Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Price Discovery in the U.S. Treasury Cash Market: On Principal Trading Firms and Dealers

James Collin Harkrader and Michael Puglia

2020-096

Please cite this paper as:
Harkrader, James Collin, and Michael Puglia (2020). "Price Discovery in the U.S. Treasury Cash Market: On Principal Trading Firms and Dealers," Finance and Economics Discussion Series 2020-096. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2020.096.

Price Discovery in the U.S. Treasury Cash Market: On Principal Trading Firms and Dealers

James Collin Harkrader
james.c.harkrader@frb.gov

Michael Puglia
michael.t.puglia@frb.gov

October 19, 2020

Abstract

We explore the following question: does the trading activity of registered dealers on Treasury interdealer broker (IDB) platforms differ from that of principal trading firms (PTF), and if so, how and to what effect on market liquidity? To do so, we use a novel dataset that combines Treasury cash transaction reports from FINRA's Trade Reporting and Compliance Engine (TRACE) and publicly available limit order book data from BrokerTec. We find that trades conducted in a limit order book setting have high permanent price impact when a PTF is the passive party, playing the role of liquidity provider. Conversely, we find that dealer trades have higher price impact when the dealer is the aggressive party, playing the role of liquidity taker. Trades in which multiple firms (whether dealers or PTFs) participate on one or both sides, however, have relatively low price impact. We interpret these results in light of theoretical models suggesting that traders with only a "small" informational advantage prefer to use (passive) limit orders, while traders with a comparatively large informational advantage prefer to use (aggressive) market orders. We also analyze the events that occurred in Treasury markets in March 2020, during the onset of the COVID-19 pandemic.

JEL Classification: G14, G12, C32

Keywords: Treasury markets, high frequency trading, market microstructure, price discovery, price impact, PTFs, dealers, TRACE, BrokerTec

* The authors would like to thank Ayeh Bandeh-Ahmadi, Alain Chaboud, Luca Guerrieri, Andrew Meldrum, Michiel De Pooter, Nick Steele, Brandon Taylor and Filip Zikes for helpful comments. All errors are our own. This analysis was conducted within the context of broader work on the Treasury TRACE data by partner agencies in the Interagency Working Group on Treasury Market Surveillance (IAWG). The IAWG's aims are to enhance official-sector monitoring of the Treasury securities market and improve understanding and transparency of this market more generally, while not impeding market functioning and liquidity. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.

1 INTRODUCTION

We combine the Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) Treasury dataset with licensed data on BrokerTec limit order activity to study the price discovery process on Treasury interdealer broker (IDB) platforms. We attempt to answer a broad question: does the trading activity of registered[1] dealers differ from that of (unregistered) principal trading firms (PTF), and if so, how and to what effect on market liquidity? More precisely, we investigate whether the trades of dealers and PTFs have dissimilar permanent price impact, where price impact is measured using an SVAR framework in the spirit of Hasbrouck (1991a).

The novelty of our datasets, and the algorithms we use to join them, permits us to study this topic in ways not formerly possible. Unlike previous studies that have relied on anonymized BrokerTec data, the transaction-level data that we use enables us to investigate new topics in Treasury market microstructure. The TRACE Treasury dataset is a regulatory collection available only to the official sector. Amongst else, it contains reports for all trades conducted on the BrokerTec platform (after April 2019) and identifies all firms that are party to the trades.

The existence of the TRACE Treasury dataset owes to the events that occurred in Treasury markets on October 15, 2014, and the subsequent Joint Staff Report (JSR) which studied those events and prescribed a course of further action for the official sector. Among its recommendations, the JSR advised "further study of the evolution of the U.S. Treasury market and its implications for market structure and liquidity" and "a review of the current regulatory requirements applicable to the government securities market *and its participants*" (emphasis added). While our study is an early contribution to this effort, and we refrain from making prescriptions, we aim to inform the policy debates surrounding these recommendations.

Though the TRACE Treasury dataset is a critical component of our study, it is not sufficient to conduct the analysis that follows. In addition, we also use licensed order book data from BrokerTec to augment the TRACE Treasury dataset, which is necessary to make the data usable in Hasbrouck's SVAR framework. In order to join these two datasets, we have developed two algorithms, one that filters and matches buy and sell trade reports in the TRACE Treasury dataset, and another which implements a fuzzy join of the BrokerTec limit order book data on the TRACE trade reports.

In a preview of results, we find that, ceteris paribus, trades have high permanent price impact when a PTF is the passive party, playing the role of liquidity provider on the BrokerTec platform. Conversely, we find that dealer trades have higher price impact when the dealer is the aggressive party and taking liquidity from the platform. Furthermore, trades in which both the buyer and seller are PTFs have very high price impact, while trades between two dealers have low price impact. In between all of these extremes, trades that are matched with multiple firms (whether dealers or PTFs) on one or both sides have very low price impact. Like trades between two PTFs, self-trades also have very high price impact. We interpret these findings in light of theoretical predictions that informed traders prefer to use (passive) limit orders when

[1] Firms that meet the definition of "dealer" as set in the Securities Exchange Act of 1934 are required to register with the Securities and Exchange Commission (SEC) and become a member of FINRA. In doing so they become subject to SEC and FINRA oversight of their Treasury market activity. Firms, such as PTFs, that do not meet the definition of "dealer" are able to avoid FINRA and many forms of SEC oversight. See 15 U.S.C. § 78c(5).

their advantage is "small" [Rosu 2020, Chaboud, Hjalmarsson and Zikes 2020], while traders with a comparatively large informational advantage prefer to use (aggressive) market orders.

After presenting our main results, we also use our models to study the events that occurred in Treasury markets during March 2020, related to the onset of the COVID-19 pandemic. We find that, during this period of acute market stress, the proportion of trades that were matched with multiple firms on one or both sides fell greatly as market depth declined (and market volume increased). Furthermore, though the price impact of all trades rose greatly during this period, the increase for these multi-party trades stands out for its magnitude.

1.1 Literature Review

The starting point of this paper is Fleming, Mizrach and Nguyen (2017, hereafter *FMN*), which estimates the price impact of trades and limit orders on the BrokerTec platform using the structural vector autoregression (SVAR) from Hasbrouck (1991a). The data that they use does not identify the participants to trades or their types, however, and so they cannot explore price discovery dynamics at the participant level. Brogaard, Hendershott and Riordan (2019, hereafter *BHR*) extend Hasbrouck (1991a) with participant-type information to study the differentiated price impact of limit and market orders across HFT and non-HFT trading strategies in Canadian equity markets. Our paper uses similar methods, though our dataset distinguishes individual traders by business model, while theirs distinguishes traders by trading strategy.[2] Finally, Chaboud, Hjalmarsson and Zikes (2020, hereafter *CHZ*) extend Hasbrouck (1991a) with participant type information to study foreign exchange markets, and explore the changing role of *limit orders* in the price discovery process on the EBS platform over an extended period. Our paper borrows heavily from *CHZ* and presents the Treasury market-version of one of their models, but also extends it to investigate the differential price impact of *trades* by participant type. In particular, we consider pairwise interactions between PTFs and dealers, in order to identify the function that maps market order flow, liquidity provider and liquidity taker into permanent price impact.

Consistent with results published in *FMN*, we find the cumulative price impact of market orders overall to be small relative to typical bid-ask spreads, which merely reflects the fact that the US Treasury cash market is large, liquid and highly efficient. Furthermore, the price impact of trades generally increases with tenor, meaning that the price impact of a trade in the 30-year on-the-run security on BrokerTec is higher than the price impact of a trade in the 10-year security and so on. Although our sample period (mid-2019 to early 2020) does not overlap that used in *FMN* (2010-2011), our benchmark results are consistent.

Fleming, Nguyen (2018, hereafter *FN*) study the workup protocol on the BrokerTec platform and find that trades occurring in the workup have lower price impact than trades occurring in the pre-workup or normal trading period. Although we cannot identify the workup very easily in our dataset, we are able to

[2] That is, the dataset used in *BHR* classifies participants according to trading strategy (i.e. HFT vs. non-HFT trading) and not by business model (i.e. registered dealers vs. PTFs). Conversely, the dataset used in this paper classifies participants very accurately by business model, but not by trading strategy. To the extent that some dealers implement HFT strategies, the distinction becomes important. The dataset used by *BHR* also identifies participants' market order *and* limit order activity. The dataset used in this paper only identifies participants' market order activity.

distinguish trades that include multiple parties on one or both sides (whether or not they occur in a workup) and those conducted between only one buyer and one seller. Consistent with *FN*, we find that trades conducted between one seller and one buyer (i.e. one-to-one) have significantly higher price impact than those that are matched between multiple buyers and/or sellers (i.e. multi-party). We are also able to identify self-trading[3] in our dataset, and find that trades matching a buyer and a seller from the same firm, although relatively rare in the data, have very high and statistically significant permanent price impact, higher than either one-to-one and multi-party trades.

These latter findings motivate the investigation at the core of this paper, regarding the difference between dealer and PTF trading activity and its effect on market liquidity. The remainder of this paper is structured as follows. In the next section, we discuss limit order book trading and the BrokerTec platform. In Section 3, we describe the TRACE Treasury dataset and the BrokerTec limit order book information that we have used. In Section 4, we detail our models and present results. In Section 5, we provide some analysis of the events in Treasury markets that occurred in March 2020 during the onset of the COVID-19 pandemic. Section 6 concludes.

2 LIMIT ORDER BOOKS AND THE BROKERTEC PLATFORM

The focus of this paper is intermediation on electronic Treasury IDB platforms. We use data on trading and limit order book activity on the BrokerTec platform, which has been the subject of many other studies on this topic, including the JSR and *FMN*.

BrokerTec, like all other Treasury IDB firms, operates a limit order book (sometimes called a central limit order book, or CLOB). When traders submit limit orders to buy and sell securities at specific prices and amounts, they are entered into a record of standing bids and offers according to price and time priority. Other participants may act upon standing limit orders and trade by submitting market orders. Trade executions resulting from market orders are assigned to limit orders according to their rank in the price-time queue. High bids and low offers in the limit order book outrank lower bids and higher offers, respectively, and at any given price, rank is assigned by time arrival, with the earliest arrivals given priority over later arrivals. Figure 1 below is a stylized example of the limit order book for a generic security. Four buyers and four sellers have entered limit orders to buy and sell, which are displayed in order of descending price/time priority.

Many order types are available to traders on the BrokerTec platform, but for the present purpose, they can be characterized simply as either market or limit. Market orders are aggressive, and entered at a bid/offer price which is high/low enough to execute immediately. Conversely, limit orders are passive and entered at prices too low/high to transact immediately, but will rest in the order book until matched with a sufficiently aggressive market order. Traders may cancel limit orders at any time before being

[3] Self-trading is a phenomenon in the Treasury market first identified in the Joint Staff Report (JSR) on October 15th 2014. It can occur when independent HFT trading algorithms operated by the same firm are matched in a limit order book. This will we described in more detail later.

matched. Using the example above, a market order to sell 2 units, entered by seller A5 will be matched with buyer B1's limit order, resulting in a trade for 2 units at a price of 99.

Figure 1: Stylized Example of a Limit Order Book

Buyer	*Bid Amount*	*Bid Price*	*Ask Price*	*Ask Amount*	*Seller*
B1	2	99	100	1	A1
B2	2	99	100	1	A2
B3	1	98	100	1	A3
B4	1	98	101	1	A4

Note: The figure displays a stylized example of a limit order book for a generic security where four buyers and four sellers have entered limit orders to buy and sell. The rows are presented in order of descending price/time priority.

In a limit order book market, trades are not necessarily matched between a single buyer and a single seller. It is possible to have multiple parties present on either or both sides of the top price level of the order book, and if the schedule of bids and offers permits, many buyers and sellers can be matched simultaneously. For example, in Figure 1 above, buyers B1 and B2 have both entered bids at the same price, and only time priority distinguishes them in the queue. If, in the previous example, seller A5 had entered a market order to sell 4 units rather than 2, two matches (but still one trade) would have resulted: one with buyer B1 for 2 units and one with buyer B2 for 2 units, both at a price of 99. For the remainder of this paper, trades conducted between a single buyer and a single seller will be referred to as "one-to-one," and trades with multiple parties on one or both sides of the trade will be referred to as "multi-party" unless noted otherwise.[4]

In addition to multi-party and one-to-one trades, self-trading, a phenomenon first identified in the JSR, is possible on the BrokerTec platform and can be observed in our dataset. Self-trading occurs when independent traders (or automated algorithms) from the same firm submit bids and offers that match in the order book.[5] Like any other match in the limit order book, a self-trade may be conducted multi-party or one-to-one. In a one-to-one self-trade, the same firm is both the buyer and the seller and there is no change in beneficial ownership. Using the example of Figure 1 again, if a trader from firm B1 (separate from the trader from firm B1 that has a standing limit order to buy 2 units at a price of 99) enters a market order to sell 2 units, a self-trade at 99 with firm B1 appearing as both the buyer and seller will occur.

Table 1 below summarizes the frequency with which these various forms of interaction – one-to-one, multi-party and self-trade[6] – occur on the BrokerTec platform across all securities, unless noted otherwise, from April 15, 2019 to February 15, 2020. Note that, on a trade *count* basis the vast majority of trades are one-to-one, but due to the higher average (aggregated) trade size, the majority of volume is multi-party. One-to-one self-trades account for only 1% of volume, but when accounting for multi-party trades

[4] The workup protocol on BrokerTec, which is an order type separate from limit and market orders, permits multiple buyers to be matched with multiple sellers. See *FN* for more detail.
[5] It is important to note that "self-trade" and "wash-trade" are not synonymous, since the former is generally considered to occur inadvertently and without fraudulent indent. For more information on self-trading, see FINRA's rule regarding self-trading, the Futures Industry Association (FIA) Principal Traders Group (PTG) response to CFTC's Concept Release on Risk Controls and System Safeguards for Automated Trading Environments, or JSR.
[6] Throughout this paper, we define self-trades to be one-to-one self-trades and use the terms interchangeably. Trades in which the same firm appears on both sides, but so does at least one other firm on at least one side are multiparty.

(not shown) in which the same firm is on both sides of a match, but so are other firms potentially, the volume that is self-traded rises to 5.4%, which is in line with figures reported in the JSR.

Table 1: Trade Matching on BrokerTec by Number of Counterparties

Type of Match	*One-to-one (ex. self-trades)*	*Multi-Party (at least one side)*	*Self-trades (one-to-one only)*
Share of Volume	42.2%	57.0%	0.8%
Share of Trade Count	71.5%	26.6%	1.8%
Avg. Trade Size (10-year, $ million)	1.5	5.4	1.3
Median Trade Size (10-year, $ million)	1	3	1

Note: The table reports descriptive statistics for trade matching activity on the BrokerTec platform from April 15, 2019 to February 15, 2020. One-to-one trades are those matched between a single buyer and single seller, excluding self-trades. Multi-party trades include more than one participant on either or both sides. One-to-one self-trades are those in which the single seller and single buyer are the same firm. Percentages may not total 100% due to rounding.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Using the TRACE data to identify individual participants on the BrokerTec platform, we find that they fall into two broad categories: FINRA registered dealers (both primary and other dealers) and their associated, global subsidiary companies[7] (which we will generically call dealers); and PTFs. There is also a third class of residual firms that we are unable to clearly identify as either dealers or PTFs, which we lump into a generic "other" category. Table 2 below summarizes activity on the BrokerTec platform by participant type. The first column indicates the share of total volume transacted between April 15, 2019 and February 15, 2020. In the second column, the share of market orders submitted (aggressive trade orders resulting in a transaction) is indicated, while in the third column the share of liquidity provided (passive limit orders that are aggressed by other participants) is indicated. Note that PTFs account for the majority of volume and that their activity is weighted towards liquidity provision, while for dealers activity is weighted towards liquidity consumption.

Table 2: Activity by Participant Type on BrokerTec

Participant Type	**Share of Volume**	**Share of Liquidity Consumption (Aggressive)**	**Share of Liquidity Provision (Passive)**
PTF	60.2%	54.6%	65.8%
Dealer	38.7%	44.7%	33.6%
Other	1.1%	0.8%	0.6%

Note: The table reports, by participant type, the share of volume, the share of market orders (aggressive trades) and the share of liquidity provision (passive trades) executed on the BrokerTec platform from April 15, 2019 to February 15, 2020. Percentages may not total 100% due to rounding.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

[7] An associated, global subsidiary may be a European or Asian branch of a domestic investment banking firm. The branch firm may not be required to register with the SEC or become a FINRA-member firm if it is regulated in the foreign country, but may still transact on BrokerTec. In these cases, we still classify the subsidiary as a dealer and not a PTF or other participant.

3 DATA SOURCES

This analysis combines two datasets: the TRACE Treasury dataset, which contains identified trade reports for all transactions conducted on the BrokerTec platform (after April 2019) and anonymized Level I (best bid and offer) order book data available from BrokerTec itself. Neither dataset is sufficient by itself to conduct the following analysis, so the datasets had to be joined. In the following, we briefly describe the datasets and our procedures for merging them.

3.1 TRACE TREASURY TRANSACTION DATA

Since July 2017, FINRA has collected data on Treasury transactions from its registered broker-dealer members through the TRACE platform. FINRA requires its members to report all transactions in marketable U.S. Treasury securities. The reporting obligation applies only to FINRA member firms and since most major broker-dealers and IDBs are members (including BrokerTec and 21 of the 24 primary dealers), most domestic Treasury market activity is reported into TRACE and all of the BrokerTec activity that we are interested in is reported. Firms that are not FINRA members and that do not report to TRACE include banks, bank branches and foreign subsidiaries of dealers, buy-side institutions and, importantly where this study is concerned, PTFs.

FINRA members report the identity of the counterparty to a trade when the counterparty is also a FINRA member. When the counterparty is not a FINRA member, however, the transaction is reported as taking place with an anonymous counterparty, identified only as "C". Thus, buy-side clients transacting directly with dealers (so called dealer-to-client or DTC activity) are anonymous in the data. Before April 2019, buy-side institutions and PTFs transacting on electronic IDB platforms like BrokerTec (so-called interdealer-broker or IDB activity) were also anonymous in the data, which prevented a study like ours from being conducted.

On April 1, 2019, a new FINRA rule took effect that requires the electronic interdealer broker platforms used by PTFs (such as BrokerTec) to identify all of their customers in trade reports. The TRACE Treasury trade reports submitted after this date provide the identifying information necessary for us to positively classify non-FINRA firms conducting trades on the BrokerTec platform as either a dealer or a PTF.[8] This in turn has enabled us to conduct this analysis.[9]

Each trade report in the TRACE dataset includes the identities of both parties to the trade, the Treasury security CUSIP and transaction price (including brokerage) and is timestamped to the microsecond.

[8] We expand the definition of dealer to include not only SEC-registered, FINRA-member broker-dealers, but also banks conducting a Treasury business under the Government Securities Act of 1986 and foreign subsidiaries of these firms that are not subject to US regulation, but still transact on Treasury IDB platforms. This group includes 3 of the 24 primary dealers and a large number of foreign subsidiaries of the primary dealers. Furthermore, some PTF firms do conduct a small amount of volume through FINRA-registered entities. We have classified these volumes as PTF, not dealer.

[9] To be clear, the participant classification has been created by the authors, using participant identifiers provided in the TRACE data. The participant classifications applicable to this analysis are not provided directly by FINRA.

Because BrokerTec is a FINRA member and reports its trades, the subset of trades in the TRACE dataset that are conducted on BrokerTec are clearly identifiable. Every trade occurring on the platform is reported by BrokerTec as two trades – one buy and one sell – which we must match together in order to determine the matched buyer and seller identities. This TRACE matching process constitutes the first step of our join algorithm.

3.2 BROKERTEC ORDER BOOK DATA

In the standard Hasbrouck (1991a) SVAR framework, the midpoint of the best bid and offer in the limit order book is used as a proxy for price when computing returns between market order events. Because the TRACE Treasury dataset only includes transactions, and not limit order book information, it is not sufficient for use in this modeling framework. However, because the order book information is available from BrokerTec directly, and because the timestamps between the two datasets are reported to the microsecond and synced well, it is possible for us to merge these two datasets and use the result in an SVAR framework.

The order book information available from BrokerTec includes the best bid price and depth of the book at that price, as well as the best offer price and the depth of the book at that price at any point in time, to microsecond precision. Each time the order book state changes (due to trade executions, the submission of new limit orders or the cancelation of existing ones) a new record appears, allowing us to match each TRACE Treasury trade report to the state of the order book when it occurred, as well as the state of the order book subsequent to the trade. Furthermore, the order book data also includes trades, which correspond one-to-one with TRACE trade reports. The transaction prices reported in the order book data are free of brokerage.

After matching BrokerTec's TRACE trade reports together, the time series of transactions that it implies is joined on the order book data using a fuzzy matching algorithm that we have written specifically for the purpose. The join is fuzzy in the sense that it must contend with:

- Imprecise trade timestamps between the two sets, which means the reported timestamps for a given trade rarely match perfectly

- The fact that the TRACE prices are reported with brokerage and the BrokerTec order book data is reported without, meaning the reported prices for a given trade will rarely match perfectly

- The fact that trades appearing in the BrokerTec data sometimes do not appear in the TRACE data

To be more clear on this latter point, the BrokerTec order book data available to us implies a slightly higher volume of trades than that implied by the TRACE data. [10] This slippage remains generally less than 2% of a day's volume, however, and anecdotally we find the slippage occurs during Asia hours when volumes are low. Regarding the timestamp precision, we note there appears to be a small reporting delay in the

[10] This is not to imply that there is a problem with the source data. The data that is available to us is processed at multiple points within the Federal Reserve System, and it is possible if not likely that the slippage occurs at one of these points.

TRACE timestamps, of less than 100 microseconds, relative to the BrokerTec trade timestamps. This does not pose great difficulty in implementing the fuzzy join, however, after considering the long average time between trades relative to the much shorter average time between order book state changes.[11]

The time series panel resulting from the fuzzy join of the TRACE and BrokerTec data includes the timestamp, CUSIP, executed price (free of brokerage) and participant-level amounts for each transaction and identifies the class of participant on each side of the trade (and self-trades) and the state of the order book when the transaction occurred. The sample used to produce our main results in Section 4 runs from April 15, 2019 to February 15, 2020, and we use only limit orders/transactions between 8am and 4pm New York time. FINRA's TRACE Treasury reporting rule change dictates the start date. We have chosen the end date of the sample to precede March 2020, in order to avoid complicating our analysis with the extraordinary events that happened in Treasury markets during of the onset of the COVID-19 pandemic. In Section 5, we use data from March 2020 to analyze those events.

4 MODELS AND RESULTS

We employ the bivariate SVAR framework of Hasbrouck (1991a) to measure the price impact of trades, which relates market order flow (trades) and returns in a vector autoregression,

$$Ay_t = \sum_{i=1}^{p} B_i y_{t-i} + D^{1/2}\varepsilon_t, \qquad \varepsilon_t \sim iid(0, I)$$

where y_t is a vector of endogenous variables, A is a matrix of structural parameters, D is a covariance matrix and the B_i are unrestricted, lagged coefficient matrices. All of the models we study are defined by 1) a specification for the vector of endogenous variables and 2) restrictions on the structural parameter matrix. We begin with the standard Hasbrouck (1991a) model, studied in *FMN*, which incorporates anonymous (signed) market order flow[12] x_t and returns r_t only:

$$y_t = \begin{pmatrix} r_t \\ x_t \end{pmatrix} \qquad A = \begin{pmatrix} 1 & -a \\ 0 & 1 \end{pmatrix} \qquad \text{(M1a)}$$

[11] See Appendix for additional detail on the process of matching sides of limit order book transactions in TRACE and the merger of TRACE and BrokerTec.

[12] That is, signed trade size, where buys are positive and sells are negative, in millions of dollars. The order flow variables used in all of our model specifications are defined similarly.

Similar to, but not exactly as *FMN*, $r_t = p_t - p_{t-1}$ is the change in the midpoint of the best bid and offer quoted[13] between the arrivals of market orders, where *t* indexes the time immediately prior to the arrival of the *t*+1[th] market order.[14] Under this specification, *A* allows order flow to contemporaneously affect returns while returns only affect order flow with a lag.

In Table 1 above, and in its discussion, we showed that the majority of trades on BrokerTec, measured on the basis of trade count, occur one-to-one, while on the basis of volume the majority are conducted multi-party. Furthermore, we showed that self-trading accounts for a small but not negligible amount of activity. In order to test for differential price impact between one-to-one, multi-party and (one-to-one) self-trades, we extend M1a in a spirit similar to *FN*, and model the market order flow for each of these types of trades separately. The vector of endogenous variables and the matrix of structural parameters for M1b are:

$$y_t = \begin{pmatrix} r_t \\ x_{one-to-one,t} \\ x_{multi-party,t} \\ x_{self-trade,t} \end{pmatrix} \qquad A^T = \begin{pmatrix} 1 & 0 & 0 & 0 \\ -a_{one-to-one} & 1 & 0 & 0 \\ -a_{multi-party} & 0 & 1 & 0 \\ -a_{self-trade} & 0 & 0 & 1 \end{pmatrix} \tag{M1b}$$

In this case, the subscripted $x_{i,t}$ denote signed market order flow for each type of trade *i*.

When estimating any of our models, we use $p = 5$ lags in the SVAR, mainly because it is consistent with *FMN* and *CHZ* and we do not want to innovate over this parameter. Permanent (long run, cumulative) price impact response to a unit shock to order flow variable *i* is measured as:

$$Price\ Impact_i = \frac{\partial r_{t+\infty}}{\partial x_{i,t}}$$

Table 3 below displays these price impact estimates (expressed in basis points of par per $100 million) for models M1a and M1b for the 5-, 10- and 30-year securities. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with an asterisk. In addition to bootstrapping the confidence intervals for the price impact estimates, bootstrap tests of differences between price impact estimates for each pairing of the order flow types in M1b were conducted as well. For the 10-year security[15], all pairwise differences are significant at the 5% level. Detailed bootstrap results can be found in Appendix B, in Table B1 and Table B2.

---

[13] In units of $100 par

[14] In *FMN*, *t* indexes the time immediately after the arrival of *t*[th] market order. In order words, there is a shift of the index between market order events. This change was mainly a matter of technical convenience; we find that it is of no consequence and we arrive at similar results.

[15] We focus much of our discussion in what follows on the 10-year security, because it is more liquid than the 30-year, and because the minimum tick size is probably less binding than the 5-year.

Table 3: Price Impact of Trades for Models M1a and M1b

	M1a	*M1b*		
Security	*All Trades*	*One-to-one*	*Multi-party*	*Self-trades*
5-year	1.27*	3.33*	1.13*	6.86*
10-year	2.89*	9.32*	2.66*	15.20*
30-year	19.78*	28.32*	15.63*	7.35

Note: The table reports estimated permanent price impact of market orders, in basis points of par per $100 million, under models M1a and M1b, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with asterisk. The bootstrap results and standard errors are detailed in Appendix B, Tables B1.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

The results for model M1a are consistent with *FMN*, despite the differences in the samples. While the data here spans a period in 2019-20 and joins both TRACE and BrokerTec data, the sample in *FMN* spans 2010-11 and is not complicated by our joining procedure. Still, the rank ordering and magnitude of the price impact estimates are little changed.

The results for M1b are interesting for a couple reasons. First, consistent with *FN*, which finds that trades executed in the workup have lower price impact than those executed in the pre-workup, we find that trades executed one-to-one (which are more likely to be pre-workup) have higher price impact than trades executed by multiple parties (whether they are workup or pre-workup). The results for multi-party trades are very similar to the same-side workup trade price impact figures presented in *FN*, and our estimates of one-to-one price impact are strictly higher than the estimates of pre-workup price impact in *FN*, which is to be expected given the differences in the order flow definitions.[16]

The results for model M1b also indicate that self-trades have very high price impact, greater than either one-to-one or multi-party trades for the 5- and 10-year securities. The price impact estimate for self-trades in the 30-year security is not significantly different than zero. (There are a small number of 30-year self-trade observations, however, averaging only 45 per day or 0.6% of average daily volume in that security.[17]) This is a new result, not found in previous studies, that is difficult to interpret in the context of just model M1b, and so we leave its discussion until later in this section.

Having demonstrated that we can benchmark previously published work on this topic with our dataset, we now turn to the central question of this study and consider the degree to which counterparty identity or class affects permanent price impact. Our next specification (M2a) follows *CHZ* model 2 and models the (aggressive) market order flow originating from PTFs, dealers and residual other firms separately from

[16] That is, since pre-workup trades can be either one-to-one trades or one-to-multiple, we'd expect the measure that isolates one-to-one trades to be higher than that which allows one-to-multiple

[17] In a bootstrap exercise, the joint hypotheses that one-to-one trades have higher price impact than multi-party trades and self-trades have the highest price impact of all was tested. Across all three securities, the null hypothesis that multi-party trades have higher price impact than one-to-one trades is rejected at the 5% level. For the 10-year security, the null hypothesis that self-trades do not have higher price impact than either one-to-one or multi-party trades is rejected at the 5% level. For the 30-year security, the null hypothesis that self-trades do not have higher price impact than multi-party trades is rejected at that level. See Appendix B for more detail.

market order flow originating from multiple firms and self-trades. The vector of endogenous variables and the matrix of structural parameters for M2a are:

$$y_t = \begin{pmatrix} r_t \\ x_{PTF-aggr,t} \\ x_{Dealer-aggr,t} \\ x_{Other-aggr,t} \\ x_{Multi-aggr,t} \\ x_{Self-aggr,t} \end{pmatrix}$$

$$A^T = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ -a_{PTF-aggr} & 1 & 0 & 0 & 0 & 0 \\ -a_{Dealer-aggr} & 0 & 1 & 0 & 0 & 0 \\ -a_{Other-aggr} & 0 & 0 & 1 & 0 & 0 \\ -a_{Multi-aggr} & 0 & 0 & 0 & 1 & 0 \\ -a_{Self-aggr} & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \qquad \text{(M2a)}$$

The subscripted $x_{i,t}$ denote signed market order flow for each participant type *i,* where "aggr" is shorthand for aggressive, meaning the participant submitted the market order, thereby consuming liquidity. For the PTF trades, all trades in which every aggressive participant is a PTF, even if there are multiple, are included; likewise for the dealer and other trades. The multi-party variable designates trades in which there are multiple participant types (e.g. PTF and dealer, or all three) on the aggressive side of the trade. For any of these variables, any number or type of participants may be found on the passive side of the trade, with the only exception being the self-trades. Consistent with model M1b, the self-trade variable includes only one-to-one self-trades where a single firm is both the buyer and the seller.

Before presenting the results for model M2a, we also specify a model M2b that begins with M2a and simply switches all order flow variables to the passive side, meaning the participant we model is providing liquidity to the market when a market order from another participant arrives. That is, for the PTF trades, all trades in which every *passive* participant is a PTF, even if there are multiple, is included in the order flow variable $x_{PTF-pass,t}$. Dealer, other and multi-party trades follow suit and the self-trade order flow variable is the same as that used in M1b and M2a.

Table 4 below displays price impact results (in basis points of par per $100 million) for models M2a and M2b for the 5-, 10- and 30-year securities. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with an asterisk. In addition to bootstrapping the confidence intervals for the price impact estimates, bootstrap tests of differences between price impact estimates for each pairing of the order flow types were conducted as well. For the 10-year security all pairwise differences are significant at the 5% level for both M2a and M2b. Detailed bootstrap results can be found in Appendix B, in Tables B3, B4 and B5.

Table 4: Price Impact of Trades for Models M2a and M2b

	M2a (Aggressive)					*M2b (Passive)*				
Security	*PTF*	*Dealer*	*Other*	*Multi*	*Self*	*PTF*	*Dealer*	*Other*	*Multi*	*Self*
5-year	1.64*	1.99*	-0.93	0.95*	6.51*	2.19*	0.67*	0.84	-0.12	6.30*
10-year	4.91*	4.35*	3.49*	2.13*	14.27*	4.92*	1.68 *	2.68 *	-0.86	13.44*
30-year	26.84*	21.91*	12.21	11.61*	6.44	28.44*	13.49 *	-4.26	-5.06	5.04

Note: The table reports estimated permanent price impact of market orders, in basis points of par per $100 million, under models M2a and M2b, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with asterisk. The bootstrap results and standard errors are detailed in Appendix B, Table B3.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

The price impact estimates for model M2a indicate that market orders submitted by PTFs for the 10-year security have slightly higher price impact than those submitted by dealers.[18] This is generally consistent with results presented in *CHZ*.[19] The price impact estimate for the residual of other firms is generally not significant and the fact that it is significant for the 10-year likely reflects the fact that this variable is likely a blend of PTF and dealer activity (which we are unable to identify clearly as either).[20] Consistent with model M1b, trades in which participants of multiple types appear on the aggressive side of a trade generally have lower price impact than PTF or dealer orders. For the 5- and 10-year securities, self-trading generally has the highest price impact of all.

The results for model M2b are interesting – and to our knowledge novel – in that they indicate that trades conducted with only PTFs on the passive, liquidity providing side have far higher price impact than those in which dealers provide liquidity. Though the price impact estimates for PTFs are little changed from model M2a, the dealer price impact estimates in M2b are much lower.[21] In addition, the price impact estimates for trades in which participants of many types are providing liquidity is effectively zero, and much lower than the corresponding estimates in model M2a. Consistent with results for M2a, the price impact of trades for the residual of other firms in model M2b is effectively zero, and the price impact of self-trades is highest of all categories.

In order to investigate these interactions in greater detail, our final model specification separates order flow pairwise by participant type, in the spirit of *BHR* (Brogaard, Hendershott and Riordan). There are nine combinations of the three participant types in the data, creating nine order flow variables to which we can attribute price impact. The vector of endogenous variables and the matrix of structural parameters for this model (M2c) are:

[18] Table B4 in the appendix confirms that this difference is significant at the 5% level.

[19] In Figure 6 of *CHZ*, over the post-2011 period, HFT market orders, which roughly correspond to PTF market orders in our data, have slightly higher price impact than Bank-AT market orders, which roughly correspond to dealer market orders in our data.

[20] Table B4 in the appendix confirms that the PTF and Dealer price impact are significantly higher than the price impact for Other.

[21] Table B4 in the appendix confirms this.

$$
y_t = \begin{pmatrix} r_t \\ x_{PTF\to PTF,t} \\ x_{Dealer\to Dealer,t} \\ x_{Other\to Other,t} \\ x_{Dealer\to PTF,t} \\ x_{PTF\to Dealer,t} \\ x_{Dealer\to PTF,t} \\ x_{Other\to PTF,t} \\ x_{PTF\to Other,t} \\ x_{Dealer\to Other,t} \\ x_{Other\to Dealer,t} \\ x_{Multi,t} \\ x_{Self,t} \end{pmatrix}
$$

$$
A^T = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{PTF\to PTF} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{Dealer\to Dealer} & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{Other\to Other} & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{Dealer\to PTF} & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a_{PTF\to Dealer} & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ -a_{Other\to PTF} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ -a_{PTF\to Other} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ -a_{Dealer\to Other} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ -a_{Other\to Dealer} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ -a_{Multi} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ -a_{Self} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \qquad \text{(M2c)}
$$

The subscripted $x_{i,t}$ denote signed market order flow for each pairing of participant types *i,* where the arrow indicates the direction of aggression (the left is responsible for the aggressive market order and the right is the passive liquidity provider in the trade). The nine variables for the participant pairs include only one-to-one trades, meaning that a trade by a PTF against a dealer is a trade by a single PTF firm on one side and a single dealer firm on the other. Any trade with multiple parties on one or both sides, even if all parties are the same type, are included in the multi-party variable. The self-trade variable is defined the same as it has been for all previous models.

Table 5 below presents the frequency of these pairwise, multi-party and self-trade interactions in the data for the 10-year security. All values are in percent, and the left entry is reported on a volume-weighted basis while the right is reported on a trade-count basis. Most volume occurs in a multi-party format while most trades are either multi-party or PTF-to-PTF. Trades in which PTFs provide liquidity also hold a high share of the total. Dealer-to-dealer transactions are not very frequent and activity involving other residual firms is rare. Values for the 5-year security are broadly consistent with the 10-year. Values for the 30-year security are weighted away from multi-party (31.6/15.5 percent on a volume-/trade-weighted basis) and *PTF→* trades; and towards interactions including dealers, which reflects the higher overall share of one-to-one trades and dealer participation in this security.

Table 5: Frequency of Participant Type Interactions in Model M2c for the 10-year Security

	Passive				
Aggressive	*PTF*	*Dealer*	*Other*	*Multi*	*Self*
PTF	13.5/30.0	6.5/11.5	0.2/0.3		
Dealer	14.3/21.9	3.2/4.4	0.1/0.1		
Other	0.2/0.4	0.1/0.1	0.0/0.0		
Multi				61.0/29.6	
Self					0.9/1.8

Note: The table reports the frequency with which the order flow variables in model M2c are observed in the data for the 10-year security. All values in percent. The entries to the left of slash are reported on a volume-weighted basis, while those on the right are reported on a trade-count basis.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table 6 below displays price impact results (in basis points of par per $100 million) for model M2c for the 5-, 10- and 30-year securities. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with an asterisk. In addition to bootstrapping the confidence intervals for the price impact estimates, bootstrap tests of differences between price impact estimates for each pairing of the order flow types were conducted as well. For the 10-year security all pairwise differences for interactions not involving an Other participant are significant at the 5%. Detailed bootstrap results can be found in Appendix B, in Tables B6, B7a, B7b and B7c.

Table 6: Price Impact of Trades for Model M2c

	M2c										
Security	*PTF* ↓ *PTF*	*Dealer* ↓ *Dealer*	*Other* ↓ *Other*	*Dealer* ↓ *PTF*	*PTF* ↓ *Dealer*	*Other* ↓ *PTF*	*PTF* ↓ *Other*	*Dealer* ↓ *Other*	*Other* ↓ *Dealer*	*Multi*	*Self*
5-year	5.70*	1.52*	-1.28	4.40*	1.07	-4.42	3.39	0.01	1.34	1.14*	7.09*
10-year	17.52*	4.83*	7.01	10.25*	3.09*	13.83*	7.30*	6.10*	3.12*	2.72*	15.95*
30-year	42.02*	12.85*	-4.99	33.00*	27.90*	-4.85	-61.59*	-11.88	49.06	15.56*	6.91

Note: The table reports estimated permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. Confidence intervals are determined by bootstrap and values that are statistically significant at the 5% level are noted with asterisk. The bootstrap results and standard errors are detailed in Appendix B, Table B6.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

There is a great deal of information in Table 6 to digest, but upon careful consideration, a few facts stand out. Judging from the collection of price impact estimates across the three securities *that are statistically significant at the 5% level*, the following hold[22]:

- The price impact estimates for *Dealer→PTF* trades are higher than *PTF→Dealer* trades for all three securities.

[22] What follows is largely confirmed, particularly for the 5-year and 10-year securities, by a bootstrap test of differences between estimated price impact values. See Appendix B, Tables B7a, B7b and B7c for details.

- Price impact estimates for self-trades and trades in which a PTF is the passive liquidity provider (i.e. *x→PTF*) are strictly greater than all other interactions, for all three securities. The price impacts of self-trades and *PTF→PTF* trades are particularly high.

- Price impact estimates for multi-party trades are strictly lower than all other interactions for the 5-year and 10-year securities, and for the 30-year security, the estimate is second to lowest.

- After accounting for multi-party trades, price impact estimates for trades in which a dealer is the passive liquidity provider (i.e. *x→Dealer*) are strictly lower than all other interactions, for all three securities. This point dovetails with the first point regarding *Dealer→PTF* and *PTF→Dealer* interactions.

To help make all of this clearer, in the chart below, cumulative price impact for the 10-year security is plotted for the first 50 market order events. It is evident that self-trading (red) has high price impact, while multi-party trades (black) have low price impact. Furthermore, the price impacts of trades in which PTFs are the passive liquidity provider (green) are strictly higher than those in which dealers are the passive party (orange). As annotated on the plot, the price impact of trades involving a dealer and another participant type (whether PTF or residual other firms) are higher when the dealer is the aggressive participant submitting the market order.[23]

Of all the results for model M2c, those for the multi-party trades are easiest to explain. It stands to reason that when many firms are party to a trade, particularly if they are of diverse types, the signal-to-noise ratio of the information embedded in the trade is lowered, relative to a trade between just two firms. Model M1b confirms this, even before we begin to consider firm types. The other results of model M2c do not lend themselves so easily to interpretation, unfortunately, but in the following we provide some discussion.

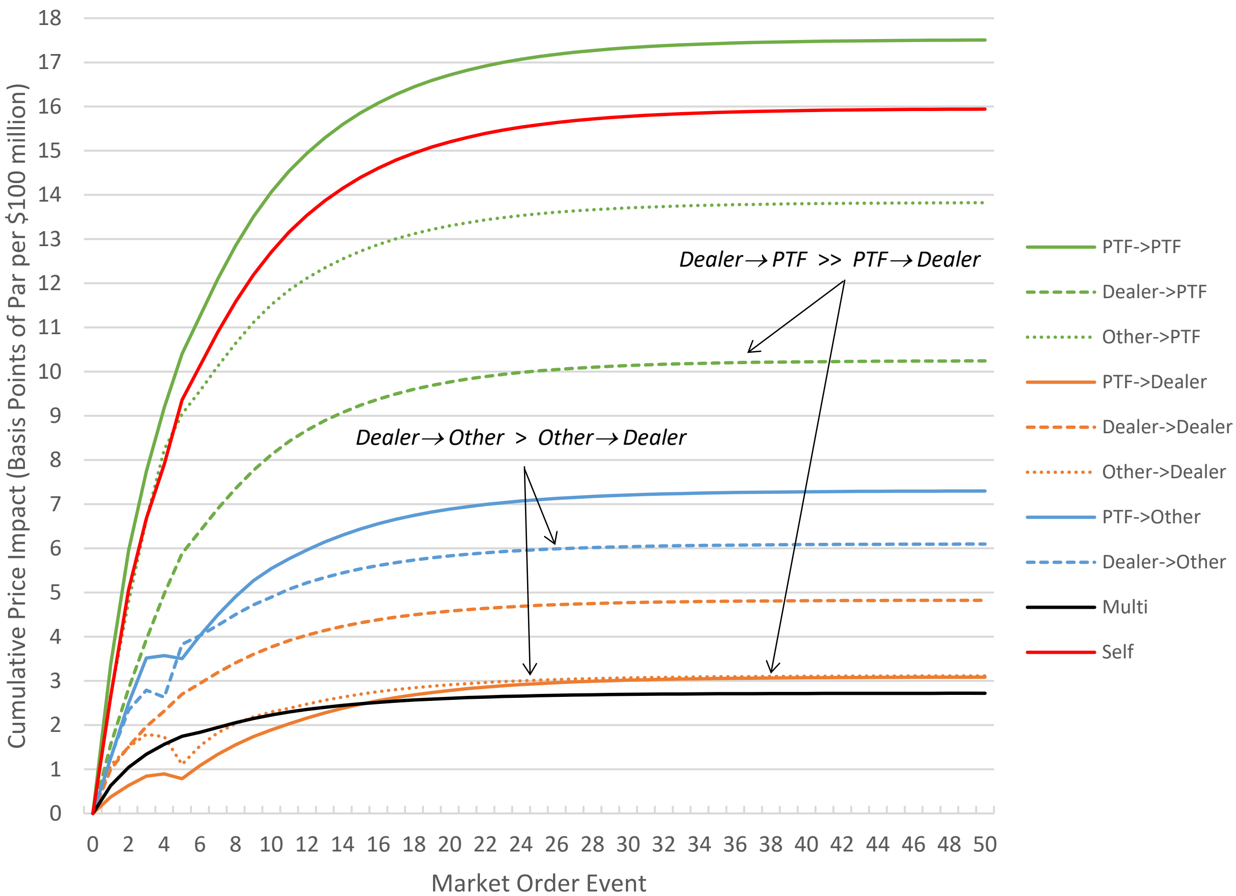
It was shown in model M2a that trades initiated by PTFs have slightly higher price impact than trades initiated by dealers. In that model, no consideration was made for the passive counterparty type (i.e. the estimates are not conditioned on the type of liquidity provider). In Figure 2 it becomes clear that the estimate for PTF price impact in model M2a was a combination really of two interactions. The first is the interaction between PTFs and other PTFs, which has very high price impact, far above most of the other interactions. The second interaction is when a PTF takes liquidity from a dealer, which has much lower price impact (only 1/6th that of the *PTF→* interaction). Looked at this way, we may re-interpret the results of models M2a and M2b to suggest that PTF trades have higher price impact when a PTF provides liquidity, and dealer trades have higher price impact when the dealer takes liquidity.

What are we to make of this result? We may consider this and other of the findings in this paper in light of theoretical results showing that informed traders tend to use more limit orders than market orders when their information advantage is small [Rosu 2020, Chaboud, Hjalmarsson and Zikes 2020]. Might it be that, when PTFs have an informational advantage over dealers it is relatively small (and transient?) and

[23] This is confirmed by a bootstrap test of differences between estimated price impact values. See Appendix B, Table B7b for details.

expressed by means of a limit order? If this is the case, we may interpret (aggressive) market order activity by PTFs as an expression of no informational advantage. Perhaps our results are an indication that PTFs use limit orders to enter positions (i.e. to take risk when in possession of information) and market orders to cut positions (i.e. manage risk down when not in possession of information).[24]

Figure 2: Cumulative Price Impact for the 10-year Security, Model M2c



Note: The figure shows estimated cumulative price impact for the first 50 market order events, for the 10-year security, for each variable under model M2c, for trades executed on BrokerTec from April 15, 2019 to February 15, 2020. Values are reported in basis points of par per $100 million. All estimates are statistically significant at the 5% level at the terminal horizon. We confirm that these estimates are statistically significant at the 5% level using bootstrap estimation with 1000 iterations.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

And what of the dealers? We may posit that, when dealers possess informational advantage it is relatively large, vis-à-vis PTFs. If this is the case, theory [Rosu 2020] would suggest market orders would be preferred to limit orders, and also that dealer market orders would have higher price impact over time than limit orders. In contrast to PTFs, perhaps (aggressive) market order activity by dealers is an expression of considerable informational advantage (such as that derived from observing client order

[24] Anecdotally, PTFs are thought to implement relatively tight limits on the directional market risk taken at any point in time. Furthermore, it is generally believed that they will not carry Treasury positions overnight, and will seek to close out all positions before the end every trading day.

flow), rather than no information advantage. As some tangential support for these ideas, in Table 2 we showed that PTF trading is skewed towards liquidity provision (limit orders) while dealer trading is skewed toward consumption (market orders).

It is not possible for us to test these hypotheses with the data available to us. We may still ponder the sources of the disparate informational advantages. We believe that market segmentation begins to explain the differences we see. Lyons (1995) and others established, prior to the emergence of PTFs, that the order flow dealers are able observe from clients is a source of private information, and we offer this as some support for our assertions regarding dealers above. PTFs are forbidden by regulation from having customers, and so client order flow is not a source of information available to them.

The exact mechanism by which PTFs may obtain private information has not yet been studied, at least that we are aware. We posit that PTF holdings of microwave network assets linking trading venues throughout New York and Chicago are a likely source. As emphasized by O'Hara (2015), speed of trading is tantamount to informational advantage in modern financial markets, and microwave communications networks confer the advantage of speed across geographically distant financial centers in ways that no other technology can. To our knowledge, all of the microwave networks catering to financial services applications in the US were built by, and are still owned by several of the major PTFs that are the subject of this paper. As a result, PTFs are able to maintain a speed advantage, and hence a (small, transient) informational advantage over dealers.

In closing this section, we address the issue of self-trading. In model M1b we showed that self-trades have higher price impact than either one-to-one or multiparty trades. The results of model M2c are largely consistent with this result. Furthermore, the results of model M2c are also internally consistent; because PTFs comprise the vast majority of self-trade volume, it stands to reason that self-trades have high price impact, if *PTF→PTF* trades also have high price impact. We'll also point out that, according to the bootstrap results in Tables B7a, B7b and B7c in the appendix, self-trades do not have significantly different price impact than *PTF→PTF* trades for the 5- and 30-year securities and self-trades have slightly lower price impact than *PTF→PTF* trades for the 10-year security. So long as we are able to maintain that the PTF firms conducting self-trades implement truly independent trading algorithms - each possessing no private information on the order activity of its other algorithms *both before and after self-trades are conducted* - then we may conclude that self-trades are an innocuous sub-category of *PTF→PTF* trades.

In the next section, we present an analysis of events that occurred in Treasury markets in March 2020, during the onset of the COVID-19 pandemic, using model M2c.

5 Liquidity Conditions in Treasury Markets during March 2020

The previous section presents evidence that the trades of dealers and PTFs have dissimilar price impact, and furthermore that the direction of interaction matters. To make clear the effect that this can have on liquidity conditions, consider Figure 2 from the vantage of a dealer that has just acquired a large inventory in the 10-year security from a client. If the dealer seeks to distribute the position to the market via an IDB platform, and hopes to minimize price impact,[25] there is a clear ordering of preferences. The dealer would seek to trade in a multi-party format or at least with other dealers, to the extent that it can, and would seek to avoid (also to the extent that it can) aggressing the limit orders of PTFs. Considering Figure 2 from the vantage of a PTF trading the cash/futures basis and attempting to hedge a position in the 10-year future or a similar security via an IDB platform, a different schedule of preferences becomes clear.

In this section, we use model M2c to analyze the events that occurred in Treasury markets during March 2020, in order to add some color to the results presented in the previous section. After presenting mainly the facts of what occurred, according to our model, we offer some light interpretation.

Beginning in early March 2020, as the global onset of the COVID-19 pandemic accelerated, realized yield volatility on the BrokerTec platform rose quickly, exceeding 300 basis points per year for the 10-year security and surpassing short term implied volatility as measured by the MOVE Index and 1-month into 10-year dollar swaption volatility. At the same time, bid-ask spreads on the BrokerTec platform increased, nearly doubling for the 10-year security and more than doubling for the 30-year security [Fleming, Ruela 2020]. Importantly - where the following analysis is concerned - market depth, as measured by the daily average of the total quantities bid and offered in the first five levels of the limit order book, fell to levels far below those observed in January 2020, particularly for the 5- and 10-year securities.

Against this backdrop, daily trading volumes on the BrokerTec platform hit record highs in early March. Then, on March 12th the PTF share of overall participation (whether in one-to-one or multi-party trades) fell noticeably. Whereas PTFs typically account for 60% of average daily volume (Table 2), the dealer share of volume began to exceed that of PTFs and this remained the case for the remainder of the month. Table 5 above displayed the frequency of each of the participant-type interactions in model M2c for the 10-year security between April 15, 2019 and February 15, 2020. In Figure 3 below the same quantities are plotted as a time series over the first five months of 2020, alongside market depth, to show how they evolved over the course of March.

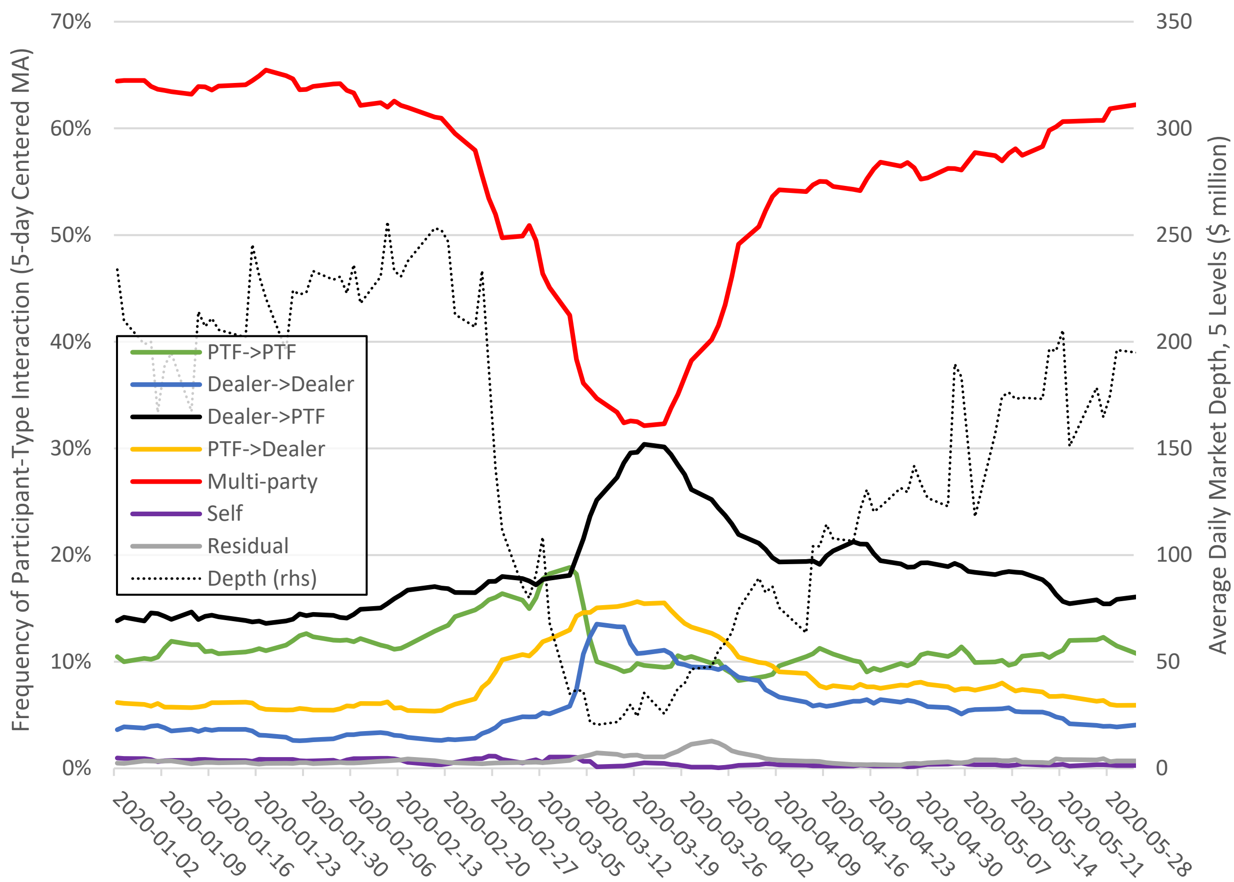
As seen in Figure 3, beginning in late February, as market depth fell, so too did the share of multi-party trade matches (red line). On February 28th the multi-party share fell below 50% and continued to fall over the course of March, reaching a low on March 20th at about half of its January average. Though daily volume in the 10-year security (not shown) peaked on March 3rd at $100 billion, by mid-March volumes were not much different than their 5-month average of $40 billion per day. This fall in the share of volume traded in a multi-party format, alongside a fall in market depth conforms to our intuition. As market participants submitted fewer limit orders to the BrokerTec platform as volatility rose, presumably for the purpose of managing risk in volatile markets and avoiding adverse selection, it became more likely that only one participant's bid or offer rested at the top level of the order book at any given time. As such, market orders submitted to the book were more likely to be matched against the limit order of only a single participant. Perhaps as a result, the average size of multi-party trades fell in tandem with the multi-party share of activity, from $5.4 million in January to a low of $3.3 million on March 23rd.

Turning to the other interactions, the share of *Dealer→PTF* activity in Figure 3 (black line) is notable for the degree to which it rose in March 2020, effectively doubling its January level. As mentioned above, daily volumes on the BrokerTec platform were historically high in March, but the 10-year security volume peaked on the 3rd before returning nearer average levels on the 23rd, when the share of multi-party activity

[25] Which is tantamount to maximizing profits in its client market making business.

hit its low and *Dealer→PTF* matching peaked. The *PTF→Dealer* and *Dealer→Dealer* share of activity also rose over this period, though not as much as the share *PTF→Dealer* activity.[26] Like the multi-party share of activity, however, the share of *PTF→PTF* activity actually fell from January 1st to March 23rd, but not before rising notably in the early part of March.

Figure 3: Frequency of Participant Type Interactions for the 10-year Security in March 2020



Note: The figure shows the frequency with which the order flow variables in model M2c, on a volume-weighted basis, are observed in the data for the 10-year security for the first five months of 2020. All values in percent. Market depth, as measured by the daily, time-weighted average of the 5-level depth of both sides of the order book is plotted on the right-hand side.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

These latter observations do not neatly conform to intuition. If the shares of all four pairwise interactions between dealers and PTFs had moved in the same direction, even while multi-party activity fell, we might attribute the phenomena observed in Figure 3 wholly to the reduced market depth and randomness in the matching of limit and market orders as they arrived to the limit order book. It is difficult to square the change in *PTF→PTF* activity with this hypothesis, however. We do know that the overall PTF share of activity in March fell noticeably on March 12th, and was surpassed by that of dealers. Figure 3 further

[26] The *PTF→Dealer* and *Dealer→Dealer* share of activity did rise in roughly similar proportion (relative to January levels) as the *Dealer→PTF* share of activity.

suggests that the fall in the PTF share of activity was actually a combination of 1) a fall in their share of participation in multi-party and *PTF→PTF* activity and 2) a *rise* in *PTF→Dealer* and *Dealer→PTF* activity. Mindful that our setting is the *anonymous* limit order book setting,[27] we posit two possible explanations for this:

- PTFs have developed some ability to form expectations about the class of firm associated with each limit order in the limit order book. Furthermore, they found multi-party and *PTF→PTF* interactions disadvantageous (or more "toxic") in March relative to normal times and sought to avoid those interactions.

- One or multiple large PTFs that account for a large proportion of multi-party and/or *PTF→PTF* activity in normal times reduced their aggregated activity in March. In other words, a PTF or PTFs with a high degree of network centrality (in a graph characterized by market order flow) withdrew from the market as liquidity conditions deteriorated.

Considering next the dealers, we observe also in Figure 3 that the share of *Dealer→Dealer* interactions, and more generally all interactions involving a dealer, rose in March, which is consistent with the fact that the dealer share of overall activity surpassed that of PTFs after March 12th. This fact is likely a consequence of the large volumes that dealers intermediated for clients in March 2020. According to Federal Reserve Bank of New York data,[28] primary dealer transactions with clients recorded their historic high on the week ended March 4th. Anecdotally this activity was very heavily weighted towards client sales of securities to dealers, which is also supported by Federal Reserve Bank of New York data showing that primary dealer net positions in Treasury securities rose to very high levels, peaking on the week ended March 18th near their historical high. The scale of these sales was ultimately more than the primary dealers could intermediate, due to the aggregate balance sheet constraint imposed by banking regulation, and as a result the Treasury markets began to show considerable strain by March 13th [Duffie, 2020].

The Federal Reserve began to intervene in Treasury markets on March 16th, purchasing Treasury securities from the primary dealers in order to stabilize markets. In the period between late February, when the client sales seemingly began, and March 15th when the Federal Reserve first announced its intention to purchase Treasuries, it is likely that the primary dealers attempted to distribute or hedge the inventory acquired from clients by means of trading on IDB platforms like BrokerTec. Though Federal Reserve purchases of coupon securities began on March 16th, they were initially subject to a soft target of "at least $500 billion." Throughout the week of March 16th, liquidity conditions in Treasury markets remained strained, however and so on March 23rd, the Federal Reserve made an extraordinary announcement that it would purchase Treasury securities in "the amounts needed" to restore market function. It is after this date that we see in Figure 3 the participant-type shares begin to return to their pre-March levels.

Now we consider liquidity conditions, as measured by the price impact of trades on the BrokerTec platform in March 2020, using model M2c and a sample that begins on March 1st and ends on March 31st.

---

[27] Meaning participants do not know the identities of the other firms submitting limit and market order to the platform.
[28] Primary Dealer Statistics

It should come as no surprise that the price impact of trades rose greatly in March, and for all of the various participant-type interactions. Table 7 below displays price impact estimates for the 10-year security under Model M2c in March 2020. The first column repeats values found in Table 6, estimated using a sample covering the period from April 15, 2019 to February 15, 2020, which we include for ease of comparison. The values in parenthesis in the first column are the asymptotic standard errors of the price impact estimate (which are fairly close to the bootstrap estimates presented in Appendix B). The second column shows the price impact estimates using the March 2020 sample. The third and fourth columns display the relative and absolute change in the price impact estimates from the first to the second period. The final column, labeled z-score, is computed as the absolute change in the price impact estimate from the first to the second period divided by the standard error of the price impact estimate for the first period.[29]

Table 7: Price Impact of Trades for the 10-year Security under Model M2c in March 2020

	April 15, 2019 – February 15, 2020	*March 2020*	*Change*	*Change*	*Z-Score*
Interaction	*Price Impact (SE)*	*Price Impact*	*Relative*	*Absolute*	
PTF→PTF	17.52 (0.13)	28.26	+61%	10.74	83.4
Dealer→Dealer	4.83 (0.10)	7.48	+55%	2.65	26.7
Dealer→PTF	10.25 (0.08)	21.55	+110%	11.30	143.6
PTF→Dealer	3.09 (0.11)	8.60	+178%	5.51	49.1
Multi	2.72 (0.02)	5.73	+110%	3.01	185.4
Self	15.95 (0.31)	15.56	-2%	-0.39	-1.3

Note: The table shows estimated permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in 10-year securities executed on BrokerTec over two periods: 1) from April 15, 2019 to February 15, 2020, and 2) from March 1, 2020 to March 31, 2020. Asymptotic standard errors for the first period price impact estimates are shown in parenthesis in the first column. The z-score is computed as the change in the price impact estimate from period 1 to 2 divided by the standard error of the price impact estimate for the first period.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

The z-score for the multi-party trades is highest of all of the interactions, which underscores the high degree to which the price impact of these trades increased in March, more than doubling its pre-March value. Perhaps not coincidentally the share of multi-party activity in March fell the most of all the interactions too. Second only to the multi-party trades, the z-score of *Dealer→PTF* trades rose greatly too, also doubling its pre-March value. In contrast, the price impact of self-trades did not change at all and remained roughly the same over the two periods. In between these two extremes, the price impact of *PTF→PTF* trades rose greatly in absolute terms, but from an already high level.

We offer several final explanations for the changes in price impact observed in March. Regarding the multi-party trades, it seems natural that their price impact would rise; these trades likely began to resemble the pairwise "one-to-one" PTF/dealer trades more closely as market depth and average trade size declined. We may interpret the *Dealer→PTF* interaction and its increased price impact as some evidence that the relative price advantage of dealers became large during March, as a result of their

[29] We considered implementing a break test, but leave this to future work. Clearly a break occurred in March 2020. The z-score metric is an attempt to quantify the size of the break for each trade type.

exclusive access to information on client flows. This would be consistent with discussion at the end of the previous section.

6 Conclusion

We use Treasury cash transaction reports from TRACE and publicly available limit order book data from BrokerTec to investigate whether the trades of registered dealers and (unregistered) principal trading firms (PTFs) have dissimilar price impact. We find that, ceteris paribus, trades have higher permanent price impact when a PTF is the passive party, playing the role of liquidity provider. Conversely, we find that dealer trades have higher price impact when the dealer is the aggressive party and taking liquidity from the platform. Furthermore, trades in which both the buyer and seller are PTFs have very high price impact, while trades between two dealers have low price impact. In between all of these extremes, trades that are matched with multiple firms (whether dealer or PTF) on one or both sides have very low price impact. We also find that, during periods of acute market stress, like that in March 2020, the amount of trades that are matched with multiple firms on one or both sides falls greatly as market depth declines. Furthermore, though the price impact of all trades rises greatly during these periods, the increase for these trades stands out for its magnitude.

References

Brain, Doug, Michiel De Pooter, Dobrislav Dobrev, Michael Fleming, Pete Johansson, Collin Jones, Michael Puglia, Frank Keane, Liza Reiderman, Tony Rodrigues, and Or Shachar (2018). "Unlocking the Treasury Market through TRACE," *FEDS Notes*. Washington: Board of Governors of the Federal Reserve System, September 28, 2018, https://doi.org/10.17016/2380-7172.2251.

Brain, Doug, Michiel De Pooter, Dobrislav Dobrev, Michael Fleming, Peter Johansson, Frank Keane, Michael Puglia, Tony Rodrigues, and Or Shachar (2018). "Breaking Down TRACE Volumes Further," *FEDS Notes*. Washington: Board of Governors of the Federal Reserve System, November 29, 2018, https://doi.org/10.17016/2380-7172.2299.

Brogaard, Jonathan, Terrence Hendershott and Ryan Riordan (2014), "High-Frequency Trading and Price Discovery," *The Review of Financial Studies*, 27(8): 2267-2306 (Aug. 2014).

Brogaard, Jonathan, Terrence Hendershott and Ryan Riordan (2019), "Price Discovery without Trading: Evidence from Limit Orders," *The Journal of Finance*, 74(4): 1621-1658 (Mar. 18, 2019).

Chaboud, Alain, Erik Hjalmarsson and Filip Zikes (2020), "The evolution of price discovery in an electronic market," Finance and Economics Discussion Series 2020-051. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2020.05

Cont, Rama, Arseniy Kukanov and Sasha Stoikov (2014), "The Price Impact of Order Book Events," *Journal of Econometrics*," 12(1): 47-88 (Winter 2014).

Fleming, Michael, Bruce Mizrach and Giang Nguyen (2017), "The Microstructure of a U.S. Treasury ECN: The BrokerTec Platform," *Journal of Financial Markets*, 40: 2-22 (Sep. 2018).

Fleming, Michael and Giang Nguyen (2013), "Order Flow Segmentation and the Role of Dark Trading in the Price Discovery of U.S. Treasuries," Federal Reserve Bank of New York Staff Report 624, August 2013.

Fleming, Michael and Giang Nguyen (2019), "Assessing the Price Impact of Treasury Market Workups," Liberty Street Economics, March 6, 2019.

Fleming, Michel and Francisco Ruela, "Treasury Market Liquidity during the COVID-19 Crisis," Federal Reserve Bank of New York Liberty Street Economics, April 17, 2020,

Fleming, Michael, Ernst Schaumburg and Ron Yang, (2015), "The Evolution of Workups in the U.S. Treasury Securities Market," *Liberty Street Economics*, August 20, 2015.

Fleming, Michael, Peter Johansson, Frank Keane and Justin Meyer, "At the New York Fed: Fifth Annual Conference on the U.S. Treasury Market," *Liberty Street Economics*, November 8, 2019.

Harkrader, James Collin, and Michael Puglia (2020). "Principal Trading Firm Activity in Treasury Cash Markets," FEDS Notes. Washington: Board of Governors of the Federal Reserve System, August 04, 2020, https://doi.org/10.17016/2380-7172.2620.

Harkrader, James Collin, and Michael Puglia (2020). "Fixed Income Market Structure: Treasuries vs. Agency MBS," FEDS Notes. Washington: Board of Governors of the Federal Reserve System, August 25, 2020, https://doi.org/10.17016/2380-7172.2622.

Harkrader, James Collin, and Michael Puglia (2020). "Retrospective: The Agency MBS Market on October 15, 2014," FEDS Notes. Washington: Board of Governors of the Federal Reserve System, September 24, 2020, https://doi.org/10.17016/2380-7172.2623.

Kyle, Albert (1985), "Continuous Auctions and Insider Trading", *Econometrica*, 53(6): 1315-1335.

Lyons, Richard K. (1995), "Tests of microstructural hypotheses in the foreign exchange market," *Journal of Financial Economics*, 39 (2-3): 321-351 (Oct-Nov 1995).

U.S. Department of the Treasury, Board of Governors of the Federal Reserve System, Federal Reserve Bank of New York, U.S. Securities and Exchange Commission, and U.S. Commodity Futures Trading Commission (2015), "Joint Staff Report, The U.S. Treasury Market on October 15, 2014," [Washington, D.C.] :U.S. Department of the Treasury, 2015.

O'Hara, Maureen (2015), "High Frequency Market Microstructure," *Journal of Financial Economics*, 116(2): 257–270.

Hasbrouck, Joel (1991a), "Measuring the Information Content of Stock Trades," *Journal of Finance*, 46(1): 179–207 (Mar. 1991).

Hasbrouck, Joel (1991b), "The Summary Informativeness of Stock Trades: An Econometric Analysis," *Review of Financial Studies*, 4(3): 571–595 (1991).

Hasbrouck, Joel (1995), "One Security, Many Markets: Determining the Contributions to Price Discovery," *Journal of Finance*, 40(4): 1175-1199 (Sep. 1995).

Pasquariello, Paolo, and Clara Vega (2007), "Informed and Strategic Order Flow in the Bond Markets," *Review of Financial Studies*, 20(6): 1975-2019 (Aug. 27, 2007).

Rosu, Ioanid (2016), "Liquidity and Information in Order Driven Markets," Working Paper hal-00515891, HEC Paris.

Roşu, Ioanid (2020), "Liquidity and Information in Limit Order Markets." *Journal of Financial & Quantitative Analysis* 55 (6): 1792–1839. doi:10.1017/S0022109019000759.

Runkle, D. E., (1987), "Vector Autoregression and Reality," *Journal of Business and Economic Statistics*, 5, 437-442.

Schrimpf, Andreas, Hyun Song Shin, and Vladyslav Sushko. 2020. "Leverage and Margin Spirals in Fixed Income Markets During the Covid-19 Crisis," BIS Bulletin, Number 2, April 2, 2020.

APPENDIX

A - MERGING THE TRACE TREASURY AND BROKERTEC LEVEL I DATASETS

Matching TRACE Trade Reports

For trades with only one buyer and/or only one seller, matching TRACE trade reports and assigning one-to-one correspondence between buyer and seller is generally straightforward. Small, but very surmountable difficulties can arise when the price reported for the buyer does not match the price reported for the seller. This discrepancy arises because BrokerTec includes the brokerage/margin it receives from each party in the prices reported to TRACE.[30] Because 1) the trades are timestamped to the microsecond and multiple trades will not occur in the same microsecond and 2) we have access to the brokerage-free price at which all trades were transacted in the Level I order book data available to us, this issue does not materially affect the analysis.

Some trades conducted on BrokerTec can have multiple buyers and/or sellers, which presents more difficulty when attempting to match trades reports. This occurs in two ways. First, if a market order to buy/sell is matched with more than one limit order to sell/buy, BrokerTec will report multiple trades: one between BrokerTec and the submitter of the market order to buy/sell, and then multiple trades between BrokerTec and the submitters of the limit orders to sell/buy that were completely or partially filled. Though this complicates the report-matching algorithm, in this case it still is possible to assign one-to-one correspondence between buyer and seller in the trade.

The second way in which BrokerTec trades can have multiple buyers and/or sellers arises from the workup feature available on the platform.[31] When trades occur in a workup, multiple buyers and multiple sellers can be matched together in the same trade, requiring BrokerTec to report multiple trades on both sides of the transaction with the same timestamp and price (subject to brokerage). In this case it is not possible to establish one-to-one correspondence between buyer and seller in the trade reports and we randomly assign counterparties in our report matching algorithm, breaking partial matches into multiple line-items if need be. The models presented in Section 4 were constructed in ways that make this detail irrelevant, as none relies on an accurate correspondence between buyer and seller in trades with more than one party on either side.

---

[30] For example, if a trade is conducted at a price of 100.00, BrokerTec may report the buyer's price as 100.01 and the seller's price as 99.98, suggesting that the buyer has payed margin equivalent of 0.01 percent of par to conduct the trade, and the seller has payed margin equivalent 0.02 percent of par to conduct the trade. BrokerTec, and all Treasury IDBs, negotiate margin rates bilaterally with all clients, so not all clients pay the same rates. Furthermore, the negotiated schedules may be written as per-trade rates subject to fixed monthly maximum amounts. This means that some trades for some firms will not have any margin reported after their monthly maximum is exceeded. We contend with this issue by reference to the executed trade prices that BrokerTec reports itself in the Level I dataset, which does not include the margin amounts but only the actual trade price that was executed in the matching engine.

[31] For more background on workups, see *Liberty Street Economics*, "The Evolution of Workups in the U.S. Treasury Securities Market".

Joining the BrokerTec Level I Data on TRACE

As mentioned in section 3, the time series of transactions implied by the TRACE data is joined on the BrokerTec Level I data using a fuzzy matching algorithm. The join is not exact for several reasons:

- The trade timestamps for a given trade rarely match perfectly
- The TRACE prices are reported with brokerage while BrokerTec Level I data is reported without
- Some trades appearing in the BrokerTec data do not appear in the TRACE data

We exploit the fact that the trade timestamps are generally within 100 microseconds of each other in implementing the join. The join is implemented by iterative search, where the tolerances for matching by trade timestamp, price and volume are gradually relaxed until all trades have been joined.

B – Bootstrap Results and Confidence Intervals

Confidence intervals for all price-impact estimates and differences between price impact estimates were calculated via a bootstrap, using 1000 samples, as presented by Runkle (1987) and used in *FMN*. Here we present the detailed results of that exercise.

Table B1: Bootstrap Confidence Intervals for M1a and M1b

5-year	*M1a*	*M1b*		
	All Trades	*One-to-one*	*Multi-party*	*Self-trades*
Price Impact Estimate	1.27	3.33	1.13	6.86
SE (Asymptotic)	0.20	0.63	0.19	3.78
Bootstrap - 5%-ile	0.96	2.42	0.84	2.33
Bootstrap - 16%-ile	1.10	2.76	0.98	4.42
Bootstrap Median	1.28	3.35	1.13	6.96
Bootstrap - 84%-ile	1.46	3.95	1.31	9.21
Bootstrap - 95%-ile	1.60	4.41	1.45	11.76
10-year	*M1a*	*M1b*		
	All Trades	*One-to-one*	*Multi-party*	*Self-trades*
Price Impact Estimate	2.89	9.32	2.66	15.20
SE (Asymptotic)	0.02	0.06	0.02	0.31
Bootstrap - 5%-ile	2.87	9.22	2.64	14.69
Bootstrap - 16%-ile	2.88	9.26	2.65	14.88
Bootstrap Median	2.89	9.32	2.66	15.19
Bootstrap - 84%-ile	2.91	9.39	2.68	15.52
Bootstrap - 95%-ile	2.92	9.42	2.69	15.72
30-year	*M1a*	*M1b*		
	All Trades	*One-to-one*	*Multi-party*	*Self-trades*
Price Impact Estimate	19.78	28.32	15.63	7.35
SE (Asymptotic)	1.81	3.13	1.85	24.22
Bootstrap - 5%-ile	16.58	23.07	12.55	-29.55
Bootstrap - 16%-ile	17.92	25.12	13.89	-14.82
Bootstrap Median	19.78	28.01	15.68	6.83
Bootstrap - 84%-ile	21.48	31.05	17.32	27.33
Bootstrap - 95%-ile	22.55	33.76	18.68	40.39

Note: The table reports the results of a bootstrap of the estimated value of the permanent price impact of market orders, in basis points of par per $100 million, under model M1a and M1b, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The price impact estimates reported in the text, the asymptotic standard errors of the estimates and the 5, 16, 50, 84 and 95th percentiles of the bootstrap distribution of the parameter estimates are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B2: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M1b

5-year	*Multi-party*	*Self-trades*
One-to-one	2.23 (1.33/3.15)	-3.61 (-8.08/1.09)
Multi-party		-5.84 (-10.54/-1.21)
10-year	*Multi-party*	*Self-trades*
One-to-one	6.66 (6.56/6.74)	-5.87 (-6.39/-5.38)
Multi-party		-12.53 (-13.05/-12.02)
30-year	*Multi-party*	*Self-trades*
One-to-one	12.50 (7.58/17.82)	21.09 (-11.50/56.94)
Multi-party		8.80 (-24.93/44.52)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per \$100 million, under model M1b, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered "row minus column." The first value is the bootstrap median of the difference in the price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B3: Bootstrap Confidence Intervals for M2a and M2b

5-year	*M2a (Aggressive)*					*M2b (Passive)*				
	PTF	*Dealer*	*Other*	*Multi*	*Self*	*PTF*	*Dealer*	*Other*	*Multi*	*Self*
Price Impact Estimate	1.64	1.99	-0.93	0.95	6.51	2.19	0.67	0.84	(0.12)	6.30
SE (Asymptotic)	0.48	0.43	4.07	0.18	3.78	0.32	0.21	2.40	0.49	3.77
Bootstrap - 5%-ile	0.89	1.30	-4.31	0.66	0.69	1.68	0.35	(0.76)	(0.73)	1.24
Bootstrap - 16%-ile	1.19	1.63	-1.73	0.80	3.61	1.91	0.51	0.48	(0.35)	3.63
Bootstrap Median	1.61	1.98	-0.92	0.94	6.54	2.18	0.67	0.84	(0.12)	6.24
Bootstrap - 84%-ile	2.02	2.37	0.00	1.07	9.03	2.46	0.83	1.31	0.13	8.96
Bootstrap - 95%-ile	2.33	2.68	2.91	1.20	11.40	2.68	0.96	2.81	0.47	11.20
10-year	*M2a (Aggressive)*					*M2b (Passive)*				
	PTF	*Dealer*	*Other*	*Multi*	*Self*	*PTF*	*Dealer*	*Other*	*Multi*	*Self*
Price Impact Estimate	4.91	4.35	3.49	2.13	14.27	4.92	1.68	2.68	(0.86)	13.44
SE (Asymptotic)	0.04	0.04	0.30	0.02	0.31	0.03	0.02	0.17	0.04	0.30
Bootstrap - 5%-ile	4.84	4.29	3.00	2.10	13.73	4.88	1.65	2.40	(0.93)	12.97
Bootstrap - 16%-ile	4.87	4.32	3.19	2.11	13.94	4.90	1.66	2.50	(0.90)	13.16
Bootstrap Median	4.91	4.35	3.49	2.13	14.26	4.93	1.68	2.67	(0.86)	13.45
Bootstrap - 84%-ile	4.95	4.39	3.78	2.14	14.56	4.95	1.69	2.85	(0.82)	13.75
Bootstrap - 95%-ile	4.98	4.41	3.98	2.15	14.75	4.97	1.70	2.96	(0.79)	13.93
30-year	*M2a (Aggressive)*					*M2b (Passive)*				
	PTF	*Dealer*	*Other*	*Multi*	*Self*	*PTF*	*Dealer*	*Other*	*Multi*	*Self*
Price Impact Estimate	26.84	21.91	12.21	11.61	6.44	28.44	13.49	(4.26)	(5.06)	5.04
SE (Asymptotic)	3.81	2.80	18.39	2.19	24.21	2.69	2.25	13.26	6.10	24.20
Bootstrap - 5%-ile	20.55	17.15	-15.68	7.96	-36.52	23.87	9.87	(26.38)	(12.51)	(32.15)
Bootstrap - 16%-ile	23.06	19.07	-2.65	9.48	-16.95	25.65	11.46	(15.33)	(8.15)	(17.69)
Bootstrap Median	26.88	21.72	12.21	11.50	6.64	28.34	13.67	(4.31)	(5.13)	4.31
Bootstrap - 84%-ile	30.64	24.43	27.01	13.56	27.93	31.15	15.61	5.47	(1.92)	26.56
Bootstrap - 95%-ile	33.22	26.19	41.16	14.96	44.35	32.91	17.32	14.48	2.64	41.63

Note: The table reports the results of a bootstrap of the estimated value of the permanent price impact of market orders, in basis points of par per $100 million, under model M2a and M2b, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The price impact estimates reported in the text, the asymptotic standard errors of the estimates and the 5, 16, 50, 84 and 95th percentiles of the bootstrap distribution of the parameter estimates are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B4: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M2a

5-year	Dealer	Other	Multi	Self
PTF	-0.37 (-1.28/0.51)	2.53 (-1.24/5.67)	0.67 (0.00/1.38)	-4.90 (-9.73/0.78)
Dealer		2.92 (-1.11/6.30)	1.04 (0.40/1.73)	-4.55 (-9.54/1.00)
Other			-1.85 (-5.15/2.02)	-7.43 (-14.34/0.27)
Multi				-5.59 (-10.37/0.21)
10-year	**Dealer**	**Other**	**Multi**	**Self**
PTF	0.56 (0.48/0.64)	1.42 (0.93/1.91)	2.78 (2.72/2.85)	-9.36 (-9.84/-8.83)
Dealer		0.86 (0.37/1.36)	2.22 (2.17/2.29)	-9.92 (-10.39/-9.39)
Other			1.37 (0.87/1.86)	-10.75 (-11.46/-10.02)
Multi				-12.14 (-12.63/-11.61)
30-year	**Dealer**	**Other**	**Multi**	**Self**
PTF	5.04 (-2.30/12.76)	14.89 (-14.57/43.13)	15.05 (8.70/22.32)	19.78 (-17.58/63.24)
Dealer		9.56 (-20.24/37.82)	10.19 (4.61/15.72)	15.10 (-22.84/58.15)
Other			0.83 (-27.07/30.97)	5.21 (-43.96/56.09)
Multi				4.93 (-32.04/48.13)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per $100 million, under model M2a, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered "row minus column." The first value is the bootstrap median of the difference in the price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B5: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M2b

5-year	Dealer	Other	Multi	Self
PTF	1.51 (0.98/2.05)	1.32 (-0.61/2.94)	2.31 (1.50/3.07)	-4.02 (-8.92/0.81)
Dealer		-0.17 (-2.07/1.37)	0.80 (0.07/1.47)	-5.55 (-10.47/-0.58)
Other			0.97 (-0.82/3.23)	-5.30 (-10.79/0.83)
Multi				-6.36 (-11.47/-1.14)
10-year	**Dealer**	**Other**	**Multi**	**Self**
PTF	3.25 (3.20/3.30)	2.25 (1.96/2.53)	5.78 (5.71/5.86)	-8.52 (-9.01/-8.05)
Dealer		-1.00 (-1.29/-0.71)	2.54 (2.46/2.61)	-11.77 (-12.26/-11.29)
Other			3.53 (3.24/3.83)	-10.78 (-11.30/-10.23)
Multi				-14.31 (-14.78/-13.83)
30-year	**Dealer**	**Other**	**Multi**	**Self**
PTF	14.63 (9.26/20.28)	32.37 (14.27/53.94)	33.54 (24.50/42.46)	23.92 (-12.75/60.49)
Dealer		17.90 (-1.67/39.88)	18.83 (9.46/27.68)	8.90 (-27.82/45.24)
Other			0.94 (-21.79/21.94)	-8.31 (-53.87/30.39)
Multi				-9.69 (-46.72/29.52)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per $100 million, under model M2a, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered "row minus column." The first value is the bootstrap median of the difference in price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B6: **Bootstrap Confidence Intervals for M2c**

5-year	PTF ↓ PTF	Dealer ↓ Dealer	Other ↓ Other	Dealer ↓ PTF	PTF ↓ Dealer	Other ↓ PTF	PTF ↓ Other	Dealer ↓ Other	Other ↓ Dealer	Multi	Self
Price Impact Estimate	5.70	1.52	-1.28	4.40	1.07	-4.42	3.39	0.01	1.34	1.14	7.09
SE (Asymptotic)	1.37	0.89	80.63	0.88	1.16	7.31	11.11	9.54	9.09	0.19	3.80
Bootstrap - 5%-ile	3.64	0.24	-8.44	3.11	-0.68	-11.02	-4.95	-3.67	-0.85	0.84	2.02
Bootstrap - 16%-ile	4.49	0.93	-5.16	3.63	0.15	-5.84	2.03	-0.89	0.52	0.98	4.59
Bootstrap Median	5.73	1.50	-1.27	4.38	1.08	-4.42	3.37	-0.03	1.36	1.15	7.07
Bootstrap - 84%-ile	7.00	2.04	3.00	5.17	1.92	-2.64	4.57	0.81	2.17	1.31	9.71
Bootstrap - 95%-ile	8.00	2.55	7.30	5.76	2.84	3.70	7.88	2.74	3.91	1.45	12.88
10-year	**PTF ↓ PTF**	**Dealer ↓ Dealer**	**Other ↓ Other**	**Dealer ↓ PTF**	**PTF ↓ Dealer**	**Other ↓ PTF**	**PTF ↓ Other**	**Dealer ↓ Other**	**Other ↓ Dealer**	**Multi**	**Self**
Price Impact Estimate	17.52	4.83	7.01	10.25	3.09	13.83	7.30	6.10	3.12	2.72	15.95
SE (Asymptotic)	0.13	0.10	8.87	0.08	0.11	0.59	0.70	0.78	0.94	0.02	0.31
Bootstrap - 5%-ile	17.30	4.65	-7.92	10.12	2.90	12.94	6.16	4.81	1.49	2.69	15.46
Bootstrap - 16%-ile	17.40	4.73	-2.18	10.18	2.97	13.32	6.60	5.29	2.14	2.71	15.65
Bootstrap Median	17.52	4.83	6.65	10.25	3.08	13.88	7.32	6.10	3.03	2.72	15.95
Bootstrap - 84%-ile	17.64	4.93	15.61	10.33	3.20	14.46	8.02	6.86	4.02	2.74	16.27
Bootstrap - 95%-ile	17.73	4.98	21.74	10.38	3.27	14.87	8.46	7.28	4.64	2.75	16.48
30-year	**PTF ↓ PTF**	**Dealer ↓ Dealer**	**Other ↓ Other**	**Dealer ↓ PTF**	**PTF ↓ Dealer**	**Other ↓ PTF**	**PTF ↓ Other**	**Dealer ↓ Other**	**Other ↓ Dealer**	**Multi**	**Self**
Price Impact Estimate	42.02	12.85	-4.99	33.00	27.90	-4.85	-61.59	-11.88	49.06	15.56	6.91
SE (Asymptotic)	6.43	5.11	275.20	4.53	6.82	24.95	36.03	32.98	37.49	1.86	24.22
Bootstrap - 5%-ile	31.84	4.33	-47.71	25.25	16.83	-47.23	-121.44	-61.26	-15.48	12.57	-33.29
Bootstrap - 16%-ile	35.61	7.81	-28.63	28.23	21.30	-27.57	-92.53	-28.32	26.10	13.68	-16.75
Bootstrap Median	41.72	12.78	-5.32	33.09	27.56	-4.06	-61.81	-11.44	48.97	15.54	7.24
Bootstrap - 84%-ile	48.14	17.55	17.18	37.72	34.11	16.77	-40.19	5.48	70.77	17.38	29.15
Bootstrap - 95%-ile	53.02	21.20	35.86	41.14	39.03	35.41	-3.53	39.96	109.57	18.73	45.49

Note: The table reports the results of a bootstrap of the estimated value of the permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in the 5-, 10- and 30-year securities executed on BrokerTec from April 15, 2019 to February 15, 2020. The price impact estimates reported in the text, the asymptotic standard errors of the estimates and the 5, 16, 50, 84 and 95th percentiles of the bootstrap distribution of the parameter estimates are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B7a: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M2c – 5-year

5-year	*Dealer ↓ Dealer*	*Other ↓ Other*	*Dealer ↓ PTF*	*PTF ↓ Dealer*	*Other ↓ PTF*	*PTF ↓ Other*	*Dealer ↓ Other*	*Other ↓ Dealer*	*Multi*	*Self*
PTF ↓ PTF	4.27 (2.03/6.64)	6.90 (-1.79/14.56)	1.34 (-0.90/3.78)	4.66 (2.15/7.23)	10.10 (2.21/16.51)	2.33 (-2.49/10.70)	5.79 (1.95/10.15)	4.39 (0.85/7.51)	4.59 (2.61/6.75)	-1.36 (-6.85/3.70)
Dealer ↓ Dealer		2.83 (-5.89/9.95)	-2.92 (-4.55/-1.38)	0.45 (-1.67/2.40)	5.89 (-2.11/12.30)	-1.88 (-6.35/6.49)	1.53 (-1.73/5.50)	0.14 (-2.87/2.71)	0.35 (-0.81/1.46)	-5.64 (-11.30/-0.34)
Other ↓ Other			-5.65 (-12.85/2.97)	-2.24 (-9.63/6.37)	3.14 (-8.09/14.52)	-4.64 (-14.49/9.64)	-1.24 (-9.98/9.92)	-2.66 (-10.95/7.38)	-2.51 (-9.63/5.98)	-8.49 (-18.20/1.55)
Dealer ↓ PTF				3.30 (1.12/5.48)	8.84 (0.75/15.48)	1.04 (-3.54/9.40)	4.41 (1.62/8.07)	3.07 (0.18/5.66)	3.24 (2.05/4.52)	-2.65 (-8.78/2.28)
PTF ↓ Dealer					5.46 (-2.91/11.92)	-2.31 (-6.85/5.99)	1.08 (-2.56/5.42)	-0.27 (-3.86/2.41)	-0.09 (-1.78/1.72)	-6.02 (-11.87/-0.86)
Other ↓ PTF						-7.67 (-17.73/7.56)	-4.35 (-13.98/8.40)	-5.78 (-15.22/3.47)	-5.57 (-12.19/2.49)	-11.47 (-21.19/-1.89)
PTF ↓ Other							3.41 (-6.73/11.94)	1.97 (-10.52/9.28)	2.23 (-5.93/6.65)	-3.81 (-14.42/3.89)
Dealer ↓ Other								-1.36 (-11.78/3.86)	-1.18 (-4.56/1.70)	-7.16 (-16.54/0.04)
Other ↓ Dealer									0.22 (-1.96/2.81)	-5.76 (-13.08/1.55)
Multi										-5.94 (-11.72/-1.06)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in the 5-year security executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered “row minus column.” The first value is the bootstrap median of the difference in price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B7b: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M2c – 10-year

10-year	*Dealer ↓ Dealer*	*Other ↓ Other*	*Dealer ↓ PTF*	*PTF ↓ Dealer*	*Other ↓ PTF*	*PTF ↓ Other*	*Dealer ↓ Other*	*Other ↓ Dealer*	*Multi*	*Self*
PTF ↓ PTF	12.69 (12.43/12.93)	10.90 (-4.06/25.42)	7.27 (7.05/7.48)	14.43 (14.19/14.68)	3.64 (2.67/4.61)	10.20 (9.07/11.42)	11.43 (10.23/12.70)	14.50 (12.80/16.03)	14.80 (14.58/15.00)	1.58 (1.04/2.06)
Dealer ↓ Dealer		-1.81 (-16.86/12.73)	-5.42 (-5.60/-5.24)	1.74 (1.51/1.96)	-9.06 (-10.05/-8.10)	-2.49 (-3.62/-1.29)	-1.28 (-2.46/-0.01)	1.78 (0.18/3.33)	2.11 (1.94/2.26)	-11.12 (-11.70/-10.61)
Other ↓ Other			-3.55 (-18.11/11.50)	3.56 (-11.05/18.67)	-7.13 (-21.81/7.83)	-0.62 (-15.29/14.68)	0.54 (-13.64/15.74)	3.90 (-11.33/18.85)	3.93 (-10.63/19.01)	-9.40 (-23.82/5.60)
Dealer ↓ PTF				7.17 (6.96/7.37)	-3.63 (-4.61/-2.67)	2.93 (1.80/4.15)	4.14 (2.97/5.43)	7.21 (5.60/8.75)	7.53 (7.40/7.64)	-5.70 (-6.23/-5.20)
PTF ↓ Dealer					-10.79 (-11.79/-9.80)	-4.23 (-5.34/-3.03)	-2.99 (-4.21/-1.71)	0.04 (-1.58/1.64)	0.36 (0.19/0.55)	-12.87 (-13.43/-12.35)
Other ↓ PTF						6.58 (5.16/8.10)	7.77 (6.29/9.31)	10.84 (9.02/12.61)	11.15 (10.21/12.14)	-2.08 (-3.11/-0.99)
PTF ↓ Other							1.19 (-0.41/2.86)	4.22 (2.26/6.21)	4.59 (3.44/5.75)	-8.64 (-9.95/-7.32)
Dealer ↓ Other								3.03 (0.97/5.03)	3.37 (2.09/4.56)	-9.85 (-11.27/-8.54)
Other ↓ Dealer									0.31 (-1.22/1.91)	-12.90 (-14.61/-11.27)
Multi										-13.23 (-13.77/-12.74)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in the 10-year security executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered "row minus column." The first value is the bootstrap median of the difference in the price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE

Table B7c: Bootstrap Confidence Intervals for Differences between Price Impact Estimates for M2c – 30-year

30-year	Dealer ↓ Dealer	Other ↓ Other	Dealer ↓ PTF	PTF ↓ Dealer	Other ↓ PTF	PTF ↓ Other	Dealer ↓ Other	Other ↓ Dealer	Multi	Self
PTF ↓ PTF	29.15 (15.93/42.95)	46.14 (4.50/91.48)	8.70 (-2.94/21.10)	14.15 (-0.93/28.44)	46.09 (4.63/91.79)	104.16 (44.74/164.43)	53.17 (2.54/105.81)	-7.48 (-70.41/57.49)	26.23 (16.40/37.43)	34.73 (-4.08/75.23)
Dealer ↓ Dealer		17.08 (-23.71/61.14)	-20.28 (-30.21/-10.24)	-14.77 (-28.38/-3.13)	16.69 (-24.80/61.29)	74.71 (14.63/135.09)	24.50 (-26.64/74.50)	-36.59 (-96.91/26.89)	-2.97 (-11.29/6.09)	5.10 (-32.54/44.70)
Other ↓ Other			-38.03 (-80.41/3.65)	-33.47 (-74.51/8.14)	-1.06 (-52.99/56.83)	57.72 (-14.57/130.07)	5.95 (-62.86/77.74)	-54.12 (-118.03/16.99)	-20.56 (-62.57/20.33)	-11.79 (-72.41/46.89)
Dealer ↓ PTF				5.43 (-8.63/18.14)	37.42 (-5.14/79.72)	94.43 (36.65/156.01)	44.57 (-6.17/94.30)	-16.24 (-76.53/46.42)	17.43 (9.52/25.60)	25.99 (-12.41/66.47)
PTF ↓ Dealer					32.55 (-11.27/75.38)	88.64 (31.67/151.42)	39.02 (-12.17/87.91)	-21.55 (-82.77/42.70)	12.10 (1.31/23.54)	20.60 (-19.73/61.44)
Other ↓ PTF						58.19 (-16.96/125.16)	6.38 (-61.70/70.52)	-53.36 (-121.93/12.81)	-19.98 (-62.34/20.99)	-11.81 (-73.17/47.53)
PTF ↓ Other							-50.21 (-134.52/23.27)	-111.04 (-195.96/-30.62)	-77.28 (-137.76/-19.46)	-69.81 (-141.02/1.42)
Dealer ↓ Other								-60.46 (-137.86/18.98)	-27.26 (-75.94/23.95)	-19.58 (-79.08/43.84)
Other ↓ Dealer									33.77 (-31.07/94.52)	42.27 (-34.74/113.15)
Multi										7.80 (-28.94/48.56)

Note: The table reports the results of a bootstrap of the differences between the estimated values of the permanent price impact of market orders, in basis points of par per $100 million, under model M2c, for trades in the 30-year security executed on BrokerTec from April 15, 2019 to February 15, 2020. The matrices are ordered "row minus column." The first value is the bootstrap median of the difference in the price impact, and within the parentheses, the 5th and 95th percentiles of the price impact difference distribution are shown.

Source: Authors' calculations based on data from the Repo Interdealer Broker Community and FINRA TRACE