Portfolio Trading in OTC Markets: Transaction Cost Discounts and Penalties*

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Abstract

This paper studies a recent innovation in the corporate bond market: portfolio trading. In contrast to sequential trading, this new protocol allows customers to trade a list of bonds as a single security. I show that these trading features have significant consequences over market liquidity. Particularly, I present novel evidence of asymmetrical transaction costs: compared to sequential trading, portfolio trading is less expensive when customers buy and more expensive when they sell. I find that dealers' balance sheet costs and portfolios' diversification explain such differences.

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1 Introduction

The corporate bond market has undergone several transformations in recent years. Market participants have shifted from trading through voice messages to doing so on electronic platforms (Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021), dealers have accommodated stricter regulations by relying more on pre-arranged trades instead of trading with their inventories (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Choi, Huh, and Seunghun Shin, 2024), and all-to-all platforms, where customers can skip dealer intermediation, are becoming increasingly popular (Hendershott, Livdan, and Schürhoff, 2021). The latest of these innovations is portfolio trading, a new protocol in which market participants can bundle a set of bonds and trade them as a single security. Although involving higher commitment from dealers, the electronic platforms that supply this new protocol claim that portfolio trading helps not only to improve execution quality but also to reduce transaction costs.[1]

In this paper, I study portfolio trading in the corporate bond market, addressing to what extent the claims made by electronic platforms hold empirically. I start by addressing the evolution of portfolio trading. I develop an algorithm to infer portfolios from individually reported trades and find that, starting in 2018, this new protocol has become increasingly popular, both in the customer-dealer and in the inter-dealer segment. Its provision is highly concentrated among top dealers, who rely on inventories to provide liquidity. I next turn to study the cost of portfolio trading. Compared to traditional sequential trading, customers sell portfolios with a penalty and buy portfolios at a discount. These transaction cost differences are explained by two forces: the overall volume and the overall risk traded. Moreover, portfolio penalties and discounts are not distributed homogeneously across bonds. I find a significant cross-subsidy within portfolios, where the traditional bond characteristic pricing is reversed once a bond is included in a portfolio.

The first task I perform is to infer portfolio trades from the Trade Reporting and Compliance Engine (TRACE). This database only recently (May 2023) adopted a protocol identifier, thus I need to develop an algorithm to track portfolios back in time. In a nutshell, I look for two counterparts executing many different bonds in the same second. As expected, the algorithm captures the rise of portfolio trading in early 2018, the period when platforms started offering the service. I find that portfolio trading accounts for more than 10 billion dollars of monthly volume during late 2020, evenly divided between the customer-dealer and the inter-dealer segments, capturing 5% of the total market. Recent estimates show that the positive trend continued during 2021 (Li, O'Hara, Rapp, and Zhou, 2023).

To understand this new protocol, I provide descriptive statistics comparing portfolio and sequential trading. Portfolios are mainly institutional trades, typically involving around one hundred bonds and 65 million dollars of nominal value. Not surprisingly, its intermediation is concentrated among top dealers, which have enough sophistication to price all bonds and inventories to back up these trades. I find that

[1] See, for example, providers Tradeweb and ICE portfolio trading descriptions.

portfolios affect dealers' balance sheets, whether because bonds were held in inventories before selling them to customers or because bonds add up to inventories after being bought in portfolios. Regarding portfolio composition, I do not find evidence suggesting that customers use this protocol to sell low-turnover bonds, as portfolios have a lower concentration of low-turnover bonds and a higher concentration of mid-turnover bonds than sequential trades. I do find evidence of customers trading riskier bonds in portfolios, measured both by interest rate risk and credit risk.

I next turn to study whether portfolio trading improves or hinders liquidity. To guide the empirical analysis, I provide a theoretical framework of transaction costs in over-the-counter (OTC) markets. Trading bonds through portfolios instead of sequentially would increase (decrease) transaction costs if it increases (decreases) customers' trading surpluses or dealers' trading costs. Several portfolio characteristics that may drive these variables are outlined. Among them, a portfolio implied balance sheet cost, how much risk a portfolio can diversify, and the likelihood of customers trading on private information at least one of the bonds included in the portfolio.

The empirical analysis starts by comparing the transaction costs paid by customers when trading bonds sequentially or through portfolios, controlling for other relevant characteristics of the trade. I find that bonds traded in portfolios pay on average 17.7% less transaction costs than those traded sequentially. However, the effect is asymmetric. When customers buy portfolios from dealers, they have a 42.6% transaction cost discount. Contrastingly, when customers sell portfolios to dealers, they pay a 9.9% penalty. These results hold robustly when considering alternative model specifications and alternative sample periods.

To understand what factors are behind these discounts and penalties, I proceed in two ways. On the one hand, I address how individual bonds are priced within the portfolios. I find a significant cross-subsidy within portfolios: characteristics that are priced in sequential trading are reversed when bonds are included in a portfolio. On the other hand, I investigate what portfolio characteristics are priced by dealers and in which direction. I find significant evidence of both balance sheet effects and portfolio diversification effects. Bonds in large-size portfolios have associated transaction costs up to 36.34 basis points (bps) higher than those in small-size portfolios. In turn, bonds in portfolios with many bonds – proxy for risk diversification – pay up to 27.67 bps less to trade than bonds in portfolios with few lines.

Overall, portfolio trading appears as a disruptive innovation in the corporate bond market. It provides a better quality execution for those customers in need of trading many bonds simultaneously. However, such improvement in execution quality does not always come for free. As this paper shows, when customers sell portfolios to dealers, they incur an extra cost compared to that of trading bonds sequentially. These higher costs can be further exacerbated if portfolios involve large volumes and do not diversify individual bond risk.

1.1 Related Literature

This paper is related to two strands of the literature. On the one hand, it complements the empirical literature that studies recent developments in the corporate bond market. For example, the rise of electronic platforms (Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021) and all-to-all trading (Hendershott, Livdan, and Schürhoff, 2021), the effect of stricter banking regulations after the global financial crisis (Anderson and Stulz, 2017; Bao, O'Hara, and Zhou, 2018; Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Dick-Nielsen and Rossi, 2019; Choi, Huh, and Seunghun Shin, 2024; Rapp and Waibel, 2023), or episodes of big turmoil as COVID-19 (Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga, 2021). I address how the latest innovation in this market, portfolio trading, is used by customers and dealers and how it affects market liquidity. On the other hand, this paper informs the theoretical literature on OTC markets, which models trading in a sequential fashion (Duffie, Gârleanu, and Pedersen, 2005; Lagos and Rocheteau, 2009; Weill, 2020), and the long-standing theoretical literature on portfolio pricing (Markowits, 1952; Acharya and Pedersen, 2005), which assumes assets can be traded continuously. In this regard, portfolio trading offers a unique opportunity to study the pricing of OTC-traded portfolios. I show that portfolio trading is associated with higher costs when customers sell and lower costs when customers buy, and provide the factors behind these asymmetries. Finally, this paper closely relates to two independent, contemporaneous works on corporate bonds portfolio trading. Meli and Todorova (2022) use proprietary data to study investment-grade portfolios. They find that transaction costs are reduced by over 40% when trading portfolios. I complement their findings by incorporating the whole universe of portfolios, both investment-grade and high-yield, and showing that portfolio transaction costs can be larger than sequential costs, especially for large-size and less diversified portfolios. In turn, Li, O'Hara, Rapp, and Zhou (2023) use the regulatory version of TRACE and find that portfolios are usually traded at a discount, although that discount is reduced the more balance sheet dealers accumulate as a result of the portfolio buy. My results show that customers pay higher costs when selling portfolios than when doing it so sequentially, and that the size of a portfolio increases its costs, both when customers buy and when they sell, indicating that dealers also translate the balance sheet costs of those bonds that were held in inventory before the trade.

2 Portfolio Trading: a New Protocol in the Bonds Market

The US corporate bond market is a typical over-the-counter market, where the lack of a centralized exchange makes customers search for trading counterparties. Typically, dealers reduce these search frictions by intermediating transactions, using their own inventories and locating counterparts within their trading network. Although communications have shifted from phone calls and Bloomberg messages, i.e. voice trading, to electronic platforms, customer-dealer interactions can still be described in the same following steps.

Customers would contact dealers requesting quotes, specifying the issue, the trade size, and whether is a buy or a sell order. Dealers with the capability of providing quotes would compete, and the best quote would execute the trade. Since neither receiving quotes from dealers nor executing the trade at the winning quote is guaranteed, the execution uncertainty adds up to the search friction as a major concern for customers in this market.

In many scenarios, customers would like to trade many bonds simultaneously, e.g. portfolio rebalancing, fixed income exchange-traded funds (ETF) create and redeem process, etcetera. In such cases, customers would need to contact dealers sequentially, repeating the process previously described for each bond. In practice, customers engage in list trading: they send a spreadsheet with all the orders to dealers, who choose whether to offer quotes or not on a bond-by-bond basis. As these quotes are usually not firm, the process often suffers many back-and-forth iterations until all bonds are traded, turning list trading into a long and laborious practice.

As an improving alternative to sequential trading, electronic platforms such as ICE, MarketAxess, and Tradeweb started offering a new trading protocol called portfolio trading. This protocol allows customers to bundle a list of bonds and trade them as a single security. Through electronic platforms, customers put dealers in competition requesting quotes for the entire portfolio of bonds, in an all-or-none fashion. If the customer agrees, the portfolio is executed at the best quote received.

Compared to sequential trading, portfolio trading offers a better execution quality, as it reduces the time it takes to execute all desired trades and guarantees that all bonds within the portfolio are executed. Notwithstanding these benefits, electronic platforms claim that portfolio trading also minimizes information leakage, as the number of dealers contacted to execute all bonds would be reduced, and helps to trade illiquid bonds, which dealers would not be willing to trade unless structured into a bigger package. Moreover, portfolio trading is supposed to be cheaper than sequential trading. The argument behind such a claim is that, through portfolio diversification, customers reduce the risk dealers are asked to trade, and so the pricing of the bonds included in the portfolio improves. In the following sections I test many of these claims.

3 Data and Portfolio Trading Summary Statistics

In this section I describe the data used and how I identify portfolio trades. I show that portfolio trades represent a significant and growing fraction of the market and that its intermediation is concentrated among top dealers, who source bonds using their balance sheets. Finally, I provide relevant summary statistics comparing portfolio and sequential trades.

3.1 Data

I rely on three databases to study portfolio trading in the corporate bond market. The first and main data source is the academic version of the TRACE database, produced by the Financial Industry Regulatory Authority (FINRA). This data contains all corporate bond secondary market transactions reported by broker-dealers registered as member firms of FINRA. Importantly, the academic version of TRACE contains dealers' identifiers, which allows me to infer portfolio trades out of bundled trades. I extend this data with the Mergent Fixed Income Securities Database (FISD), which contains a broad set of bond characteristics not present in TRACE. Finally, I obtain complementary time-series variables from the Federal Reserve Economic Data (FRED). The period considered spans from January 2016 to December 2019.

To produce the final data set, I start by filtering TRACE out of reporting errors, duplicated observations, and book-keeping observations. This database is built out of reported trades, and thus it may contain reporting errors. I follow the procedure outlined in Dick-Nielsen and Poulsen (2019) to remove such errors [2]. I further remove duplicated inter-dealer trades, i.e. trades that are reported twice as both counterparts are reporting dealers. Finally, I delete those trades in which dealers transfer bonds to their non-FINRA affiliates for book-keeping purposes (Adrian, Boyarchenko, and Shachar, 2017).[3]

Next, I extend the filtered database by adding bond-level variables from FISD. To remove idiosyncratic features of bond contracts that may bias the transaction costs analysis, I follow the empirical literature and apply several filters (e.g., Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Friewald and Nagler, 2019; Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga, 2021). Among them, the most significant ones are dropping bonds that are preferred, convertible or exchangeable, yankee bonds, bonds with a sinking fund provision, variable coupon, with time to maturity of less than a year, or issued less than two months before the transaction date. I also remove bonds that are security-backed, equity-linked, putable, denominated in foreign currency, privately placed, perpetual, sold as part of a unit deal, or secured lease obligations bonds.

Finally, aiming at capturing only institutional investors, I remove trades of less than ten thousand dollars in face valuation. In this regard, Pinter, Wang, and Zou (2024) shows that transaction costs paid by retail and institutional investors significantly differ. As it will be shown in subsection 3.3, unlike sequential trades, portfolio trades are mostly institutional-size trades. Therefore, removing small trades allows for a fair comparison between sequential and portfolio trades. The final database is composed of 24,782,434 observations from 15,231 different bonds.

[2]Both the algorithm and the filter results can be downloaded from my personal website.

[3]Starting on November 2, 2015, FINRA provides explicit labels for the so-called book-keeping trades.

3.2 Portfolio Trades Identification

The structure of the data requires a strategy to identify portfolio trades. On the one hand, every bond traded is reported as a single observation, regardless of the trading protocol used, i.e. portfolio or sequential trading. On the other hand, there is no trading protocol flag for the period analyzed in this study. In this regard, although electronic platforms started offering portfolio trading in early 2018, its potential economic significance among scholars and researchers has been acknowledged only recently. As a result, an explicit flag for portfolio trades is absent in TRACE for observations reported before May 15, 2023.[4] In the following paragraphs, I describe how I identify portfolio trades by using observations' characteristics.

A portfolio trade is the exchange of a bundle of bonds by two counterparts at a unique price. Clearly, the characteristics of this trade impose several restrictions on the individual reporting of the bonds that form the portfolio. I use these restrictions to identify portfolio trades. First, all bonds should be traded at the same time. Second, only two counterparts should be involved in the transaction. Third, the amount of bonds traded should be enough to be considered a bundle. Finally, there should be no duplicated bonds within a portfolio. The following algorithm identifies as portfolio trades those bundles of individual reports that satisfy the aforementioned restrictions:

1. Build bundles of bonds traded by the same dealer, in the same second, against the same counterpart.
2. Remove the duplicated bonds within those bundles.
   - a If the counterpart is another dealer:
     - i. Remove all duplicated bonds
   - b If the counterpart is a customer:
     - i. Remove those duplicated bonds that have the same trade side, i.e. buy or sell.
     - ii. Keep bundles in which there are no duplicated bonds or where all bonds are duplicated with observations of the same volume but with opposite trade sides.
3. Tag as portfolio trades those bundles that, after the duplicated bonds removal, include ≥ 30 bonds.

In the first step of the algorithm, I build bundles of bonds that are traded by the same dealer, in the same second, against the same counterpart. In the second step, I clean those bundles from duplicated bonds. As can be seen, this latter step treats inter-dealer and customer-dealer trades differently. This responds to the lack of customer identifiers in TRACE. Specifically, when the algorithm requires to build bundles of bonds traded against the same counterpart, in the case of customer-dealer trades we cannot be sure if the bonds are being traded with a unique customer or with many customers. Thus, I cannot remove all

[4] See FINRA Regulatory Notice 22-12.

duplicated bonds in a customer-dealer bundle, as I may be dealing with a case where a dealer buys a portfolio from a customer and sells the same portfolio to another customer at the same time. Instead, I approach the removal of duplicated bonds in customer-dealer bundles in two steps. First, I remove only those duplicated bonds that have the same trade side, i.e. buy or sell. This step mostly captures bundles formed entirely by observations of the same bond and same trade side (95.46% of observations removed belong to such bundles). Second, after the removal of duplicated bond-side observations, I only keep bundles with no duplicated bonds or those in which we can clearly observe two symmetric buy and sell portfolios. Finally, the third step is a portfolio minimum-size filter consistent with the discussions held by the Securities Industry and Financial Markets Association (SIFMA) and FINRA about the appropriate threshold to trigger a portfolio trading flag in TRACE. [5]

The strategy to identify portfolio trades is in line with strategies used by other authors. Meli and Todorova (2022) matches proprietary data on investment-grade portfolio requests for quotes with TRACE. With those matched observations, they build a clustering algorithm that resembles the one here presented. In turn, Li, O'Hara, Rapp, and Zhou (2023) uses TRACE and improves over the clustering algorithm of Meli and Todorova (2022) performing different refinements. Among these refinements, their algorithm deletes all duplicated bonds in a cluster, thus mechanically removing any customer-dealer portfolio trade that is immediately offloaded with another customer. By capturing those portfolios, I can speak to the sourcing of portfolios and how they impact transaction costs.

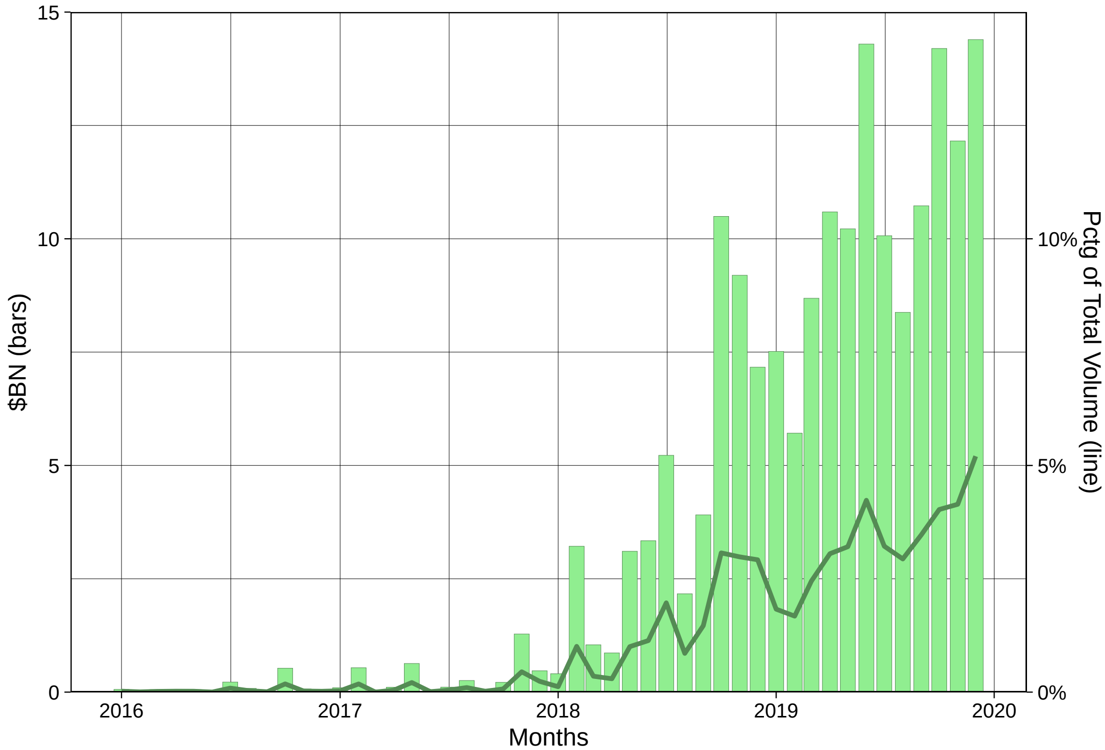
Finally, it is worth noting that the algorithm to identify portfolio trades better suits an environment of infrequent trading. In other words, if dealers execute several transactions every second, a bundle of sequential trades randomly executed at the same second against the same counterpart could be mistakenly inferred as a portfolio trade. This is especially problematic in the case of customer-dealer inferred portfolios, as the counterpart identity is unknown. In the Appendix A.1 I show that dealers do not trade frequently. Particularly, Table A.1 shows, for those dealers that perform portfolio trades, both how many seconds pass by between two customer-dealer trades and how many customer-dealer trades are performed in every second in which at least one trade is performed. The distribution of these variables shows that bundles of more than 30 bonds traded between dealers and customers are a rare event, which only happens at the extreme tail of the distribution.

Figure 1 shows the monthly evolution of the identified portfolio trading volume. As expected, the identified portfolio trading volume sharply rose in early 2018, i.e. when electronic platforms started offering the protocol, reaching more than 10 billion dollars of monthly trading during the second half of 2019. The market share mimics this pattern, reaching 5% of the total volume traded in the secondary corporate bond market. In the Appendix A.2 I show that these patterns hold in the two market segments, i.e. inter-dealer

[5] See SIFMA response to FINRA's Regulatory Notice 20-24 - Proposed Changes to TRACE Reporting Relating to Delayed Treasury Spot and Portfolio Trades.

and customer-dealer, and if we consider the number of trades instead of volume.

Figure 1: Portfolio trading volume - All segments



Note: This figure depicts the monthly time-series of portfolio trading volume, including both customer-dealer and inter-dealer trades. The bars –left axis– indicate total face value, expressed in billion dollars. The line –right axis– indicates market share, expressed in percentage points.

3.3 Portfolio Characteristics

In this subsection, I present descriptive statistics of the portfolios identified in subsection 3.2. I restrict the sample in two ways. On the one hand, since the main focus of this paper is to study transaction costs, I restrict the analysis to customer-dealer trades. Two reasons explain this decision. First, in the customer-dealer segment it is clear who demands liquidity (customers) and who provides it (dealers). Thus, transaction costs reflect the price paid to dealers to supply liquidity. Second, I will show that the trade side is a leading factor of transaction costs, and this variable is only relevant when we know who is providing liquidity. On the other hand, as electronic platforms started offering the portfolio trading alternative in early 2018, I restrict the sample to the period that goes from January 2018 to December 2019. The final sample consists of 7,633,744 customer-dealer individual trades, including 1,558 portfolios that account for 154,587 of those trades.

I start by addressing the size of portfolios. Table 1 shows that these are typically comprised of around one hundred bonds, although they can reach up to more than three hundred issues. The bonds in a portfolio are usually distributed across several issuers. Regarding the volume traded, it is clear that portfolio trading is performed by institutional investors: the average portfolio involves 65.4 million dollars and 95% of portfolios involve more than 2 million dollars (face value).

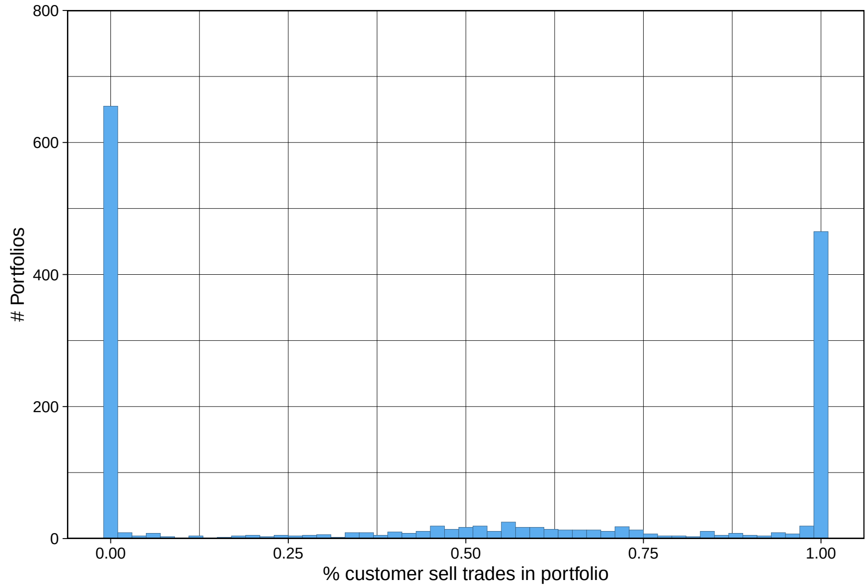
Table 1: Portfolios Size.

	Mean	Std. dev.	.05	.25	.50	.75	.95
Bonds #	99.2	108.5	31.0	39.0	57.0	109.0	323.2
Issuers #	74.5	65.0	27.0	35.0	49.0	86.0	213.2
Portfolio Size $M	65.4	155.3	2.1	8.9	23.0	58.8	255.4
Trades Size $M	0.81	1.75	0.04	0.14	0.34	0.68	3.00

Next, I turn to the question of whether customers use portfolio trading to buy, sell, or change the composition of the bonds they hold. This is particularly relevant as electronic platforms allow to mix buy and sell orders within a portfolio, thus customers can use the protocol to rebalance positions avoiding a timing mismatch between buying and selling and the risk implied by it. Figure 2 shows that portfolio trading is used for different strategies. 42% of portfolios are full customer buys and 30% are full customer sells, representing 40% and 28% of the portfolio volume of our sample. The remaining fraction is composed of mixed portfolios.

A small caveat should be mentioned at this point. Given my portfolio identification strategy, if a dealer decides to upload the buy orders and the sell orders of a mixed portfolio at different times, I will consider that mixed portfolio as two independent buy and sell portfolios. Although rare, Meli and Todorova (2022), by matching portfolio requests for quotes with actual trades from TRACE, shows that such cases exist. To address this concern, I combine those buy and sell portfolios executed by the same dealer within a 15-minute window (the maximum time allowed by FINRA to report trades after execution), and obtain that only 4% of the full buy or full sell portfolios can be considered as two legs of mixed portfolios.

Figure 2: Share of customer sell trades in portfolios



Note: This figure depicts the distribution of customer sell trades percentage in portfolios. For each portfolio, I compute the percentage of customer sell trades. Bars express the number of portfolios with a certain percentage of customer sells.

Turning to the supply side, I observe that portfolio trading is highly concentrated among top dealers. The top three portfolio dealers accumulate 86% of the volume traded (87.46% of the bonds traded). These dealers happen to account for a large market share in the sequential protocol as well, suggesting that only big sophisticated dealers are able to price and trade the large number of bonds and volume implied by portfolios. In Appendix A.3 I show that this concentration is stable over time, although the market shares of some dealers fluctuate, as is expected with any new technology.

Table 2: Concentration of dealer intermediation of portfolio trades

	Trades % share		Volume % share	
Dealer	Portfolio	Sequential	Portfolio	Sequential
1	35.29	6.66	49.93	10.20
2	21.17	4.29	18.65	8.88
3	31.00	1.73	17.40	0.71
4	3.17	3.12	6.50	8.09
5	2.32	2.86	3.33	8.51
6	3.29	3.95	2.46	7.49
7	1.46	2.72	0.72	8.18
8	0.27	1.76	0.25	5.35
9	0.30	0.09	0.20	0.03
10	0.21	0.32	0.16	0.34

The aforementioned market concentration is related to how bonds are sourced. In this regard, I find that dealers use their balance sheets when performing portfolio trades. To get this result, I follow the literature (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Kargar, Lester, Lindsay, Liu, Weill, and Zúñiga, 2021; Choi, Huh, and Seunghun Shin, 2024) and classify all customer-dealer trades into three categories: those that are quickly offset with other customers, those that are quickly offset with other dealers, and those that are not offset. Specifically, for each customer-dealer trade, I look for all the offsetting trades of the same dealer in the same bond, within a 15-minute window. If at least 50% of its volume was offset, and the majority of such volume was offset with customers (dealers), I label it as "Offset ≤ 15 - C" ('Offset ≤ 15 - D"). If less than 50% of its volume was offset, I label it as "Non-Offset". [6] Only this last "Non-Offset" category of trades affects dealers' balance sheets. Table 3 shows that the large majority of bonds traded through portfolios belong to such a category. These figures are much higher than those of sequential trading, where dealers tend to offset a larger fraction with other customers. These results are in line with the high concentration of portfolio trading among large dealers, as these are the ones with large enough balance sheet capacity to accommodate portfolios. [7]

Table 3: Sourcing of Portfolio - Volume

	Market Share		Portfolio Sourcing			Sequential Sourcing		
			Offset ≤15m		Non-Offset	Offset ≤15m		Non-Offset
Dealer	Portfolio	Sequential	C	D		C	D	
1	49.9	10.2	3.5	1.7	94.8	16.6	3.4	80.0
2	18.6	8.9	4.3	1.7	94.0	17.4	3.3	79.3
3	17.4	0.7	0.0	1.7	98.3	0.0	1.6	98.4
4	6.5	8.1	3.2	1.2	95.6	16.6	3.4	79.9
5	3.3	8.5	14.7	0.3	85.0	21.7	2.3	76.0
6	2.5	7.5	0.7	0.3	99.0	15.9	2.5	81.5
7	0.7	8.2	0.1	1.6	98.4	18.1	2.5	79.4
8	0.2	5.3	0.0	0.1	99.9	24.1	3.7	72.2
9	0.2	0.0	0.0	99.5	0.5	0.6	70.4	29.0
10	0.2	0.3	0.0	100.0	0.0	0.0	100.0	0.0

Note: This tables shows, for each of the top ten portfolio trading dealers, its portfolio trading market share (column 2), its sequential trading market share (column 3), the distribution in the three categories – Offset ≤ 15 - C, Offset ≤ 15 - D, Non-Offset – of its portfolio trading activity (columns 4-6) and sequential trading activity (columns 7-9). All statistics are computed using volume traded, measured at face value.

Finally, I turn to the characteristics of the bonds included in a portfolio. In Table 4, I look at trade size, turnover, time to maturity, and credit rating, comparing how these variables are distributed in the portfolio and sequential trading subsamples. Appendix A.5 explains in detail the construction of these variables. As previously noted, portfolio trading is mostly formed by institutional-size trades. Whereas more than 60%

[6] Two subtleties about this categorization are worth mentioning. First, this procedure allows for multiple matching, in the sense that a single trade can be offset by several trades of the opposite direction. Second, the algorithm may encounter competing trades. In such case, I form pairs with the trades that are closer in time firstly, and closer in volume secondly.

[7] These patterns hold if we perform the categorization using a 30-minute window, or if we consider the number of trades instead of the volume traded. See Appendix A.4.

of sequential trades do not surpass 100 thousand dollars, less than 30% of portfolio trades belong to that category. Surprisingly, portfolios do not seem to be biased towards bonds with smaller turnover. Electronic platforms claim that portfolio trading could improve the liquidity of low-turnover bonds, as packaging helps dealers mitigate the risk of miss-pricing bonds for which transactions are rare.[8] I cannot find evidence supporting such a claim. Finally, we observe that portfolios have a somewhat higher concentration of riskier bonds, both considering time to maturity as a proxy for interest rate fluctuation risk and (to a lesser extent) credit risk. This higher concentration of riskier bonds in portfolios is not surprising, as the implied diversification reduces the overall risk of the position.

[8]See for example electronic platform Tradeweb's "Portfolio Trading: An Innovative Solution for Corporate Bond Trading".

Table 4: Trade characteristics of portfolio and sequential trades

	Trades % share		Volume % share	
	Portfolio	Sequential	Portfolio	Sequential
Trade Size				
Micro (≤100K)	29.24	60.76	2.52	2.63
Odd (100K-1M)	59.02	24.32	34.44	12.60
Round (1M-5M)	10.19	11.75	34.61	40.49
5M and above	1.55	3.17	28.44	44.28
Turnover				
(0%-10%]	18.30	25.47	21.34	17.43
(10%-25%]	43.29	45.46	44.55	40.17
(25%-50%]	29.28	20.52	26.49	27.70
>50%	9.13	8.54	7.63	14.70
Time to Maturity				
(1-3]	9.96	22.47	11.57	15.70
(3-5]	21.32	23.17	20.50	19.47
(5-10]	46.36	37.24	43.14	40.50
>10	22.36	17.12	24.78	24.33
Rating				
IG superior	3.98	6.52	5.44	5.30
IG inferior	42.50	65.99	57.35	59.10
HY superior	48.59	23.51	33.96	28.06
HY inferior	4.93	3.98	3.25	7.54

Note: This tables shows how portfolio trades and sequential trades are distributed across partitions of trade size, turnover, time to maturity, and credit rating. The first two columns compute percentages using the number of trades. The last two columns compute percentages using the face value volume traded.

4 Transaction Costs

By construction, portfolio trading offers some advantages to those customers seeking to trade many bonds. For example, the protocol binds customers from holding temporary unwanted positions that would occur if they were to trade the bonds sequentially. Notwithstanding, it has been argued that portfolio trading is also cheaper than sequential trading, as dealers provide better prices for portfolios than for the sum of the individual bonds that compose them. In this section, I study such a claim. I start by providing a theoretical framework of transaction costs. Later, I provide trade-level evidence of transaction cost differences between portfolio and sequential trading and which factors drive those differences.

4.1 Theoretical Framework

To study whether portfolios are traded at a discount or penalty, I start by providing a theoretical framework that explains how transaction costs are settled. I follow the bulk of the literature on OTC markets and assume that the terms of trade are the outcome of bilateral bargaining, a natural assumption as counterparts in this market trade bilaterally instead of in a centralized exchange. [9] In particular, I assume that the quantity traded q and the transaction cost that a customer pays to a dealer $\phi(q)$ are solved through Nash bargain[10]:

$$[q^*, \phi(q)^*] = \arg\max_{(q,\phi)} \Big\{ \mathrm{CS}(q) - \phi(q) \Big\}^{1-\eta} \Big\{ \phi(q) - \mathrm{DC}(q) \Big\}^{\eta}$$

where CS and DC denote the customer surplus and the dealer cost, respectively, and $\eta \in [0, 1]$ reflects the dealer's bargaining power. The solution to this maximization problem tells us that, if there are gains from trade (CS>DC), the resulting transaction cost is a convex combination of the dealer cost and the customer surplus:

$$\phi(q)^* = \eta \mathrm{CS}(q) + (1-\eta)\mathrm{DC}(q) \tag{1}$$

Equation (1) reveals that the effect of portfolio trading over transaction costs will be explained by how this new protocol affects customers' surpluses and dealers' costs. On the one hand, the customer surplus is increased due to better execution quality. As previously mentioned, when customers need to trade many bonds, they may be temporarily exposed to unwanted positions while all their trades are executed. Portfolio trading allows for simultaneous execution, thus avoiding such a risk. This larger consumer surplus should translate into higher transaction costs for portfolios. On the other hand, the dealers face different costs when trading portfolios or trading sequentially. First, as it was documented in subsection 3.3, portfolios are large institutional-size trades that affect dealers' balance sheets. In contrast with sequential trading, where a dealer can gradually offset positions keeping its balance sheet close to its target, portfolio trading implies large deviations from it. These deviations are costly to dealers (e.g. regulatory cost) and thus should translate into higher transaction costs. Second, portfolios comprise a large number of bonds issued by several firms. The resulting diversification of expected payoffs reduces the amount of risk being traded, decreasing thus dealers' costs. The more diversified a portfolio is, the smaller the transaction costs we should expect to observe. Last but not least, portfolio trading may be used by customers who have private information

[9] For a review of this literature, see Weill (2020)

[10] Duffie, Gârleanu, and Pedersen (2007) model explicitly a bilateral bargaining game where agents make alternate offers. They show that the powers of the Nash product equal the probabilities of making an offer in such a game.

about some assets but do not want to signal it through an individual order. Dealers may anticipate this strategy and penalize the entire portfolio. Consequently, this channel would decrease the transaction costs of the bonds for which private information is held and increase that of the remaining bonds.

In the next subsection, I initially answer whether portfolios are trading at a penalty or at a discount. Later, I study the drivers behind the differences found, following the hypotheses aforementioned.

4.2 Transaction Costs Discounts and Penalties

Transaction costs are computed as the Spread1 measure of Choi, Huh, and Seunghun Shin (2024). Particularly, the transaction cost TC compares each customer-dealer trade price with a reference price, the latter given by the (volume-weighted) average price that the same bond has during the same day in the inter-dealer market.[11]

$$TC_{i,b,d} = Q \times (\frac{p_{i,b,d} - p_{b,d}^{DD}}{p_{b,d}^{DD}}) \times 10,000 \qquad , \qquad p_{b,d}^{DD} = \frac{\sum_{i \in DD_{b,d}} vol_{b,d,i}^{DD} p_{b,d,i}^{DD}}{\sum_{i \in DD_{b,d}} vol_{b,d,i}^{DD}}$$

where i, b, and d denote trade, bond, and day, respectively, Q is a trade side indicator that equals 1 (-1) if the customer buys (sells) bonds, and the multiplication by 10.000 expresses transaction costs as basis points deviations from the inter-dealer price.[12]

As a first approximation, in Table 5 I present how transaction costs are distributed within the portfolio and sequential subsamples. Clearly, those bonds that are traded within portfolios do so at smaller transaction costs: while the average transaction cost in portfolio trading is 8.6 bps, the average cost in sequential trading is 31.3 bps.

Table 5: Transaction costs by trade type.

	Transaction Costs (bps)						
	Mean	Std. dev.	.05	.25	.50	.75	.95
Portfolio	8.6	41.5	-42.5	-7.4	5.9	23.0	67.7
Sequential	31.3	82.3	-19.3	0.5	10.9	37.7	164.4

Of course, these transaction cost differences may be driven by factors other than the inclusion of a trade in a portfolio. I improve the analysis by computing the transaction costs differential associated with the

[11] Alternative transaction costs measures had been used in the empirical fixed income literature, among them Amihud (2002) price impact and Feldhütter (2012) round trip costs. The accuracy of these measures relies on having close-in-time consecutive trades of the same bond, a feature hardly observed in the portfolio trading subsample.

[12] As is the case with any measure of transaction costs, the elements needed for its construction restrict the sample for which we can compute it. In this case, the only restriction is for dealer-customer trades to match with an inter-dealer trade of the same bond happening on the same day. In Appendix A.6 I show how such restriction affects the samples of portfolio trades and sequential trades.

inclusion of a bond in a portfolio trade, conditional on several bond and trade characteristics. Specifically, I estimate through OLS the following empirical model:

$$TC_i = \alpha + \beta \mathbf{1}_{i=\text{Portfolio}} + \Gamma C_i + \Lambda FE + \epsilon_i, \tag{2}$$

where TC_i denotes the transaction cost of trade i, the dummy variable $\mathbf{1}_{i=\text{Portfolio}}$ indicates if such trade belongs to a portfolio trade, and the vectors C_i and FE includes bond and trade characteristics and several fixed effects, respectively. Regarding bond and trade characteristics, I control for age, amount outstanding, time to maturity, credit rating, trade size, and whether the trade was performed by a dealer who performs portfolio trading.[13]. In turn, the model includes day, issuer industry, dealer, and bonds fixed effects, which are used according to each specification of equation (2). Standard errors are double clustered by bond and date.

The first column of Table 6 presents the baseline estimation results. The coefficient associated with including a bond in a portfolio, controlling for several priced characteristics, is negative and significant. The transaction cost of a bond executed through portfolio trading is expected to be 5.53 bps smaller than that of a bond executed through sequential trading. Taking into account the mean transaction costs presented in Table 5, this represents a 17.7% discount. The results show that transaction costs are also led by the type of dealer that intermediates: dealers who trade portfolios (typically big dealers) charge smaller transaction costs. The coefficients associated with the remaining controls are in line with previous findings in the literature (e.g., Edwards, Harris, and Piwowar, 2007). Bonds issued in large amounts have smaller transaction costs, as these are easier to price and trade. Bonds far away from maturity are more expensive to trade, a result related to these bonds having higher interest rate risk and more uncertainty in their valuation. Larger trades ($>$ 100K) are cheaper than smaller trades, driven probably by the identity of the investors, a variable not available in my data sets (Pinter, Wang, and Zou, 2024). As expected, worse credit-rated bonds are traded at higher transaction costs, as dealers translate the implied risk cost to customers.

[13]See Appendix A.5 for the detailed computation of these variables.

Table 6: Transaction costs regression on trade characteristics.

Dependent Variable:	Transaction Cost					
	Baseline	Dealer FE	Bond FE	No DST	No Offset	No Mixed
Portfolio	-5.53***	-4.54***	-3.32***	-4.91***	-6.24***	-4.87***
	(0.74)	(0.64)	(0.67)	(0.84)	(0.76)	(0.89)
Portfolio Dealer	-26.11***		-20.75***	-26.08***	-26.63***	-26.07***
	(0.45)		(0.36)	(0.45)	(0.47)	(0.45)
Age	0.04	-0.26***		0.03	0.02	0.03
	(0.13)	(0.09)		(0.13)	(0.13)	(0.13)
Amount Outstanding	-2.71***	-1.93***		-2.71***	-2.75***	-2.71***
	(0.40)	(0.31)		(0.40)	(0.40)	(0.40)
Time-to-maturity 3-5	7.76***	6.97***		7.75***	8.05***	7.77***
	(0.60)	(0.51)		(0.60)	(0.61)	(0.60)
Time-to-maturity 5-10	18.74***	14.98***		18.77***	19.41***	18.78***
	(0.72)	(0.55)		(0.72)	(0.73)	(0.72)
Time-to-maturity >10	48.49***	36.06***		48.65***	49.76***	48.63***
	(1.53)	(0.96)		(1.53)	(1.55)	(1.53)
Odd (100K-1M)	-20.23***	-8.51***	-16.68***	-20.29***	-20.13***	-20.33***
	(0.43)	(0.22)	(0.37)	(0.43)	(0.43)	(0.43)
Round (1M-5M)	-28.32***	-12.82***	-22.82***	-28.47***	-28.10***	-28.49***
	(0.65)	(0.39)	(0.56)	(0.65)	(0.64)	(0.65)
5M and above	-23.79***	-9.44***	-19.19***	-23.99***	-22.65***	-23.98***
	(0.62)	(0.37)	(0.49)	(0.62)	(0.63)	(0.62)
IG (A-BBB)	8.04***	3.63***		8.06***	8.20***	8.06***
	(0.67)	(0.46)		(0.67)	(0.68)	(0.67)
HY (BB-B)	24.17***	15.73***		24.25***	25.34***	24.27***
	(0.99)	(0.67)		(0.99)	(1.02)	(0.99)
HY (CCC-D)	48.34***	39.85***		48.48***	52.17***	48.54***
	(3.33)	(3.06)		(3.33)	(3.57)	(3.34)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Industry FE	Yes	Yes	No	Yes	Yes	Yes
Dealer FE	No	Yes	No	No	No	No
Bond FE	No	No	Yes	No	No	No
Observations	6,300,985	6,300,985	6,307,999	6,279,622	6,021,275	6,276,809
Adjusted R^2	0.095	0.202	0.141	0.095	0.109	0.095
Within R^2	0.093	0.030	0.031	0.093	0.107	0.092

Note: This tables provides OLS estimates of the trade-level equation (2). The baseline specification regresses transaction cost on a portfolio trade dummy, a portfolio dealer dummy, age, amount outstanding, time to maturity, credit rating, trade size, day fixed effects and issuer industry fixed effects. Alternative specifications include dealer fixed effects (column 2), bond fixed effects (column 3), the exclusion of portfolios executed within a 5-minute window of delayed spot times (column 4), the exclusion of "Offset$\leq 15m$ - C" trades (column 5), and the exclusion of mixed portfolios (column 6). Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

The main result of transaction costs being smaller for those trades included in portfolio trading holds under alternative specifications. I firstly account for dealer-heterogeneity and its effect on transaction costs (e.g. Colliard, Foucault, and Hoffmann, 2021). The second column of Table 6 shows that the result holds when imposing dealers' fixed effects. To fully account for bond time-insensitive characteristics, in specification three I include bond fixed effects. I observe that the portfolio discount holds, although to a lesser extent than in the baseline model. I also consider a specification where I remove those portfolio trades executed within a 5-minute window of popular delayed spot times: 11.00, 15.00, 15.30, 16.00, and 16.30. These times of the day are used to execute trades that had been priced as a spread over some reference price, leading thus to an accumulation of trades that may be mistakenly inferred as portfolio trading. Column four tells us that removing those observations does not affect the results. Another robustness check performed is to remove from the sample trades that are offset within a 15-minute window with other customers. In this kind of trade, there are no dealers' balance sheets involved, and thus transaction costs are typically smaller. As such trades are more prevalent in sequential trading, its presence in the sample would underestimate the portfolio trading discount. The estimated coefficient of column five confirms the claim. In addition to the previous robustness checks, I estimate the model using only full buy or full sell portfolios. Mixed portfolios may not imply balance sheet cost, as buy and sell orders net out, removing one of the channels that affect transaction costs. Again, column six shows that results hold robustly. Finally, given that portfolio trading is a new protocol, it may be the case that dealers initially offered better pricing as a strategy to gain market power. In that case, the discount observed would not be sustained when the market matures. In untabulated estimations, I see that all results hold if we restrict the sample to the period June 2019 to December 2019, discarding thus this hypothesis.

Considering that, among the four hypotheses cited, only portfolio diversification would reduce transaction costs, it is surprising to see a discount holding robustly across all specifications. To further understand this result, I study whether customers pay different transaction costs when buying or selling portfolios. If dealers' balance sheet costs respond asymmetrically to deviations from the target, e.g. penalizing more positive deviations than negative ones, it would be expected to observe a portfolio trading asymmetric effect on transaction costs. I formally test for asymmetric effects by estimating an extended version of equation (2):

$$TC_i = \alpha + \beta_1 \mathbf{1}_{i=\text{Portfolio}} + \beta_2 \mathbf{1}_{i=\text{Cust. sells}} + \beta_3 \mathbf{1}_{i=\text{Portfolio}} \mathbf{1}_{i=\text{Cust. sells}} + \Gamma C_i + \Lambda FE + \epsilon_i, \tag{3}$$

Equation (3) decomposes the portfolio trading subsample into those trades in which customers buy and those in which customers sell bonds, with associated coefficients β_1 and $\beta_1 + \beta_3$, respectively. The estimation results are presented in Table 7. The estimates of the coefficients in Γ, similar to those presented in Table 6, are left untabulated to ease the presentation.

I find strong evidence about portfolio trading being correlated with asymmetric pricing. When customers buy portfolios from dealers, they pay 13.34 bps less for each bond compared to what they would pay when buying them sequentially. In turn, when customers sell portfolios to dealers, they pay 3.09 bps more than when doing it sequentially. These numbers represent a 42.6% discount when buying and a 9.9% penalty when selling portfolios, respectively. The asymmetric coefficients hold robustly when I estimate all the alternative model specifications described when presenting Table 6.

Table 7: Transaction costs regression on trade characteristics and trade side.

Dependent Variable:	Transaction Cost					
	Baseline	Dealer FE	Bond FE	No DST	No Offset	No Mixed
Portfolio	-13.34***	-10.78***	-10.92***	-13.45***	-14.32***	-13.16***
	(0.92)	(0.79)	(0.85)	(1.01)	(0.94)	(1.02)
Customer Sell	-9.54***	-6.94***	-9.13***	-9.55***	-9.00***	-9.55***
	(0.47)	(0.43)	(0.43)	(0.47)	(0.48)	(0.47)
Portfolio × Customer Sell	16.43***	13.34***	15.96***	17.99***	16.92***	18.69***
	(1.53)	(1.42)	(1.46)	(1.72)	(1.56)	(1.87)
$\beta_1 + \beta_3$	3.09**	2.56**	5.04***	4.54***	2.6**	5.53***
	(1.22)	(1.11)	(1.12)	(1.38)	(1.24)	(1.56)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Industry FE	Yes	Yes	No	Yes	Yes	Yes
Dealer FE	No	Yes	No	No	No	No
Bond FE	No	No	Yes	No	No	No
Observations	6,300,985	6,300,985	6,307,999	6,279,622	6,021,275	6,276,809
Adjusted R^2	0.098	0.204	0.144	0.098	0.113	0.098
Within R^2	0.096	0.032	0.034	0.096	0.110	0.096

Note: This tables provides OLS estimates of the trade-level equation (3). The baseline specification regresses transaction cost on a portfolio trade dummy, a customer sell dummy, the interaction of the portfolio trade and customer sell dummies, a portfolio dealer dummy, age, amount outstanding, time to maturity, credit rating, trade size, day fixed effects and issuer industry fixed effects. Alternative specifications include dealer fixed effects (column 2), bond fixed effects (column 3), the exclusion of portfolios executed within a 5-minute window of delayed spot times (column 4), the exclusion of "Offset$\leq 15m$ - C" trades (column 5), and the exclusion of mixed portfolios (column 6). To ease the exposition, some estimates are left untabulated. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

The evidence in Table 7 suggests that large balance sheet expansions may be playing a role when dealers price portfolios, as incoming portfolios are penalized. These results are in sharp contrast with those found in previous studies (Meli and Todorova, 2022; Li, O'Hara, Rapp, and Zhou, 2023), where portfolio trading is consistently less expensive than sequential trading. In the next section, I formally study the alternative drivers behind the found discounts and penalties.

5 Transaction Costs Drivers

To study what drives the differences in transaction costs between portfolio and sequential trading, I proceed in two steps. Firstly, I address how individual bonds are priced within the portfolios. This analysis answers questions regarding whether some segments of the market, e.g. risky bonds or small issues, are driving the effects seen in subsection 4.2. I find a significant cross-subsidy within portfolios: characteristics that are priced in sequential trading are reversed when the bond is included in a portfolio. Secondly, I investigate what portfolio characteristics are priced by dealers and in which direction. I enhance the trade-level estimations using portfolio characteristics and find significant evidence of both balance sheet effects and portfolio diversification effects.

5.1 Bonds Transaction Cost Drivers and Portfolio Trading

I start by extending the baseline equation (2) interacting all variables in the vector C with the portfolio trading dummy. Since trades within portfolios are priced differently according to their side, I estimate this equation for buy trades and sell trades separately.

$$TC_i = \alpha + \beta \mathbf{1}_{i=\text{Portfolio}} + \Gamma_1 C_i + \Gamma_2 C_i \mathbf{1}_{i=\text{Portfolio}} + \Lambda FE + \epsilon_i, \tag{4}$$

The estimation results are presented in Table 8. To simplify the exposition, I present in the second and fourth columns the estimated coefficients of the interacted variables. As can be seen, there is a clear pricing reversal within portfolios. For example, bonds with high credit risk (CCC-D) are costly to trade when doing so sequentially, paying 44.2 bps and 31.4 bps more than low-credit-risk bonds (A-BBB). However, when those low-rated bonds are included in a portfolio, their pricing improves and the risk effect is partially canceled out. A similar pattern happens with virtually all variables included in vector C.

The observed price reversal is not surprising, as portfolios allow to diversify the risk implied by holding a single security. To deepen into this idea, I follow the long-standing Capital Asset Pricing Model tradition and compute what fraction of a bond (excess) returns variance is explained by factors other than markets' fluctuations (see Appendix A.5). The higher this fraction is, the larger the diversification gains a bond inherits when it is included in a portfolio, and so we should expect large price reversals. Table 8 supports this hypothesis, with a full reversal for customer buys and a partial reversal for customer sells.

On top of estimating all the different specifications described in Tables 6 and 7, under which the price reversal holds robustly (untabulated), I perform one additional check specific to this result. Although dealers should report the price of each specific bond traded to FINRA, portfolios are traded at a unique price. Since the portfolio price is the one with economic significance, it may be the case that the individual prices reported for portfolio trading bonds are non-informative. Taking the argument to the limit, any vector of prices for which its (volume-weighted) sum equals the portfolio price could be reported. This would give room for a mechanical price reversal, in which all bond prices within a portfolio are reported to be equal. I discard such a claim relying on two facts. First, TRACE provides incentives for dealers to upload prices according to market valuation, regardless of the trading protocol used. Particularly, "*TRACE will validate the price that the user has submitted by comparing it to other recent transactions in the same security. If the reported price is substantially different than the price determined by TRACE to be the "current market" for that security, an error message will be generated.*".[14] Second, in Appendix A.7, I show that the pricing of bond characteristics within portfolios follows the same patterns as in sequential trading, rejecting thus the hypothesis of a non-informative reported price vector.

[14]See TRACE User Guide 2023, p31.

Table 8: Transaction costs regression on trade characteristics interacted with portfolio trading.

Dependent Variable:	Transaction Cost			
	Customer buys		Customer sells	
		× Portfolio		× Portfolio
Portfolio	41.80***		22.04***	
	(2.87)		-2.56	
Portfolio Dealer	-30.94***		-14.93***	
	(0.57)		-0.4	
Age	-0.39**	0.59***	0.73***	-1.02***
	(0.17)	(0.21)	(0.1)	(0.21)
Amount Outstanding	-0.82**	1.10**	-1.76***	-0.75*
	(0.37)	(0.48)	(0.3)	(0.40)
Time-to-maturity 1-3	-13.56***	12.80***	-4.56***	3.74***
	(0.72)	(1.12)	(0.88)	(1.26)
Time-to-maturity 5-10	16.75***	-16.92***	6.08***	-2.28**
	(0.88)	(1.12)	(0.6)	(0.96)
Time-to-maturity >10	60.05***	-49.47***	19.93***	-14.86***
	(2.08)	(3)	(0.97)	(3.07)
Micro (<100K)	24.49***	-25.34***	11.54***	-8.07***
	(0.54)	(1.16)	(0.38)	(1.48)
Round (1M-5M)	-12.83***	19.93***	-4.72***	8.84***
	(0.58)	(1.48)	(0.47)	(1.93)
5M and above	-10.12***	34.24***	0.85	11.45***
	(0.76)	(9.7)	(0.56)	(2.46)
IG (AAA-AA)	-6.50***	5.89***	-1.39***	2.60**
	(0.76)	(1.29)	(0.45)	(1.30)
HY (BB-B)	20.85***	-19.21***	9.50***	-8.61***
	(1.11)	(1.6)	(0.65)	(1.64)
HY (CCC-D)	44.20***	-36.75***	31.38***	-26.73***
	(4.21)	(5.04)	(3.69)	(4.67)
Idiosync. var. share	35.89***	-37.30***	27.42***	-13.48***
	(2.81)	(3.46)	(2.07)	(3.09)
Day FE	Yes		Yes	
Issuer Industry FE	Yes		Yes	
Observations	3,814,350		2,349,074	
Adjusted R^2	0.145		0.051	
Within R^2	0.142		0.046	

Note: This tables provides OLS estimates of the trade-level equation (4). Transaction cost is regressed on a portfolio trade dummy, a portfolio dealer dummy, trade characteristics –age, amount outstanding, time to maturity, credit rating, trade size, and idiosyncratic variance share–, the interaction of trade characteristics and the portfolio trade dummy, day fixed effects and issuer industry fixed effects. Equation (4) is estimated for customer buy trades and customer sell trades separately. Columns 2 and 4 show the estimates for the interacted trade characteristics. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

5.2 Portfolios Transaction Cost Drivers

Once shown that the characteristics that drive transaction costs in sequential trading are partially reversed when bonds are traded through portfolios, I proceed to address what portfolio characteristics determine its transaction costs. I expand equation (2) decomposing the portfolio dummy into a vector that locates portfolios into several categories:

$$TC_{i,p} = \alpha + \beta \mathbf{1}_{i=\text{Portfolio}} + \Gamma C_i + \boldsymbol{\Delta} \mathbf{1}_{i=\text{Portfolio}} D_p + \Lambda FE + \epsilon_{i,p}, \tag{5}$$

where vector D includes portfolio characteristics: number of bonds, volume Herfindahl-Hirschman Index (HHI), credit rating average, standard deviation compared to its i.i.d. counterfactual, amount outstanding average, and aggregate volume (see Appendix A.5). Except for the HHI, the remaining variables are incorporated as dummies that indicate if a portfolio belongs to a specific bin regarding quartile partitions.

The set of portfolio variables aims to cover alternative hypotheses that may drive dealers to charge customers different prices when trading portfolios than when trading those bonds sequentially. First, the aggregate volume of each portfolio tells us how much balance sheet space a dealer needs to incur, thus addressing directly the balance sheet channel. Second, I use several variables that indirectly measure the gains from risk diversification a portfolio can provide. The variance of portfolio returns mechanically decreases in the number of bonds and increases when portfolio weights are concentrated, the latter considering a scenario where all bonds have similar individual variances. Additionally, when the average credit rating is high, there is more room for portfolios to diversify away the default risk. Finally, I compute the ratio between the return volatility of the portfolio and the one it would have should all the bonds in it be independently distributed. The smaller this ratio the higher the gains from diversification. The last channel tested is the asymmetric information channel: dealers may penalize portfolios when they infer that customers have private information about one or many bonds in the portfolio. I use the average amount outstanding as a proxy of customers' (lack of) private information, as larger bonds tend to have a wider investor base Brugler, Comerton-Forde, and Martin (2022). To further investigate the asymmetric information channel, I also estimate alternative equations where I exploit time-series information and the ex-post performance of the bonds traded.

Equation (5) is estimated for full buy, full sells, and mixed portfolios separately. In each case, portfolio trading bonds are compared with sequential buys, sells, and buys and sells, respectively. Again, the coefficients associated with bond characteristics in C are not shown to ease the exposition. Table 9 presents the estimation results.

Table 9: Transaction costs regression on portfolio characteristics.

Dependent Variable:	Transaction Cost		
	Full Cust Buy	Full Cust sell	Mixed Cust Buy and Sells
Balance Sheet			
Portfolio × Volume 25-50 pctl	16.89***	5.66*	2.72
	(2.10)	(3.00)	(1.96)
Portfolio × Volume 50-75 pctl	24.78***	6.61**	9.59***
	(2.71)	(2.97)	(2.30)
Portfolio × Volume 75-100 pctl	36.34***	9.11**	25.29***
	(3.31)	(4.30)	(4.22)
Risk Diversification			
Portfolio × # Bonds 25-50 pctl	-9.11***	-0.11	-8.30***
	(2.48)	(2.48)	(2.17)
Portfolio × # Bonds 50-75 pctl	-17.45***	8.02**	-12.82***
	(3.67)	(3.56)	(3.45)
Portfolio × # Bonds 75-100 pctl	-27.67***	-5.74	-21.60***
	(4.98)	(6.48)	(5.27)
Portfolio × HHI	-104.45	-53.22	-35.16**
	(66.14)	(44.38)	(16.76)
Portfolio × Avg Rating 25-50 pctl	-1.06	4.28	-0.76
	(2.93)	(2.87)	(3.46)
Portfolio × Avg Rating 50-75 pctl	-5.25	-6.69*	-10.53**
	(3.26)	(3.63)	(4.27)
Portfolio × Avg Rating 75-100 pctl	-8.66***	-5.37	-9.52**
	(3.25)	(3.63)	(4.13)
Portfolio × SD/SDiid 25-50 pctl	2.76	-1.44	4.50**
	(2.42)	(2.78)	(1.97)
Portfolio × SD/SDiid 50-75 pctl	0.39	-2.27	1.77
	(3.84)	(4.47)	(2.29)
Portfolio × SD/SDiid 75-100 pctl	-5.67	4.82	1.76
	(4.99)	(7.61)	(2.90)
Asymmetric Information			
Portfolio × Amount Outs. 25-50 pctl	1.91	1.53	4.08*
	(2.29)	(3.23)	(2.35)
Portfolio × Amount Outs. 50-75 pctl	4.44**	-4.85*	-1.19
	(2.14)	(2.88)	(3.18)
Portfolio × Amount Outs. 75-100 pctl	4.27	-0.36	-2.89
	(3.26)	(4.41)	(3.90)
Day FE	Yes	Yes	Yes
Issuer Industry FE	Yes	Yes	Yes
Observations	3,890,730	2,384,982	6,230,081
Adjusted R^2	0.141	0.049	0.095
Within R^2	0.138	0.045	0.093

Note: This tables provides OLS estimates of the trade-level equation (5). Transaction cost is regressed on a portfolio trade dummy, a portfolio dealer dummy, age, amount outstanding, time to maturity, credit rating, trade size, and the interaction of the portfolio trade dummy with portfolio characteristics –number of bonds, volume HHI, credit rating average, standard deviation compared to its i.i.d. counterfactual, amount outstanding average, aggregate volume–, day fixed effects and issuer industry fixed effects. Equation (5) is estimated using full customer buy portfolios and sequential customer buy trades (column 1), full customer sell portfolios and sequential customer sell trades (column 2), and mixed portfolios and all sequential trades (column 3). To ease the exposition, some estimates are left untabulated. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

As can be seen in Table 9, the balance sheet and diversification channels are economically and statistically significant. Portfolios that involve larger volumes pay higher transaction costs. Compared to those bonds in portfolios below the 25th percentile of the aggregate volume distribution, bonds in portfolios above the 75th percentile pay 36.34 bps, 9.11 bps, and 25.29 bps more transaction costs, according to the trade side considered. Since almost all bonds traded through portfolios imply balance sheet costs, the larger those costs the larger the transaction costs dealers translate to customers. Table 9 also shows that, for portfolios where customers buy bonds, the transaction costs are reduced as we increase the number of bonds. In particular, bonds in full customer-buy portfolios in the 4th quartile pay 27.67 bps less transaction costs than those in the 1st quartile, with a similar pattern happening for mixed portfolios. The other variables considered to address portfolio diversification present no clear evidence in favor or against the hypothesis.

I do not find strong evidence about asymmetric information driving portfolio transaction costs. The estimated coefficients associated with the average amount outstanding of a portfolio go in opposite directions according to buy and sell trades and are typically not significant. As the lack of significance may be due to the variable considered not being an accurate proxy for asymmetric information, in Appendix A.8 I estimate two alternative models that speak to this channel. First, I extend equation (2) by replacing the day fixed effects for time-series variables. Among them, the Volatility Index produced by the Chicago Board Options Exchange (VIX) measures the uncertainty related to stock price movements. If the asymmetric information channel plays a role when pricing portfolios, it is expected that such a role gains importance in uncertain times. I find no evidence regarding this claim. Second, I compute the evolution of bond prices after these had been traded, at different horizons. If portfolios are traded on information, it is expected that the prices of those portfolio bonds sold (bought) would decrease (increase) after the trade more than what they do after sequential trades (Di Maggio, Franzoni, Kermani, and Sommavilla, 2019; Pinter, Wang, and Zou, 2024). Again, I find no evidence supporting this hypothesis.

Overall, the evidence presented suggests that dealers price portfolios differently according to the aggregated volume traded and the amount of risk they can diversify. Larger portfolios imply higher balance sheet costs and thus are traded with a penalty. In turn, conditional on the aggregated volume traded, portfolios with more bonds reduce their return volatility and thus are traded with a discount.

6 Conclusion

This paper empirically studies portfolio trading in the corporate bond market. This new protocol allows customers to trade a bundle of bonds simultaneously, reducing the time it would take to trade these bonds sequentially and the consequent execution uncertainty. In line with the novelty of the protocol, data sets do not explicitly account for it. To overcome this issue, I develop an algorithm to infer portfolios from specific characteristics of bundles of bonds. I find that portfolio trades represent a significant and growing fraction of the market and that its intermediation is concentrated among top dealers, who source bonds using their balance sheets. Finally, I turn to the liquidity implications of portfolio trading. I do so by comparing the transaction costs charged in this protocol and in the alternative one, i.e. traditional sequential trading. I present novel evidence of asymmetrical transaction costs: compared to sequential trading, portfolio trading is 42.6% less expensive when customers buy and 9.9% more expensive when they sell. To address which factors drive these results, I proceed in two steps. On the one hand, I show there is a significant cross-subsidy within portfolios: bond characteristics that are priced in sequential trading are reversed when the bond is included in a portfolio. On the other hand, I study several hypotheses of portfolio pricing. I find that dealers penalize portfolios that involve large balance sheet costs and offer discounted transaction costs to those portfolios that diversify risk. I find no evidence of asymmetric information driving portfolio pricing.

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A Appendix

A.1 Customer-dealer trades frequency

Here I show that bundles of 30 or more bonds being traded by the same dealer at the same second are rare, a fact that supports my portfolio identification strategy. Table A.1 presents statistics for the top ten dealers performing portfolio trades. Both taking into account the extensive margin, i.e. how often a customer-dealer trade is observed, and the intensive margin, i.e. how many customer-dealer trades happen in every trading second. It is observed that trading is rather infrequent, with bundles of 30 or more bonds only observed at the extreme tail of the distribution.

Table A.1: Customer-dealer trades frequency, per portfolio dealer. Period 2018-2019

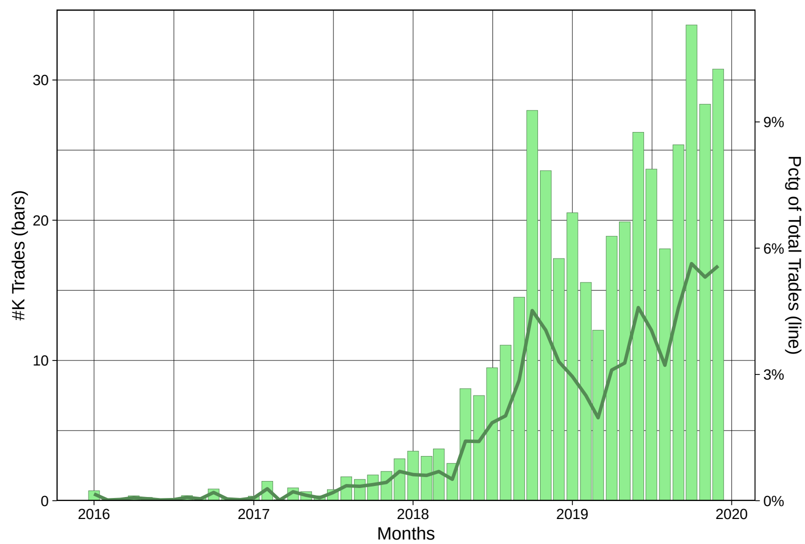
	Vol % share		Seconds between trades in an hour				Number of trades in a second			
Dealer	Port.	Seq.	p50	p90	p99	p99.9	p50	p90	p99	p99.9
1	49.9	10.2	51	26	21	16	1	3	6	57
2	18.6	8.9	65	34	26	19	1	2	4	38
3	17.4	0.7	157	45	33	20	1	3	10	147
4	6.5	8.1	86	45	36	24	1	2	4	15
5	3.3	8.5	97	51	38	21	1	2	4	10
6	2.5	7.5	90	40	31	20	1	3	6	10
7	0.7	8.2	103	53	40	19	1	2	4	10
8	0.2	5.3	138	73	56	43	1	1	2	5
9	0.2	0.0	1,800	240	93	67	1	9	11	69
10	0.2	0.3	720	95	59	48	1	6	14	28

Note: This table shows statistics for the top ten portfolio trading dealers. Columns 2 and 3 show the market share of each dealer, for portfolio and sequential trading, respectively. Columns 4-7 measures how often a customer-dealer trade is observed. To compute this variable, I initially calculate how many customer-dealer trades a dealer executes in every hour in which she executes a trade (avoiding thus the hours in which there is no market). Then I divide 3600 by such a figure to re-express the variable as the number of average seconds between trades in each hour. For example, if in an hour there are 10 trades, that means that a trade happens on average every 3600/10=360 seconds during that hour. Columns 8-11 measure how many customer-dealer trades happen in every trading second.

A.2 Portfolio Trades Market Share

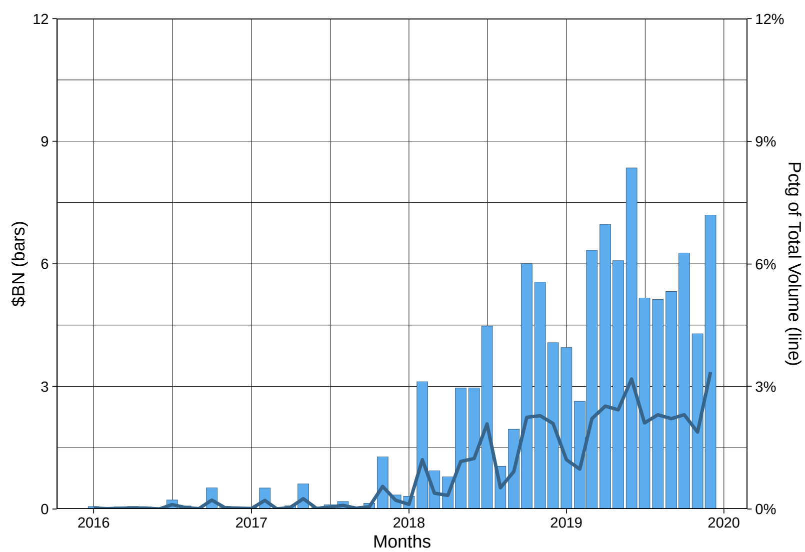
Here I present the monthly time series of portfolio trading shares considering both volume and the amount of trades, and for alternative market segments.

Figure A.1: Portfolio trading trades - All segments



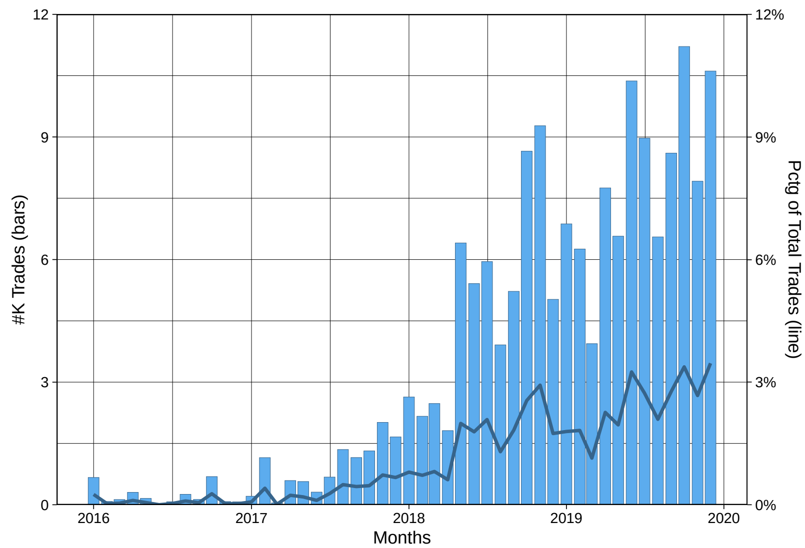
Note: This figure depicts the monthly time-series of trades performed through portfolio trading, including both customer-dealer and inter-dealer trades. The bars –left axis– indicate the number of trades, expressed in thousands. The line –right axis– indicates market share, expressed in percentage points.

Figure A.2: Portfolio trading volume - Customer dealer segment



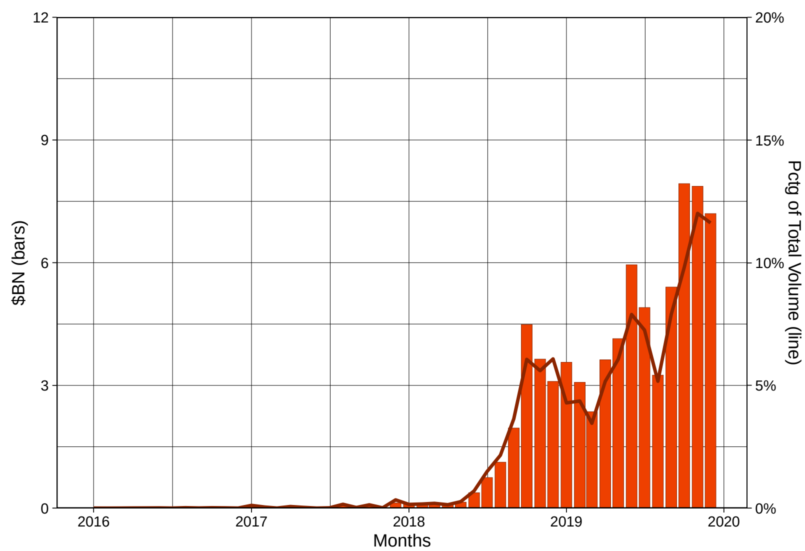
Note: This figure depicts the monthly time-series of portfolio trading volume, including only customer-dealer trades. The bars –left axis– indicate total face value, expressed in billion dollars. The line –right axis– indicates market share, expressed in percentage points.

Figure A.3: Portfolio trading trades - Customer dealer segment



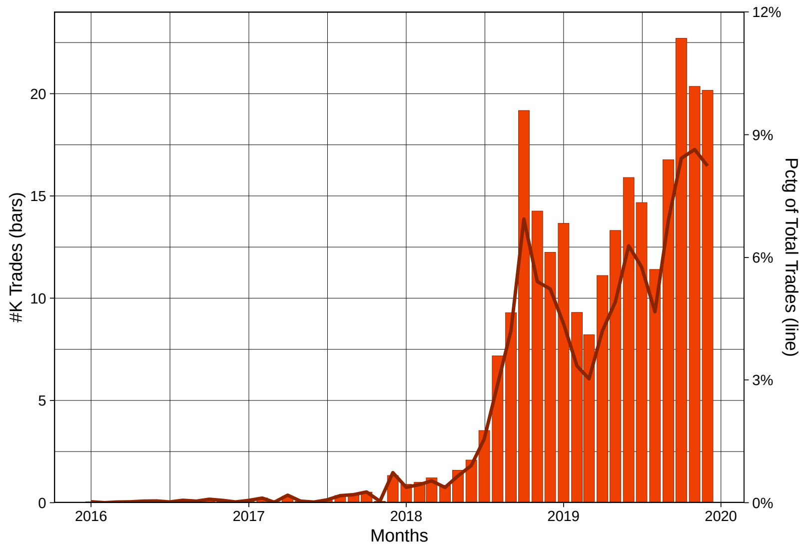
Note: This figure depicts the monthly time-series of trades performed through portfolio trading, including only customer-dealer trades. The bars –left axis– indicate the number of trades, expressed in thousands. The line –right axis– indicates market share, expressed in percentage points.

Figure A.4: Portfolio trading volume - Inter-dealer segment



Note: This figure depicts the monthly time-series of portfolio trading volume, including only inter-dealer trades. The bars –left axis– indicate total face value, expressed in billion dollars. The line –right axis– indicates market share, expressed in percentage points.

Figure A.5: Portfolio trading trades - Inter-dealer segment

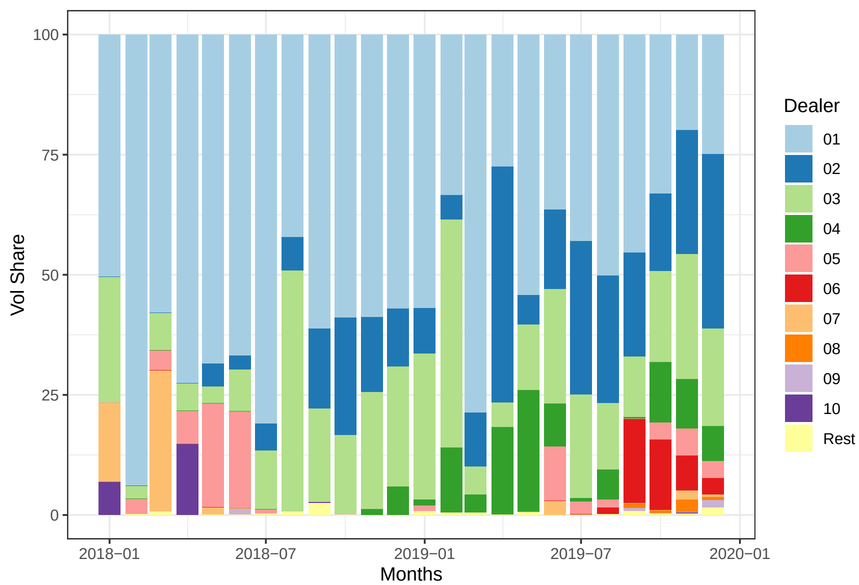


Note: This figure depicts the monthly time-series of trades performed through portfolio trading, including only inter-dealer trades. The bars –left axis– indicate the number of trades, expressed in thousands. The line –right axis– indicates market share, expressed in percentage points.

A.3 Dealers' Market Share Evolution of Portfolio Trading

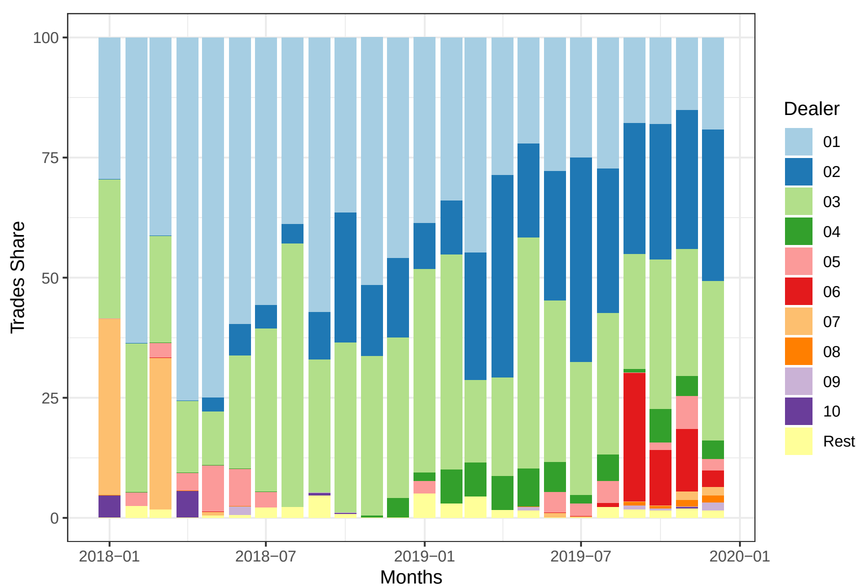
Here I present the evolution of the market share of each one of the top ten portfolio trading dealers, considering both volume traded and number of bonds traded.

Figure A.6: Portfolio Trading Market Share Evolution - Volume



Note: This figure depicts dealers' monthly share of the portfolio trading (face value) volume. Dealers are ordered according to their volume share in the entire period 2018-2019.

Figure A.7: Portfolio Trading Market Share Evolution - Trades



Note: This figure depicts dealers' monthly share of the portfolio trading trades. Dealers are ordered according to their volume share in the entire period 2018-2019.

A.4 Bonds Sourcing using Number of Trades

Table A.2 shows how the top ten portfolio dealers source their portfolio and sequential trades: offsetting with other dealers or customers, or involving their own inventories. The figures express percentage points computed out of the number of trades.

Table A.2: Sourcing of Portfolio - Number of Trades

	Market Share		Portfolio Sourcing			Sequential Sourcing		
			Offset ≤15m		Non-Offset	Offset ≤15m		Non-Offset
Dealer	Portfolio	Sequential	C	D		C	D	
1	35.3	6.7	2.6	0.4	97.0	4.0	7.6	88.3
2	21.2	4.3	2.0	1.0	97.0	5.5	2.2	92.3
3	31.0	1.7	0.0	1.1	98.9	0.0	1.1	98.9
4	3.2	3.1	2.4	1.2	96.4	6.0	17.2	76.8
5	2.3	2.9	14.1	0.1	85.8	9.4	1.2	89.5
6	3.3	4.0	0.6	0.4	99.1	4.5	1.3	94.2
7	1.5	2.7	0.2	0.2	99.6	8.7	1.6	89.7
8	0.3	1.8	0.2	0.5	99.3	10.0	5.4	84.6
9	0.3	0.1	0.0	98.5	1.5	0.2	72.5	27.3
10	0.2	0.3	0.0	100.0	0.0	0.0	100.0	0.0

Note: This tables shows, for each of the top ten portfolio trading dealers, its portfolio trading market share (column 2), its sequential trading market share (column 3), the distribution in the three categories – Offset ≤ 15 - C, Offset ≤ 15 - D, Non-Offset – of its portfolio trading activity (columns 4-6) and sequential trading activity (columns 7-9). All statistics are computed using the non-weighted number of trades.

A.5 Variables Computation

This subsection describes the computation of the variables used in trade-level and portfolio-level analysis.

Trade-level variables:

- Portfolio dealer: Dummy variable that equals 1 if the trade was performed by a dealer that accumulates more than 0.01% of the total portfolio trading volume.
- Age: Number of years between the day of offering and the trading day.
- Amount Outstanding: Total amount outstanding of the bond being traded, measured in face value and expressed in billions of dollars.

- Time to Maturity: Number of years between the day of maturity and the trading day.

- Trade Size: Par-value of the transaction, expressed in millions of dollars.

- Credit Rating: I initially compute the average letter ratings of the three agencies present in FISD (S&P, Moodie's, and Fitch) by using standard letter-number equivalences (e.g., AAA=1, D=25). I then go back to letter ratings using the same equivalence and classify bonds as Investment Grade Superior, Investment Grade Inferior, High Yield Superior, or High Yield Inferior if they belong to credit rating brackets AAA-AA, A-BBB, BB-B, or CCC-D, respectively.

- Turnover: I compute the turnover of a bond over the last 3 months previous to the month in which it is traded. For each bond, past turnover equals $\sum_{s=1}^{s=3} vol_{t-s}/(\sum_{s=1}^{s=3} iao_{t-s})/3)$, where t is the month in which the trade happens, vol_{t-s} is the total face value traded in month $t-s$, and iao_{t-s} is the mean amount outstanding during month $t-s$.

- Idiosyncratic variance share: I firstly compute bond i weekly returns $R_{i,w}$ using volume-weighted average prices, including accrued interest rates and coupon payments. Second, I compute the OLS residuals of the regression $R_{i,w} - R_w^f = \alpha + \beta(R_w^m - R_w^f) + \epsilon_{i,w}$, where R_w^f is the weekly interpolated 1M Treasury rate and R^m is the weekly return of the Bank of America Merrill Lynch US Corporate Index (IG or HY according to the bond considered). Finally, I compute the idiosyncratic variance share as the ratio $Var(\hat{\epsilon}_{i,w})/Var(R_{i,w} - R_w^f)$. This variable is only computed for those bonds with at least 30 weekly returns.

Portfolio-level variables:

- Number of bonds: Sum of bonds in a portfolio

- Herfindahl-Hirschman Index (HHI): $\sum_{i\in p}(\text{vol}_i/\sum_{i\in p}\text{vol}_i)^2$, where vol_i denotes the Trade Size of trade i in portfolio p.

- Average Rating: Simple average of the Credit Rating of the bonds in a portfolio, where the Credit Rating character variable is turned to numeric by using standard letter-number equivalences (e.g., AAA=1, D=25).

- Portfolio Standard Deviation compared to its iid counterfactual (SD/SDiid): I initially compute the portfolio return standard deviation SD. For this, I take bond returns $R_{i,w}$ as previously described and impute weights W_i using the net volume (face value) of bonds in the portfolio. Secondly, I compute the counterfactual iid portfolio return standard deviation $SD_{iid} = [\sum_i w_i^2 Var(R_i)]^{1/2}$. Finally, I compute the percentage deviation and express it in percentage points $100(SD/SD_{iid} - 1)$. This variable is only computed using those bonds that, in the previous 30 weeks before the portfolio was traded, have at least 15 weekly returns computed.

- Amount Outstanding: Simple average of the Amount Outstanding of the bonds in a portfolio.
- Volume: Sum of Trade Size of the bonds in a portfolio.

A.6 Subsample of Customer-Dealer Trades with Reference Price Available

To construct the transaction cost measure for customer-dealer trades, there should exist at least one same bond-day inter-dealer trade from which to take the reference price. In this Appendix, I present how this requirement reduces the portfolio and sequential trading subsamples.

Table A.3 shows how the overall number of observations and volume implied is reduced when we only consider those customer-dealer trades with an associated reference price. The reduction is higher in the portfolio trade subsample.

Table A.3: Trades with associated reference price

Sample	Observations (%)	Volume (%)
Portfolio	60.03	62.86
Sequential	83.10	69.88

The reduction in the samples that are used for the transaction costs analysis can represent a concern if the lack of reference price correlates with trade characteristics. In such a case, our estimations may suffer from a selection bias. Tables A.4 and A.5 decompose portfolio and sequential samples into those trades with and without an associated reference price, and present the distribution of relevant characteristics in the two partitions. Although there are clear differences between the partitions with and without a reference price, we still have enough variation in each characteristic so that we can control for them in the estimations, thus lessening the selection bias concern.

Table A.4: Variables distribution differences within portfolio trades

Variables	Ref Price	Mean	Std. dev.	.05	.25	.50	.75	.95
Age (years)	No	3.27	3.11	0.35	1.15	2.38	4.41	9.09
	Yes	3.23	2.75	0.36	1.32	2.63	4.41	7.63
Amount Outstanding $B	No	0.80	0.57	0.30	0.50	0.64	1.00	1.80
	Yes	1.25	1.00	0.40	0.62	1.00	1.50	3.00
Customer Sell	No	0.43	0.50	0.00	0.00	0.00	1.00	1.00
	Yes	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Maturity (years)	No	11.18	9.53	2.48	4.76	6.99	17.95	28.93
	Yes	8.81	7.77	2.18	4.30	6.33	8.63	27.85
Rating 1-25	No	10.81	3.78	5.00	8.00	11.00	14.00	17.00
	Yes	10.79	3.73	5.00	8.00	11.00	13.00	16.00
Trade Size $M	No	0.61	1.77	0.02	0.10	0.20	0.50	2.19
	Yes	0.69	2.00	0.02	0.10	0.25	0.50	2.50
Turnover 3m	No	21.42	42.02	2.85	9.47	17.27	27.51	52.91
	Yes	27.58	38.40	6.32	13.83	22.16	34.23	66.82

Table A.5: Variables distribution differences within sequential trades

Variables	Ref Price	Mean	Std. dev.	.05	.25	.50	.75	.95
Age (years)	No	3.40	3.18	0.33	1.13	2.51	4.70	9.00
	Yes	4.01	3.34	0.47	1.79	3.31	5.38	8.82
Amount Outstanding $B	No	0.81	0.64	0.28	0.45	0.60	1.00	2.00
	Yes	1.27	1.21	0.28	0.50	1.00	1.50	3.10
Customer Sell	No	0.50	0.50	0.00	0.00	1.00	1.00	1.00
	Yes	0.38	0.49	0.00	0.00	0.00	1.00	1.00
Maturity (years)	No	11.29	10.04	1.85	4.30	6.93	18.98	29.24
	Yes	7.39	7.40	1.40	3.05	5.15	7.86	26.30
Rating 1-25	No	9.69	3.77	5.00	7.00	9.00	12.00	17.00
	Yes	9.09	3.64	4.00	7.00	9.00	11.00	16.00
Trade Size $M	No	1.39	3.08	0.01	0.07	0.30	1.42	5.91
	Yes	0.66	2.32	0.01	0.02	0.05	0.25	3.50
Turnover 3m	No	19.70	24.07	2.37	7.78	14.57	25.11	53.79
	Yes	23.15	23.84	4.06	10.19	16.60	27.93	64.97

A.7 Transaction Costs Drivers Within Portfolios

In this Appendix I provide evidence on individual reported prices of portfolio trading bonds being economically significant. I do so by showing that the pricing of bond characteristics within portfolios follows the same patterns as in sequential trading. Using only the portfolio trading observations, I estimate the following equation:

$$TC_{i,p} = \alpha + \Gamma C_i + \delta FE_p + \Lambda FE + \epsilon_{i,p},$$

where I include portfolio fixed effects to capture how characteristics included in vector C are priced within each portfolio. Table A.6 shows the same pricing pattern as in sequential trading: smaller issues, with higher time to maturity and worse credit risk are more expensive to trade. These results hold under an alternative specification in which, instead of using portfolio fixed effects, I re-compute variables as quartile bins for each portfolio.

Table A.6: Transaction costs regression on trade characteristics within portfolios.

Dependent Variable:	Transaction Cost
	(1)
Age	0.15*
	(0.08)
Amount Outstanding	-0.65***
	(0.17)
Time-to-maturity 3-5	0.54
	(0.54)
Time-to-maturity 5-10	1.18*
	(0.63)
Time-to-maturity >10	5.77***
	(1.48)
Odd (100K-1M)	0.23
	(0.49)
Round (1M-5M)	0.63
	(0.81)
5M and above	3.87**
	(1.71)
IG (A-BBB)	-0.16
	(0.56)
HY (BB-B)	2.21**
	(1.12)
HY (CCC-D)	7.01***
	(1.83)
Idiosync. var. share	1.41
	(1.17)
Customer Sell	3.79**
	(1.90)
Day FE	Yes
Portfolio FE	Yes
Issuer Industry FE	Yes
Observations	89,104
Adjusted R^2	0.134
Within R^2	0.003

Note: This tables provides OLS estimates of the trade-level regression of transaction cost on age, amount outstanding, time to maturity, credit rating, trade size, idiosyncratic variance share, day fixed effects , portfolio fixed effects and issuer industry fixed effects. The sample consists of portfolio trades. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

A.8 Asymmetric Information Channel Robustness Checks

In this Appendix, I provide two alternative model specifications searching for evidence of an asymmetric information channel in portfolio transaction costs. The first model provided is an extension of equation (2) in which I replace day fixed effects for time-series variables. This model allows me to include the Volatility Index (VIX), which is a time-series measure of market uncertainty. If the asymmetric information channel plays a role when pricing portfolios, it is expected that such a role gains importance in uncertain times.

$$TC_{i,t} = \alpha + \beta_1 \mathbf{1}_{i=\text{Portfolio}} + \gamma C_i + \beta_2 \text{VIX}_t + \beta_3 \mathbf{1}_{i=\text{Portfolio}} \text{VIX}_t + \beta_4 \text{T2Y-T1M} + \beta_5 \text{TED Spread} + \Lambda FE + \epsilon_{i,t}$$

In Table A.7, I estimate the model for customer buy and customer sell bonds separately. To control for the time varying financial costs of dealers, I include the difference between the 2 years and 1 month Treasury rates (T2Y-T1M) and the difference between the 3 months LIBOR rate and 3 month Treasury rate (TED Spread). In columns 1 and 2 I estimate the model using bond fixed effects, while in columns 3 and 4 I use the vector C of bond characteristics plus dealer and industry fixed effects. The portfolio transaction costs differential with sequential trading does not change significantly in times of high expected volatility. This non-significance result holds if I control for VIX non-linearities by using quartile dummies.

Table A.7: Transaction Costs regression on time series macro variables.

Dependent Variable:	Transaction Cost			
	Customer buys	Customer sells	Customer buys	Customer sells
T2Y-T1M	5.82***	-2.91***	-0.51	-2.02***
	(0.61)	(0.60)	(0.53)	(0.54)
TED Spread	2.47	7.74***	3.25**	8.90***
	(1.79)	(1.74)	(1.47)	(2.24)
VIX	0.51***	0.14*	0.32***	0.15
	(0.05)	(0.08)	(0.03)	(0.11)
Portfolio × VIX	-0.32	0.38	-0.12	0.30
	(0.21)	(0.30)	(0.21)	(0.30)
Bond FE	Yes	Yes	No	No
Dealer FE	No	No	Yes	Yes
Issuer Industry FE	No	No	Yes	Yes
Observations	3,851,178	2,370,309	3,847,660	2,366,885
Adjusted R^2	0.197	0.082	0.283	0.109
Within R^2	0.036	0.006	0.057	0.012

Note: This tables provides OLS estimates of the trade-level regression of transaction cost on a portfolio trade dummy, trade size, VIX, 2 year Treasury rate minus 1 month Treasury rate, TED Spread, and bonds fixed effects, for customer buy trades (column 1) and customer sell trades (column 2) separately. Alternatively, columns 3 and 4 replace bond fixed effects for age, amount outstanding, time to maturity, credit rating, dealer fixed effects and issuer industry fixed effects, for customer buy and customer sell trades, respectively. To ease the exposition, some estimates are left untabulated. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.

For the second model, I compute the (ex-post) performance of bonds, at different horizons h (Di Maggio, Franzoni, Kermani, and Sommavilla, 2019; Pinter, Wang, and Zou, 2024):

$$\text{Performance}_{b,t,h} = [ln(P_{b,t+h}) - ln(P_{b,t})] * Q,$$

where Q is a trade side indicator that equals 1 (-1) if the customer buys (sells) and $P_{b,t}$ is the simple average price of bond b at day t. In this way, each trade i will have attached a performance measure. Then I estimate a model where the performance attached to each trade is a function of its inclusion in portfolio trading, trade side, and relevant fixed effects.

$$\text{Performance}_{i,h} = \alpha + \beta_1 \mathbf{1}_{i=\text{Portfolio}} + \beta_2 \mathbf{1}_{i=\text{Cust. sells}} + \beta_3 \mathbf{1}_{i=\text{Portfolio}} \mathbf{1}_{i=\text{Cust. sells}} + \Lambda FE + \epsilon_{i,h}$$

If portfolios are traded on information, it is expected that the prices of those portfolio bonds sold (bought) would decrease (increase) after the trade more than what they do after sequential trades. Table A.8 shows no evidence supporting this story. On the contrary, bonds sold through portfolios show a significant worse performance (price increase) than those sold through sequential trading after 20 days of the trade.

Table A.8: Return Performance regression on portfolio trading.

Dependent Variables:	Performance		
	h = 1 day	h = 10 days	h = 20 days
Portfolio	-0.89	-1.16	5.23
	(1.45)	(5.64)	(6.30)
Portfolio Dealer	6.23***	6.42***	5.93***
	(0.21)	(0.65)	(0.77)
Customer Sell	-6.41***	-10.43	-13.18
	(1.76)	(6.33)	(8.27)
Portfolio × Customer Sell	-3.22	-12.76	-32.87**
	(2.49)	(9.00)	(13.34)
Day FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Observations	5,381,271	3,473,835	4,975,786
Adjusted R^2	0.020	0.019	0.020
Within R^2	0.002	0.001	0.001

Note: This tables provides OLS estimates of the trade-level regression of performance on a portfolio trade dummy, customer sell dummy, the interaction between portfolio trade and customer sell dummies, trade size, day fixed effects, and bonds fixed effects. Estimates for the measured of performance at 1 day, 10 days, and 20 days horizon are presented in columns 1, 2, and 3, respectively. To ease the exposition, some estimates are left untabulated. Clustered day-bond standard-errors are shown in parentheses. One, two, and three stars indicate statistical significance at the 0.1, 0.05, and 0.01, respectively.