are prearranged, 38.1% of small dealers' customer order flow is offloaded through the interdealer market on the same day (Table A.4 in the Appendix). This speed and ease for which small dealers offload in the interdealer market is consistent with other dealers being willing to take in those flows because these flows are uninformed. For a search model to incorporate such a fast inventory reversion, it would require a fairly high search intensity for small dealers.

Second, as a group, large dealers are more likely to provide liquidity to smaller dealers and client brokers. For instance, in the high yield market, large dealers absorb 13.3%, 43.3%, and 37.0% of medium, small, and client brokers' daily customer order flows, respectively. In contrast, medium dealer and small dealers only absorb 1.3% and 0.4%, respectively of large dealers' aggregate customer flows. As previously mentioned, this empirical fact is consistent with a number of different economic channels.

In Table 5, we take a further look at offloading at the individual dealer level for large and medium dealers. We run the following regression separately for large dealers and medium dealers:

$$ID_{i,j,t} = 0 + \alpha_0 DC_{i,j,t} + \alpha_1 DCG_{i,-j,t} + \sum_{h \notin g(j)} \beta_h DCG_{i,h,t} + \epsilon_{i,j,t}, \tag{4}$$

where $DC_{i,j,t}$ and $ID_{i,j,t}$ are the signed customer order flow and the signed interdealer order flow for bond i, dealer j, day t. $DCG_{i,h,t}$ is the aggregate customer order flow for bond i, dealer group $h \in$

Table 4: **Offloading regression: dealer group level:** The following tables present the results from regression (3). Panel (a) presents the results for investment grade bonds, and panel (b) presents the results for high-yield bonds. Heteroskedasticity-consistent stnadard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(a) Investment grade

	large (1)	medium (2)	small (3)	client broker (4)
DCG_{large}	−0.022***	0.010***	0.004***	0.002***
	(0.001)	(0.0004)	(0.0002)	(0.0003)
DCG_{medium}	0.059***	−0.094***	0.012***	0.009***
	(0.003)	(0.004)	(0.001)	(0.001)
DCG_{small}	0.241***	0.111***	−0.382***	0.011***
	(0.008)	(0.005)	(0.010)	(0.001)
DCG_{CB}	0.350***	0.185***	0.065***	−0.646***
	(0.013)	(0.010)	(0.003)	(0.011)
Observations	3,006,140	3,006,140	3,006,140	3,006,140
Adjusted R^2	0.109	0.078	0.247	0.560

(b) High yield

	large (1)	medium (2)	small (3)	client broker (4)
DCG_{large}	−0.046***	0.013***	0.004***	0.006***
	(0.003)	(0.001)	(0.0003)	(0.001)
DCG_{medium}	0.133***	−0.206***	0.014***	0.012***
	(0.007)	(0.009)	(0.002)	(0.002)
DCG_{small}	0.433***	0.082***	−0.635***	0.019***
	(0.052)	(0.011)	(0.035)	(0.006)
DCG_{CB}	0.370***	0.113***	0.029***	−0.626***
	(0.018)	(0.008)	(0.004)	(0.013)
Observations	749,991	749,991	749,991	749,991
Adjusted R^2	0.146	0.123	0.492	0.520

$S = \{large, medium, small, CB\}$, day t. $g(j)$ is the dealer group for which dealer j is a part of, and $DCG_{i,-j,t} = DCG_{i,g(j),t} - DC_{i,j,t}$, or in other words, the aggregate customer volume of the group that j is in but excluding dealer j's own order flow.

Column (1), for instance, shows that in investment-grade bonds, a large dealer on average offloads 4.5% of its net customer order flow through the interdealer market. The average large dealer also absorbs 0.3% of other large dealers' order flow and 0.6% of medium dealers' order flow. In contrast, column (2) shows that the average medium dealer offloads 11.4% of its net customer order flow through the interdealer market; and absorbs 0.05% of large dealers' order flow and 0.1% other medium dealers' order flow. Overall, the results in this table show that large dealers do not share risk much amongst themselves but do provide liquidity to other types of dealers.

Table 5: **Offloading regression: Individual dealer level:** The following table presents the results from regression (4). Heteroskedasticity-consistent stnadard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	IG		HY	
	large	medium	large	medium
	(1)	(2)	(3)	(4)
DCG_{large}	0.003***	0.0005***	0.007***	0.001***
	(0.0001)	(0.00002)	(0.0003)	(0.00005)
DCG_{medium}	0.006***	0.001***	0.013***	0.001***
	(0.0003)	(0.00005)	(0.001)	(0.0002)
DCG_{small}	0.024***	0.006***	0.043***	0.004***
	(0.001)	(0.0003)	(0.008)	(0.0004)
DCG_{CB}	0.035***	0.009***	0.037***	0.006***
	(0.002)	(0.001)	(0.003)	(0.0004)
DC_j	−0.045***	−0.114***	−0.110***	−0.228***
	(0.001)	(0.004)	(0.004)	(0.008)
Observations	27,216,362	54,254,879	7,086,222	14,134,429
Adjusted R^2	0.017	0.048	0.053	0.113

Next, we take a look at which counterparties large dealers offload customer order flow and provide liquidity through. We run the following regression separately by each counterparty group g:

$$ID_{j,g,t} = 0 + \alpha_0 DC_{j,t} + \alpha_1 DCG_{-j,t} + \sum_{h \notin g(j)} \beta_h DCG_{h,t} + \epsilon_{j,t} \tag{5}$$

We suppress bond subscript i for readability. We consider large dealers only for j and all dealer types for the counterparty g. $ID_{j,g,t}$ is the sum of the signed interdealer flow for dealer j in which the counterparty is in group g. The sum of $ID_{j,g,t}$ for all g would equal $ID_{j,t}$. The right hand side of the regression is exactly same as in (4).

Table 6: **Offloading regression: Individual dealer level for large dealers:** The following table presents the results from regression (5) for large dealers. Heteroskedasticity-consistent stnadard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	large	medium	small	ATS	IDB	client broker
	(1)	(2)	(3)	(4)	(5)	(6)
DCG_{large}	0.0004***	−0.00004**	0.0001***	0.0004***	0.002***	0.0003***
	(0.0001)	(0.00001)	(0.00002)	(0.00002)	(0.0001)	(0.00003)
DCG_{medium}	0.00004	0.003***	0.0001***	0.0004***	0.002***	0.001***
	(0.00003)	(0.0002)	(0.00005)	(0.00005)	(0.0001)	(0.0001)
DCG_{small}	0.0003**	0.0002***	0.021***	0.001***	0.003***	0.001***
	(0.0001)	(0.0001)	(0.001)	(0.0001)	(0.0002)	(0.0001)
DCG_{CB}	0.0002*	0.0003***	0.001***	0.001***	0.002***	0.031***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.001)
DC_j	−0.005***	−0.003***	−0.004***	−0.006***	−0.027***	−0.008***
	(0.001)	(0.0002)	(0.0003)	(0.0002)	(0.001)	(0.001)
Observations	34,302,584	34,302,584	34,302,584	34,302,584	34,302,584	34,302,584
Adjusted R^2	0.001	0.003	0.014	0.002	0.009	0.018

Table 6 presents the results, and Table A.5 in the Appendix presents the results for medium dealers. We first consider how large dealers offload and absorb risk. Looking across all columns for the coefficient on $DC_{j,t}$, we find that when the customer order flow for a large dealer increases by 1, he offloads 0.027 through IDBs and smaller amounts through other dealers. Looking across the first row (coefficient for $DCG_{-j,t}$), when the customer order flow for all other large dealers increases by 1, a large dealer absorbs 0.0004 of it by trading directly with other large dealers (column 1) and 0.002 of it by trading with IDBs (column 4).[7] This means that when a large dealer provides liquidity to other large dealers, they are five times as likely to do so through IDBs than bilaterally. Overall, the results point to large dealers offloading risk to each others mostly through IDBs.

[7]While 0.0004 and 0.002 may also seem minuscule, recall that the left hand side is for a single dealer–so overall, if the customer order flow increases by 1 for a large dealer, all other nine large dealers on aggregate would absorb about 0.0036 directly and 0.018 through IDBs.

When large dealers provide liquidity to other dealer types, they are more likely to do so bilaterally than through IDBs. For instance, comparing the coefficient for $DCG_{small,t}$ between columns (3) and (5), we find that small dealers are about nine times more likely offload to large dealers directly through bilateral trades than through IDBs. Medium dealers are somewhere in the middle in which large dealers are still twice as likely to absorb medium dealers' customer order flow bilaterally than through IDBs (coefficient for $DCG_{medium,t}$ in columns 2 and 5).

If search frictions were most relevant, large dealers finding each other would have the lowest possible costs, and thus they would have no reason to trade through IDBs. Moreover, smaller dealers will utilize IDBs more if search frictions were large. Our results are not consistent with search frictions but are rather consistent with large dealers contacting others through IDBs to minimize information leakage. Moreover, given that small dealers have uninformed or less informed customer order flow, they do not have the need to conceal their trading intent through IDBs. Thus, use of IDBs in sharing risk overall points to information friction being most relevant in the interdealer markets.

4.2 Interdealer prices

Next, we look at interdealer trade prices to determine whether search or information frictions are of first-order importance, as each case creates starkly different predictions.

If search frictions were dominant, large dealers should receive the best prices because they have lowest search costs and highest outside opportunity. Furthermore, since large dealers are more likely to provide liquidity, they should receive the most favorable prices. In contrast, if information frictions were most dominant, large dealers would receive the worst prices when they are taking liquidity since they are most likely to be informed. However, because large dealers are also more likely to be providing liquidity, the predictions are less clear cut when not conditioned on liquidity demand. However, we can confidently say that if large dealers do not receive the best prices, search frictions likely are not the most dominant friction in the interdealer market.

In the first regression, we compare prices of interdealer trades on the same bond-day by including bond times day fixed effects. We run the following regression:

$$P_{i,t,\tau} = P^*_{i,t} + \sum_{j \in S} \beta_j 1(seller(\tau) = j) + \sum_{k \in S} \gamma_k 1(buyer(\tau) = k) + \epsilon_{i,t,\tau}, \tag{6}$$

where $P_{i,t,\tau}$ is the traded price for bond i, day t, interdealer trade τ. $P^*_{i,t}$ is the "fundamental" value for

Table 7: **Interdealer price regression with bond-day interacted fixed effects.:** Following table present results of regression (6). Standard errors are double clustered by cusip and date. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	< 100k		≥ 100k	
	IG	HY	IG	HY
	(1)	(2)	(3)	(4)
seller = medium	3.185***	9.793***	2.984***	4.534***
	(0.134)	(0.342)	(0.097)	(0.299)
seller = small	2.373***	4.859***	3.149***	5.198***
	(0.222)	(0.480)	(0.129)	(0.353)
seller = ATS	−1.087***	−1.827***	2.959***	3.665***
	(0.137)	(0.442)	(0.145)	(0.338)
seller = IDB	5.550***	12.977***	2.772***	4.944***
	(0.319)	(0.485)	(0.133)	(0.275)
seller = client broker	1.125***	−1.580***	2.409***	2.201***
	(0.166)	(0.412)	(0.121)	(0.280)
buyer = medium	−3.637***	−11.891***	−1.021***	−2.980***
	(0.185)	(0.465)	(0.082)	(0.243)
buyer = small	−2.340***	−5.365***	−0.441***	−2.380***
	(0.284)	(0.432)	(0.116)	(0.363)
buyer = ATS	5.279***	1.935***	0.507***	−2.561***
	(0.133)	(0.374)	(0.148)	(0.345)
buyer = IDB	0.243	−10.577***	−2.573***	−5.172***
	(0.209)	(0.544)	(0.116)	(0.265)
buyer = client broker	0.985***	4.015***	0.354***	−0.272
	(0.125)	(0.341)	(0.117)	(0.298)
sell side = DC-ID	−19.293***	−25.115***	−7.447***	−11.086***
	(0.352)	(0.620)	(0.227)	(0.556)
buy side = DC-ID	12.838***	20.808***	7.119***	11.885***
	(0.211)	(0.432)	(0.135)	(0.448)
bond times day f.e.	Yes	Yes	Yes	Yes
Observations	5,316,663	1,754,726	1,799,483	802,867
Adjusted R^2	0.999	0.999	1.000	0.999

bond i on day t, which we proxy with bond-day interacted fixed effects. Large dealer type is the omitted category for both the buyer and the seller. We also include indicator variables for whether the trade was a DC-ID trade from the seller's perspective and from the buyer's perspective because the middle dealer in a DC-ID trade is taking liquidity in the interdealer trade and should get worse prices. Because we include bond-day interacted fixed effects, we are in effect comparing prices of trades for the same bond on the same day but with different seller group or the buyer group.

The results presented in Table 7 indicate that large dealers receive worse prices than medium and small dealers. For example, medium dealers sell an investment-grade bond in a transaction that is 100K or larger (column 3) for 3 bps higher than large dealers. Small sellers, in the same bond and transaction size, sell at 3.1 bps higher than large dealers. Comparing columns (3) and (4), we can see that the differences between large and other dealers are somewhat larger for high-yield bonds, which is consistent with the notion that high-yield bonds have more information asymmetry.

In some specifications, trading costs have a U-shape in which the largest and the smallest dealers pay higher prices than medium dealers. For instance, in column (4), medium buyers pay less than both large and small buyers. This would mean that when comparing smallest dealers to others, search costs may be more important. Or in other words, that up to the top 30-40 dealers, information asymmetry friction matters more, and that beyond those, search frictions matter more. Given that trading tends to be dominated by the top 30-40 dealers, on a trade-by-trade basis, information would be more important. Also, because short positions are costly, dealers would have more incentive to offload customer buy trades regardless of information, so information frictions are likely weaker for buyers. This asymmetry may explain why the trading cost difference between large dealers and medium/small dealers are smaller for buyers and why trading costs are more of a U-shape for buyers. Client brokers, which tend to be on average smaller than small dealers, pay higher trading costs than small dealers, also adding to the U-shape.

Lastly, the coefficient on IDBs indicate that large dealers pay about 2.5 bps (IG) and 5 bps (HY) more to trade through IDBs than bilaterally with each other and that this spread accrues to IDBs. We will look more closely into IDBs in Section 4.3.

Because bond-days with multiple interdealer trades may be relatively scarce and different from other interdealer trades, we also estimate (6) in a different way. Instead of including bond-day fixed effects for $P^*_{i,t}$, we take the first difference of (6) and proxy $\Delta P^*_{i,t}$, the change in fundamental price of bond i between

Table 8: **Interdealer price first difference regression:** Following table presents results of regression (7). Heteroskedasticity-consistent standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	< 100k		≥ 100k	
	IG	HY	IG	HY
	(1)	(2)	(3)	(4)
MKT	0.457***	1.107***	0.686***	1.092***
	(0.009)	(0.173)	(0.009)	(0.052)
TERM	0.267***	−0.276	0.207***	−0.037
	(0.009)	(0.185)	(0.009)	(0.055)
DEF	−0.150***	0.313***	−0.207***	0.534***
	(0.004)	(0.065)	(0.004)	(0.025)
seller = medium	3.024***	9.759***	2.984***	4.697***
	(0.030)	(0.206)	(0.040)	(0.204)
seller = small	1.744***	5.949***	2.535***	5.402***
	(0.053)	(0.279)	(0.062)	(0.349)
seller = ATS	−1.362***	−3.176***	2.535***	3.953***
	(0.041)	(0.242)	(0.067)	(0.323)
seller = IDB	4.115***	13.928***	2.243***	4.904***
	(0.046)	(0.199)	(0.048)	(0.177)
seller = client broker	0.894***	−2.304***	2.003***	2.496***
	(0.047)	(0.235)	(0.057)	(0.233)
buyer = medium	−3.534***	−13.050***	−1.109***	−3.339***
	(0.043)	(0.225)	(0.043)	(0.211)
buyer = small	−2.268***	−7.010***	−0.212***	−3.599***
	(0.060)	(0.304)	(0.057)	(0.296)
buyer = ATS	4.912***	1.377***	0.278***	−3.127***
	(0.045)	(0.237)	(0.068)	(0.296)
buyer = IDB	0.112**	−13.456***	−2.307***	−5.748***
	(0.050)	(0.240)	(0.048)	(0.179)
buyer = client broker	0.816***	5.521***	0.351***	−0.115
	(0.026)	(0.152)	(0.047)	(0.213)
sell side = DC-ID	−18.415***	−29.517***	−7.354***	−14.571***
	(0.050)	(0.231)	(0.072)	(0.285)
buy side = DC-ID	12.295***	22.889***	6.843***	13.547***
	(0.030)	(0.166)	(0.041)	(0.217)
Constant	0.560***	0.733***	0.239***	0.487***
	(0.014)	(0.087)	(0.018)	(0.085)
Observations	5,195,774	1,738,731	1,706,691	792,720
Adjusted R^2	0.193	0.077	0.189	0.040

two consecutive trades, using market, default, and term factors:

$$
\begin{aligned}
ret_{i,t,\tau} = &\alpha_0 + \alpha_1 MKT_{t(\tau-1),t(\tau)} + \alpha_2 DEF_{t(\tau-1),t(\tau)} + \alpha_3 TERM_{t(\tau-1),t(\tau)} \\
&+ \sum_{j=1}^{6} \beta_j [1(seller(\tau) = j) - 1(seller(\tau - 1) = j)] \\
&+ \sum_{j=1}^{6} \gamma_j [1(buyer(\tau) = j) - 1(buyer(\tau - 1) = j)] + \epsilon_{i,t,\tau}
\end{aligned} \tag{7}
$$

where $ret_{i,t,\tau}$ is the return of bond i between $(\tau - 1)$-th trade and τ-th trade, and $t(\tau)$ is the date of trade τ. $MKT_{t(\tau-1),t(\tau)}, DEF_{t(\tau-1),t(\tau)}, TERM_{t(\tau-1),t(\tau)}$ are the market, default, term factor calculated from index values at end of day $t(\tau - 1)$ (previous trade date) and $t(\tau)$. These factors are calculated from BAML indices. This method of estimating bid-ask spreads is often used for fixed income markets (Edwards et al., 2007, Bessembinder et al., 2006).

Results for this first difference regression (7) are presented in Table 8. Overall, the results are both qualitatively and quantitatively similar to those in Table 7.

4.3 Who trades through interdealer brokers?

In Section 4.1 and Table 6, we have established that large dealers are more likely to use IDBs and that this pattern is consistent with information friction than search friction. In this subsection, we look at the use of IDBs in more detail.

In Table 9, we look at who trades with whom through IDBs. About 46% of trading volume through IDBs are large dealers trading with other large dealers. As argued before, these are precisely the cases with the lowest search costs and highest information frictions. Thus, the use of IDBs is mostly motivated by information frictions. Another 30% is medium dealers trading with large dealers, which also has relatively low search costs.

Considering that large dealers trade bilaterally with other large dealers for about 9% of their interdealer volume and through IDBs for about 49% (Table 1(d)), the composition of IDB trades suggests that a significant portion of large dealers' volume is traded with other large dealers via IDBs rather than through direct bilateral transactions. The fact that they do so despite having to pay more to trade with IDBs than bilaterally with other large dealers (Table 7) implies that there are benefits for large dealers to trade through IDBs with each other despite the higher cost, such as lower risk of information leakage when trades fall through.

Table 9: **Who trades with whom through IDBs:** We focus on cases in which it is possible to identify the two end parties of trades that happen through IDBs. To do so, we match buy and sell trades of IDBs in which the two trades are in the same bond, within one minute apart, same IDB is the reporting party, but in opposite directions. In these cases, we say that the two counterparties of the two trades are the actual end parties that traded through the IDB. Within these trades, we pull the share (by volume) for the pairs.

dealer type	large	medium	small	ATS	IDB	client broker
large	46.15%	30.00%	6.71%	0.17%	1.41%	2.81%
medium		4.44%	3.22%	0.30%	0.58%	0.83%
small			0.63%	0.11%	0.26%	0.86%
ATS				0.01%	0.06%	0.91%
IDB					0.17%	0.30%
client broker						0.06%

Because results in Table 9 could in part be driven by the fact that large dealers trade more, we also study whether large dealers are more likely to trade with an IDB in a regression setting. Table 10 runs the following regression using trade-level data:

$$1(\text{counterparty is IDB})_{i,j,\tau} = \alpha + \sum \beta_g 1(j \text{ in dlr grp } g) + \gamma_1 log(size_\tau) + \epsilon_{i,j,\tau}$$

where interdealer trade τ is in bond i and reporting party is dealer j. We also include bond ratings and trade size. Results indicate that large dealers are more likely to trade with IDBs, especially for large trades. The fact that results are stronger in institutional sized trades is consistent with information asymmetry being higher for large trades. Also, dealers are more likely to use IDBs for large trades and for lower-rated bonds, which is consistent with these trades having higher information asymmetry and IDB usage being driven by information frictions.

In Table 11, we test whether IDBs allow dealers to trade with dealers that they normally do not trade with. We find that for large dealers, around 96% of their ultimate counterparties in IDB trades are those that they already trade with bilaterally. Therefore, IDBs do not help large dealers reach new counterparties. For small dealers, IDBs do help in part with reaching new counterparties; about 47% of their trades with IDBs are with dealers that they do not trade bilaterally with.

Overall, dealers use IDBs to mitigate information frictions, and IDBs are an important part of the interdealer market. To the best of our knowledge, in most papers studying OTC markets, and especially those studying the U.S. corporate bond markets, the role of IDBs has not been studied. Without isolating them separately, IDBs can be classified as central dealers together with large dealers, which can obscure some of the effects.

Table 10: **IDB use regression:** For interdealer trades in which the reporting party is not a ATS or a IDB, we look at the likelihood that the counterparty is a IDB. We run the following regression:

$$1(\text{counterparty is IDB})_{i,j,k} = \alpha + \sum \beta_g 1(j \text{ in dlr grp } g) + \gamma_1 log(size_k) + \epsilon_{i,j,k}$$

where trade k is in bond i and rerporting party is dealer j. We also include bond rating group fixed effects. We report heterogeneity-consistent standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	all (1)	$<$ 100k (2)	$\geq$ 100k (3)
medium	-0.040^{***}	-0.015^{***}	-0.073^{***}
	(0.0002)	(0.0002)	(0.001)
small	-0.034^{***}	0.025^{***}	-0.147^{***}
	(0.0003)	(0.0003)	(0.001)
client broker	0.041^{***}	0.088^{***}	-0.074^{***}
	(0.0002)	(0.0002)	(0.001)
log(size)	0.047^{***}	0.019^{***}	0.087^{***}
	(0.0001)	(0.0001)	(0.0002)
rating BBB+:BBB-	0.001^{***}	0.002^{***}	0.004^{***}
	(0.0002)	(0.0002)	(0.001)
rating BB+:BB	0.064^{***}	0.058^{***}	0.081^{***}
	(0.0004)	(0.0004)	(0.001)
rating BB- or lower	0.104^{***}	0.100^{***}	0.095^{***}
	(0.0003)	(0.0003)	(0.001)
Constant	-0.048^{***}	-0.003^{***}	-0.230^{***}
	(0.0002)	(0.0003)	(0.001)
Observations	13,525,402	10,047,278	3,478,124
R^2	0.083	0.047	0.076
Adjusted R^2	0.083	0.047	0.076

Table 11: **IDB relationship:** For IDB trades in which the end parties are identified (those used in Table 9), we look at whether the two end parties have a direct trading relationship outside of trading through IDBs or ATS. "Current month" column shows the share of volume in which the two end parties have at least one trade with each other in the same month, "prior month" column shows the share in which the two end parties have at least one trade with each other in the prior month.

dealer type	current month	prior month
large	95.78%	93.92%
medium	78.55%	76.56%
small	52.51%	51.45%
ATS	29.05%	28.94%
ID_broker	62.84%	61.61%
client_broker	59.45%	57.92%

4.4 Interdealer market efficiency

How much do information frictions matter for market efficiency? The main function of interdealer markets is for dealers to share risk that arises from making markets for their clients (Viswanathan and Wang, 2004). The clearest case of gains from trade in the interdealer market would be when one dealer had a net customer buy flow and another had a net customer sell flow in the same bond. In this case, the two dealers can trade to offload their inventory, and there would be clear positive gains from trade. Using these clearly identifiable potential gains from trades between large dealers, we look at what share of potential gains are realized, either through direct (bilateral) trades between the two dealers or through indirect chains.

We calculate the interdealer market efficiency in the following way. For bond i on day t, if dealer A has bought on net amount v_A from his customers, and if dealer B has sold on net amount v_B to her customers, the potential gains from trade between dealer A and B is $v_P = min(v_A, v_B)$. If A sells bond i of amount v_D to B between day t and $t + k$, then $\frac{min(v_D, v_P)}{v_P}$ of potential gains from trade is realized directly. If A sells bond i of amount v_I to B through dealer C between day t and $t + k$, then $\frac{min(v_D + v_I, v_P)}{v_P}$ of potential gains from trade is realized either directly or indirectly. We only focus on cases in which both dealers A and B are large dealers, and use $k = 0, 2, 5$.

Table 12 present the share of potential gains that is realized. Only a very small share of potential gains are realized through bilateral trades, and slightly more (but still relatively small) is realized through indirect trades. For instance, only 1.54% of potential gains from trade between two large dealers in a high-yield bond is realized on the same day by direct trade between the two dealers. Another 9.8% is realized through indirect trades, mostly from trades through IDBs. Looking over multiple days increases gains from trade somewhat, but the numbers are still fairly low. There is less direct gains but overall higher gains from trades in high-yield bonds, which is consistent with the notions that high-yield bonds have higher information asymmetry and also higher gains from trade due to greater risk reduction.

Table 12: **Interdealer market efficiency for large dealers:** Following table presents the share of potential gains-from-trade between large dealers that are realized. Direct gains only include realized gains from two large dealers trading bilaterally, and all gains include both the direct gains and indirect gains from trading through one additional dealer.

	IG		HY	
k	direct	all	direct	all
0	1.21%	6.16%	1.54%	11.34%
2	1.51%	9.82%	1.99%	17.21%
5	1.89%	13.33%	2.54%	22.52%

Results overall indicate that information friction decreases interdealer market efficiency, especially between large dealers. Large dealers use IDBs to get around the issue, but it does not fully solve the inefficiency.

5 Conclusion

In this paper, we show that information frictions matter in the interdealer segment of OTC markets. Despite the focus in the literature on search frictions and network formation, we show that on average, information frictions matter more in the interdealer market for U.S. corporate bonds. This is not to say that search frictions in the dealer-customer segment do not matter. The ease of finding customer buyers and sellers likely contributes to the lower holding cost for large dealers.

Since the adoption of Dodd-Frank and Volcker Rule in the mid-2010's, corporate bond liquidity has structurally shifted from dealers providing immediacy and inventory space to dealers acting more as matchmakers because of higher inventory costs (Choi et al., 2024; Bessembinder et al., 2018). Our results show that information frictions limit dealers from fully sharing risks among themselves, which would limit overall dealer capacity (Eisfeldt et al., 2024). Thus, there is room to improve market structure so that dealers, especially large dealers, can free up inventory space and provide more liquidity to customers.

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A What kind of information does order flow contain?

Customer order flow can contain information about fundamentals or about future order flows, or both. The fact that information asymmetry is higher for high yield bonds (Table 2) suggests that customer order flow contains information about fundamentals. In this section, we provide evidence that suggests that customer order flow also contains information about future order flow. Because order flow impacts prices (Chordia et al., 2002), knowing customer order flow would be useful for the dealers. We show that customer order flow to large dealers contains more information about future order flow.

We test whether current and past order flows can predict future order flow, and which dealer groups' order flows have higher explanatory power. We run the following regression:

$$\begin{aligned} DC_{i,t} = & \sum_{k=1}^{5} \beta_{large,k} DC_{i,large,t-k} + \sum_{k=1}^{5} \beta_{med,k} DC_{i,med,t-k} + \sum_{k=1}^{5} \beta_{small,k} DC_{i,small,t-k} \\ & + \sum_{k=1}^{5} \beta_{CB,k} DC_{i,CB,t-k} + \epsilon_{i,t} \end{aligned} \tag{8}$$

where $DC_{i,t}$ is the net aggregate customer order flow for bond i on time period t, and $DC_{i,g,t-k}$ is the aggregate order flow for bond i, dealer group g on time period $t-k$. We first run the regression and get the R-squared, and then rerun the regression taking out the dependent variables for a single dealer group to gauge the explanatory power of that dealer group's past order flows.

Table A.1 presents the R-squared statistics for the full regression and the regressions excluding single dealer group. The overall explanatory power is fairly low—for daily regressions, it is 0.20% or lower, and for the weekly regression, it is around 1%. Most of the explanatory power is driven by past order flows of large dealers. For instance, for investment grade weekly order flow, the R-squared is 1.028% if we include all dealer groups' past order flows, but decreases to 0.114% if we exclude large dealers' past order flows. Dropping other dealer groups' past order flows decreases the R-squared little.

Ultimately, we are interested in both sources of information asymmetry—private information about fundamentals and order flow—because they both affect dealers' trading behavior and execution quality. We find evidence for both types of private information in customer trades. We document that the price continuation among customer trades is larger in high-yield bonds, which suggests that private information about fundamentals matter. We then use the predictive regressions in (8) to document the ability of past customer order flow to predict current customer order flow. Although, the order flow is inherently noisy and the R-squared across all regressions is low, we show that the customer order flow which matters the most

Table A.1: **Predictive power of past order flows by dealer group:** The following table presents the R-squared statistics from regression (8). Row "Full" shows the R-squared from a regression that includes all dealer group order flows, and the other four rows show the R-squared from regressions that excludes order flows for one dealer group. Columns marked "Daily" uses daily data, and columns marked "Weekly" uses weekly data.

	Daily		Weekly	
	IG	HY	IG	HY
Alll	0.201%	0.15%	1.028%	0.923%
Excluding large	0.015%	0.091%	0.114%	0.151%
Excluding medium	0.194%	0.132%	0.967%	0.86%
Excluding small	0.199%	0.113%	1.023%	0.881%
Excluding CB (client broker)	0.199%	0.113%	1.02%	0.892%

for prediction is that of the large dealers. We do not take a stance on which source of private information is larger, but we do document both a fundamental and flow pattern that is concentrated in the customer trades of the large dealer group.

Tables IA.3 through IA.6 of the Internet Appendix provides the regression results for (8).

B Robustness tests for information asymmetry

Given the OTC nature and the relatively infrequent trades in the corporate bond market, comprehensive firm quote data like the NBBO (national best bid and offer) of the stock market does not exist for the corporate bond market. Therefore, in Section 3.2, we used bond price data from Fixed Income Data Feed, which contains end-of-day daily prices and are calculated from dealer quotes, traded prices, and a matrix pricing model, to measure information asymmetry. There are two potential issues with using this data. First is that a large share of high-yield bonds are deleted in cleaning the price data from Fixed Income Data Feed. Prices are stale for some bonds in the dataset, so we delete bonds in which prices remain exactly same in consecutive days for more than 10% of the sample. Unfortunately, a significant share of high-yield bonds are deleted in this step. Second is that because dealer quotes are not necessarily firm (i.e., it is not clear whether a customer can actually trade at this price), information asymmetry calculated using this data may be incorrect.

To check whether the results are robust to these two issues, we calculate information asymmetry using interdealer prices from the TRACE data. Prices in the TRACE data are actual traded prices, so there are no staleness issues and the second issue is also moot. However, the major downside is that a large share of bond-days do not have interdealer trades. Relatedly, since whether there is an interdealer trade on a given bond and day is not random, information asymmetry calculated from TRACE data may be biased. Also, as we have shown in the paper, interdealer prices are affected by the identity of the dealer.

To calculate the market-adjusted return $r_{i,[t,t+\tau]}$ used in (1), we first calculate the return from day t to the week of τ weeks from day t using average interdealer price on day t and week $t+\tau$.[8] We use prices over the week because interdealer trades are fairly sparse. To adjust the return for market-wide movements, we divide bonds into portfolios by rating and time-to-maturity, and subtract the portfolio return from bond i return, similar to the calculation used in Section 3.2. We look at τ of 1 through 4, that is, we look at how prices move up to four weeks after the customer trade. Rest of the calculation follows (1).

Table A.2 shows the average information asymmetry for each dealer group, ratings category, and τ. Across both ratings categories and τ, large dealers have the highest information asymmetry, medium dealers have somewhat lower, and small dealers and client brokers have the lowest information asymmetry. The differences across dealer groups are more pronounced for high yield bonds, consistent with the notion that high yield bonds are more sensitive to information.

Table A.2: **Information asymmetry summary: Using TRACE data, portfolio by rating and maturity**

	Investment grade				High yield			
	1 wk	2 wk	3 wk	4 wk	1 wk	2 wk	3 wk	4 wk
large	8.13	11.09	11.48	11.25	24.76	32.02	31.48	30.61
medium	5.74	7.92	9.33	8.76	10.96	12.63	14.48	11.38
small	-4.59	-1.6	0.67	1.67	-13.97	-15.63	-9.92	-2.5
client broker	-9.33	-5.37	-4.73	-0.49	-6.98	-0.19	8.42	11.19

We test the above by regressing information measure on dealer groups indicator variables, similar to Table 3:

$$InfoAsym_{j,k,y,\tau} = \alpha + \sum_g \beta_g 1[j \text{ in dlr group } g] + \epsilon_{j,k,y} \tag{9}$$

where $InfoAsym_{j,k,y}$ is the information asymmetry measure for dealer j, ratings group k (either IG or HY), year y, using returns over τ weeks. We run the regression separately for investment grade bonds and high-yield bonds and for $\tau = 1, 2, 3, 4$.

Table A.3 presents the regression results. For both investment grade and high yield bonds, large dealers have highest information asymmetry, medium dealers have somewhat lower, and small dealers and client

[8] We use interdealer prices from interdealer trades that are 100K and above in size.

brokers have the lowest information asymmetry. The differences across dealer groups are more pronounced for high yield bonds, consistent with the notion that high yield bonds are more sensitive to information. For investment grade bonds, information asymmetry measured over the three and four week horizon are not statistically significantly different, although lower, for medium dealers compared with large dealers. One possibility is that over longer horizons, noise in market-adjusted returns dominates. Another possibility is that information contained in order flow, at least for investment grade bonds, tends to be about near-future order flows, which put temporary pressures on returns. It would then impact returns in the next few days to few weeks but not much beyond that.

Internet Appendix provides further robustness tests. Tables IA.1 and IA.2 are robustness tests of Tables 3 and A.3, where instead of using portfolio matched by rating and time-to-maturity, we use portfolio matched by rating and trading volume.

Table A.3: **Information asymmetry regression using TRACE data**: The following tables present the results from regression (9). Large dealer group is the omitted category. Standard errors are clustered by dealers. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(a) Investment grade

	1 wk (1)	2 wk (2)	3 wk (3)	4 wk (4)
medium	−2.398***	−3.185***	−2.169	−2.582
	(0.838)	(1.213)	(1.478)	(1.632)
small	−12.718***	−12.714***	−10.775***	−9.510***
	(1.888)	(2.856)	(2.988)	(3.567)
client broker	−17.460***	−16.484***	−16.163***	−11.600***
	(1.463)	(2.243)	(2.406)	(2.988)
Observations	1,409	1,410	1,417	1,410
Adjusted R^2	0.009	0.001	0.001	0.003

(b) High yield

	1 wk (1)	2 wk (2)	3 wk (3)	4 wk (4)
medium	−13.830***	−19.426***	−17.094***	−19.316***
	(2.876)	(4.206)	(3.905)	(4.611)
small	−38.698***	−47.982***	−41.844***	−33.632***
	(3.763)	(5.497)	(5.603)	(6.612)
client broker	−31.659***	−32.697***	−23.910***	−20.269***
	(3.922)	(5.032)	(5.435)	(5.616)
Observations	1,312	1,305	1,304	1,302
Adjusted R^2	0.003	0.005	0.007	0.002

C Additional Results

Table A.4: **Offloading regression: Dealer group level, unmatched:** The following tables present the results from regression (3) but using unmatched trades only. Panel (a) presents the results for investment grade bonds, and panel (b) presents the results for high-yield bonds. Heteroskedasticity-consistent stnadard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(a) Investment grade

	large (1)	medium (2)	small (3)	client broker (4)
DCG_{large}	−0.008*** (0.0005)	0.006*** (0.0003)	0.002*** (0.0002)	0.0004*** (0.0001)
DCG_{medium}	0.026*** (0.002)	−0.034*** (0.003)	0.005*** (0.0005)	0.002*** (0.0004)
DCG_{small}	0.129*** (0.008)	0.048*** (0.004)	−0.191*** (0.008)	0.004*** (0.001)
DCG_{CB}	0.085*** (0.007)	0.041*** (0.004)	0.018*** (0.003)	−0.152*** (0.007)
Observations	2,961,361	2,961,361	2,961,361	2,961,361
Adjusted R^2	0.020	0.013	0.096	0.063

(b) High yield

	large (1)	medium (2)	small (3)	client broker (4)
DCG_{large}	−0.017*** (0.002)	0.009*** (0.001)	0.002*** (0.0003)	0.002*** (0.0005)
DCG_{medium}	0.062*** (0.005)	−0.095*** (0.007)	0.008*** (0.001)	0.002 (0.001)
DCG_{small}	0.260*** (0.015)	0.055*** (0.006)	−0.381*** (0.017)	0.020*** (0.007)
DCG_{CB}	0.104*** (0.011)	0.025*** (0.005)	0.011*** (0.004)	−0.156*** (0.010)
Observations	724,667	724,667	724,667	724,667
Adjusted R^2	0.028	0.036	0.248	0.056

Table A.5: **Offloading regression: Individual dealer level for medium dealers:** The following table presents the results from regression (5) for medium dealers. Heteroskedasticity-consistent stnadard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	large	medium	small	ATS	IDB	client broker
	(1)	(2)	(3)	(4)	(5)	(6)
DCG_{large}	0.0001***	−0.00000	0.00002***	0.00005***	0.0002***	0.0001***
	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00001)
DCG_{medium}	−0.00001	0.001***	0.00003***	0.0001***	0.0002***	0.0002***
	(0.00001)	(0.00003)	(0.00001)	(0.00001)	(0.00003)	(0.00002)
DCG_{small}	−0.0001**	−0.00001	0.004***	0.0004***	0.0003***	0.0004***
	(0.00004)	(0.00002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
DCG_{CB}	−0.0002***	−0.00001	0.0003***	0.0001***	0.0001*	0.008***
	(0.0001)	(0.00002)	(0.0001)	(0.00003)	(0.00005)	(0.0005)
DC_j	−0.039***	−0.012***	−0.011***	−0.007***	−0.027***	−0.026***
	(0.003)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.002)
Observations	68,389,308	68,389,308	68,389,308	68,389,308	68,389,308	68,389,308
Adjusted R^2	0.027	0.007	0.008	0.002	0.007	0.015