Chapter Two

OTC market facts

This introductory chapter sets the stage for our subsequent theoretical analyses by providing a number of empirical observations about OTC markets.

To start, Section 2.1 describes some general facts, including the overall size of global OTC markets and several important dimensions of heterogeneity across these markets that are relevant for our theoretical models.

In the remainder of the chapter, we document a series of stylized facts about a specific market—namely, the market for U.S. corporate bonds. First, in Section 2.2, we describe the Trade Reporting and Compliance Engine (TRACE) data set and the standard procedure for cleaning the data and making it suitable for empirical economic analysis. Then, in Section 2.3, we describe the patterns of trade in this market: the characteristics of trades, the process of intermediation, and estimates of the time it takes to complete a trade. Section 2.4 then offers a discussion of how to measure trading costs, and reports a number of their empirical properties.

The corporate bond market is a natural market to study for several reasons. For one, as noted above, it is a large OTC market and plays a key role in the allocation of capital in the U.S. corporate sector. In addition, since the TRACE data is publicly available, this market has been studied extensively. Lastly, the market structure of the U.S. corporate bond market is similar to that of several other large OTC markets. Importantly, the regularities we glean from this market motivate a number of modeling considerations throughout the book,

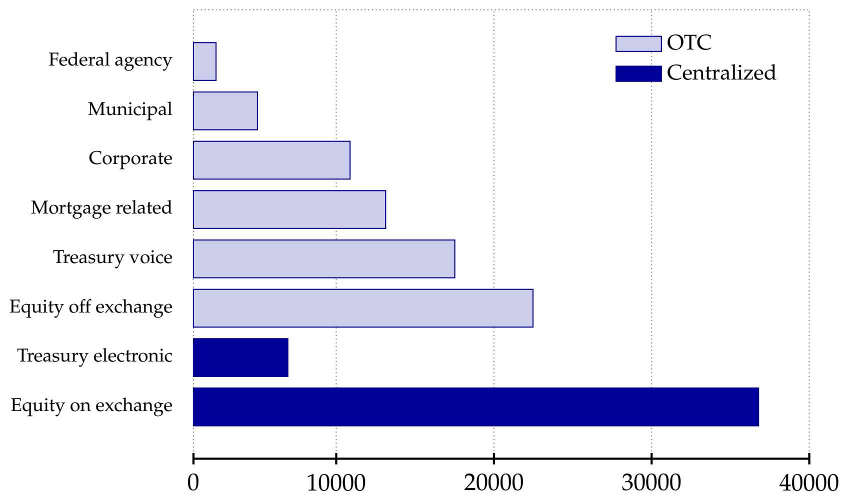

FIGURE 2.1: Supply of U.S. securities

This figure lists the supply of different types of publicly listed U.S. securities across centralized exchanges and OTC markets in billions of USD. See Online Appendix A of Weill [2020] for a description of the data and method.

and provide a quantitative benchmark for those interested in taking this class of models to the data.

2.1 THE BASICS

HOW LARGE ARE OTC MARKETS?

Figure 2.1 breaks down the supply of publicly listed U.S. securities that are traded on exchanges (dark blue) and in OTC markets (light blue) in the year 2021. It reveals that a wide variety of securities trade OTC, most notably those in the fixed-income segment. Some securities, namely equities and Treasuries, actually trade in both OTC markets and exchanges. The figure illustrates that OTC markets are extremely large: the total supply of publicly listed securities traded in OTC markets is about \$66 trillion, which was approximately 50% more than the supply of assets traded on exchanges in 2021.

In addition to the securities listed in Figure 2.1, several prominent classes of derivative products also trade OTC. According to the Bank for International Settlements, which regularly publishes global OTC derivative statistics, the two largest classes of OTC derivatives are interest rate and foreign exchange derivatives with a combined traded notional of close to $700 trillion in the first semester of 2023. Many important credit markets also operate over the counter, including the Federal Funds market [Ashcraft and Duffie, 2007], the market for short term loans between banks and money market funds [Beltran, 2021], and a significant portion of the market for repurchase agreements [Eisenschmidt, Ma, and Zhang, 2024]. Finally, many non-financial assets trade OTC, such as used capital [Gavazza, 2011a], real estate [Han and Strange, 2015], and even ideas [Silveira and Wright, 2010].

Heterogeneity across OTC markets.

No two OTC markets are exactly alike. One key dimension of heterogeneity is that some markets have designated intermediaries who handle most of the trading volume, while others do not. For example, most of the volume in the U.S. corporate bond market is executed through dealers, whereas banks in the Fed Funds market tend to trade directly with one another without the help of a designated intermediary.

OTC markets also differ according to the protocols used to solicit quotes and/or determine the terms of trade. In many OTC markets, investors request quotes to buy or sell on a bilateral basis, contacting dealers or other investors sequentially and bargaining over the terms of trade. However, several markets have introduced platforms that allow investors to solicit requests for quotes (or "RFQs") from multiple dealers at once. Using these new platforms, investors essentially conduct auctions that determine the price at which they trade.

The network of trading relationships also differs substantially across OTC markets. In some OTC markets, investors trade with a wide range of different counterparties, depending on their immediate trading needs, and the resulting network of relationships is relatively dispersed. In other markets, however, investors trade almost exclusively with a small number of counterparties with whom they have long-term relationships, so that the resulting network exhibits a so-called core-periphery structure.

Still another important dimension of heterogeneity across OTC markets is the method by which trades are settled or cleared. More specifically, some OTC markets specify that trades are settled bilaterally, so that counterparty risk is borne exclusively by the parties involved in a given trade. Alternatively, some markets have introduced a third party called a "central counterparty" (CCP) to assist in clearing the transfer of funds and assets and to collectively insure market participants against counterparty risk.

While each of these dimensions of heterogeneity across OTC markets has potentially interesting economic implications, we are not able to analyze all of them in this book, in part because the literature has not yet settled on a suitably unified framework. As a result, in the theoretical analyses that follow, we will focus on some specific features of OTC markets, like whether they are intermediated by dealers and how investors solicit quotes, and leave other dimensions of heterogeneity, like the method by which trades clear, for future work.

OTC market data.

Since OTC markets historically provided little pre-trade and post-trade price transparency, transaction data was much less readily available than data from markets that operated through an exchange. However, in the last two decades, regulatory efforts to improve transparency have fostered the availability of data for several important OTC markets in the U.S. For example, dealers trading corporate and municipal bonds, as well as various asset-backed securities, are now required to report transactions to the Trade Reporting and Compliance Engine (TRACE), which are aggregated and disseminated to the public after a short delay. These new datasets offer investors a benchmark for the valuations of the securities they seek to trade and, more importantly for our purposes, enable researchers to empirically study trading activity, transaction costs, and intermediation in OTC markets.

In the remainder of this chapter, we document a number of empirical regularities for one particular dealer-intermediated OTC market: the market for U.S. corporate bonds. We choose this market for several reasons. First, as noted above, it is a large and important market. Second, the data on corporate bonds has been made widely available and offers a relatively long time series of prices and quantities traded. Third, there are well-documented algorithms available for cleaning and analyzing this data. Finally, since this market has been widely studied, there are a number of stylized facts that have been established in the academic literature.

To be clear, we do not intend to provide an exhaustive list of stylized facts. Rather, our goal is to establish some general properties of the corporate bond market—many of which are shared by other OTC markets—and to motivate the models that follow. In particular, we describe how customers trade with dealers and the process by which securities are reallocated within the dealer sector. We document that trading costs in OTC markets are often substantial; that they vary significantly depending on the characteristics of the bond, and both the size and the direction of the trade; and that there is a considerable amount of dispersion in trading prices after controlling for observables. At this stage, we resist the temptation to formulate economic interpretations of these facts, choosing instead to explore these empirical regularities within the context of the theoretical frameworks we develop in subsequent chapters.

2.2 U.S. CORPORATE BOND MARKET DATA

DATA.

In July 2002, the Financial Industry Regulatory Authority (FINRA) introduced the Trade Reporting and Compliance Engine (TRACE), which requires dealers to report all transactions within fifteen minutes of execution. These transaction reports include the time of the trade, a unique identifier for the bond that was traded, the trade size, the transaction price, the side of the trade on which the dealer participated, and some information about the counterparty. Since most trades in the corporate bond market involve at least one dealer, these reports constitute a near-comprehensive record of all secondary-market transactions in U.S. corporate bonds.

Upon receiving these TRACE reports, FINRA disseminates the information to the investment and academic communities with varying level of details. For example, while FINRA does not collect information about customers, different versions of the dataset provide varying levels of information about the identity of the dealer(s) involved in a transaction. The various versions of the TRACE data also differ with respect to top-coding: some versions only report trading volume up to a cap of $5 million for investment-grade bonds and $1 million for high-yield bonds. The academic version of the dataset that we study here is one of the most detailed available: it is not top-coded and provides anonymized identifiers that allow to follow a dealer's transactions over time.

CLEANING THE DATA.

Dick-Nielsen [2014, 2019] describes a cleaning process for the TRACE data that has become standard in the academic literature. The data must be cleaned for several reasons. First, dealers sometimes correct their initial reports, perhaps because some details were entered incorrectly in the system or because the transaction was canceled. As a result, some transactions are associated with several reports: the original, and the subsequent corrections or cancellation. Second, each interdealer transaction appears twice in the dataset because both dealers are required to report their trades. As a result, one must remove these duplicate reports so that each transaction appears only once, with the most up-to-date information about the terms of trade. Third, one often removes bonds with exotic features, such as convertibility or foreign currency denomination, so as to keep the sample homogeneous. Fourth, since trading activity differs markedly for newly issued bonds and bonds close to maturity, one typically removes trades that occur within two months of a bond's issuance and less than one year to maturity. Focusing on trades for bonds outside of the beginning and end of their lifespan allows us to focus on trading activity when it has reached a relatively stationary level, as envisioned in the steady state equilibrium of the models studied in this book

Since the TRACE data set is continuously growing, the implementation of the basic algorithm proposed in Dick-Nielsen [2014] has become increasingly time-consuming. To overcome this computational challenge, Palleja [2022] developed an alternative, recursive algorithm that is sufficiently efficient to be run on a laptop computer. In this chapter, we apply this novel algorithm to the academic version of the TRACE data for the two-year window of 2016 and 2017, which contains more than 14 million transactions.

2.3 TRADING ACTIVITY

BASIC FACTS.

The first four rows of Table 2.1 provide some of the characteristics of bonds traded during these two years. On average, bonds in the sample are about 4 years removed from issuance and have approximately 8 years to maturity. The average coupon rates and yield spreads are around 4 percent, though yield spreads vary substantially based, in part, on differences in credit risk.

Next, the middle section of Table 2.1 provides insight into the frequency and size of trades. The first observation is that individual bonds do not trade very often: the average bond trades a little more than 700 times per year. Assuming that there are about 250 trading days, this means that the average bond trades less than three times per day. There is, however, a lot of dispersion: bonds at the 5th percentile trade only 8 times per year, while bonds at the 95th percentile trade approximately 3,000 times. Consistent with these observations, the average yearly turnover is close to 50%, but ranges from about 2% at the 5th percentile to more than 140% at the 95th percentile. By contrast the World Bank reports that the average turnover for U.S. equities over the same period was about 105%. The table also reveals that trade sizes are large—with an average of nearly $500,000—and that there is considerable dispersion in the size of trades. Presumably, a significant portion of this dispersion reflects heterogeneity among market participants, with retail investors trading small quantities of bonds and institutional investors trading larger blocks.

Finally, the bottom section of Table 2.1 reports statistics for three separate segments of the market: the Customer-to-Dealer (CD) segment that records sales of bonds by customers to dealers; the Dealer-to-Customer (DC) segment that records sales by dealers to customers; and the Dealer-to-Dealer (DD) segment that records inter-dealer trades. The DC and CD turnover are approximately equal, implying that most of what dealers buy from customers is sold to other customers, and not absorbed into the inventory of the dealer sector as a whole. At the same time, DD turnover is substantial as well. This reflects the fact that, when a customer sells an asset to a dealer, this asset is often re-traded between dealers before being reallocated to another customer. Finally, note that trade size differs across market segments. Indeed, DD trades tend to be much smaller than trades between customers and dealers. Moreover, there is

Variables	Obs.	Mean	P5	P25	P50	P75	P95
Bond age (year)	14,246,209	3.84	0.42	1.51	2.99	5.01	10.11
Time-to-maturity (year)	14,246,209	8.11	1.57	3.67	5.74	8.67	26.60
Coupon rate (pp)	14,246,127	4.72	2.05	3.25	4.50	6.00	8.00
Yield Spread (pp)	14,133,403	3.89	0.40	0.87	1.62	3.49	10.14
All - Trades per bond-year	19,810	719.14	8.00	70.00	254.00	781.00	2,986.00
All - Yearly Turnover (pp)	19,810	48.75	1.98	14.74	33.82	63.84	142.91
All - Trade par value ($K)	14,246,209	475.00	3.00	10.00	25.00	150.00	2,500.00
CD - Trades per bond-year	19,810	174.25	2.00	19.00	69.00	195.00	700.55
CD - Yearly Turnover (pp)	19,810	19.89	0.56	5.34	13.23	26.52	60.79
CD - Trade par value ($K)	3,451,841	815.75	2.00	10.00	35.00	350.00	5,000.00
DC - Trades per bond-year	19,810	244.82	2.00	23.00	89.00	265.00	993.55
DC - Yearly Turnover (pp)	19,810	19.22	0.36	5.22	12.78	25.61	58.91
DC - Trade par value ($K)	4,849,866	562.35	3.00	10.00	28.00	200.00	3,000.00
DD - Trades per bond-year	19,810	300.08	2.00	21.00	87.00	305.00	1,293.55
DD - Yearly Turnover (pp)	19,810	9.63	0.12	1.79	5.33	12.17	32.25
DD - Trade par value ($K)	5,944,502	205.86	2.00	10.00	23.00	90.00	1,000.00

TABLE 2.1: Trading activity statistics from TRACE, 2016–2017.

In this table the notations *pp* and $*K* refer to refers to percentage points and to 1,000 USD, respectively. The variables have different numbers of observations because they are calculated using different samples.

an asymmetry in trade size between customers and dealers: CD trades are, on average, larger than DC trades. Since CD and DC turnover are approximately equal, this mechanically means that there are more CD trades than DC trades, which suggests that customers tend to split their trades more often when they buy than when they sell.

Market segment	30%	60%	90%	100%
Total dealer-customer volume	4	8	29	1,161
CD volume	4	8	26	1,086
DC volume	4	8	32	1,040
Inter-dealer volume	8	21	72	1,228

TABLE 2.2: Distribution of volume across dealers

INTERMEDIATION.

Given the substantial volume of trade between dealers, several researchers have explored the process of reallocation that occurs within the intermediation sector. In particular, Li and Schürhoff [2019] have shown that, in the market for municipal bonds, dealers trade together along so-called *intermediation chains*. A chain begins when a customer sells to a dealer (a CD trade), and is followed by a series of DD trades until a dealer re-sells to a customer (a DC trade). We can use the trading volume data in Table 2.1 to derive a rough estimate of the length of these intermediation chains in the corporate bond market. To do so, let $\bar{n}$ denote the number of dealers in a typical intermediation chain, so that the number of DD trades in a chain is $\bar{n} - 1$. Assuming, for simplicity, that CD and DD trades have the same size, the ratio of DD to CD volume is $\bar{n} - 1$. In the data, this ratio is approximately equal to 0.5, implying that the average length of intermediation chains in the corporate bond market is $\bar{n} = 1.5$. Finally, Table 2.1 reveals that DD trades are typically smaller than CD and DC trades which suggests that intermediation chains often involve splitting up the initial block into smaller quantities that are easier to trade.

Existing empirical studies have documented substantial heterogeneity in the frequency with which dealers participate in intermediation chains and in their typical position within a chain. Table 2.2 reports that trading volume is very unevenly distributed across dealers: Among all trades between customers and dealers, 90% of the volume is accounted for by about 30 dealers (out of the 1,161 active dealers). Concentration is also substantial in the DD segment of the market, though less pronounced—approximately 90% of the volume is concentrated among 72 dealers. Concentration in the inter-dealer segment is

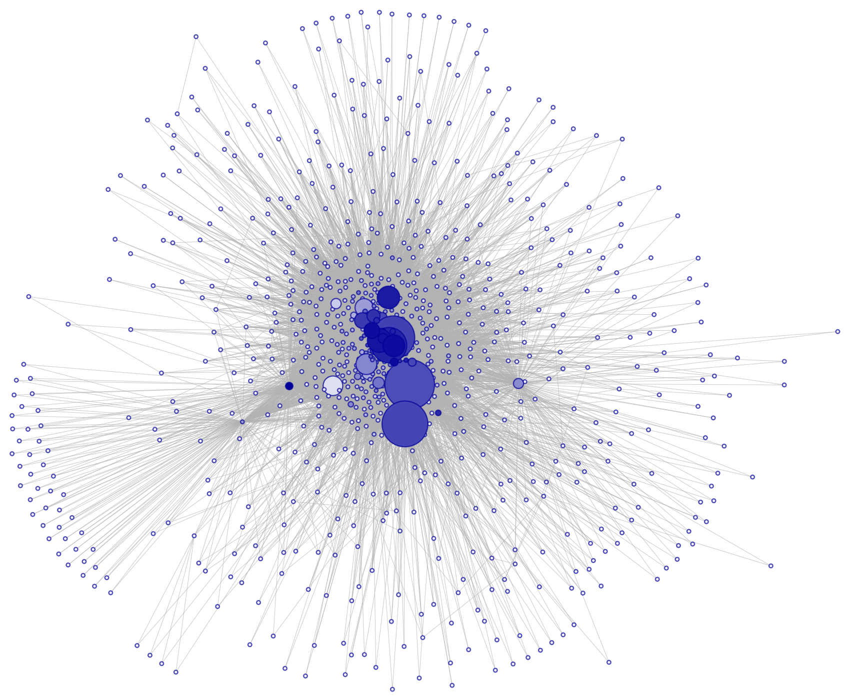

FIGURE 2.2: The network of interdealer trades

This figure illustrates the core-periphery structure of the interdealer network. Nodes in the graph represent dealers, edges represent trades, and the size and color of the nodes reflect the number and size of executed trades.

related to an observation made by Hollifield, Neklyudov, and Spatt [2017] and Li and Schürhoff [2019], among others, that inter-dealer markets have a *core periphery* network structure. That is, there is a core of large dealers who trade actively with each other and a periphery of small dealers who mostly trade with the core. Figure 2.2 confirms this observation by plotting the network of interdealer trades in our two-year sample. In the picture, each node represents a dealer, and the size of the node is proportional to the number of trades executed. The picture reveals that dealers in the core trade frequently and that they are often in the middle of an intermediation chain, whereas dealers in the periphery trade less often and typically find themselves at one end of a chain.

TRADING DELAYS.

A premise of the search models that we study in this book is that investors in OTC markets have to find a counterpart to trade and, hence, executing a trade can take time. Unfortunately, the data studied so far in this chapter—as well as most existing data from OTC markets—cannot provide direct evidence about this search process. The reason is simple: since most data sets (including TRACE) only collect information about executed transactions, it is only informative about the *end* of a *successful* search. This is in sharp contrast with data from other frictional markets, such as labor or real estate markets, where one can observe how long sellers stay on the market. For example, labor market data contains detailed information about the duration of search for unemployed workers, while residential real estate data sets record time on the market for listed homes.

In recent work, Kargar, Lester, Plante, and Weill [2023a] leverage data from the leading electronic trading platform for corporate bonds to estimate time to trade. The data they use contains information about when investors initiate their search by sending a request for quotes (RFQ) and about the subsequent responses submitted by dealers. The data is unique in that it contains all of the details for each RFQ, including the time at which it occurred, the bond and quantity that the investor wanted to trade, and the replies from dealers, regardless of whether the RFQ is successful or not.

Kargar et al. [2023a] document that RFQs fail fairly frequently: investors reject the offers they receive (or, less frequently, don't receive any offers) about 30% of the time. When this occurs, investors often come back to the market and send additional RFQs for the same quantity of the same bond. Kargar et al. [2023a] interpret these repeat attempts as evidence of sequential search in the market for corporate bonds. After correcting for biases, they estimate that, after an unsuccessful RFQ, it takes about 2 to 3 days for investors to complete a trade. They show that time to trade varies considerably depending on the trade and investors characteristics, as well as the state of the market. For example, they document that it takes longer to trade larger quantities, that attempts to sell are completed faster than attempts to buy, and that certain customers who appear to be more connected trade substantially faster than other customers who have fewer connections to the dealer sector.

2.4 TRADING COSTS

MEASUREMENT.

Measuring trading costs in OTC markets is a challenging task. In contrast to exchanges, where prevailing bid and ask prices are available at all times, round-trip trading costs in OTC markets have to be constructed from trades between customers and dealers that are recorded at different points in time. Moreover, as noted above, it is often hours (or even days or weeks) between consecutive CD and DC trades for a particular bond.

There are a number of different methodologies that have been proposed to overcome the challenge of measuring trading costs. In what follows, we use the methodology of Choi, Huh, and Seunghun Shin [2024] because it has a close theoretical counterpart in the models we study throughout the book. Specifically, following Choi et al. [2024], we calculate the markup (markdown) that dealers charge customers who buy (sell) relative to a reference inter-dealer price. To compute this reference inter-dealer price at the bond-day level, we calculate the volume-weighted average inter-dealer price of a particular bond in a given day. Then, for all trades in the same bond on the same day, we let the trading cost be the percentage markup (if the dealer sells to a customer) or markdown (if the dealer buys from a customer) relative to this reference price.

Since we only consider CD and DC trades that can be matched with a DD trade on the same bond-day, the sample is selected. Table 2.3 provides summary statistics. Comparing with the last rows of Table 2.1, one sees that about 14% of the full sample of CD and DC trades could not be matched to a reference interdealer price. However, the resulting sample does not seem to be dramatically selected; for example, the distribution of turnover in the restricted sample is quite similar to that in the overall sample.

The table reveals information about the typical magnitude and variation in trading costs. For example, it shows that the median trading cost is 18bps. The trading cost at the 5th percentile is actually negative—a phenomenon that Choi et al. [2024] interpreted as customer liquidity provision—while the trading cost at the 95th percentile exceeds 200bps.

	Observations	Mean	P5	P25	P50	P75	P95
Bond age (year)	7,098,957	3.79	3.43	1.50	2.96	4.93	9.73
Time-to-maturity (year)	7,098,957	7.83	1.55	3.63	5.68	8.49	26.00
Coupon rate (pp)	7,098,940	4.64	2.00	3.20	4.45	5.95	7.88
Yield Spread (pp)	7,045,916	3.71	0.38	0.83	1.55	3.38	9.69
Trades per bond-year	19,293	429.97	6.00	50.00	175.00	485.00	1,712.00
Yearly Turnover (pp)	19,293	39.74	1.48	11.33	26.74	52.62	119.74
Trade par value ($K)	7,098,957	541.07	2.00	10.00	25.00	125.00	3,000.00
Transaction Cost (bp)	7,098,957	47.42	-21.72	1.99	17.78	65.84	215.28

TABLE 2.3: Properties of trades in the selected trading cost sample.

THE DETERMINANTS OF TRADING COSTS.

Following the methodology of Edwards, Harris, and Piwowar [2007], we study the empirical determinants of trading costs using regression analysis, including fixed effects for day, dealer, and the industry of the bond's issuer. The results are reported in Table 2.4.

The first two lines of the table reveal that transaction costs increase in the age and time to maturity of the bond being traded. The next lines show that transaction costs are higher for riskier bonds, as measured by the yield spread or by credit rating. Note that the relationship between transaction cost and credit rating is economically quite significant: the difference in trading cost between a bond in the highest and the lowest credit rating bins is more than 40 bps on average. The next lines confirm that transaction costs decrease with trade size. This relationship is economically significant, but also non-linear: relative to the omitted micro trade category, all trades above USD 100,000 have a similar discount of approximately 15 bps.

We noted earlier that there is an asymmetry between the trade size of DC and CD trades—namely, that DC trades are smaller than CD trades. Moving down the table reveals that there is a similar asymmetry between transaction costs. In particular, we find that DC trades are more expensive, by about 10 bps, than CD trades.

Finally, the last lines of Table 2.4 introduce an important distinction between two types of transactions that dealers facilitate. The first type is called a *risky principal* (or just *principal*) trade, when a dealers buys bonds from a customer on her own account, holds them in inventory for some period of time, and then sells to a different customer. The second type of transaction is called an *agency* trade. Under this trading arrangement, the dealer is essentially a matchmaker: she does not use her own inventory capacity to facilitate the trade, but rather matches a customer who wants to sell with a customer who wants to buy (like a real estate agent).

Empirical studies typically identify agency trades by finding pairs of trades, one CD trade and one DC trade, that are reported in rapid succession for the same quantity of the same bond. Intuitively, when a dealer facilitates an agency trade, she buys from one customer, sells immediately to another, and reports the two trades to TRACE at the same time. After distinguishing between these two types of trades in our data, Table 2.4 reveals that agency trades are less costly than principal trades, and that the effect is twice as large for DC trades than for CD trades.

Dealer-to-dealer vs. customer-to-dealer frictions.

How large are the frictions in the DD segment relative to the CD/DC segments? One way to answer this question is to compare the realized dispersion of prices in the DD market to that of prices in the CD/DC markets.

Figure 2.3 plots a histogram of the level of dispersion in the DC/CD and DD market segments. To generate this figure, we compute the realized dispersion of log prices in the DD market and in the CD/DC market at the bond-day level. For each bond, we restrict attention to days in which there are at least 10 trades in each market segment, which obviously biases the sample towards relatively active bonds. Despite this bias, the figure clearly suggests that dispersion is significantly lower in the DD segment: the DD segment has a mean of about 40bps, while the CD/DC segment has a mean of about 74bps. Clearly, the *level* of dispersion reflects both the arrival of news about fundamental values and frictions. However, the *difference* in dispersion is likely to reflects differences in frictions.

One could argue that some of this difference reflects sample selection, since the two segments are active for different bonds at different times. To address

Independent Variable	Coefficient	Standard Error
Bond age	0.5247***	(0.0985)
Time-to-maturity	2.189***	(0.0698)
Yield spread	0.4447***	(0.0642)
Credit Rating		
IG (A-BBB)	5.285***	(0.8990)
HY (BB-B)	25.02***	(1.1320)
HY (CCC-D)	42.78***	(1.7710)
Trade Size		
Odd (100K-1M)	–13.94***	(0.3290)
Round (1M-5M)	–17.30***	(0.4252)
5M and above	–13.38***	(0.4046)
DC	9.588***	(0.5208)
Agency	–3.035***	(0.4425)
Agency × DC	–12.98***	(0.6454)
Day FE	Yes	
Dealer FE	Yes	
Issuer Industry FE	Yes	
Observations	6,896,251	
Adjusted R^2	0.36189	

TABLE 2.4: Transaction cost regression

Bond age and time-to-maturity are expressed in years while yield spreads are expressed in percentage points, and transaction costs in basis points. Credit ratings are split into four bins, of which IG (AAA-AA) is used as baseline. Similarly, trade sizes, expressed in million dollars, are split into four bins, with micro (0-100K) used as baseline. Bond-day clustered standard errors are presented in parenthesis with superscripts *,** and *** denoting statistical significance at 10%, 5% and 1%. Detailed credit ratings are obtained from the FISD database.

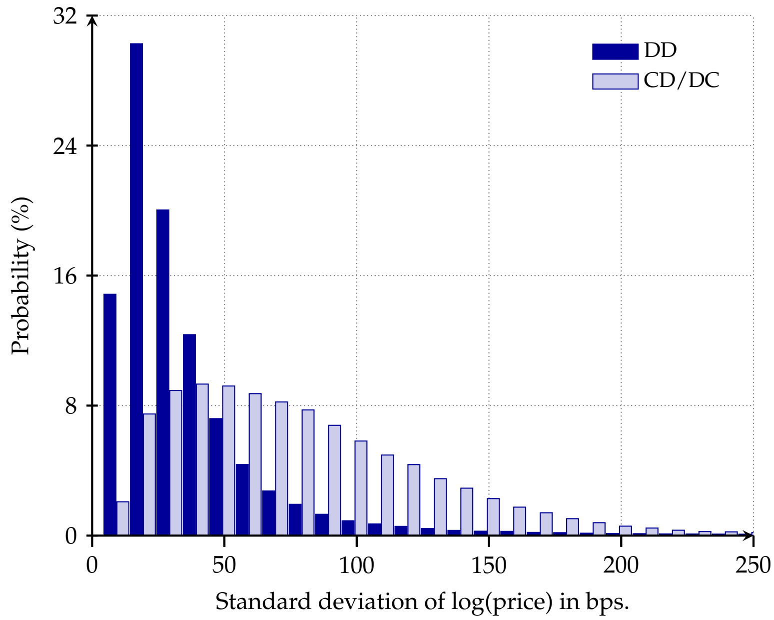

FIGURE 2.3: Price dispersion in the corporate bond market

This figure illustrates the extent of price dispersion in the DD and CD/DC segments of the U.S. corporate bond market over the period 2016–17.

this concern, we regress our measure of realized price dispersion on a market segment indicator (DD or CD/DC), trade size category dummies, as well as bond and day fixed effects. Interestingly, the results of this regression, which are reported in Table 2.5, suggest an even larger difference between the price dispersion in the two segments—about 44bps—which is close to the size of the median round-trip trading cost paid by customers.

2.5 NOTES AND REFERENCES

While there has been some early studies of OTC markets, such as Garbade and Silber [1976], much of the empirical research on the topic traces back to the early 2000's, when trade-level data first became available for some OTC markets. Seminal contributions include Harris and Piwowar [2006a] for the

Independent Variable	Coefficient	Standard Error
Customer-Dealer	43.69***	(1.147)
Odd (100K-1M)	0.6941***	(0.250)
Round (1M-5M)	2.808***	(0.533)
5M and above	–17.02***	(2.562)
Day FE	Yes	
Bond FE	Yes	
Observations	182,969	
Adjusted R^2	0.61971	
% Vol	25.3	
% Trades	15.9	

TABLE 2.5: Price dispersion regression

Standard errors clustered at the bond level are presented in parenthesis with superscripts *,** and *** denoting statistical significance at 10%, 5% and 1% respectively.

U.S. Corporate Bond Market, Harris and Piwowar [2006b] and Green, Hollifield, and Schürhoff [2006] for the U.S. Municipal Bond market, and Ashcraft and Duffie [2007] for the Federal Funds Market. The literature has grown significantly in the interim, particularly in certain fixed income markets [see the survey by Bessembinder, Spatt, and Venkataraman, 2020].

While it is impossible to do justice to every paper in this extensive literature, it is worthwhile to mention some of the markets and economic phenomena that have been studied empirically, and that we will discuss later in the book. Bao, Pan, and Jiang [2011] , Friedwald and Nagler [2019] and He, Khorrami, and Song [2022] document certain dimensions of commonality in illiquidity across corporate bonds. Bessembinder, Maxwell, and Venkataraman [2006], Goldstein, Hotchkiss, and Sirri [2007], Bessembinder and Maxwell [2008] and Asquith, Covert, and Pathak [2013] study the impact of regulations promoting price transparency on OTC market liquidity. Hendershott and Madhavan

[2015] and O'Hara and Zhou [2021] study the rise of electronic platforms in the corporate bond market. Afonso, Kovner, and Schoar [2014] and Hendershott, Li, Livdan, and Schürhoff [2020] offer evidence on the importance of trading relationships in the Fed Funds and the U.S. corporate bond markets, respectively. Bessembinder, Jacobsen, Maxwell, and Venkataraman [2018], Adrian, Boyarchenko, and Shachar [2017], Trebbi and Xiao [2017], Choi, Huh, and Seunghun Shin [2024], Bao, O'Hara, and Zhou [2018] study the adverse impact of balance sheet constraints and other regulations on bond market liquidity, while Dick-Nielsen, Feldhütter, and Lando [2012], Friewald, Jankowitsch, and Subrahmanyam [2012], Di Maggio, Kermani, and Song [2017], Dick-Nielsen and Rossi [2019], O'Hara and Zhou [2021], and Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga [2021a] study the performance of OTC markets under stress. Foley-Fisher, Gissler, and Verani [2019] study security lending in the corporate bond market, while Li, O'Hara, Rapp, and Zhou [2023] analyze the effects of the recent trend towards exchanging portfolios instead of individual bonds. Credit derivative markets have been studied empirically in Arora, Gandhi, and Longstaff [2012], Siriwardane [2019], and Riggs, Onur, Reiffen, and Zhu [2018] using proprietary data. Finally, Kondor and Pinter [2022] and Pinter, Wang, and Zou [2021] exploit a unique feature of data from the UK bond market—the ability to track the identity of customers over time—to study the importance of customers' identities on trading outcomes.