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The microstructure of a U.S. Treasury ECN: The BrokerTec platform[☆]

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ABSTRACT

We assess the microstructure of the U.S. Treasury securities market following its migration to electronic trading. We model price discovery using a vector autoregression model of price and order flow. We show that both trades and limit orders affect price dynamics, suggesting that traders also choose limit orders to exploit their information. Moreover, while limit orders have a smaller price impact, their greater variation contributes more to the variance of price updates. Lastly, we find an increased price impact of trades and especially limit orders following announcements, suggesting that the private information derived from public information is disproportionally exploited through limit orders.
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1. Introduction

Since the early 2000s, interdealer trading in the most recently auctioned U.S. Treasury securities has migrated from voice-assisted brokers to two electronic communications networks (ECNs): BrokerTec and eSpeed. In this paper, we examine the microstructure of the U.S. Treasury securities market using tick data from the BrokerTec ECN. We are the first to provide a comprehensive picture of this important market in the electronic trading era, as well as to analyze any fixed income ECN.[1] Our study is motivated by the fact that many previous papers on the microstructure of the Treasury market are based on data from GovPX, which consolidates data from voice-assisted brokers.[2] The migration of bond trading to the electronic platforms (which do not contribute to GovPX) sharply reduced GovPX coverage of the interdealer market, as noted by Boni and Leach (2004) and others, and naturally shifted interest to the electronic platforms.

However, it is not only the change in coverage, but also the change in the trading environment that warrants a further examination of this market. Barclay et al. (2006) suggest that automated trading systems will grow to dominate human intermediation as trading activity increases, especially in the actively traded Treasury securities. Electronic trading facilitates greater speed of order manipulation and execution, permits an increased role for computer-driven and automated trading processes, and enables better market information collection, dissemination, and processing. Accordingly, trading activity, market liquidity, and price discovery might differ from the earlier market structure in important ways, which we analyze in this paper.

Using tick data from 2010 and 2011, we examine trading activity and liquidity on the BrokerTec platform for the on-the-run 2-, 3-, 5-, 7-, 10-, and 30-year Treasury securities.[3] Our findings suggest that liquidity on the BrokerTec platform is markedly greater than that found by earlier studies using data from GovPX (Fleming, 1997, 2003). BrokerTec trading volume in the on-the-run securities has increased sharply over the years, except for a decline during the recent financial crisis. During the 2010–2011 sample period, trading volume is about $126 billion per day on average. Inside bid-ask spreads for maturities of five years or less average less than one 100th of 1%. An average depth of over $300 million is available on the platform at the best price on either side of the book for the 2-year note, $80 million for the 3-year note, and roughly $30 million for the 5-, 7-, and 10-year notes. The breadth of the BrokerTec tick data allows us to examine market liquidity beyond the inside tier for the first time and, in fact, there are even greater amounts available at the adjacent price tiers. Across the whole book, there is about $2.4 billion on each side for the 2-year note, $700 million for the 3-year note, and around $400 million for the 5- and 10-year notes.

In addition to describing the BrokerTec platform, our paper makes two further contributions. First, we examine the price impact of not only trades but also of order book activities. Previous studies based on GovPX data (e.g., Fleming, 2003; Brandt and Kavajecz, 2004; Green, 2004), or more recent papers based on data from either of the electronic platforms (e.g., Jiang and Lo, 2014), are only concerned with the price impact of trades. However, given the sheer levels of limit order book activities in comparison to trades, there is much to be learned about how such activities affect price dynamics. As discussed in O'Hara (2015), in today's high-frequency trading (HFT) world, the classical notion of trades being the basic unit of market information is no longer sufficient. Instead, underlying limit orders are also likely to contain information. Earlier studies of equity markets that incorporate order book information into the market impact function show that limit orders also have a significant impact (e.g., Engle and Patton, 2004; Mizrach, 2008; Hautsch and Huang, 2012).

We first calculate the permanent price impact of trades following the framework in Hasbrouck (1991a). We find that the price impact of trades on BrokerTec is generally quite small, but increases in the maturity of the securities considered, ranging from 0.006 256ths of 1% of par per $1 million buyer-initiated volume for the 2-year note to 0.450 256ths for the 30-year bond. Equivalently, it takes about $363 million in signed trading volume to move the price of the 2-year note by 2 256ths (one tick), whereas the required volume is only $4.5 million to move the price of the 30-year bond by the same amount (or roughly $9 million to move the price by one tick, which is twice as wide for the 30-year bond as it is for the 2-year note). Taking into account individual securities' variability in trading sizes and price changes, we find that a one standard deviation shock in trade order flow increases the price permanently by about 0.2–0.3 standard deviations of the trade-to-trade price change.

More importantly, we show that limit order activities affect prices, and in fact contribute more to the variance of efficient price updates than trades, given limit orders' much higher intensity and variation as compared to trades. The evidence that limit orders also contain value-relevant information suggests that, contrary to the conventional assumption that traders with

[1] Campbell and Hendry (2007) examine price discovery in the 10-year U.S. Treasury note using transactions data from BrokerTec. Mizrach and Neely (2006) estimate bid-ask spreads and market impact using transactions data from eSpeed. Additional studies examine the euro area sovereign debt market using data from MTS, including Cheung et al. (2005), Menkveld et al. (2005), and Beber et al. (2009). In addition, several recent studies look at different aspects of the U.S. Treasury market using data from BrokerTec or eSpeed. For example, Dungey et al. (2013) model trade duration on the eSpeed platform, Engle et al. (2012) examine intraday dynamics of market liquidity and volatility on the BrokerTec platform, Fleming and Nguyen (2015) study the order flow segmentation induced by the workup protocol on BrokerTec and evaluate the informational content of workup and non-workup trades, and Jiang and Lo (2014) quantify the intensity of private information flow on BrokerTec and examine its impact on price discovery.

[2] Fleming (1997) characterizes intraday liquidity, Fleming and Remolona (1997), Fleming and Remolona (1999), Balduzzi et al. (2001), Huang et al. (2002), and Fleming and Piazzesi (2005) look at announcement effects, Fleming (2002) examines the relation between issue size and liquidity, Fleming (2003), Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007) assess the information content of trades, Goldreich et al. (2005) gauge the relation between liquidity and value, and Brandt et al. (2007), Campbell and Hendry (2007), and Mizrach and Neely (2008) compare the information content of trades in spot and futures markets.

[3] On-the-run securities are the most recently auctioned securities of a given maturity.

better information are liquidity demanders (i.e., trade immediately via aggressive orders), they also use limit orders in their trading strategies. Our results support the view in O'Hara (2015) that the nature of information in a high-frequency world has changed, and that learning from market data is more complex than observing merely the aggressive side to each trade. From an empirical perspective, our findings show that ignoring limit orders in analyzing price discovery results in an overestimation of trades' price impact. Specifically, the price impact of trades is about 20–50% higher when limit orders are ignored than when they are accounted for.

Furthermore, one commonly cited characteristic of a high-speed market is the large number of order submissions and cancellations. On the BrokerTec platform, cancellation rates during our sample period exceed 95%. Quickly submitting and cancelling orders appears to have become the new normal in electronic markets [see O'Hara (2015) and Baruch and Glosten (2016), and the references therein]. Nevertheless, as O'Hara (2015) points out, the information effects of these activities are not yet well understood. Given that submissions and cancellations occur much more frequently than trades, and that trading algorithms draw inferences from market data to devise trading strategies, it is natural to expect that these activities play a non-trivial role in the price discovery process. To this end, we incorporate order submissions and cancellations separately in our price discovery analysis, and find that they do have significant and differential price effects, with submissions having a price impact that is about 4–11% higher than that of cancellations.

Another contribution of our paper is to provide a further understanding of the nature of "private information" in the Treasury market. We perform price discovery analysis around major announcements to explore the idea put forth by Pasquariello and Vega (2007), among others, that Treasury traders obtain an information advantage from public information. The information events we study include the Federal Open Market Committee (FOMC) rate decision announcements, and five key macroeconomic reports, including employment, retail sales, GDP, CPI, and PPI (Faust et al., 2007). We find that trades and limit orders are generally more informative in the 60-minute window after these announcements as compared to a similar time window on non-announcement days, and that they also contain relatively more information in the post-announcement period than in the pre-announcement period. Moreover, the proportionate increase in information content is greater for limit orders than it is for trades. These findings suggest that the private information derived from public information in the Treasury market is disproportionately exploited through limit orders.

The paper is organized as follows. In Section 2, we discuss evolution of the U.S. Treasury market structure to provide essential background for the main analysis. In Section 3, we describe the BrokerTec data and the microstructure of the BrokerTec platform, and present univariate analyses of trading activity and market liquidity. Next, we discuss evidence on the information content of trades and limit orders in Section 4. We describe our price discovery analysis around key public information events in Section 5. In Section 6, we summarize our key results and provide concluding remarks.

2. The evolution of U.S. Treasury market structure

The secondary market for U.S. Treasury securities is a multiple dealer, over-the-counter market. Traditionally, the predominant market makers were the primary government securities dealers, those dealers with a trading relationship with the Federal Reserve Bank of New York. The dealers trade with the Fed, their customers, and one another. The core of the market is the interdealer broker (IDB) market, which accounts for nearly all interdealer trading. Trading in the IDB market takes place 22–23 hours per day during the work week, although we find that slightly over 90% of trading occurs during New York hours, roughly 7:00 to 17:30 Eastern Time (ET) [comparable with what Fleming (1997) finds using GovPX data].

Until 1999, nearly all trading in the IDB market occurred over the phone via voice-assisted brokers. Voice-assisted brokers provide dealers with proprietary electronic screens that post the best bid and offer prices called in by the dealers, along with the associated quantities. Quotes are binding until and unless withdrawn. Dealers execute trades by calling the brokers, who post the resulting trade price and size on their screens. The brokers thus match buyers and sellers, while ensuring anonymity, even after a trade.

Most previous research on the microstructure of the Treasury market has used data from voice-assisted brokers, as reported by GovPX, Inc. GovPX receives market information from IDBs and re-disseminates the information in real time via the Internet and data vendors. The information includes the best bid and offer prices, the quantity available at those quotes, and trade prices and volumes. In addition to the real-time data, GovPX sells historical tick data, which provides a record of the real-time data feed, for use by researchers and others.

When GovPX started operations in June 1991, five major IDBs provided it with data, but Cantor Fitzgerald did not, so GovPX covered about two-thirds of the interdealer market. The migration from voice-assisted to fully electronic trading in the IDB market began in March 1999 when Cantor Fitzgerald introduced its eSpeed electronic trading platform.[4] In June 2000, BrokerTec Global LLC, a rival electronic trading platform, began operations.[5] As trading of on-the-run securities migrated to these two electronic platforms, and the number of brokers declined due to mergers, GovPX's data coverage dwindled. By the

[4] Cantor spun eSpeed off in a December 1999 public offering. After many ownership changes, eSpeed merged with BGC Partners, an offshoot of the original Cantor Fitzgerald. In 2013, eSpeed was purchased by NASDAQ OMX Group.

[5] BrokerTec had formed the previous year as a joint venture of seven large fixed income dealers. BrokerTec was acquired in May 2003 by ICAP PLC.

end of 2004, GovPX was receiving data from only three voice-assisted brokers. After ICAP's purchase of GovPX in January 2005, ICAP's voice brokerage unit was the only brokerage entity reporting through GovPX.[6]

The BrokerTec and eSpeed ECNs are fully automated electronic trading platforms on which buyers are matched to sellers. A comparison of BrokerTec trading activity with that of eSpeed reported in Luo (2010) and Dungey et al. (2013) shows that BrokerTec accounts for about 60% of electronic interdealer trading in the on-the-run 2-, 5-, and 10-year notes and slightly above 50% for the 30-year bond.

Both brokers provide electronic screens that display the best bid and offer prices and associated quantities. On BrokerTec, for example, a manual trader can see five price tiers and the corresponding total size for each tier on each side of the book, plus individual order sizes for the 10 best bids and offers. For computer-based traders, the complete order book information is available. Traders enter limit orders or hit/take existing orders electronically. As with the voice brokers, the electronic brokers ensure trader anonymity, even after a trade, and charge a small fee for their services.

In the early days of BrokerTec, market participants were mainly government securities dealers. However, since 2004, BrokerTec has opened access to non-dealer participants, including hedge funds and HFT firms. Table 3.3 (p. 59) in the Joint Staff Report (2015) on the U.S. Treasury market shows that bank-dealers account for 34.7% of trading volume in the on-the-run 10-year note, compared to HFT firms' share of 56.3%. The remaining 9% is split among non-bank dealers and hedge funds.[7] These statistics show that the interdealer market for U.S. Treasury securities, despite the name, is no longer solely for dealers.

The BrokerTec platform operates as an electronic limit order market. Traders send in orders that can be aggressive (market orders) or passive (limit orders), but they must all be priced. The priority of execution for limit orders is based on price and time. The minimum order size is $1 million par value. Traders can enter aggressive orders at a price worse than the current best price. This is typically the case when a trader needs to trade a large quantity for which the limit order quantity at the best price is not sufficient. The order will first exhaust all depth, both displayed and hidden, at better price levels, until it reaches the originally stated price. Therefore, large aggressive orders can be executed at multiple prices. However, the incidence of market orders walking up or down the book is very small. This is likely because of the large amount of depth usually available at the best price tier, and the ability to work up volume at a given price point.[8]

The BrokerTec platform allows iceberg orders, whereby a trader can choose to show only part of the amount he is willing to trade. As trading takes away the displayed portion of an iceberg order, the next installment of hidden depth equal to the pre-specified display size is then shown. This process continues until trading completely exhausts the iceberg order. It is not possible to enter iceberg orders with zero displayed quantity; that is, limit orders cannot be completely hidden.

Beside iceberg orders, the electronic brokers have retained the workup feature similar to the expandable limit order protocol of the voice-assisted brokers, but with some important modifications.[9] On BrokerTec, the most important change is that the right-of-first-refusal – previously given to the original parties to the transaction – has been eliminated, giving all market participants immediate access to workups. All trades consummated during a workup are assigned the same aggressive side as the original market order.[10]

3. Data

Our analysis is based on tick data from the BrokerTec platform. The database provides a comprehensive record of every trade and order book change in the BrokerTec system for the on-the-run 2-, 3-, 5-, 7-, and 10-year Treasury notes, as well as the 30-year Treasury bond. We choose to focus on the period from January 2, 2010 to December 31, 2011 to provide a characterization of the market's microstructure in a non-crisis trading environment.[11]

3.1. Data processing

From BrokerTec's detailed record of every trade and order book change, time-stamped to the millisecond, we process the data into two main parts: the trade data and the order book data. The trade data include price, quantity, and whether a trade was seller-initiated or buyer-initiated. The trading process on BrokerTec takes place as follows. When a marketable order arrives, it is instantaneously matched with outstanding limit order(s) in the book to the extent possible. The market then enters a workup during which additional quantity can be transacted *at the same price* as that of the initial marketable order execution, until there is no further trading interest.

[6] See Mizrach and Neely (2006) for a detailed description of the migration to electronic trading, and Mizrach and Neely (2011) for a summary of the evolution of the microstructure in the Treasury market.

[7] The statistics are based on trading activity on the BrokerTec platform for the April 2–17, 2014 period.

[8] Fleming and Nguyen (2015) show that, with the workup protocol in place, marketable orders rarely walk the book. The percentage of marketable orders sweeping more than one price level is less than 0.5%.

[9] Boni and Leach (2004) provide a thorough explanation of this feature in the voice-assisted trading system. The feature allows a Treasury market trader whose order has been executed to have the right-of-first-refusal to trade additional volume at the same price. As a result, the trader might be able to have his market order fulfilled even though the original quoted depth is not sufficient. That is, the quoted depth is expandable.

[10] For a detailed analysis of workup activity on BrokerTec, see Fleming and Nguyen (2015).

[11] For market dynamics during the crisis period, see Engle et al. (2012).

BrokerTec records the execution of each marketable order against multiple limit orders, as well as further matches during the ensuing workup, as separate trade records. We aggregate these multiple trade records as one trade (and use the ending time of the workup as the time of trade from which we compute trade-to-trade price changes).[12] The aggregation is in line with BrokerTec's workup patent document, which states that a workup is conceptually a "single deal extended in time." There are further reasons for the aggregation. First, treating the individual trade records as separate and distinct trades would artificially inflate the serial correlation in both trade initiation and signed trade flow and might compromise econometric modeling and inferences. Furthermore, our aggregation permits a more precise analysis of market order submission and the price impact of market orders, the size of which is better measured by the total volume exchanged during a trade and its associated workup. Nevertheless, the aggregation is not without cost in that it sometimes overestimates the market order size.

The second part of the data concerns the limit order book, which we recreate from order book changes on a tick-by-tick basis. Each order book change record specifies the price, quantity change, shown and total quantities for that order, whether the order is a bid or an ask, and the reason for the change. The book can be changed as a result of limit order submission, modification, cancellation, or execution against market orders. The order book data provide a view of the Treasury market far more detailed than that provided by GovPX data. In particular, our processed dataset not only provides the best bid and offer and associated sizes at any given time, but also the depth available outside of the first tier. Moreover, we can discern what quantities were visible to market participants at the time and what quantities were hidden.

3.2. Summary statistics

Over our sample of 500 trading days in 2010 and 2011, BrokerTec intermediated almost $63 trillion in trading of on-the-run coupon securities, or $125.6 billion per day. The activity involved nearly 6 million transactions (each comprised of one or more order matches), or almost 12,000 per day. Moreover, there were roughly 2.4 billion order book changes at the first five price tiers alone for these securities over our sample period, amounting to over 4.7 million per day.

Table 1 provides summary statistics of the transaction data. Trade size is the total quantity transacted through the execution of a market order and associated workup trades. Trading in the 2-year note averages about $28 million per trade, with a standard deviation of about $54 million, indicating the presence of very large trades. Average trade sizes in the other securities are markedly lower, ranging from $3 million to $13 million, and with less variability. Each trade on average consists of about 2 to 8 individual order matches, of which less than half typically arise from the initial instantaneous execution of a marketable order against standing limit orders, and the rest during the ensuing workup. Average trade-to-trade price changes (in 256ths of 1% of par) are roughly zero, with standard deviations ranging from 1.01 to 8.17. Average absolute price changes increase monotonically with maturity, except for the 10-year note, from 0.55 256ths for the 2-year note to 4.27 256ths for the 30-year bond.

We next report the volume of limit orders that flow into and out of the best price level between trades. These quantities are partly dependent on the trade arrival rate of a given security and thus show a considerable cross-sectional variation. A key observation is that the volume of limit orders canceled is almost as large as the volume of limit orders submitted. Accordingly, the average limit order flow net of cancellations is quite small, less than $2 million for all securities except for the 2-year note, which has about $6-7 million in average net limit order flow between trades. We notice that limit order flows are highly variable, suggesting that at times there are extremely large flows into or out of the limit order book. For example, at the beginning of each trading day, traders start sending in orders and the order book fills up quickly. Likewise, the data show that there are massive withdrawals of limit orders immediately before important announcements and the subsequent entry of limit orders after such announcements.

3.3. Trends in trading activity

To provide historical perspective of trading activity on the BrokerTec platform, we plot in Fig. 1 the average daily trading volume for the respective on-the-run coupon securities for each year from 2001 to 2011. The figure shows that there has been a sharp increase in trading activity over time, especially in the early years of the platform's history before the financial crisis intensified in late 2008. For the 10-year note, for example, average daily trading volume grew from $2.9 billion in 2001 to a level over ten times larger in 2007 and, except for 2009, remained above $30 billion after. It is worth noting that activity in the 2-year note, which used to exceed that of any other security, with an average daily trading volume of nearly $50 billion in 2008, did not quickly recover after the crisis. This contrasts with the post-crisis recovery observed in other securities. In 2010 and 2011, the 5-year note was the most actively traded, followed by the 10-year note and the 2-year note. The post-crisis stagnation in activity for the 2-year note may be due to the prolonged period in which the overnight rate was held at the zero lower bound, effectively dampening volatility and trading interest in the note.

[12] In the BrokerTec database, the arrival of each marketable order, as well as the start and finish of the ensuing workup, is clearly marked. Therefore, the aggregation of trade records is unambiguous.

Table 1
Summary statistics of transaction data.

Variable	2-Year	3-Year	5-Year	7-Year	10-Year	30-Year
Trade Size ($m par)	28.22	12.49	11.88	6.43	10.26	2.97
	(53.53)	(21.38)	(17.47)	(10.64)	(14.48)	(3.66)
# of Order Matches	8.38	6.32	7.02	4.47	6.73	2.42
	(13.71)	(9.28)	(9.40)	(6.72)	(8.85)	(2.52)
# of Initial Matches	3.43	2.75	3.05	2.16	3.05	1.30
# of Workup Matches	4.95	3.57	3.97	2.31	3.68	1.12
Price Change	0.0005	0.0004	0.0008	0.0011	0.0011	0.0088
	(1.01)	(1.51)	(1.90)	(4.08)	(4.18)	(8.17)
Absolute Price Change	0.5461	0.7642	0.9731	1.9930	1.8300	4.2746
	(0.73)	(0.87)	(1.05)	(2.21)	(1.93)	(5.31)
Bid Submission ($m par)	92.65	43.01	18.08	50.11	13.55	5.59
	(199.79)	(70.40)	(30.11)	(80.93)	(22.88)	(10.24)
Bid Cancellation ($m par)	86.67	42.16	16.97	48.49	12.52	4.37
	(190.03)	(67.79)	(28.82)	(79.63)	(21.79)	(8.87)
Bid Net Flow ($m par)	5.98	0.84	1.12	1.62	1.04	1.22
	(84.76)	(35.78)	(18.70)	(32.64)	(14.05)	(4.89)
Ask Submission ($m par)	102.50	44.82	18.05	50.04	13.59	5.52
	(224.97)	(76.29)	(30.05)	(81.52)	(23.23)	(10.12)
Ask Cancellation ($m par)	95.13	43.59	17.05	48.46	12.59	4.33
	(215.74)	(71.69)	(28.99)	(79.96)	(22.03)	(8.75)
Ask Net Flow ($m par)	7.37	1.24	1.00	1.58	1.00	1.19
	(110.41)	(41.70)	(18.57)	(32.63)	(14.42)	(4.87)
# of Observations	466,873	648,542	1,526,109	749,896	1,532,851	960,375

The table reports the averages (with standard deviations in parentheses) of trade and limit order activities at the transaction frequency for on-the-run Treasury coupon securities on the BrokerTec platform over the 2010–2011 sample period. *Trade Size* is the dollar par volume per transaction, while *# of Order Matches Per Trade* is the number of order matches per transaction. *Price Change* is the price difference between consecutive transactions, in 256ths of 1% of par. *Bid Submission* (*Bid Cancellation*) is the volume of bid limit orders submitted to (canceled from) the best bid price queue in the order book between consecutive transactions. *Bid Net Flow* equals bid submission volume minus cancellation volume. *Ask Submission*, *Ask Cancellation*, and *Ask Net Flow* are computed similarly for ask limit orders.

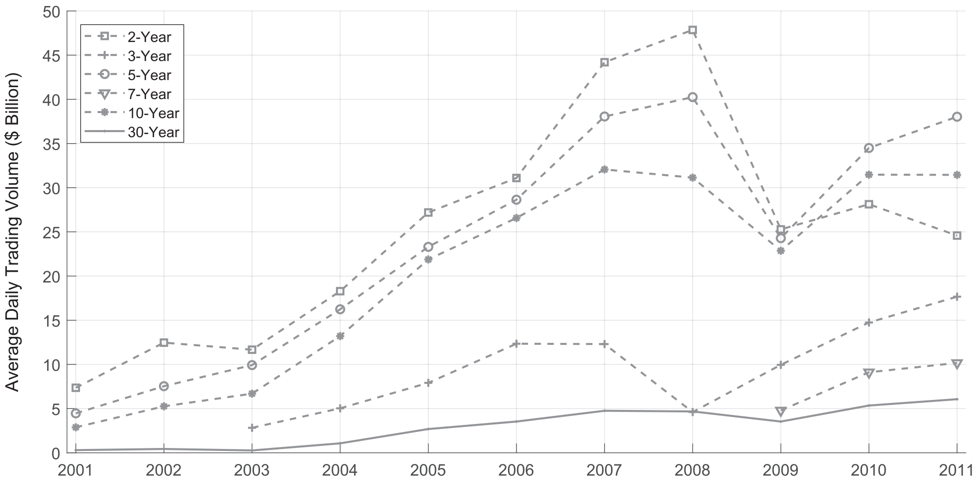

Fig. 1. Trading activity over time. The figure shows the average daily trading volume by year in billions of dollars (par value) from 2001 through 2011 for on-the-run Treasury coupon securities on the BrokerTec platform. The 2007 and 2008 figures for the 3-year note are based on data through August 2007 and from November 2008 respectively, due to the suspended issuance of this note between August 2007 and November 2008. The 2009 figure for the 7-year note is based on data from February 2009, when this note was reintroduced.

Table 2
Daily trading activity.

	Trading Volume			Trade Frequency		
Security	Total	Buy	Sell	Total	Buy	Sell
2-Year	26,354	12,967	13,387	934	463	471
3-Year	16,204	8,005	8,198	1,297	646	651
5-Year	36,262	18,005	18,257	3,052	1,524	1,529
7-Year	9,640	4,816	4,824	1,500	754	746
10-Year	31,462	15,664	15,798	3,066	1,534	1,532
30-Year	5,705	2,823	2,882	1,921	954	967

The table reports the average daily trading activity for on-the-run Treasury coupon securities on the BrokerTec platform over the 2010–2011 sample period. For each day, trading volume is the total dollar volume (in $ million par), while trade frequency is the total number of transactions. For each variable, we report the total and provide a break-down by whether a transaction is buyer-initiated ("Buy") or seller-initiated ("Sell").

3.4. Daily trading activity

Focusing on the most recent years of 2010 and 2011, Table 2 reports the average daily trading volume and trading frequency for each security. The table shows that trading in the 5- and 10-year notes is most frequent, with over 3,000 transactions per day, on average. The 5-year note is the most actively traded in terms of volume, with a daily trading volume exceeding $36 billion. The 30-year bond is also quite frequently traded with nearly 2,000 transactions per day, but each trade is of much smaller size than that of the other securities, so that its total daily trading volume of nearly $6 billion is far below the others. On the other hand, the 2-year note has the lowest trading intensity. However, as noted earlier, trades in this security tend to occur in larger sizes, so the total trading volume per day is still the third highest, grossing about $26 billion per day.

We also examine the balance between buying and selling pressures in this market. The buy and sell volume figures appear to split rather evenly, with the sell dollar volume being slightly higher than the buy volume across all securities. For example, the average daily excess selling pressure in the 10-year note is $135 million, which is less than one half of 1% of the daily trading volume of $31.5 billion in this security. Even though the magnitude of the imbalance is economically small, a formal statistical test (not shown) allows us to reject the null hypothesis that daily net order flow (buy volume minus sell volume) is zero.

3.5. Liquidity around the clock

We plot the average BrokerTec trading volume by half-hour interval over the round-the-clock trading day in Fig. 2. To make the intraday patterns comparable across securities, we standardize the half-hour volume figures by the total daily volume of the relevant security. The patterns are consistent with what Fleming (1997) finds using GovPX data from 1994 and are strikingly similar across the six securities. Trading activity is extremely low during Tokyo trading hours (roughly 18:30 or 19:30 the previous day to 3:00 ET), picks up somewhat during morning trading hours in London, then rises sharply during morning trading hours in New York, peaking between 8:30 and 9:00, and then peaking locally between 10:00 and 10:30. Trading reaches a final local peak between 14:30 and 15:00 and then tapers off by 17:30. Engle et al. (2012) also find increased volatility and temporary disappearance of market depth around the 8:30, 10:00, 13:00, 14:15, and 15:00 time marks.[13] The patterns are probably largely due to public information events, the hours of open outcry Treasury futures trading (8:20 to 15:00), and the pricing of fixed income indices at 15:00.

3.6. Spreads

In Table 3, we report quoted bid-ask spreads for the New York trading hours of 7:00 to 17:30. The inside quoted spread, shown in column (6), is the difference between the highest bid price and lowest ask price expressed in multiples of tick size of the relevant security.[14] To compute the spreads, we sample bid and ask prices every five minutes, and then average over all five-minute observations in our sample period (we have about 62,000 such five-minute observations for each security). Spreads generally increase in maturity, from 1.03 ticks (2.06 256ths) at the 2-year maturity to 2.66 ticks (10.64 256ths) at the

[13] Many important scheduled macroeconomic announcements are released at 8:30 and 10:00. U.S. Treasury auctions typically close at 13:00. Most FOMC announcements in recent years have been made at 14:15, although three FOMC announcements were made at 12:30 in 2011.

[14] The tick size for the 2-, 3-, and 5-year securities is 1/128 of 1% of par, equivalent to $78.125 per $1 million par, and that for the 7-, 10-, and 30-year securities is 1/64 of 1% of par, or $156.25 per $1 million par.

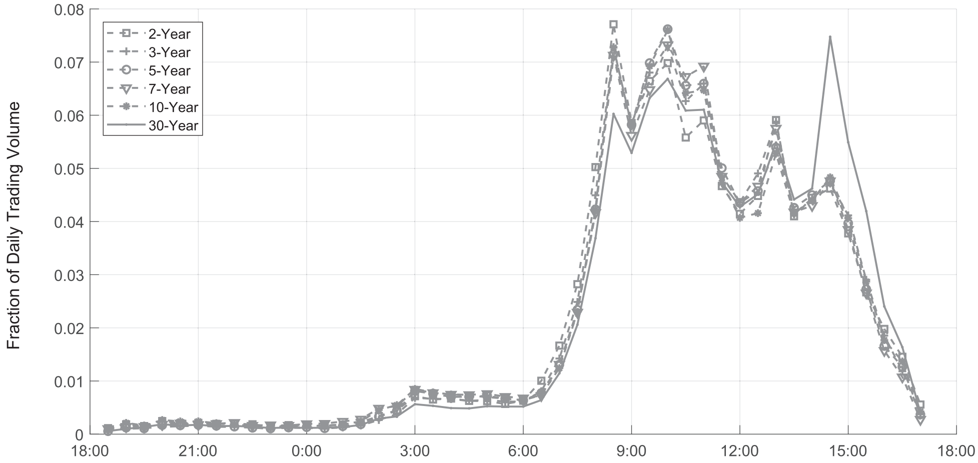

Fig. 2. Round-the-clock trading activity. The figure shows the fraction of daily total trading volume by half-hour interval for on-the-run Treasury coupon securities on the BrokerTec platform for the 2010-2011 sample period. Times are Eastern Time and indicate start of half-hour interval.

Table 3
Bid-ask spread and inter-tier price distance.

Security	# Obs	Bid 5-4	Bid 4-3	Bid 3-2	Bid 2-1	Bid-ask Spread	Ask 1-2	Ask 2-3	Ask 3-4	Ask 4-5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2-Year	62,418	1.02	1.01	1.01	1.00	1.03	1.01	1.01	1.03	1.03
3-Year	62,311	1.10	1.05	1.03	1.03	1.14	1.03	1.03	1.05	1.08
5-Year	62,333	1.06	1.04	1.03	1.03	1.18	1.03	1.04	1.05	1.09
7-Year	62,289	1.13	1.09	1.05	1.04	1.33	1.04	1.04	1.06	1.10
10-Year	62,341	1.04	1.03	1.02	1.02	1.15	1.02	1.02	1.04	1.06
30-Year	62,305	1.48	1.35	1.33	1.29	2.66	1.32	1.34	1.39	1.49

The table reports the average bid-ask spread and the average price distance between adjacent price levels on each side of the book. All numbers are in multiples of the tick size of the corresponding security. The tick size for the 2-, 3-, and 5-year maturities is 1/128 of 1% of par (or $78.125 per $1 million par), and that for the 7-, 10-, and 30-year maturities is 1/64 of 1% of par (or $156.25 per $1 million par). The numbers are computed from five-minute snapshots of BrokerTec's limit order book for the respective securities for the hours 7:00–17:30 over the 2010–2011 sample period. The column "# Obs" shows the number of five-minute snapshots without missing data from which these statistics are computed.

30-year maturity. The 10-year note, however, has a narrower spread than the 7-year note. Statistical tests (not shown) indicate that the spreads are significantly different across the various maturities.

It is also helpful to compare these spreads to those reported in earlier studies using GovPX data. In general, BrokerTec spreads are narrower. Fleming (2003), for example, reports average bid-ask spreads of 3.12 256ths for the 5-year note and 6.24 256ths for the 10-year note, whereas the corresponding BrokerTec spreads are 1.18 ticks (or 2.36 256ths) and 1.15 ticks (or 4.60 256ths) respectively for these securities.[15] As discussed in the Joint Staff Report (2015, pp. 37–39), there has been a major change in the composition of market participants in recent years, leading to increased competition in liquidity provision. A narrower spread is consistent with this development.

A noteworthy feature of the average BrokerTec spreads is that they are quite close to one tick for all of the notes, suggesting that the minimum increment is constraining. Further examining the frequency distribution of inside spreads, shown in Fig. 3, we observe a high degree of clustering at one tick (e.g., 97% for the 2-year note), except for the 30-year bond whose distribution is more spread out and peaks at two ticks. Compared to equity markets' tick size of one cent, the minimum tick size in the U.S. Treasury market appears large given its relatively low volatility. This means that the compensation for liquidity provision is relatively large, but also means that the transaction costs for those who need to trade is large. Crossing the spread in the 2-year note – the shortest maturity among the coupon Treasury securities – is particularly costly in the zero rate environment.

Furthermore, we show in Table 3 that these securities, except for the 30-year bond, have tightly populated order books over the first five price levels. As reported in columns (2)–(5) for the bid side and columns (7)–(10) for the ask side, the average price distance between adjacent price levels (up to the fifth level in the book) is roughly one tick, although it gets slightly wider further away from the inside tier.

[15] Note that the prices in both databases do not reflect brokerage fees. Such fees are proprietary, and can vary by customer and with volume, but are unquestionably lower for the electronic brokers than the voice-assisted brokers.

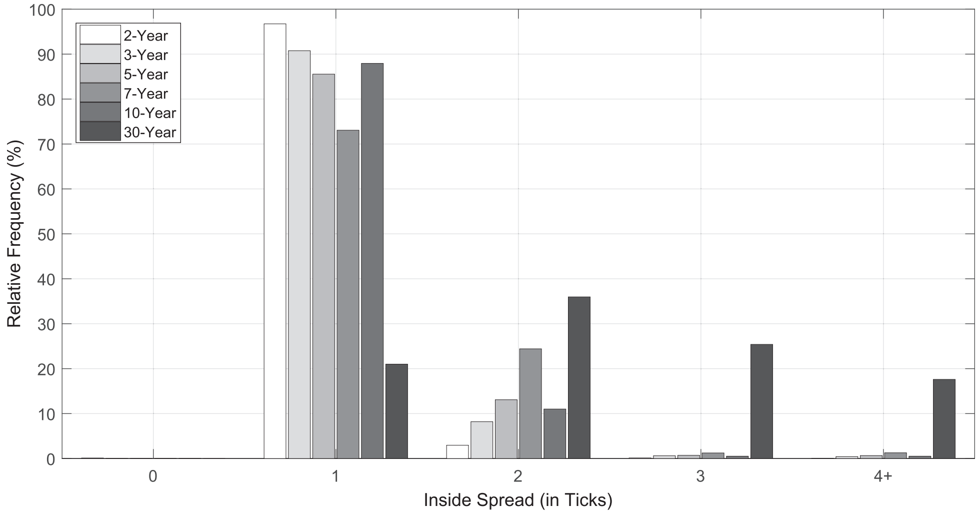

Fig. 3. Frequency distribution of inside spread. The figure shows the frequency distribution of the inside spread (measured in number of ticks) on the BrokerTec platform. The tick size for the 2-, 3-, and 5-year maturities is 1/128 of 1% of par, and that for the 7-, 10-, and 30-year maturities is 1/64 of 1% of par. The numbers are computed from five-minute snapshots of BrokerTec's limit order book for the respective securities for the hours 7:00-17:30 over the 2010-2011 sample period.

3.7. Market depth

As a limit order market, liquidity on BrokerTec is supplied by limit orders submitted by market participants. Table 4 reports the average total visible quantity of limit orders available at the best price level on each side of the market. We compute market depth variables from five-minute snapshots of the limit order book – the same data used in our analysis of the bid-ask spread. We also report for the first time the amount of standing limit orders at the best five price levels, as well as the total depth across all price levels in the limit order book. This provides a complete overview of liquidity supply in the market at a given point in time, and helps further our understanding of the extent to which liquidity supply is concentrated at the top of the book.

Table 4 shows that market depth generally declines in maturity, and is greatest at the 2-year and lowest at the 30-year segment. At the inside price tier, there is about $300 million available on either side for trading in the 2-year note. We observe that, despite being the most actively traded, the 5- and 10-year notes' market depth is on the lower end, averaging $26–31 million, suggesting higher replenishment rates of liquidity to meet the high trading activity levels. Our observations are supported by statistical tests (not reported) that confirm that the differences in market depth among various maturities are statistically significant.

The inside depths reported here greatly exceed average depths on GovPX reported by earlier studies. For the 2-year note, for example, Fleming (2003) reports average depth on GovPX at the first tier of just $25 million (averaging across the bid and ask side), less than one-tenth the level observed on BrokerTec.

Additionally and importantly, earlier studies using GovPX data are limited to the inside tier, leaving market liquidity beyond the first tier unknown. We show that market liquidity away from the first tier is substantial, several orders of magnitude larger than that available at the inside tier. Collectively across the best five tiers on each side, there is over $1.5 billion market depth for the 2-year note, about $460 million for the 3-year note, in the range of $210–280 million for each of the 5-, 7-, and 10-year notes, and $28 million for the 30-year bond. The first five tiers account for about 55–79% of total market depth for the notes and 47% of total market depth for the bond. That is, the first five tiers collect a disproportionately large amount of depth, given that there are typically around 16–18 price tiers with positive depth on each side (slightly higher for the 5- and 10-year notes).[16]

While depth in the book concentrates among the best five tiers, the inside tier is not the one with the greatest depth. To learn more about the depth distribution in the book away from the inside tier, we graph the average depth at each of the best five tiers on the bid and ask side of the order book in Fig. 4. The figure illustrates again that order book depth outside the first tier is considerable. A common pattern emerges across all securities in that there is consistently more quantity available at the second and third price tiers (and even fourth and fifth for some securities) than the first. The available quantity generally peaks at the second tier on both the bid and ask sides for the notes, and at the third tier for the bond. Depth then declines monotonically as one moves further away from the inside quotes. Biais et al. (1995) also find depth lower at the first tier than the second tier, but find similar depths at the second through fifth tiers.

[16] The maximum number of price levels on one side during our sample period ranges from 43 for the 30-year bond (on the bid side) to 101 for the 2-year note (on the ask side).

Table 4
Limit order book depth.

Security	First Tier		First 5 Tiers		All Tiers	
	Bid	Ask	Bid	Ask	Bid	Ask
2-Year	308	300	1,561	1,538	2,422	2,355
3-Year	77	77	460	455	664	639
5-Year	31	31	278	275	465	443
7-Year	37	36	236	236	301	297
10-Year	26	26	213	211	393	376
30-Year	3	3	28	28	59	59

The table reports the average visible depth (in $ million of par) on BrokerTec at the best price level (*First Tier*), the best five price levels (*First 5 Tiers*), and across the whole limit order book (*All Tiers*). The statistics are computed from five-minute snapshots of the limit order book for the respective securities for the hours 7:00–17:30 over the 2010–2011 sample period. The number of observations is as reported in Table 3.

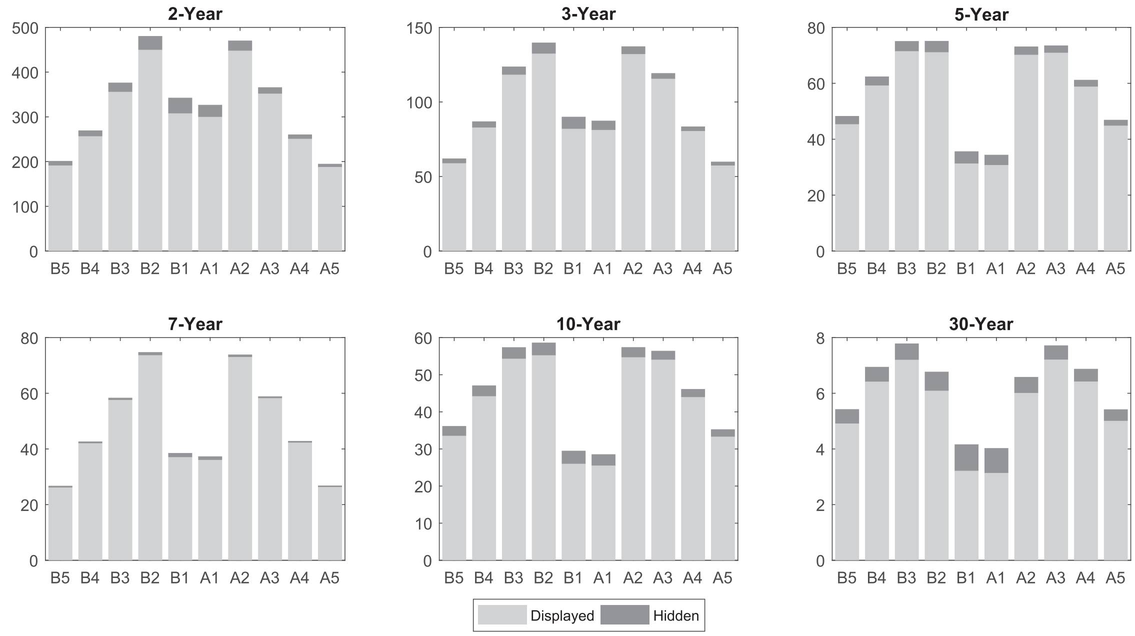

Fig. 4. Displayed and hidden liquidity at the first five tiers. The figure shows the average displayed depth and hidden depth by price tier up to the fifth level on each side of the market. The numbers are computed from five-minute snapshots of BrokerTec's limit order book for the respective securities for the hours 7:00–17:30 over the 2010–2011 sample period. Depth is reported in millions of dollars (par value).

3.8. Hidden depth

On the BrokerTec platform, traders have the option to hide part of their order size. Therefore, the visible depth might not reflect the full extent of liquidity in the market. However, as revealed in Fig. 4, hidden depth is only a small share of total depth at each price tier on average, with the first tier having proportionally more hidden depth than the others. Our data show that less than 2% of the limit orders submitted to the top tier of the book contains hidden volume, which helps to explain the low level of hidden depth in the limit order book at any given point in time.[17]

4. Price impact analysis

In this section, we address the question of whether, and the extent to which, trading and limit order activities convey value-relevant information. It is often believed that there is no private information in the Treasury market, as everyone has access to the same set of public information. However, as noted in Pasquariello and Vega (2007), an information advantage in

[17] Studies on hidden depth in equity markets reveal a greater prevalence of iceberg orders. For example, Bessembinder et al. (2009) show that iceberg orders account for 18% of order flow for stocks on Euronext-Paris, while Frey and Sandas (2017) report 9% for 30 German blue chip stocks on Deutsche Borse's Xetra platform.

this market might come from private knowledge of client order flow, or a superior ability in processing and interpreting public information. As a result, some market participants might be more informed than others.

We quantify the information content of traders' activities by the permanent price impact of these activities, building on the vector autoregression (VAR) model of trade and price revision developed by Hasbrouck (1991a) to measure the information content of stock trades. This VAR model is rooted in theoretical microstructure models of information asymmetry. Upon observing a trade, the market maker infers the probability of trading with an informed trader, and update prices accordingly. The price revision process thus reflects the information set of the market maker at each price update, which includes the contemporaneous trade, as well as the history of prices and trades up to that point. The dynamics of trade are modeled to account for the possible autocorrelation in trade flow, as well as the possibility that past price movements play a role in a trade decision, by including lagged trades and the price history up to the trade. As clearly laid out by theory, price revision is contemporaneously affected by trades, but not vice versa.

Empirically, we estimate a structural VAR model with five lags for a vector of endogenous variables that consist of return and order flow variables. We measure the return as the change in the best bid-ask midpoint, i.e., $r_t = m_t - m_{t-1}$, where t indexes transaction time, and m_t is the midpoint prevailing at the end of the t^{th} transaction. We let X_t denote order flow variables (X_t can be a vector), so that the general structural VAR model is:

$$B_0 \begin{bmatrix} r_t \\ X_t \end{bmatrix} = \sum_{j=1}^{5} B_j \begin{bmatrix} r_{t-j} \\ X_{t-j} \end{bmatrix} + \begin{bmatrix} u_{r,t} \\ u_{X,t} \end{bmatrix},$$

where u_t is the structural innovation vector. The matrix B_0 captures the contemporaneous effects among the variables in the system. More specifically, as discussed above, order flow variables affect price revision contemporaneously, whereas price has only lagged effects on order flow.

The VAR representation as developed in Hasbrouck (1991a) is theoretically of an infinite order (to reflect the history of trades and prices in the information set of the market maker at each price update). We choose to truncate the VAR at five lags as in Hasbrouck (1991a).[18] In addition, given the many specifications we estimate, and the need for comparison of price impact estimates across specifications, we adopt the same lag length throughout the analysis.

We then measure the information content of trades and/or order activities by the long run cumulative response of price to a unit shock in order flow, that is,

$$\frac{\partial r_{t+\infty}}{\partial X_t}.$$

The focus on the long-run price response is to ensure that our measure is not contaminated by transitory price effects, and at the same time incorporates any delayed response. For empirical purposes, we truncate the impulse response function at a sufficiently long lag at which it has stabilized. We compute the impulse response out to 50 transactions after the shock.[19] The permanent price impact is approximated by the cumulative return over this horizon. We compute confidence intervals for our price impact estimates by bootstrapping with 1000 replications.[20]

4.1. Price impact of trades

We begin the estimation of market impact with a bivariate VAR model of return and signed trade volume q_t (i.e., volume of the t^{th} transaction, signed positive if it is buyer-initiated and negative if seller-initiated). Trade initiation is recorded in the BrokerTec dataset, so all trades are classified properly. Moreover, in an ECN like BrokerTec, we can be sure that transactions, as well as the sequence of events associated with each transaction, are recorded in the proper order. That is, a market order arrives, executes against available limit orders on the opposite side, and the order book subsequently updates to reflect the transaction just taking place. This supports the identifying assumption that trade flow contemporaneously affects return, but not vice versa. Accordingly, the model specification is:

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[18] We examine the autocorrelation of residuals of the VAR models presented later in the paper and find that there is little autocorrelation of residuals, providing econometric support for the choice of lag length. See Table 10 in the Online Appendix for more details.

[19] Visual inspection of the impulse response function indicates that the 50-transaction horizon is sufficiently long for the price response to stabilize. For further information on the pattern of price adjustment over the 50-transaction horizon, see Figs. 1 and 2 in the Online Appendix.

[20] We calculate the standard errors for the estimates using the bootstrapping method developed by Runkle (1987). First, we draw a random sample with replacement from the model residuals ($T \times n$ matrix of model residuals, where T is the number of observations and n is the number of dependent variables in the VAR model). Second, using this sample of residuals and model parameter estimates, we reconstruct the dependent variable series. Third, we re-estimate the VAR model on the reconstructed dependent variable series and compute the corresponding cumulative impulse response function. We repeat this procedure 1000 times and obtain a bootstrap sample of our price impact estimates. The 2.5–97.5% percentiles computed from the bootstrap sample serve as the 95% confidence band.

Table 5
Price impact of trades.

	Model 1	Model 2		Asymmetry Test
Security	Signed Volume (1)	Buy Volume (2)	Sell Volume (3)	Buy/Sell - 1 (4)
2-Year	0.0055*	0.0057*	−0.0054*	6% *
3-Year	0.0166*	0.0168*	−0.0164*	2%
5-Year	0.0276*	0.0281*	−0.0271*	4%
7-Year	0.0780*	0.0807*	−0.0753*	7%
10-Year	0.0658*	0.0663*	−0.0654*	1%
30-Year	0.4476*	0.4352*	−0.4602*	−5%

The table reports the 50-transaction cumulative impulse response of price (price impact) to a $1 million shock in trade volume, based on two alternative models. Model 1 is a bivariate VAR(5) model of signed trade volume (positive for buys and negative for sells) and return (based on the best bid-ask midpoint). Model 2 is a VAR(5) model of buy trade volume, sell trade volume, and return (based on the best bid-ask midpoint). Price impacts are in 256ths of 1% of par. Estimation is based on BrokerTec tick data for the 2010–2011 sample period. The number of observations used in the estimation is the same as reported in Table 1. The column "Asymmetry Test" reports the difference in magnitude between the price impact of buy trades and that of sell trades, expressed as a percentage of the latter. An asterisk (*) indicates statistical significance at the 5% level, based on standard errors computed by bootstrapping with 1000 replications.

$$\begin{bmatrix} 1 & -\alpha_{1,2} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} r_t \\ q_t \end{bmatrix} = \sum_{j=1}^{5} B_j \begin{bmatrix} r_{t-j} \\ q_{t-j} \end{bmatrix} + \begin{bmatrix} u_{r,t} \\ u_{q,t} \end{bmatrix}. \tag{1}$$

We report the permanent price impact estimates from Eq. (1) in column (1) in Table 5. They are statistically greater than zero, indicating that there is value-relevant information revealed through trading activity, although the magnitude of such effects is generally small. The smallest price impact is observed for the 2-year maturity, for which a $1 million increase in buyer-initiated trade flow moves price by a minuscule 0.006 256ths of 1%. In economic terms, it means that it takes about $363 million in buyer-initiated transaction volume to move the price permanently by one tick (or 2 256ths). On the other hand, for the least liquid among the six benchmark securities, the 30-year bond, a $1 million shock in the buyer-initiated order flow permanently increases the price by 0.448 256ths. Equivalently, only $8.9 million is sufficient to move the price by one tick (or 4 256ths).

If we consider the variability of trade sizes and price changes across securities, the price impact estimates are more comparable. For example, a one standard deviation shock in trade order flow for the 2-year note ($53.53 million from Table 1) moves the price by 0.2944 256ths, which is 0.29 standard deviations of the trade-to-trade price change (1.01 from the same table). By the same calculation, the permanent price impact of a one standard deviation shock in trading volume for the other securities is in the range of 0.2-0.25 standard deviations of price change.

Finally, to entertain the possibility that the price impact does not increase linearly in trade size, we also estimate a specification that includes both signed trade volume and signed squared volume. We find that the concavity of the price impact function is quite mild, almost visually indistinguishable from linearity for the notes.[21]

4.2. Asymmetric effects of buys and sells

We extend the baseline specification in Eq. (1) to explore if there is any asymmetry in the price impact of buyer-initiated versus seller-initiated trades. Saar (2001), for example, motivates theoretically an asymmetric response to buyer- and seller-initiated block trades. The model we estimate is:

$$\begin{bmatrix} 1 & -\alpha_{1,2} & -\alpha_{1,3} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_t \\ VB_t \\ VS_t \end{bmatrix} = \sum_{j=1}^{5} B_j \begin{bmatrix} r_{t-j} \\ VB_{t-j} \\ VS_{t-j} \end{bmatrix} + \begin{bmatrix} u_{r,t} \\ u_{VB,t} \\ u_{VS,t} \end{bmatrix}, \tag{2}$$

where VB and VS are the buy and sell transaction volume respectively. For buyer-initiated transactions, VB_t is equal to the transaction volume and VS_t=0 (and vice versa for seller-initiated transactions).

We report the permanent price impact estimates separately for buy and sell trades in columns (2) and (3) in Table 5. The estimates are not statistically different in magnitude to the baseline estimates from model 1. More importantly, there is little evidence to suggest that the market responds asymmetrically to buy versus sell trade initiation. In column (4) in Table 5, we report the difference in magnitude between the price impact of buy trades and sell trades as a percentage of the latter. While we find that buy trades generally have a higher price impact than that of sell trades by a few percent, most of these differences are not statistically significant.

[21] For a graph of this non-linear price impact function, see Fig. 3 in the Online Appendix.

Table 6
Price impact of trades and limit orders.

Security	Trade		Limit Order		Asymmetry Tests	
	Buy (1)	Sell (2)	Bid (3)	Ask (4)	Buy/Bid-1 (5)	Sell/Ask-1 (6)
Panel A: Permanent Price Change Per $1 Million Shock						
2-Year	0.0043*	−0.0043*	0.0017*	−0.0009*	153% *	378% *
3-Year	0.0109*	−0.0115*	0.0087*	−0.0053*	25% *	117% *
5-Year	0.0220*	−0.0220*	0.0179*	−0.0183*	23% *	20% *
7-Year	0.0530*	−0.0507*	0.0273*	−0.0254*	94% *	100% *
10-Year	0.0536*	−0.0545*	0.0457*	−0.0407*	17% *	34% *
30-Year	0.3686*	−0.3931*	0.3598*	−0.3579*	2%	10% *
Panel B: Contribution to Price Variation						
2-Year	9.0% *	9.5% *	6.7% *	3.4% *	34% *	182% *
3-Year	3.7% *	4.3% *	12% *	6.1% *	−70% *	−29% *
5-Year	4.8% *	4.8% *	6.2% *	6.5% *	−24% *	−26% *
7-Year	2.9% *	2.8% *	13% *	11% *	−78% *	−75% *
10-Year	4.0% *	4.3% *	4.8% *	4.0% *	−16% *	6% *
30-Year	3.3% *	3.7% *	8.5% *	8.3% *	−61% *	−55% *

The table reports price impacts (Panel A) and information shares (Panel B) of trades and limit orders. These statistics are computed from a VAR(5) model of buy trade volume, sell trade volume, bid limit order flow, ask limit order flow, and return (based on the best bid-ask midpoint). Estimation is based on BrokerTec tick data for the 2010–2011 sample period. The number of observations used in the estimation is the same as reported in Table 1. The limit order flow variables are measured as the total volume of limit orders submitted to the inside tier between trades, net of modifications/cancellations. Price impacts are in 256ths of 1% of par. The "Asymmetry Test" columns show the differences in price impact (in Panel A) or contribution to efficient price variation (in Panel B) between types of trades and limit orders. An asterisk (*) indicates statistical significance at the 5% level, based on standard errors computed by bootstrapping with 1000 replications.

4.3. *Price impact of limit orders*

We now extend our price impact analysis to incorporate information on limit order activities. Given that the order book information is observable by market participants, the decision to place a trade and its size can be influenced by activities in the book. As noted earlier, there are about 4.7 million order book changes per day across the six securities in the best five tiers alone, overwhelmingly outnumbering trading activity (about 12,000 transactions per day). Boulatov and George (2013) suggest the concept of an "informed liquidity provider"; that is, informed traders can also be on the supply side, as opposed to the common assumption that informed traders merely consume liquidity. If so, relevant information might also be present in limit order flow. Empirically, Mizrach (2008) shows that excluding this order book information is likely to overstate the market impact of trades. Hautsch and Huang (2012) document significant price impact of limit orders for select NASDAQ stocks.

We extend the model in Eq. (2) by adding the inside bid and ask net order flow between trades:

$$\begin{bmatrix} 1 & -\alpha_{1,2} & -\alpha_{1,3} & -\alpha_{1,4} & -\alpha_{1,5} \\ 0 & 1 & 0 & -\alpha_{2,4} & -\alpha_{2,5} \\ 0 & 0 & 1 & -\alpha_{3,4} & -\alpha_{3,5} \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_t \\ VB_t \\ VS_t \\ lb_t \\ la_t \end{bmatrix} = \sum_{j=1}^{5} B_j \begin{bmatrix} r_{t-j} \\ VB_{t-j} \\ VS_{t-j} \\ lb_{t-j} \\ la_{t-j} \end{bmatrix} + \begin{bmatrix} u_{r,t} \\ u_{VB,t} \\ u_{VS,t} \\ u_{lb,t} \\ u_{la,t} \end{bmatrix}, \tag{3}$$

where *lb*, the bid limit order flow, is the volume of limit buy orders submitted to (positive) or canceled from (negative) the first tier between trades, i.e., between the $(t-1)$ and t transactions. Similarly, *la* is the ask limit order flow. The measurement timing of the endogenous variables supports the direction of contemporaneous effects from limit order flow to trade flow to return in the above specification.

The measurement of limit order flow variables warrants some further discussion. Because our model already incorporates the effects of trades directly, we explicitly exclude order book changes caused by trade execution from our limit order flow measures. Specifically, the net flow of limit orders on each side of the market is computed as the difference between the quantity of new order submissions and that of cancellations from the last trade until immediately before the current trade. Our resulting measures of limit order flow account for the non-trade related change in liquidity supply in the market. As a result, our model can capture the dynamic interactions of liquidity demand (trade flow), liquidity supply (limit order flow) and price revisions. The model thus enables the delineation of the price impact of liquidity supply change from the price impact of liquidity demand change, a novel feature of our empirical exercise.[22]

[22] Hautsch and Huang (2012) measure the price impact of limit orders by modeling the limit order book as a co-integrating vector comprised of price and depth up to the third level in the limit order book. Our model has a similar spirit in that it also incorporates limit order information in the vector of variables of interest. However, our model differs from Hautsch and Huang (2012) in its focus on the trading process and the price dynamics as affected by both trading and limit order activities.

4.3.1. Price impact estimates

We analyze the permanent price impact of trades and limit order activities by computing the cumulative price response to a shock vector that is zero everywhere except for the relevant order flow variable, which has a unitary shock. The estimates are reported in Panel A, columns (1)–(4), in Table 6. All estimates, including those for the price impact of limit orders, are statistically significant at the 5% level. Consistent with equity market evidence (e.g., Hautsch and Huang, 2012), our results show that limit order activity also has a significant permanent effect on price. For example, a $1 million increase in bid limit order volume raises the best bid-ask midpoint by approximately 0.0017 256ths, 0.0179 256ths, and 0.0457 256ths for the 2-, 5-, and 10-year notes. This implies that an increase in bid depth of $1.18 billion, $112 million, and $88 million is required to raise the best bid-ask midpoint of the respective notes by one tick. In the less liquid 30-year bond, the price impact of 0.3598 256ths per $1 million shock in bid order flow implies that it takes an $11 million shock to raise the midpoint by one tick (4 256ths).

To put these price impact estimates in perspective, we can translate them into standard deviation terms by computing the permanent response of price to one standard deviation shocks in the order flow variables, and then scaling the resulting price impact by the corresponding standard deviation of the trade-to-trade price change. For example, a one standard deviation shock in bid limit order flow permanently raises the price by 0.14, 0.21, 0.18, 0.22, 0.15, and 0.22 standard deviations respectively for the 2-, 3-, 5-, 7-, 10-, and 30-year maturities. The standardized price impacts have much smaller cross-sectional variation, but they still suggest that the 2-, 5-, and 10-year notes are more liquid than the other securities.

That limit order activities play a role in the price discovery process is consistent with O'Hara's (2015) suggestion that information in high-frequency markets no longer pertains to only the active side of a trade. For example, algorithms and dynamic trading strategies enable traders to chop a large order into smaller ones and hide them in the limit order book at various layers. They subsequently show up on the passive side in resultant executions. Thus, a study of price discovery based on solely trade data is not likely to be complete.

The increased presence of HFT activities, however, also raises a natural question of whether limit orders placed away from the market also contribute to price discovery.[23] To address this question, we estimate the same specification as in Eq. (3) except that the limit order flow variables are the bid and ask net order flow to the best five price tiers between trades. To save space, we summarize our key findings here, and provide the detailed results from this analysis in Tables 1 and 2 of the Online Appendix. We find that the price impact of limit orders, when averaged across all orders submitted to the best five price levels, is somewhat smaller than the price impact of limit orders submitted to the best price level (as reported in Panel A in Table 6), for all securities except the 7-year note. This suggests that orders placed at the inside tier are the most informative among limit orders. Intuitively, limit order traders with information would prefer to have their orders executed sooner rather than later, so it is not surprising to find that informative limit orders are likely to rise to the top of the book. It is also for this reason that we continue to use limit order flows at the inside tier in our subsequent analyses.

4.3.2. Do limit orders carry more information than trades?

Having established that both trades and limit orders affect prices, we analyze and compare the price impact estimates in order to assess the relative importance of different order types in the price discovery process. Do limit orders carry more or less information than trades? To answer this question, we test (1) whether price responds differently to a buy trade versus a bid limit order, and (2) whether price responds differently to a sell trade versus an ask limit order. The findings are presented in columns (5) and (6) in Panel A in Table 6. Specifically, column (5) shows the extent to which the impact of a buyer-initiated trade exceeds that of a bid limit order of equal size, expressed as a percentage of the latter. Column (6) shows a similar statistic for seller-initiated trade and ask limit order.

The numbers reported in both columns (5) and (6) are all positive and almost always significant, providing clear evidence that trades have greater permanent price impact than limit orders of equal size. Consider the 2-year note, for example. The price impact of market orders is 153% higher than that of limit orders of equal size on the buying side, and 378% higher on the selling side. A similar comparison for the 10-year note shows that trades have effects that are 17% and 34% larger than the corresponding impact of limit orders on the buying and selling sides respectively.

Furthermore, our results show that including information on limit order activities affects estimates of the price impact of trades. This is because trade flows are correlated with limit order flows. Examining the impulse response of trade flow to limit order flow shocks, we observe that an unexpected increase in limit order flow to the bid side subsequently increases buyer-initiated trade flow.[24] Likewise, seller-initiated trade flow increases following an increase in the ask order flow. Arguably, limit order activities might provide important information that enters into the decision to trade. Once this relation is taken into account, trades show smaller price impact estimates than those estimated from earlier specifications without limit order flow (as in Table 5). Our results suggest that ignoring limit order activity overstates the price impact of trades by about 20%–50%. Based on the bootstrap confidence intervals of price impact estimates from the two models, we confirm that the differences are statistically significant.

[23] We thank a referee for raising this point.

[24] This impulse response analysis is available upon request.

4.3.3. Do limit orders have higher impact in thin markets?

Lastly, we examine whether the same shock to limit order flow has different effects under different market depth conditions.[25] We begin by expanding the VAR model in Eq. (3) to include two additional variables: (1) the interaction of the bid limit order flow with the contemporaneous market depth at the best bid price level, and (2) the interaction of the ask limit order flow with the contemporaneous market depth at the best ask price level. From the estimated VAR model, we then compute the impulse response of price to a unit shock in the bid (ask) limit order flow when the inside bid (ask) depth is low, medium, and high (corresponding to the 5th, 50th, and 95th percentile of the inside bid (ask) depth distribution). We find that the price impact is monotonically decreasing as market depth is increasing, indicating that a shock to the limit order flow has greater price impact when the market is thin than when it is deep.[26]

4.4. Information shares of trades and limit orders

While price impact provides an indication of how much price changes permanently in response to a unit shock in trade or limit order flow, it does not indicate the extent to which the variation in these order flow variables drives the variation in the efficient price updating process. For instance, trades may have a significantly higher price impact, but if there is not much variation in trade flow, its role in the price updating process might be limited. Thus, to complement the price impact measure, we also compute the information shares of trades and limit orders following Hasbrouck (1991b).[27] Our information share estimates are reported in Panel B in Table 6. Similar to Panel A, we also report the results of asymmetry tests to determine if the information share of trades is significantly different from that of limit orders.

In general, trade and limit order flow variation collectively explains between 17% and 30% of the variance of price updates. The most important observation from Panel B is that the asymmetry between trade and limit order flow remains, but that limit order flow generally contributes more to efficient price variance because limit order activities occur at much greater intensity than trades. This is especially the case for the less actively traded securities, namely the 3-, 7-, and 30-year, for which the variation of trade flow contributes 29–78% less to price discovery than the variation of limit order flow, despite the fact that trades have a higher price impact per $1 million shock. For example, variation in bid and ask limit order flows collectively explain about 24% of the efficient price variance for the 7-year note, compared to the 5.7% explained by buy and sell trade flows.

The 2-year note is an exception in that both the price impact and the information share of trades are far greater than those of limit orders. In other words, trades have a higher per unit price impact, as well as a higher total variance contribution to the price discovery process. This result supports the idea that better-informed traders are more likely to trade than to submit limit orders in the 2-year note. This result is not surprising given that there is typically a very large quantity of standing limit orders in the book for the 2-year note, which in turn implies that a marginal limit order might take longer to be executed. The potentially delayed execution of limit orders appears to make limit orders less appealing for traders with some information advantage.

4.5. Price impact of limit order submissions and cancellations

The Treasury “flash rally” event of October 15, 2014 has drawn significant attention to the changing structure of the U.S. Treasury market, following the migration to electronic trading (of on-the-run Treasury securities) and the increased participation of non-traditional high-frequency market participants. As the Joint Staff Report (2015, p. 59) documents, HFT firms now account for the majority of trading activity on the interdealer trading platforms. One of the key characteristics of these firms is their massive number of order submissions and cancellations (as identified in the SEC's Concept Release on Equity Market Structure).[28] An important question that arises out of the current debate on HFT is whether such submissions and cancellations have potentially disruptive effects.

While there are potentially many aspects of the market that might be affected by HFT and that warrant further study, we focus specifically here on measuring the price impact of order submissions and cancellations separately. We seek to answer the question of whether these respective activities have differing effects on price discovery. According to O'Hara (2015), order submissions and cancellations are an important part of market data gathered and processed by trading algorithms, but whose role in the price discovery process is not yet well understood. There are only a few studies that have examined the role of order submissions and cancellations in price discovery (e.g., Brogaard et al., 2015).

Ex ante, it is not clear whether a submission should have a smaller or larger price impact than a cancellation. On the one hand, one might argue that an order submission (an active undertaking) is more likely to depend on some information, whereas a cancellation is more likely in response to a change in market conditions (a reactive undertaking). Accordingly, the information content of a submission would be higher than that of a cancellation. On the other hand, if limit orders are

[25] We thank a referee for suggesting this additional analysis.

[26] The results for this specification are provided in Table 9 in the Online Appendix.

[27] In this framework, the variance of the random walk component of the price process is decomposed into parts that are due to variation in trade and limit order flows respectively.

[28] Securities Exchange Act Release No. 34-61358. 75 FR 3594, 3606 (January 21, 2010).

submitted then quickly canceled with the intention of driving price in a certain direction, it is plausible that the cancellation might have a greater (permanent) effect because one is not only learning about the lack of trading interest in that direction, but that the trading interest may actually lie on the other side of the book.

Up to this point, we have mainly focused on exposing the differences in the price impact between limit orders and trades, and thus have worked with net limit order flow in our specifications. In this subsection, we include submissions and cancellations as separate variables. Due to the lack of asymmetry in the price impact of buy and sell trades, and to keep the econometric model manageable, we use signed trade volume q_t in place of two separate variables for buy volume and sell volume. The specification is as follows:

$$\begin{bmatrix} 1 & -\alpha_{1,2} & -\alpha_{1,3} & -\alpha_{1,4} & -\alpha_{1,5} & -\alpha_{1,6} \\ 0 & 1 & -\alpha_{2,3} & -\alpha_{2,4} & -\alpha_{2,5} & -\alpha_{2,6} \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_t \\ q_t \\ BSub_t \\ BCan_t \\ ASub_t \\ ACan_t \end{bmatrix} = \sum_{j=1}^{5} B_j \begin{bmatrix} r_{t-j} \\ q_{t-j} \\ BSub_{t-j} \\ BCan_{t-j} \\ ASub_{t-j} \\ ACan_{t-j} \end{bmatrix} + \begin{bmatrix} u_{r,t} \\ u_{q,t} \\ u_{BSub,t} \\ u_{BCan,t} \\ u_{ASub,t} \\ u_{ACan,t} \end{bmatrix}, \tag{4}$$

where $BSub_t$, $BCan_t$, $ASub_t$, and $ACan_t$ measure the quantity of limit orders submitted to or canceled from the top of the limit order book on each side of the market in between the $(t-1)^{th}$ and t^{th} transactions. We report the price impact estimates resulting from this specification in columns (1)–(5) in Panel A in Table 7, and information share estimates in the same columns in Panel B. The magnitudes of the price impact estimates for trades remain close to those reported in Table 6. In addition, we continue to find that limit orders have significant market impact and that such price impact estimates are smaller than those of trades.

The most interesting takeaway from Table 7, however, comes from the asymmetry tests that examine whether submissions have statistically different price impact from cancellations. We perform these tests for both the bid and the ask side, and report the results in columns (6) and (7). The results indicate that submissions tend to have greater price impact, especially for the medium- and long-term maturities. Specifically, as observed for the 5-, 7-, 10-, and 30-year securities, the price impact of a limit order submission is 4%-11% higher than that of a cancellation of equal size.

If we take into account not only the respective unit price impacts, but also the varying degree of variation in submission and cancellation activities of each security, we find an even stronger result. The asymmetry tests based on information shares (reported in Panel B) show that limit order submissions contribute more to the price discovery process than cancellations, across all securities and for both the bid and the ask side. More specifically, depending on security, submissions contribute 6%–65% more to the variation of price updates as compared to cancellations. Our evidence thus supports the notion that submissions are more likely induced by information than is the case for cancellations, consistent with the results for equity markets documented in a similar type of analysis by Brogaard et al. (2015).

Table 7
Price impact of limit order submissions and cancellations.

	Trade	Bid Limit Order		Ask Limit Order		Asymmetry Tests	
Security	Signed Trade (1)	Submission (2)	Cancellation (3)	Submission (4)	Cancellation (5)	Bid Limit Order Sub/Can-1 (6)	Ask Limit Order Sub/Can-1 (7)
Panel A: Permanent Price Change Per $1 Million Shock							
2-Year	0.0043*	0.0017*	−0.0018*	−0.0009*	0.0009*	−6% *	0%
3-Year	0.0112*	0.0087*	−0.0088*	−0.0053*	0.0054*	−1%	−2%
5-Year	0.0220*	0.0183*	−0.0173*	−0.0188*	0.0178*	6% *	6% *
7-Year	0.0516*	0.0281*	−0.0262*	−0.0263*	0.0244*	7% *	8% *
10-Year	0.0540*	0.0466*	−0.0446*	−0.0415*	0.0396*	4% *	5% *
30-Year	0.3792*	0.3704*	−0.3328*	−0.3710*	0.3367*	11% *	10% *
Panel B: Contribution to Price Variation							
2-Year	12% *	18.4% *	17.4% *	6.9% *	6.4% *	6% *	8% *
3-Year	4.6% *	21.5% *	20.1% *	9.2% *	8.4% *	7% *	9% *
5-Year	7.8% *	10.6% *	8.7% *	11.2% *	9.3% *	23% *	21% *
7-Year	2.0% *	22.3% *	18.8% *	19.7% *	16.4% *	19% *	20% *
10-Year	7.7% *	9.2% *	7.6% *	7.5% *	6.1% *	21% *	23% *
30-Year	4.4% *	18.1% *	11.0% *	17.7% *	10.9% *	65% *	62% *

The table reports price impacts (Panel A) and information shares (Panel B) of trades, limit order submissions, and cancellations. These statistics are computed from a VAR(5) model of trade volume, limit order submissions, cancellations, and return (based on the best bid-ask midpoint). Estimation is based on BrokerTec tick data for the 2010–2011 sample period. The number of observations used in the estimation is the same as reported in Table 1. The limit order flow variables are measured as the total volume of limit orders submitted to or canceled from the inside tier on each side between transactions. Price impacts are in 256ths of 1% of par. The "Asymmetry Tests" columns show differences in price impact (in Panel A) or contribution to efficient price variation (in Panel B) between submission and cancellation of bid limit orders and ask limit orders respectively. An asterisk (*) indicates statistical significance at the 5% level, based on standard errors computed by bootstrapping with 1000 replications.

Table 8
Price discovery around FOMC announcements.

Security	Buy (1)	Sell (2)	Bid (3)	Ask (4)	# of Observations FOMC (5)	Non-FOMC (6)
Panel A: Post-Announcement Incremental Price Impact						
2-Year	56% *	134% *	140% *	460% *	3,174	10,600
3-Year	91% *	101% *	201% *	131% *	4,442	16,524
5-Year	−2%	24% *	153% *	89% *	7,450	38,411
7-Year	118% *	42% *	132% *	0%	5,051	20,345
10-Year	−33% *	26% *	121% *	97% *	7,543	37,863
30-Year	48% *	116% *	54% *	155% *	6,333	32,674
Panel B: Pre-Announcement Incremental Price Impact						
2-Year	39% *	74% *	67% *	17% *	1,552	10,427
3-Year	66% *	58% *	0%	107% *	1,878	16,591
5-Year	83% *	1%	−8% *	44% *	4,155	38,293
7-Year	2%	56% *	226% *	−91% *	2,069	20,514
10-Year	49% *	35% *	−21% *	5% *	3,910	37,461
30-Year	−46% *	35% *	12% *	18% *	2,861	29,712

The table reports changes in the price impact of trades and limit orders in the 60 minutes before and after FOMC announcements as compared to the same intervals on non-FOMC days. Panel A shows the incremental price impact in the 60-minute post-announcement period on FOMC days as compared to non-FOMC days, expressed in percentage of the latter. Panel B shows a similar comparison for the 60-minute period before FOMC announcements. Price impact estimates are based on a VAR(5) model of buy trade volume, sell trade volume, bid limit order flow, ask limit order flow and return (based on the best bid-ask midpoint). Estimation is based on BrokerTec tick data around FOMC announcements and a similar time interval on non-FOMC days over the 2010–2011 sample period. Non-FOMC days include five days before and five days after each FOMC announcement. An asterisk (*) indicates statistical significance at the 5% level. Tests of difference in mean are based on bootstrap samples of price impact estimates with 1000 replications.

5. Price impact around public information events

As our price impact estimates are based on all transactions over the sample period, one question that arises is whether price impact varies by the information environment. Answering this question can help further our understanding of what constitutes an information advantage in this market. Pasquariello and Vega (2007) point out two main sources of information in the Treasury market: one based on private information about future demand shocks (e.g., a dealer may know of a large incoming order by one of its mutual fund clients) and the other based on the ability to process and interpret publicly available information better and faster.

While we do not have data to test for the presence of the first source of information, the Treasury market provides a great laboratory for studying the second source of information advantage. Important macroeconomic announcements and monetary policy decisions present shocks in public information and are publicly released at pre-scheduled times. If some traders derive an information advantage from public information, we expect to see trading and/or limit order activities more informative around these events. Indeed, Green (2004) shows that the information content of trades increases following 8:30 macroeconomic announcements. Our analysis adds to this line of inquiry by examining the price impact of not only trades but also limit orders around these information events, given that limit order activities constitute an increasingly large share of market activity.

For our analysis, we focus on two types of announcements: rate decision announcements by the FOMC and 8:30 macroeconomic reports. We focus on the five most important of these reports, as documented in Faust et al. (2007), comprised of employment, retail sales, GDP, CPI, and PPI. Our approach is to quantify the price impact of trades and limit orders during a short period before and after these announcements, and compare with that computed for the same time windows on non-announcement days. Any evidence of increased private information prior to announcements would suggest that some information advantage comes from the ability to forecast the market ahead of public news arrival. On the other hand, evidence of increased private information after announcements would suggest that some traders can better interpret the implications of public news.

5.1. FOMC announcements

FOMC announcements communicate the Federal Reserve's monetary policy decisions and are key information events for the formation of Treasury security prices. Fleming and Piazzesi (2005) document that these events precipitate high price volatility, high trading volume, and wide bid-ask spreads.[29] During our sample period, there are 16 announcements following FOMC meetings, three of which occurred at about 12:30, and the rest of which occurred around 14:15. We collect the exact time at which the announcements reached the market using the time stamp of the first news report in Bloomberg. We focus

[29] Gao and Mizrach (2018) show that price impact in the equity market rose substantially following regularly scheduled Permanent Open Market Operations during the Federal Reserve's first large-scale asset purchase program.

on the 60-minute intervals before and after these announcements. The pre-announcement interval finishes at the second immediately before announcement time, and the post-announcement interval starts the second immediately after the announcement time. We choose the same time window on the five days preceding and five days following each FOMC announcement to serve as the non-announcement counterpart, effectively controlling for time-of-day effects and general market conditions.

We estimate model (3) using data in the pre- and post-announcement windows on FOMC days and in the comparable windows on non-FOMC days. In Table 8, Panel A, we report the price impact differentials following FOMC announcements as compared to non-announcement days (expressed in percentage of the latter). The results in columns (1)–(4) show that the price impact is higher following FOMC announcements for all types of orders, as indicated by most numbers being positive and significant. Four of the six securities experience an increase in the average price impact of buy trades in the 48–118% range. Meanwhile, for all six securities, sell trades result in average permanent price impact that is 24–134% higher than normal, depending on security.

Moreover, and perhaps more strikingly, the increase in the price impact of limit orders after FOMC announcements is much more pronounced than the corresponding increase in the price impact of trades. This can be seen by comparing the percentage increase in the price impact of bid limit orders from column (3) with that of buy trades from column (1), and similarly that of ask limit orders from column (4) with that of sell trades from column (2). The former is almost always greater than the latter. For the 2-year note for example, the price impact of buy trades is 56% higher than on non-announcement days, while that of bid orders is 140% higher. The extent of the increase in the price impact of limit orders is as high as 460%. The evidence implies that in the post-FOMC information environment, disproportionally more information is conveyed through limit orders.[30]

With respect to the time period immediately before FOMC announcements, there is presumably heightened uncertainty with regard to the actual information to be released at announcement time. It is therefore natural to expect the permanent price impact of trades and limit orders to be also higher as compared to the same window on non-FOMC days. Indeed, the results, reported in Panel B in Table 8, indicate that there is generally greater information content of trades and limit orders in the 60 minutes leading up to FOMC announcements, as compared to that on non-FOMC days. However, the increase in price impact is more moderate, and not as widespread, as that in the post-announcement period.

Considering Panels A and B in Table 8 together, it appears that the post-FOMC price impact is generally higher than its pre-FOMC counterpart, especially for limit orders. Unreported tests (available upon request) confirm that the differences are statistically significant in many cases. One might think that the announcements would clear out any uncertainty among market participants with respect to the public information revealed. Accordingly, adverse selection should be lower after such announcements. However, our results indicate that uncertainty is not completely and immediately resolved upon announcement releases. Instead, the continued (and increased) informativeness of trades and limit orders in the 60-minute period following FOMC announcements suggests that an information advantage does not cease with the announcements and that some market participants continue to derive an information advantage from the announced public information.

5.2. Macroeconomic announcements

The releases of macroeconomic reports are also major public information events in the Treasury market. Faust et al. (2007), among others, show that the release of employment, retail sales, GDP, CPI, and PPI reports affects U.S. interest rates significantly. Accordingly, these announcements provide another valuable opportunity to examine whether some market participants can derive valuable insights from pre-scheduled public information announcements.

Since the examined macroeconomic reports are released monthly, there are 120 announcements in total over our two-year sample period. Similar to the FOMC analysis, we compute the permanent price impact of trading and limit order book activities in the 60-minute period before and after these announcements. Given that these announcements are all released at 8:30, our pre-announcement period is from 7:30 to 8:30, and our post-announcement period is from 8:30 to 9:30. For comparison, the "control group" consists of days in our sample period without any announcements between 7:00 and 9:59 (there are 113 such days). We report the results in Table 9.

Panel A in Table 9 shows the extent to which the post-announcement price impact exceeds that usually observed on non-announcement days during the same time interval (i.e., 8:30–9:30). While the incremental price impact is mostly small or even negative for buy trades, we observe positive and significant increases in price impact for sell trades and limit orders in most cases. The increase ranges from 1% to 23%. The extent of the increase is clearly smaller than that which occurs after FOMC announcements.

A similar comparison for the pre-announcement period is shown in Panel B in Table 9. Here, the evidence is more indicative of lower price impact leading up to the announcements than that observed on non-announcement days. It is a rather puzzling result in that the uncertainty leading up to these announcements should be conducive to exploitation of information asymmetry. It is perhaps harder to forecast reliably these macroeconomic reports ahead of announcement times

[30] Unreported analysis of market depth and bid-ask spreads in the period immediately after FOMC announcements reveals that spreads are significantly wider while market depth is significantly lower than usual. Placing a limit order in such market conditions arguably allows those traders who have an advantage in rapidly processing public information to better monetize their information advantage, as compared to placing a market order.

Table 9
Price discovery around 8:30 macroeconomic announcements.

Security	Buy	Sell	Bid	Ask	# of Observations	
					Ann.	Non-Ann.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Post-Announcement Incremental Price Impact						
2-Year	31% *	12% *	−17% *	22% *	30,502	8,760
3-Year	1% *	11% *	23% *	11% *	46,995	13,165
5-Year	−8% *	13% *	23% *	−8% *	100,496	30,584
7-Year	−20% *	14% *	10% *	−4% *	56,467	15,598
10-Year	−12% *	−14% *	8% *	9% *	98,012	29,286
30-Year	1%	−3% *	8% *	1% *	68,834	19,713
Panel B: Pre-Announcement Incremental Price Impact						
2-Year	−10% *	−9% *	−9% *	−14% *	21,896	7,929
3-Year	−3% *	7% *	2% *	−6% *	29,028	10,438
5-Year	4% *	−12% *	−17% *	0%	66,913	24,005
7-Year	12% *	−15% *	23% *	−13% *	31,879	11,281
10-Year	12% *	−6% *	−15% *	1% *	65,725	23,787
30-Year	−8% *	−19% *	−21% *	−9% *	37,726	12,936

This table reports changes in the price impact of trades and limit orders in the 60 minutes before and after five important 8:30 macroeconomic announcements as compared to the same intervals on non-announcement days. The five announcements considered are employment, retail sales, GDP, CPI, and PPI. Panel A shows the incremental price impact in the 60-minute post-announcement period on announcement days as compared to non-announcement days, expressed in percentage of the latter. Panel B shows a similar comparison for the 60-minute period before these announcements. Price impact estimates are based on a VAR(5) model of buy trade volume, sell trade volume, bid limit order flow, ask limit order flow, and return (based on the best bid-ask midpoint). Estimation is based on BrokerTec tick data around these announcements and a similar time interval on non-announcement days over the 2010–2011 sample period. Non-announcement days are days for which there is no announcement between 7:00 and 9:59. An asterisk (*) indicates significant difference at the 5% level. Tests of difference in mean are based on bootstrap samples of price impact estimates with 1000 replications.

to derive some information advantage and form a basis for trading and limit order activities. Therefore, market activities in the pre-announcement period might be disproportionately liquidity-motivated.[31]

Finally, similar to our FOMC analysis, we compare the incremental price impact between the post- and pre-announcement periods.[32] Consistent with the FOMC results, we find evidence of a higher price impact in the post-announcement period, as supported by 17 positive and significant statistics out of 24 tested pairs. Both results indicate that trading and limit orders contain relatively more information *after* announcements than *before* announcements.

5.3. Additional analysis

The preceding analysis shows increased information content of trades and limit orders after announcements, suggesting the presence of private information. A key question arises as to the nature or source of this private information. If private information is indeed derived from the announced public information, we would expect to see this private information being exploited right after the announcements. This is because, as Hasbrouck (1991a, p. 189) notes, the value of the information advantage generally dissipates over time, so there is an incentive for those traders who possess such an advantage to trade as soon as possible after the announcements.

This intuition allows us to formulate a formal test for possible information decay following announcements as follows. We estimate the VAR model over three post-announcement window lengths: 30 minutes, 60 minutes, and 90 minutes. We then test to see whether the average price impact estimated over the 30-minute window is greater than that for the longer 60-minute window, and similarly with the 60-minute window versus the 90-minute window. If the conjecture discussed above were true, we would expect that the price impact estimated over shorter periods after announcements would be *higher*. The results, which are reported in Tables 3 and 4 in the Online Appendix, are highly indicative of information decay following announcements, suggesting that the increased information content of trades and limit orders after announcements reflects an information advantage derived from the announced public information.

This finding is further corroborated by our analysis of trade size, the use of iceberg orders, and workups around these information events, the details of which are provided in Tables 6–8 in the Online Appendix. Larger trade sizes following announcements could indicate increased trading demand, perhaps coming from traders who possess some information advantage related to the just announced public information. Likewise, there is a greater incentive for those with better information to use hidden liquidity channels, namely iceberg orders and the workup protocol. If so, the use of such channels is expected to increase in the post-announcement periods. Indeed, the results provide support for the increased presence of private information after announcements.

[31] It is also possible that the expectation of an announcement induces traders to arrive earlier in the day (given that the announcement time is 8:30) and perhaps fine-tune their positions in advance of the announcement, both of which might benefit liquidity.

[32] Formal test results are available upon request.

6. Conclusion

The microstructure of the U.S. Treasury securities market has changed markedly in recent years, with trading activity migrating from voice-assisted brokers to fully electronic platforms. We use tick data from one of these platforms, BrokerTec, over the 2010–2011 sample period, to reassess market liquidity. We find that the market is more liquid than that found by earlier studies using data from the voice-assisted brokers, with much greater depth, higher trading activity, and bid-ask spreads that are narrow (and often constrained by the minimum tick size). Our price discovery analysis reveals that the price impact of trades is generally quite small in magnitude, supporting the common belief that the U.S. Treasury market is highly liquid and that information-based trading in this market is limited. A one standard deviation shock in trade order flow moves the price permanently by about 0.2–0.3 standard deviations of the trade-to-trade price change.

In addition, we show that limit orders also contribute to the price discovery process. Although the price impact of limit orders is generally smaller than that of trades of equal size, such orders contribute more to the variance of the efficient price updates because there is much higher variation in limit order activities than trades. Our evidence is consistent with O'Hara's (2015) argument that sophisticated and dynamic trading strategies in electronic marketplaces allow traders to be much more flexible with their trading choices, and informed traders may choose limit orders over market orders to exploit their information advantage.

Our analysis also addresses a topical question with regard to the impact of order cancellations. With cancellation rates averaging above 95%, a natural question to ask is whether these cancellations have a significant impact on price discovery. We show that cancellations have a significant price impact, but that the impact is somewhat smaller than that of order submissions. Consistent with earlier findings for equity markets, our results suggest that submissions, which tend to reflect an active undertaking by traders, are more likely induced by information than cancellations, which might more commonly be in response to changes in market conditions.

To further our understanding of the nature of "private information" in the Treasury securities market, we quantify and examine the information content of trades and limit order activities around important public information events, including FOMC and key macroeconomic announcements. We find that the price impact of trades and limit orders increases in the 60-minute period immediately following such announcements, compared to both non-announcement days and the corresponding pre-announcement period. Moreover, the increase in information content tends to be proportionately greater for limit orders than it is for trades. Our findings suggest that there are valuable insights to be gained from interpreting public information better (or faster) than other market participants, and that this information is disproportionately exploited through limit orders.

Overall, we highlight how the electronic market for trading in U.S. Treasury securities differs from its voice-assisted predecessor and from other markets studied in the literature. Compared to the voice-assisted trading system, the electronic market facilitates a much higher frequency and volume of trades and limit order activities, resulting in greater competition for liquidity provision and thus lower bid-ask spreads and market impact. The electronic market also makes it easier for traders to dynamically manage limit orders, and such orders are shown to also contribute to the price discovery process. These findings contribute to the growing discussion on the changing structure of securities markets and the effects of electronification.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.finmar.2017.05.004.

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