The Microstructure of a U.S. Treasury ECN: The BrokerTec Platform
Michael J. Fleming, Bruce Mizrach, and Giang Nguyen
Federal Reserve Bank of New York Staff Reports, no. 381
July 2009; revised May 2014
JEL classification: G12, G14, C32

Abstract

We assess the microstructure of a U.S. Treasury electronic communications network (ECN) and show that limit orders as well as trades affect prices, with greater effects following announcements by the Federal Open Market Committee. We also find that use of iceberg orders, a form of hidden liquidity, is less common than in equity markets. Using logistic regression, we find support for the hypothesis that iceberg orders are used to prevent information leakage and mitigate adverse selection risk. However, volatility and iceberg order use are negatively linked, likely reflecting market participants’ preference for an alternative channel of hidden liquidity that gives them greater control over order exposure and execution.

Key words: microstructure; Treasury market, bid-ask spread, price impact, hidden orders

Fleming: Federal Reserve Bank of New York (e-mail: michael.fleming@ny.frb.org). Mizrach: Rutgers University (e-mail: mizrach@econ.rutgers.edu). Nguyen: University of North Carolina at Chapel Hill (e-mail: gnguyen@email.unc.edu). We thank Bruno Biais, Peter Dunne, Sergio Ginebri, Frank de Jong, Carol Osler, Jennifer Roush, and seminar participants at the Bank of Canada, the Third Annual Central Bank Workshop on the Microstructure of Financial Markets, the Federal Reserve System Conference on Financial Markets and Institutions, the Fourth MTS Conference on Financial Markets, and the University of Cambridge conference High Frequency Dynamics and Bond Markets for helpful comments. We thank Nicholas Klagge, Neel Krishnan, Michal Lementowski, and Weiling Liu for invaluable research assistance. We also thank Arthur D'Arcy, Dan Cleaves, and Stuart Wexler from ICAP for clarifying how the BrokerTec platform works. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.
1 Introduction

Since the early 2000’s, trading in the U.S. Treasury securities market has migrated from voice-assisted brokers to fully electronic platforms (Mizrach and Neely (2006)). For the most recently auctioned securities in particular, the transition has been nearly complete, with nearly all interdealer trading now taking place via one of two electronic communications networks, BrokerTec and eSpeed (Barclay, Hendershott, and Kotz (2006)). BrokerTec accounts for about 60% of trading activity (based on comparison with earlier studies using data from eSpeed).

This paper assesses the microstructure of the U.S. Treasury securities market using tick data from BrokerTec. It is the first paper to closely study a U.S. Treasury market electronic communications network (ECN) and one of the first to analyze any fixed income market ECN. Many previous papers have examined the microstructure of the Treasury market using data from GovPX, which consolidates data from voice-assisted brokers. The migration of bond trading to the electronic platforms (which do not contribute to GovPX) has sharply reduced GovPX coverage of the interdealer market, as noted by Boni and Leach (2004) and others. The breadth of the BrokerTec tick data allows us to provide a comprehensive analysis of the market’s microstructure as orders enter and leave the order book, and characterize market liquidity beyond the inside tier for the first time. This is an important improvement.

\footnote{Campbell and Hendry (2007) examine price discovery in the 10-year 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 (e.g., Cheung, de Jong, and Rindi (2005), Menkveld, Cheung, and de Jong (2005), and Beber, Brandt, and Kavajecz (2009)). In addition, since the first draft of this paper, there are several studies that look at different aspects of this market, including Dungey, Henry, and McKenzie (2013) for trade duration on eSpeed, Engle, Fleming, Ghysels, and Nguyen (2012) for intraday dynamics of market liquidity and volatility on BrokerTec, and Fleming and Nguyen (2013) for the order flow segmentation induced by the workup protocol on BrokerTec and the informational content of workup and non-workup trades.}

as the BrokerTec data shows that the inside tier depth is often not greatest in the book, and accounts for only a small fraction of the book’s total depth.\(^3\)

In addition, 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. Coupled with the rise in electronic trading is a newly emergent trend in high frequency and/or algorithmic trading, the so-called “rise of the machines” (Chaboud, Chiquoine, Hjalmarsson, and Vega (2013)). Therefore, there is a great interest in understanding this new market structure and its level of trading activity and market liquidity from both academic and practitioner points of view.

Using tick data from 2010 to 2011, we characterize trading activity and liquidity on the BrokerTec platform for the on-the-run 2-, 3-, 5-, 7-, 10-, and 30-year Treasury securities.\(^4\) Our findings suggest a level of liquidity on the BrokerTec platform that is improving over time and markedly greater than that found by earlier studies using data from GovPX. Since BrokerTec’s inception, trading activity has grown many folds, e.g., starting at below $5 billion per day in 2001 to between $30-40 billion per day in 2011 for the 5- and 10-year notes. Over the 2010-2011 period, inside bid-ask spreads for maturities of five years or less average less than 1/100th of one percent. An average of over $300 million is available on the platform at the best price on either side for the 2-year note, $80 million for the 3-year note and in the $30 million range for each of the three remaining notes. 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.

Besides being the first paper to provide a comprehensive picture of a U.S. Treasury ECN, our paper makes two further contributions. First, while previous studies have assessed price impact using GovPX trade data (e.g. Fleming (2003), Brandt and Kavajecz (2004), and Green (2004)), we examine the price impact of not only trades but also of order book activities not

\(^3\)This fact has also been documented for equity limit order markets (e.g., Biais, Hillion, and Spatt (1995)).

\(^4\)On-the-run securities are the most recently auctioned securities of a given maturity.
previously available for the Treasury market. In fact, given the sheer amount of limit order book activities in comparison to trades, there is a lot to be learned about how these activities affect price dynamics. Furthermore, limit orders are often considered as supplying liquidity and market orders consuming it. Accordingly, it is important to delineate the response of price to shocks in liquidity supply from that to shocks in liquidity demand.

We first calculate the permanent price impact of trades following the framework in Hasbrouck (1991). We then extend this model to include limit order flow, separately for the bid and ask sides. The paper builds upon earlier studies of equity markets that incorporate order book information into the market impact function (e.g., Engle and Patton (2004), and Mizrach (2008)). A recent paper by Hautsch and Huang (2012a) uses a vector error correction model to analyze the dynamics of the limit order book for select NASDAQ stocks, and compute the price impact of orders of different types, sizes, and levels of price aggressiveness. They show that limit orders also have significant market impact.

We find that the price impact of trades on BrokerTec is quite small, but increases in maturity of the securities considered, ranging from 0.006/256th for the 2-year note to 0.450/256th for the 30-year bond per $1 million buyer-initiated volume. Equivalently, it takes about $182 million in signed trading volume to move the price of the 2-year note by 1/256th of one percent of par, whereas the required volume is only $2.2 million to move the price of the 30-year bond by the same amount. Moreover, limit order activities affect prices, and play an especially large role in the price dynamics of longer-dated maturities. Accounting for the impact of limit order activities on trading activities and price dynamics, the price impact of trades is about 9-14% lower for the 2-, 5-, 10-, and 30-year securities, and 26% and 40% lower for the 3- and 7-year notes, respectively. Our analysis also shows that trades and especially limit orders have a larger price impact immediately following Federal Open Market Committee (FOMC) rate decision announcements.

Another contribution lies in our analysis of hidden liquidity in the form of iceberg orders. The ability to enter “iceberg” orders (partially hidden orders) on the BrokerTec platform

3
allows analyses not heretofore possible for Treasury securities.\textsuperscript{5} Hidden orders in equity markets have been examined by Harris (1996), Aitken, Berkman, and Mak (2001), Hasbrouck and Saar (2002), Anand and Weaver (2004), Tuttle (2006), De Winne and D’Hondt (2007a), De Winne and D’Hondt (2007b), Bessembinder, Panayides, and Venkataraman (2009), Pardo and Pascual (2012), and Hautsch and Huang (2012b), among others. We add to this literature by providing the first analysis of iceberg orders in the trading of Treasury securities. In particular, we study traders’ order submission decision and explore whether certain order characteristics as well as prevailing market conditions might help predict the likelihood as well as the extent of hidden size of an iceberg order.

Several of our findings are consistent with the equity market evidence. For example, the use of hidden depth increases with order size and the prevailing bid-ask spread, intuitively highlighting the benefit of hidden orders as a mechanism to prevent information leakage and mitigate adverse selection risk. Additionally, when there is lower prevailing depth or lower likelihood of future orders whose display size will take precedence over the current hidden size, hidden orders tend to be used more often, as the cost of using them in terms of execution probability is lower.

Perhaps more valuable is our contribution of findings that are novel to the U.S. Treasury market. We find that iceberg orders are used much less often than in other markets examined in the literature. Typically iceberg orders account for less than 2\% of order flow in the Treasury market, compared to 18\% for stocks on Euronext-Paris (Bessembinder, Panayides, and Venkataraman (2009)), and 9\% for 30 German blue chip stocks on Deutsche Borse’s Xetra platform (Frey and Sandas (2012). Furthermore, contrary to the evidence documented in Bessembinder, Panayides, and Venkataraman (2009) that traders are more likely to use iceberg orders when they select a more aggressive limit order price, Treasury traders are generally less likely to do so for quote improving orders, except for the less liquid 7- and 30-year securities.

\textsuperscript{5}Iceberg orders are not used on eSpeed, the other electronic platform for trading U.S. Treasury securities, leaving BrokerTec the only venue to study traders’ choice with respect to such hidden orders.
Another interesting finding of our paper is that volatility and hidden order usage are negatively linked. At first blush, the finding seems counter-intuitive, as it suggests that the more volatile the market, the less likely that hidden orders will be used, precisely when traders need greater protection. However, if we place this finding in the context of the Treasury market, in which there exists another mechanism for order exposure management, namely the workup protocol, we can better understand how it could be the case for this market. The workup protocol gives market participants the ability to workup order sizes if and when desired, whereas iceberg orders can be adversely executed when the market is moving so fast that traders cannot cancel soon enough. As documented in Fleming and Nguyen (2013), workups tend to be used more frequently in more volatile times, undermining the popularity of iceberg orders. Likewise, hidden orders are used less often around the release of key macroeconomic reports, FOMC rate decision announcements, and Treasury auctions. These are moments when the market is eagerly waiting for and trading on the newly released announcements, so priority in the order queues seems to be an important consideration.

Overall, our paper highlights how the electronic market for trading in U.S. Treasury securities differs from its voice-assisted precedent and from other markets studied in the literature. Comparing with the voice-assisted trading system, the electronic market facilitates a much greater 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. Comparing with other market setups, the high level of market liquidity and the presence of the more preferred protocol to manage order exposure in this market are likely related to the lower usage of iceberg orders and the seemingly greater importance of execution probability in traders’ decisions.

The paper proceeds as follows. Section 2 describes the structure of the interdealer Treasury market. Section 3 describes the BrokerTec data, characterizing trading activity and liquidity in the market. Section 4 presents the VAR model of returns and trades, and discusses a number of specifications and the resulting estimates of the price impact of trades. In Section
5, we add order book information to the model and quantify the price impact of limit orders. Section 6 presents our analysis of hidden orders. Section 7 concludes.

2 Market Structure

The secondary market for U.S. Treasury securities is a multiple dealer, over-the-counter market. The predominant market makers are 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 week, although we find that slightly over 90% of trading occurs during New York hours, roughly 07:00 to 17:30 Eastern time (comparable with what Fleming (1997) finds using GovPX data).

Until 1999, nearly all trading in the IDB market for U.S. Treasury securities 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. In compensation for their services, brokers charge a fee.

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. 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.

In June 2000, BrokerTec Global LLC, a rival electronic trading platform, began operations. BrokerTec had been formed the previous year as a joint venture of seven large fixed income
dealers. BrokerTec was acquired in May 2003 by ICAP PLC. Mizrach and Neely (2006) describe the migration to electronic trading in greater detail, and Mizrach and Neely (2011) provide a summary of the evolution of the microstructure in the Treasury market.

2.1 The Electronic Platforms

BrokerTec and eSpeed are fully automated electronic trading platforms where buyers are matched to sellers without human intervention. A comparison of BrokerTec trading activity with that of eSpeed reported in Luo (2010) and Dungey, Henry, and McKenzie (2013) shows that BrokerTec accounts for around 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.

The brokers provide electronic screens which display the best bid and offer prices and associated quantities. On BrokerTec, for example, a manual trader can see five price tiers and corresponding total size for each tier on each side of the book, plus individual order sizes for the best 10 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.

The BrokerTec platform operates as an electronic limit order market. Dealers send in orders that can be aggressive (market orders) or passive (limit orders), but they must all be priced. The minimum order size is $1 million par value. Dealers can enter aggressive orders at a price worse than the current best price. This is typically the case when dealers need 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 (below 0.5%). This is likely due to the large amount of depth usually available at the best price tier, and the ability to work up volume at a given price point.
The BrokerTec platform allows traders to enter 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.

The priority of execution of limit orders is based on price, display status and time. That is, limit orders with better prices have higher priority of execution. Displayed limit orders in the same price queue are executed on a first in, first out basis. Once all displayed depth at a particular price level is exhausted, hidden depth at that same price – if there is any – is then shown and executed.

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. 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. For a detailed analysis of workup activity in this market, see Fleming and Nguyen (2013).

2.2 The Voice-Assisted Brokers: GovPX

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.

---

6Boni and Leach (2004) provided a thorough explanation of this feature in the voice-assisted trading system. This 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.

7For a detailed description of the workup process on the BrokerTec platform, see “System and Method for Providing Workup Trading without Exclusive Trading Privileges”, U.S. Patent number US8,005,745B1, dated August 23, 2011.
Information provided 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 that GovPX covered about two-thirds of the interdealer market. Over time, the number of brokers declined due to mergers, and a new non-contributing electronic broker (BrokerTec) was formed. By the end of 2004, GovPX was receiving data from three voice-assisted brokers, but neither eSpeed nor BrokerTec, even though nearly all trading of on-the-run securities had migrated to these fully electronic brokers. After ICAP’s purchase of GovPX in January 2005, ICAP’s voice brokerage unit was the only brokerage entity reporting through GovPX.

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 over 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. This is the most recent period for which we have available data. It is a sufficiently long sample period for a microstructure study, and relatively distanced from the 2007-2009 financial crisis, so that our analysis can provide an up-to-date characterization of the market’s microstructure in a typical trading environment. For market dynamics during the crisis period, see Engle, Fleming, Ghysels, and Nguyen (2012).

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 (a “hit”) or buyer-initiated (a “take”). It should be noted that BrokerTec records the execution of a market order against multiple limit orders, as well as further matches during workups, as separate trade records. We aggregate these multiple trade records that belong to the same workup as one market transaction for the following reasons. 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. Our treatment is in line with BrokerTec’s workup patent document which states that a workup is conceptually a “single deal extended in time”. Nevertheless, the aggregation is not without cost in that it will sometimes overestimate 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, saving as much of the richness of the data as is practical. 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 tells us the best bid and offer and associated sizes at any given time, but also the depth available outside of the first tier. Moreover, we see the number of individual orders comprising the quantities available at particular prices. In addition, we are able to discern what quantities were visible to market participants at the time and what quantities were hidden.

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 trades), 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 order book ticks per day.

3.2 Trends in Trading Activity

To provide a historical perspective of trading activity on the BrokerTec platform since its beginning in the early 2000’s, Figure 1 plots the average daily trading volume by year for the respective on-the-run coupon securities. As can be observed from the figure, there has been a sharp increase in trading activity over time, especially in the first seven 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, has remained above $30 billion since. Another interesting observation is that the 2-year note – which used to be the most actively traded security with an average daily trading volume of nearly $50 billion in 2008 – has seen lower activity since the crisis as the short rate has stayed at the zero bound. This contrasts with the post-crisis recovery observed in other securities. In 2010 and 2011, the 5-year note is the most actively traded, closely followed by the 10-year note. Trading in the other on-the-run securities is far below the level of the 2-, 5- and 10-year notes, although trading in the 3-year note rose quickly between late 2008 and 2011.

[Figure 1 – Trading Activity over Time]

Focusing on the most recent years of 2010 and 2011, Table 1 reports average daily trading volume, trading frequency and trade size 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, but the largest average trade size, nearly ten times larger than that of the 30-year bond.

Table 1 – Trading Activity

3.3 Liquidity Around the Clock

Figure 2 plots average BrokerTec trading volume by half-hour interval over the round-the-clock trading day for our six notes and bonds. 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 findings are very consistent with what Fleming (1997) finds using GovPX data from 1994, and the patterns 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 03:00 Eastern time), then picks up somewhat during morning trading hours in London. Trading then rises sharply during morning trading hours in New York, peaking between 08:30 and 09:00, 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. This pattern is probably largely explained by scheduled macroeconomic announcements (most of which are made at 08:30 and 10:00), the hours of open outcry Treasury futures trading (08:20 to 15:00), and the pricing of fixed income indices at 15:00.

Figure 2 – Round-the-Clock Trading Activity

3.4 Spreads

The most basic measure of the bid-ask spread is the quoted spread. The inside quoted spread, \( s_t \), is defined as the gap between the best (lowest) ask price, \( p_a^t \), and the best (highest) bid
price, \( p^b_t \), i.e.:

\[ s_t = p_t^b - p_t^b. \]

The middle column of Table 2 shows the average inside bid-ask spread in multiples of tick size of the relevant security.\(^8\) Spread is generally increasing in maturity, from 1.03 128ths (2.06 256ths) at the 2-year maturity to 2.66 64ths (10.64 256ths) at the 30-year maturity. The 10-year note, however, has a narrower spread than the 7-year note. An interesting feature of the BrokerTec spreads is that they are quite close to the tick size for all of the notes (but not the 30-year bond), suggesting that the minimum tick increment may be constraining. Comparing to earlier studies using GovPX data, BrokerTec spreads are generally narrower. Fleming (2003), for example, reports average bid-ask spreads of 0.39 32nds (3.12 256ths) for the 5-year note and 0.78 32nds (6.24 256ths) for the 10-year note, whereas the corresponding BrokerTec spreads are 1.18 128ths (2.36 256ths) and 1.15 64ths (4.60 256ths) respectively for these securities.\(^9\)

Providing new information on how market depth is spaced along the price dimension beyond the inside tier, Table 2 shows the average price distance between adjacent price levels up to the fifth level in the book. All of the securities except for the 30-year bond have tightly populated order books at the first five price levels: adjacent depths are roughly one tick apart, although they get slightly wider further away from the inside tier.

[Table 2 – Average Bid-Ask Spread and Inter-Tier Price Distance]

To supplement the information provided in Table 2, we show in Figure 3 the frequency distributions of inside spreads for the six securities. Immediately apparent from the figure is the high degree of clustering of inside spreads at one tick, except for the 30-year bond whose distribution is more spread out at wider spread levels and peaks at two ticks. In particular,\( ^8 \)The tick size for the 2-, 3-, and 5-year securities is 1/128\(^{th}\) of one percent of par and that for the 7-, 10- and 30-year securities is 1/64\(^{th}\) of one percent of par.\( ^9 \)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.
nearly 97% of inside spreads for the 2-year note are 2/256ths, another 3% are 4/256ths, and the negligible remainder is split between 0/256ths and above 4/256ths. Zero spreads, or “locked” markets, are possible, albeit infrequent, because prices exclude the brokerage fee, and because passive limit orders at the same price are not automatically executed against one another.

[Figure 3 – Frequency Distribution of Inside Spread]

3.5 Market Depth

As a limit order market, liquidity on BrokerTec is supplied by limit orders submitted by market participants. Table 3 reports the total visible quantity of limit orders available on average at the best price level, the best five price levels, and across all price levels on each side of the market. Market depth is generally declining in maturity, 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. It is interesting to observe that while being the most actively traded, the 5- and 10-year notes’ market depth is on the lower end, averaging $26-31 million, suggesting a higher replenishment rate of liquidity to meet the high trading activity level. 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).

In addition, earlier studies using GovPX data are limited to the inside tier, leaving market liquidity beyond the first tier unknown. As Table 3 shows, 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 $470 million for the 3-year note, in the range of $210-280 million for each of the 5-, 7- and 10-year note, 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 disproportionally large amount of
depth, given that there are typically around 16-18 price tiers on each side (slightly higher for the 5- and 10-year notes). The maximum number of price levels on one side during our sample ranges from 43 for the 30-year bond (on the bid side) to 101 for the 2-year note (on the ask side).

[Table 3 – Limit Order Book Depth]

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 display a depth histogram of the order book in Figure 4. The figure illustrates again that order book depth outside the first tier is considerable. A notable feature of the depth distribution patterns is 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, Hillion, and Spatt (1995) also find depth lower at the first tier than the second tier, but find similar depths at the second through fifth tiers.

[Figure 4 – Displayed and Hidden Liquidity at the First Five Tiers]

3.6 Hidden Depth

In addition to information on visible depth at the best five tiers, Figure 4 also shows information on hidden depth. Hidden depth is only a small share of total depth at each price tier on average. The first tier has proportionally more hidden depth than other tiers. Among the securities, the 30-year bond has a greater share of depth that is hidden from view.

Next, we examine more closely the extent of hidden depth at the inside tier as well as across all tiers, and report the results in Table 4. The column “Full Sample” shows the percentage of hidden depth calculated across all five-minute snapshots over the whole sample period, representing an unconditional estimate of the extent of hidden depth. We then
compute the percentages over only those snapshots when there is positive hidden depth (column “Hidden>0”). The percentages of those snapshots with positive hidden depth are reported in column “% of Obs.”. These numbers indicate the probability of having hidden depth in the order book at any given time.

[Table 4 – Unconditional and Conditional Percentage of Hidden Depth]

Since the results are quite similar between the bid and the ask side (although the numbers on the ask side are slightly lower), we discuss the findings for the bid side only. We find that on the bid side, hidden depth as a share of total depth at the inside tier is roughly in the vicinity of 10% for the 2-, 3-, 5-, and 10-year notes. The extent of hidden depth is particularly low at the 7-year maturity (just under 4%). In contrast, the share of hidden depth for the 30-year bond is far larger, about 23%. In terms of how likely it is for the inside tier to have hidden depth, the 2-year note is at the top with a 45% probability, followed by a nearly 25% probability for the 3-year. When there is hidden depth, the percentage hidden can be quite high, and in the extreme case of the 30-year bond, the average percentage reaches nearly 70%. The 7-year remains at the lower extreme in terms of both the extent and the likelihood of having hidden depth. When analyzing the overall percentages of hidden depth across the whole book, the numbers are much smaller, indicating that depth outside the first tier contains relatively less hidden depth. This finding is consistent with the belief that there is a greater need to hide exposure of orders closer to the market.

4 Price Impact of Trades

In this section, we quantify the price impact of trades as the long run cumulative response of price to a unit shock in trades, following Hasbrouck (1991). This framework allows us to approximate the permanent price impact of trades that incorporates any delayed response and that is not contaminated by transitory effects. Accordingly, it provides a measure for the informational content of trades in this market.
Specifically, we estimate a structural VAR model with five lags for a vector of endogenous variables that consist of return and trade-related variables. We measure returns as changes 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 trade-related 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 within the endogenous variable vector. We will explain the chosen direction of contemporaneous effects when we present specific model estimates in subsequent subsections. The model is estimated by Seemingly Unrelated Regressions (SUR).

Based on the estimated dynamics of return and trade-related variables, we then compute the impulse response function (IRF) to a unitary shock in trade, that is,

\[
\frac{\partial r_{t+h}}{\partial X_t}.
\]

We compute the IRF out to 50 transactions after the shock \((h = 50)\).\(^{10}\) The permanent price impact is approximated by the cumulative return over this horizon.

We consider a number of specifications so as to gain a deeper understanding of how trading affects price dynamics, such as the extent to which trade direction contributes to price impact, both by itself and in conjunction with trade size. We present each specification and the corresponding price impact estimates in turn below.

\(^{10}\)Visual inspection of the IRF indicates that the 50-tick horizon is sufficiently long for the IRF to stabilize.
4.1 Baseline Specification

We begin the estimation of market impact with a bivariate VAR of return and order flow \( q_t \). We consider two alternative measures of order flow. The first is the direction of trade initiation \( x_t \) with a buy order signed +1 and a sell order signed -1. Trade initiation is recorded in the BrokerTec dataset, so all trades are classified properly. The second is the signed volume \( x_t V_t \) where \( V_t \) is the actual volume of the \( t^{th} \) transaction.

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 order flow contemporaneously affects return, but not vice versa. Accordingly, the model specification is:

\[
\begin{pmatrix}
1 & -\alpha_{12} \\
0 & 1
\end{pmatrix}
\begin{bmatrix}
r_t \\
q_t
\end{bmatrix}
= \sum_{j=1}^{5} B_j \begin{bmatrix}
r_{t-j} \\
q_{t-j}
\end{bmatrix}
+ \begin{bmatrix}
r_{q,t} \\
q_{q,t}
\end{bmatrix},
\]

(1)

where \( B_j \) are \((2 \times 2)\) matrices. We estimate model (1) separately for \( q_t = x_t \) and \( q_t = x_t V_t \).

The permanent price impact estimates from model (1) are reported in Table 5. Under the column titled “Trade Direction” is the price response across maturities to a buyer-initiated trade (i.e., computed from the specification with trade initiation), while the column “Signed Trade Volume” shows the response to a $1 million shock in buyer-initiated trade flow (i.e., computed from the specification with signed trade volume). The price impact rises with maturity, except for the 7-year note which has a higher price impact than the 10-year note in the model using signed trade volume. A buy market order results in a permanent price increase, ranging from 0.357/256th for the 2-year note to 2.921/256th for the 30-year bond.

Since transaction size varies across maturities, a better cross securities comparison may be obtained by looking at the price impact per $1 million shock in the order flow of the respective
securities. A $1 million increase in buyer-initiated trade flow moves the 2-year note’s price by 0.006/256th, or alternatively, it takes about $363 million increase in buyer-initiated transaction volume to move the price by one tick (or 2/256th). The 30-year bond is much less liquid: a $1 million shock in the buyer-initiated order flow permanently increases the price by 0.450/256th, or equivalently, only $8.9 million is needed to move the price by one tick (or 4/256th).

[Table 5 – Baseline Price Impact of Trades]

4.2 Separate Effects of Trade Direction and Size

In the spirit of Hasbrouck (1991), we also estimate a specification that incorporates both trade direction and size in order to explore their respective market impact:

\[
\begin{bmatrix}
1 & -\alpha_{1,2} & -\alpha_{1,3} \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
r_t \\
x_t \\
xV_t
\end{bmatrix}
= \sum_{j=1}^{5} B_j \begin{bmatrix}
r_{t-j} \\
x_{t-j} \\
xV_{t-j}
\end{bmatrix}
+ \begin{bmatrix}
u_{r,t} \\
u_{x,t} \\
u_{xV,t}
\end{bmatrix}.
\]

Based on the model estimates, we compute the permanent price impact of trade direction and the marginal market impact of trade size beyond the minimum size.

We report the results in Table 6. The first column shows the price impact of a minimum-sized trade ($1 million), which ranges from 0.271/256th for the 2-year note to 2.378/256th for the 30-year bond. From here, price impact increases directly with trade size. Essentially, this specification disentangles the price impact of trade into two separate components: a “fixed” component due to trade initiation and a “variable” component that scales directly with the volume of the trade. For example, for a $100 million buyer-initiated transaction in the 10-year note, the buy direction increases price by 1.033/256th, and the $99 million increment in trade size from the $1 million minimum increases price by an additional 3.265/256th, for a total price impact of 4.298/256th.
To entertain the possibility that the price impact of trade size does not increase linearly in trade size beyond the minimum size, we explore a further specification that allows for the non-linearity of trade size by incorporating signed trade volume squared in the system, as in Hasbrouck (1991). Specifically,

\[
\begin{bmatrix}
1 & -\alpha_{1,2} & -\alpha_{1,3} & -\alpha_{1,4} \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
r_t \\
x_t \\
xV_t \\
V^2_t \\
\end{bmatrix}
= \sum_{j=1}^{5} B_j
\begin{bmatrix}
r_{t-j} \\
xV_{t-j} \\
V^2_{t-j} \\
\end{bmatrix}
+ \begin{bmatrix}
u_{r,t} \\
u_{x,t} \\
u_{xV,t} \\
u_{V^2,t} \\
\end{bmatrix}.
\]

We plot the permanent price impact calculated from this model for varying trade sizes in Figure 5. It is clear from the figure that price impact is increasing in trade size. The concavity of the price impact function of the notes is quite mild, almost visually indistinguishable from linearity for the notes, especially the 2-year note whose price impact is already very small. Only the 30-year bond demonstrates a pronounced concavity in the price impact function. Parameter estimates (not shown) reveal that the squared trade size variable has a significant and negative contemporaneous effect on mid-quote return for all notes and bonds, but the magnitude is overwhelmed by the positive effects of trade direction and size. This suggests that a very large trade size is required for the concavity effect of price impact to kick in. We are able to see the concavity of the price impact function for the 30-year bond as trade size in this bond is typically very small ($3 million).

4.3 Asymmetric Effects of Buys and Sells

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

\[
\begin{bmatrix}
1 & -\alpha_{1,2} & -\alpha_{1,3} \\
0 & 1 & 0 \\
0 & 0 & 1 
\end{bmatrix}
\begin{bmatrix}
\tilde{r}_t \\
\tilde{V}B_t \\
\tilde{V}S_t 
\end{bmatrix}
= \sum_{j=1}^{5} B_j \begin{bmatrix}
\tilde{r}_{t-j} \\
\tilde{V}B_{t-j} \\
\tilde{V}S_{t-j} 
\end{bmatrix}
+ \begin{bmatrix}
\tilde{u}_{r,t} \\
\tilde{u}_{V}B_{t} \\
\tilde{u}_{V}S_{t} 
\end{bmatrix},
\] (4)

where \( \tilde{V}B \) and \( \tilde{V}S \) are the buy and sell transaction volume respectively. For buyer-initiated transactions, \( \tilde{V}B_t \) is equal to the transaction volume and \( \tilde{V}S_t = 0 \) (and vice versa for seller-initiated transactions).

The permanent price impact estimates are reported in Table 7. The estimates are quite similar in magnitude to the baseline estimates. In addition, there is little evidence to suggest that the market responds asymmetrically to buy versus sell trade initiation.

[Table 7 – Price Impact of Buyer-Initiated versus Seller-Initiated Trades]

### 4.4 Asymmetric Effects on the Bid and Ask

Econometric modeling of the order book by Engle and Patton (2004) has stimulated interest in models which allow for a possibly asymmetric price impact on the bid and ask. Escribano and Pascual (2006) provide a detailed review of empirical evidence showing that bid and ask quotes do not adjust symmetrically after a trade. However, most prior evidence of such asymmetry is documented for equity markets. We explore if this asymmetry also prevails in the Treasury market.

We follow Escribano and Pascual (2006)’s generalization of Hasbrouck (1991)’s structural model. The model allows bid and ask prices to follow separate stochastic processes, but imposes a vector error correction mechanism through the spread. That is, bid and ask prices can follow different dynamics but cannot deviate too much from each other given the spread. Buy and sell volumes are also separated to allow for their price effects to differ. This more flexible specification allows us to explore asymmetries, if any, in the market effects of buyer-
versus seller-initiated transactions on bid versus ask prices. Escribano and Pascual (2006)'s generalization leads to the following structural vector error correction representation:

\[
\begin{bmatrix}
1 & 0 & -\alpha_{1,3} & -\alpha_{1,4} \\
0 & 1 & -\alpha_{2,3} & -\alpha_{2,4} \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\Delta p^b_t \\
\Delta p^a_t \\
x^b_t \\
x^a_t
\end{bmatrix}
= \gamma(L)s_{t-1} + \beta(L)
\begin{bmatrix}
\Delta p^b_{t-j} \\
\Delta p^a_{t-j} \\
x^b_{t-j} \\
x^a_{t-j}
\end{bmatrix}
+ \begin{bmatrix}
\upsilon^b_{p,t} \\
\upsilon^a_{p,t} \\
\upsilon^b_{x,t} \\
\upsilon^a_{x,t}
\end{bmatrix},
\]

where \(\gamma\) is a 4 x 1 vector of error correction coefficients, \(s\) is the bid-ask spread, and \(\beta(L)\) are matrices of autoregressive coefficients. The data also support a more parsimonious specification of the AR structure in which bid (ask) prices depend only upon lagged bid (ask) prices, and buys (sells) depend only upon changes in the ask (bid) prices:

\[
\begin{bmatrix}
\beta_{1,1}(L) & 0 & \beta_{1,3}(L) & \beta_{1,4}(L) \\
0 & \beta_{2,2}(L) & \beta_{2,3}(L) & \beta_{2,4}(L) \\
0 & \beta_{3,2}(L) & \beta_{3,3}(L) & \beta_{3,4}(L) \\
\beta_{4,1}(L) & 0 & \beta_{4,3}(L) & \beta_{4,4}(L)
\end{bmatrix}.
\]

The system of dynamic structural equations (5) is estimated using SUR to allow for the possible correlation among the error terms. Indeed, as shown in Escribano and Pascual (2006), they have common components and therefore cannot be treated as mutually uncorrelated. Based on the model estimates, we compute the impulse response function of bid and ask prices to a unitary shock in buy (or sell) trades by forecasting this dynamic system over a 50-tick horizon following the shock. Before the shock, the system is assumed to be at rest with constant bid and ask prices, no trades and zero spread.

Table 8 reports the cumulative impact after 50 transactions following a $1 million shock to buyer-initiated transaction volume (on the bid and ask prices), and similarly a $1 million shock to seller-initiated transaction volume (on the bid and ask prices) in that order. The evidence presented in this table again suggests that there is little difference in the impact on
bid price versus ask price induced by the same shock to order flow. Likewise, prices appear to respond similarly to a buyer-initiated order flow shock versus a seller-initiated one. In addition, the magnitudes of the price impact estimates remain quite similar to the baseline estimates, further highlighting the lack of asymmetry in the price impact of trades in this market.

[Table 8 – Bid and Ask Price Impact of Buys and Sells (VECM)]

5 Price Impact of Limit Orders

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 reported earlier, there are about 4.7 million order book changes in the best five tiers alone, overwhelmingly outnumbering trading activity (about 12,000 transactions per day across the six securities). Theoretically, Boulatov and George (2013) suggest the concept of “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 the 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 (2012a) document significant price impact of limit orders for select NASDAQ stocks. We now extend our specification to incorporate information on limit order activities. We first estimate the price impact of trades and limit orders unconditionally. We then examine the price impact of both trades and limit orders following FOMC announcements in order to shed light on how price discovery varies with the information environment.
5.1 Price Impact of Limit Orders

We modify our specification (4) by adding the visible inside bid and ask net order flow between trades:

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

where \( lb \), the bid limit order flow, is the volume of limit buy orders submitted to (positive) or cancelled 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 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 then allows for delineating the price impact of liquidity supply change from the price impact of liquidity demand change, a novel feature of our empirical exercise.\(^{11}\)

\(^{11}\)Hautsch and Huang (2012a) 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
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 Table 9. In line with the evidence on the impact of limit orders for equity markets (e.g., Hautsch and Huang (2012a)), our results show that limit order activity also leaves a permanent impact on price, although the impact is of smaller magnitude than that of trades. For example, a $1 million increase in bid limit order volume permanently raises the best bid-ask midpoint by 0.001/256th, 0.014/256th, and 0.035/256th for the 2-, 5- and 10-year notes. This implies that an increase in bid depth of $1.85 billion, $144 million and $113 million is required to raise the best bid-ask midpoint of the respective notes by one tick. In the less liquid 30-year bond, it takes as little as an $11.5 million increase in the bid limit order flow to raise the midpoint by one tick.

[Table 9 – Price Impact of Trades and Limit Orders]

Additionally, the price impact of limit orders is higher for longer-maturity securities, both in magnitude as well as in comparison with the corresponding price impact of trades. For the 2-year note, the price impact of limit orders is about one fifth the impact of market orders of equal volume. A similar comparison for the 10-year note shows that limit orders have effects that are roughly two-thirds the corresponding impact of trades. For the 30-year bond, limit orders have almost as large effects as market orders.

The results also show that including information on order book depth affects market impact estimates. In particular, across all securities, trades now show smaller price impact estimates than those estimated from earlier specifications without limit order flow (as in Tables 5 and 7). These results suggest that ignoring limit order activity overstates the price impact of trades by 9-14% for the 2-, 5-, 10- and 30-year securities. The extent of overestimation is particularly acute for the 3- and 7-year notes: 27% and 40% respectively.
5.2 Market Impact Following FOMC Announcements

As our price impact estimates are based on all transactions over our sample period, one question that can naturally arise is whether price impact varies by the information environment. For example, Green (2004) shows that the information content of trades increases following macroeconomic announcements. We explore this question by choosing FOMC announcements as an exemplified information event around which to study the extent to which price impact might differ. FOMC announcements are key information events for the formation of Treasury prices, precipitating high price volatility, high trading volume, and wide bid-ask spreads (Fleming and Piazzesi (2005)). The idea is to quantify price impact using only limit orders and transactions that take place during a short period following FOMC announcements, and compare with that computed during the same time window on non-FOMC days. The choice of the window and the “control” sample is discussed below.

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 timestamp of the first news report appearing in Bloomberg. We focus on the 90-minute intervals after these announcements. In order to avoid the effect of price jumps that typically occur at announcement times without requiring trades, as documented in Fleming and Remolona (1999), we start the post-announcement window two minutes following the actual announcement times. 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 the time-of-day effect and general market conditions.

We estimate model (6) using data in the post-announcement window on FOMC days and in the comparable window on non-FOMC days. The corresponding market impact estimates are reported in Panel A and B respectively in Table 10. Two important results

\(^{12}\)Gao and Mizrach (2013) 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.
can be observed. First, market impact is pervasively higher following FOMC announcements. The market impact of a buyer-initiated trade is about 20-40% larger than in the same time interval on non-FOMC days, except for the 10-year note and 30-year bond where the price impact is slightly weaker on FOMC days. The increase in price impact of seller-initiated trades following FOMC announcements varies more widely across securities, ranging from about 5% for the 7-year note to over 100% for the 3-year note.

[Table 10 – Price Impact of Trades after FOMC Announcements]

Secondly, and perhaps more strikingly, limit order flows have a much greater impact after FOMC announcements than during the comparable time window on non-FOMC days. For example, for the 2-year note, the price impact of limit order flow to the bid side is about triple the non-FOMC price impact, and that to the ask side increases nearly five fold. Accordingly, limit order flows become nearly as important as, or occasionally even more important than, trade flows in the price discovery process following FOMC announcements.

In order to address the concern that our comparable sample, which includes both the five days before and five days after each of the FOMC announcements, may be contaminated by the effect of these announcements, we alternatively include in the non-FOMC sample only the five days preceding each of the announcements. The results are qualitatively similar. Furthermore, we check the robustness of our estimates by varying the starting time of the window between two and five minutes after announcement times, as well as using a shorter window of 60 minutes. These sensitivity analyses all confirm the results obtained above.

6 Hidden Orders

The preceding price impact analysis characterizes market liquidity as observable by market participants. However, traders on the BrokerTec platform have the option to submit iceberg, or partially hidden, orders. The hidden quantity represents a source of liquidity that is not known to the marketplace until and unless it is later revealed in trade executions. From the
perspective of the hidden order traders, this type of order helps them manage their order exposure, reducing information leakage and front running.

To gain a more complete understanding of this market, we explore the pattern of iceberg order usage on BrokerTec and examine the effects of order characteristics and market conditions on the likelihood and hidden size of iceberg orders. Given the sheer amount of data at the order level, we choose to work with newly submitted orders to the first tier only, and for a subset of trading days in the sample, in order to keep our analysis computationally manageable. Specifically, of the 500 trading days in the sample, we randomly select 100 days for analysis.

6.1 Descriptive Analysis of Hidden Orders

Hidden order usage and some basic features of orders, whether completely transparent or partially hidden, are shown in Table 11. The number of order submissions per day varies across securities. For the 5-, 7- and 10-year notes, there are over 145,000 orders submitted to the first tier per day, on average. The 2- and 3-year notes have over 60,000 orders per day, and the 30-year bond has the lowest number of orders at 38,000 per day. While order submission activity is quite high, most of the order flow is completely visible – only about 2% or less of orders are iceberg orders. This is much lower than the extent of hidden order usage in other markets. For example, Bessembinder, Panayides, and Venkataraman (2009) report that iceberg orders on average account for 18% of order flow for stocks on Euronext-Paris.

[Table 11 – Descriptive Statistics of Normal versus Iceberg Orders]

There are several additional observations of interest from this table. First, iceberg orders tend to be several orders of magnitude larger than normal orders. For example, an average iceberg order in the 10-year note is about $11.6 million, whereas an average visible order is only $1.4 million. This finding helps reconcile the low percentage of iceberg orders with the much higher percentage of hidden depth residing in the book at any given point in time.
That is, iceberg orders, while used sparingly, tend to hide a large quantity, so the hidden depth proportion tends to be higher.

Secondly, iceberg orders tend to be more price-aggressive, as the percentage of orders placed inside the prevailing spread is higher among iceberg orders than completely visible orders. This is especially the case with the 30-year bond with over 53% of iceberg orders that are price-improving. Contributing to this result is the fact that the bid-ask spread for the 30-year bond is typically much wider than the spread for the notes, making it easier to undercut the best price.

Thirdly, the arrival rate of similar limit orders around the time of order submission shows some noticeable differences between visible and iceberg orders. Iceberg orders tend to be used when similar limit orders arrive more slowly. Given the priority rule favoring displayed depth, the hidden part of an iceberg order has lower priority than the displayed depth of future limit orders at the same price point. Accordingly, the higher the expected arrival rate of future competition, the less likely the use of iceberg orders.

6.2 Determinants of Hidden Orders

We proceed to analyze factors that might contribute to the likelihood of hidden orders in a multivariate framework. The order-level data from BrokerTec allows us to examine hidden orders directly as they enter the limit order book. This provides for a clean analysis of factors that might be driving the exposure choice. We employ a logistic model to predict the likelihood that an incoming limit order contains some hidden size, building upon the approach in De Winne and D’Hondt (2007b) and Bessembinder, Panayides, and Venkataraman (2009). The dependent variable is a binary variable that takes the value of 1 if the order is an iceberg order, and 0 otherwise.

Findings in the literature help guide our selection of explanatory variables. First, in Bessembinder, Panayides, and Venkataraman (2009) and references therein, the price aggressiveness of an order has been shown to affect the use of hidden orders. That is, more
aggressively priced orders are more likely to be iceberg orders. Since our study is concerned with only the orders coming to the first tier of the book, we measure price aggressiveness by $IMP$, an indicator variable for whether the order is improving the current best price on the relevant side.

The next explanatory variable is $SIZE$, the total size of the order (logged and standardized by its daily mean and standard deviation). This variable relates to the benefits and costs of order exposure as articulated in Harris (1997). Traders choose to expose their orders in order to attract potential counterparties who otherwise may not have known about the existence of such trading interest. However, exposing their trading interest, especially when such interest is large, can reveal useful information about trading intention and potential future price impact. Such exposure can provide free trading options to other market participants who may then take actions detrimental to the exposing traders. Accordingly, large traders may find it useful to hide part of their orders from the market.

Another possible factor in hidden order usage, as suggested by Moinas (2010), is that informed traders may use hidden orders to mitigate information leakage. As a result, it is predicted that hidden orders are more likely when adverse selection risk is higher. Following Bessembinder, Panayides, and Venkataraman (2009), we use the bid-ask spread $SPR$ (measured in basis points of the bid-ask midpoint) as a proxy for the degree of adverse selection and test whether a wider bid-ask spread is associated with a greater probability of an iceberg order and a greater hidden size. Empirically, results reported in Bessembinder, Panayides, and Venkataraman (2009) support this prediction for a sample of Euronext-Paris stocks during April 2003.

Furthermore, the state of the order book has been shown to affect the choice of order exposure. Buti and Rindi (2013) argue that uninformed liquidity suppliers use hidden orders to reduce picking-off risk and discourage undercutting in liquidity provision. This has several implications for iceberg order usage concerning the level of depth and price volatility in the order book.
On the one hand, a higher level of prevailing depth on the same side (especially relative to the order size and the prevailing depth on the opposite side) indicates a lower probability of a new limit order being picked off. That is, the greater depth queueing in front of the incoming order provides a greater protection against adverse execution of such order. This in turn reduces the need to use an iceberg order. On the other hand, fully displaying the order size and adding to the already high level of prevailing depth can potentially induce future order submitters to undercut and post price-improving orders instead of joining the current price queue. As a result, higher prevailing depth may lead to a higher probability of hidden order. Therefore, while prevailing depth on the same side, $DSAME$, is argued to be an important determinant of hidden order usage, whether it is negatively or positively linked with hidden order usage is an empirical question.

Moreover, as documented in De Winne and D’Hondt (2007b), the order book imbalance (positive-valued if the book is heavier on the same side as the order) decreases the likelihood of an iceberg order. Thus, it appears that the relative magnitude of same side depth and opposite side depth also matters in explaining hidden order usage. Our model includes prevailing depth on the opposite side of the market, $DOPP$, to explore this conjecture.

Besides the effect of depth, the degree of market volatility increases the risk of adverse execution of limit orders, thereby making hidden orders more useful in helping traders manage their order exposure and reduce the chance of being picked off. We measure this risk by $VOLA$, the prevailing five-minute realized volatility of one-second returns based on the best bid-ask midpoint.

In addition, there is abundant empirical evidence suggesting that the level of trading activity and the rate of limit order arrival in the market helps explain the use and extent of hidden orders (for example, see Bessembinder, Panayides, and Venkataraman (2009), De Winne and D’Hondt (2007b), Aitken, Berkman, and Mak (2001), and references therein). In particular, Aitken, Berkman, and Mak (2001) argue that a higher trading activity level indicates a lower expected time-to-execution of limit orders, thereby reducing the need to hide
part of a limit order as a way to mitigate the free trading option inherent in limit orders. If this argument applies, we expect to see a negative link between trading activity, as captured by $NTRANS$ – the number of transactions over the last five minutes – and hidden order usage.

On the contrary, during periods when limit orders on the same side are slow to arrive, the threat of future (displayed) limit orders taking priority over the hidden portion is lessened, resulting in higher likelihood of hidden order usage. The expected arrival rate of similar limit orders is measured by $WAIT$, the average inter-order duration (in seconds) for the last three limit orders on the same side.

Finally, we include several dummy variables to account for potential differences in the order exposure choice around the announcement of important news and overnight trading hours. In particular, $PRENEWS$ and $POSTNEWS$ are indicator variables for whether the order is submitted within the five-minute time window before and after an announcement. $OFFHR$ is an indicator variable that is equal to 1 if the order is submitted outside the New York trading hours of 7:00 to 17:30.

Our model is estimated using data on all order submissions on the 100 randomly selected days. We note that continuous explanatory variables (namely $SIZE$, $SPR$, $DSAME$, $DOPP$, $VOLA$, $WAIT$, $NTRANS$) are standardized by the corresponding daily mean and standard deviation so that they are comparable across days. Table 12 presents the model parameter estimates along with the odds ratios. Since continuous variables in the model are demeaned and variance-rescaled by daily statistics, the odds ratios correspond to a one standard deviation change in the relevant variable.

As shown by the significantly negative coefficients for IMP for four out of the six securities (the 2-, 3-, 5-, and 10-year notes), price-improving orders are less likely to contain hidden

\[ We consider the same set of key macroeconomic reports, FOMC rate decisions and Treasury auction results as in Engle, Fleming, Ghysels, and Nguyen (2012) \]
volume, after controlling for other factors believed to affect hidden order usage. This result is opposite to that reported in De Winne and D’Hondt (2007b) and Bessembinder, Panayides, and Venkataraman (2009). By achieving price priority with a price-improving order, the order submitter seems to indicate an eagerness for faster execution and the result suggests that the trader prefers to display the full order size so as not to lose the priority to future orders that join the queue at the new price. However, this is not the case for the 7- and 30-year securities, which are traded much less actively, and for which orders are hence less likely to lose priority to future orders.

Consistent with the prior literature, we find that large orders are more likely to be partially hidden, because posting a large order may give away information to the market as suggested by Harris (1997). A one standard deviation increase in the logged order size is associated with more than twice the odds of the order having hidden size. Furthermore, comparing the odds ratios across explanatory variables shows that order size is uniformly the most important driver of the hidden order decision.

With regard to adverse selection risk, we find that hidden orders are more likely when the bid-ask spread is wider for all of the notes, in line with the prediction by Moinas (2010) and the empirical evidence reported in Bessembinder, Panayides, and Venkataraman (2009). A one standard deviation increase in the prevailing spread is associated with a roughly 10% increase in the odds of hidden size. The 30-year bond is an exception, in which the bid-ask spread has a negative effect on the likelihood of an iceberg order. That is, when the spread is wide, liquidity providers seem to prefer to submit a fully displayed order rather than an iceberg order, possibly to achieve faster execution in order to earn the spread. As documented earlier, the 30-year bond has a markedly wider spread, on average, and is much less liquid than the notes (i.e., lower trading volume and lower standing depth), indicating a lower degree of competition for liquidity provision. Accordingly, although a wider spread makes it easier for an order to be front-run, the front-running risk is probably not substantial, thereby reducing the need to use iceberg orders. While this finding is somewhat unexpected, the
same effect has been documented by De Winne and D’Hondt (2007b) for non-marketable limit orders for the majority of their sample of 40 stocks on Euronext.

The prevailing depth on the same side as the incoming order has a significantly negative effect on the probability of hidden volume across all securities, except for the 2-year note. This finding provides support for the hypothesis that an order is less likely to have hidden volume if the prevailing depth is high, since the plentiful depth on the same side provides a reassuring signal that orders on that side are less subject to being picked-off. In addition, Treasury securities have very tight spreads, providing less scope for undercutting, so that the opposite effect of depth on iceberg order usage relating to undercutting risk is less pronounced. Even for the 30-year bond, whose wider bid-ask spread makes undercutting easier, this risk is evidently not a large concern for traders. However, depth on the opposite side is generally also negatively related with iceberg order usage, suggesting that the likelihood of an iceberg order is lower when the standing order book is deeper.

Interestingly, the consistently negative coefficients on volatility across maturities do not support theoretical predictions of a positive relationship discussed earlier. We suspect that, when prices are moving fast, Treasury traders refrain from using hidden orders altogether since they have an alternative mechanism, namely the workup protocol, to protect themselves from adverse price movements. That mechanism affords them complete control over how much to bid/offer based on changing market conditions, as opposed to making a firm commitment over the total quantity they want to bid/offer, even if part of that commitment is hidden from view. In fact, Fleming and Nguyen (2013) show that workups are utilized more in volatile times.

The rates of limit order arrivals, as captured by the average wait time between recent same-side orders, show expected effects on hidden order usage. Specifically, a longer wait time suggests a slower arrival rate for future orders, and thus, the threat of the order’s hidden volume losing priority to future orders is lessened. The positive and significant coefficients on \textit{WAIT} across securities support this hypothesis. In contrast, there is mixed evidence as
to the effect of trading rates, \textit{NTRANS}, on hidden order choice. It is negative for the 3- and 7-year notes, but positive for the 5-, 10- and 30-year securities and insignificant for the 2-year note.

Importantly, there is consistent evidence that hidden orders are used less often around announcement times. This appears to be the period when the market is geared up to receive and then incorporate the news. Accordingly, the lower priority of hidden volume may make hidden orders less attractive around these moments. Lastly, we find that hidden orders are more likely during the overnight trading hours.

\section*{6.3 Determinants of Hidden Volume}

Conditional on the choice to partially hide an order’s volume, the next natural step is to explore how hidden volume is determined. For this purpose, we regress the hidden size (logged) of hidden orders on the same set of explanatory variables in the hidden order choice model, and report the results in Table 13. To facilitate interpretation, we also report the exponential of parameter estimates so that one can see the effect of each explanatory variable directly on the hidden size, as opposed to logged hidden size.

| [Table 13 – Determinants of Hidden Size Conditional on Hidden Order Choice] |

A few key observations from this table are in order. First, \textit{SIZE} continues to be a key driver of hidden orders: the larger the size, the larger the hidden volume. A one standard deviation increase in the logged order size is associated with an increase in the hidden size ranging from 47\% for the 30-year bond to 140\% for the 2-year note. \textit{IMP} also appears to play an important role in the extent of volume hidden: those hidden orders placed inside of the spread have about 3-10\% higher hidden volume than similar hidden orders that are not price-improving. In addition, the \textit{PRENEWS} and \textit{POSTNEWS} variables are generally negative, suggesting that hidden orders placed around announcement times tend to have lower hidden volume, in addition to the earlier reported evidence that these hidden orders
are less likely around these times. The effects of other variables on hidden volume are less determinative and vary across securities, suggesting that these variables matter more to the choice of hidden orders than the extent of hidden volume once the choice has been made.

### 7 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 brokers. We use tick data from one of these platforms, BrokerTec, to reassess market liquidity. We find that the market is notably more liquid than earlier reports based on GovPX data, and that there has been an increase in liquidity over time, except for the crisis period. In addition, our paper offers the first look into market liquidity beyond the inside tier. We show that market liquidity concentrates more heavily at the price tiers immediately behind the market, and that the first five tiers collect over half of the total market liquidity in the order book at any given point in time.

We formally quantify the price impact of trading and limit order book activities. The price impact of trades on BrokerTec is quite small but generally increasing in maturity. Baseline estimates based on the specification with price dynamics and trading activities suggest that it takes $182 million in signed trading volume to move the price of the 2-year note by 1/256th of one percent of par, but only slightly over $2 million to move the price of the 30-year bond by the same amount. Accounting for the impact of limit order activities on trading activities and price dynamics, we find that limit order flow itself affects prices, and is especially important in the price dynamics of longer-dated maturities. We also find that part of the price impact of trades initially estimated from the model of trade flow alone can be attributed to limit order activities: including limit order activities reduces the price impact of trades by about 9-40%, on average, for the on-the-run securities. Finally, price impact is larger following FOMC announcements, particularly that of limit orders.
We find that iceberg orders are used sparingly in the Treasury market. However, the hidden portion of these iceberg orders is several orders of magnitude larger than the displayed part, thus occupying a proportionately larger portion of depth residing in the order book at any point in time. We find that the use of hidden depth increases with the order size and the prevailing bid-ask spread, highlighting the benefit of hidden orders as a mechanism to prevent information leakage and mitigate adverse selection risk. Additionally, when there is lower prevailing depth or lower likelihood of future orders whose display size will take precedence over the current hidden size, hidden orders tend to be used more often, as the cost of using them in terms of execution probability is lower. These results are generally in line with the evidence reported for other markets.

However, we also find a number of results in this market that have not been documented elsewhere. Unlike Bessembinder, Panayides, and Venkataraman (2009), we find that traders are less likely to use iceberg orders when their orders are price improving, except for the less liquid 7- and 30-year securities. Considering that this market is highly liquid, in which the inside spread is restrained at one tick the majority of the time, opportunities to undercut the market are limited and thus, whenever such opportunities are present, execution probability seems to take on greater importance. The extent of iceberg order usage in this highly liquid market is also much smaller than what has been documented in the literature for equity markets. In this regard, our findings actually support the evidence from equity markets that hidden order usage is lower for the more liquid stocks.

Another interesting departure from both theoretical predictions and previous empirical evidence is that volatility and hidden order usage are negatively linked. At first blush, the finding seems counter-intuitive, as it suggests that the more volatile the market, the less likely that hidden orders will be used, precisely when traders need greater protection. However, if we place this finding in the context of the Treasury market, in which there exists another mechanism for order exposure management, namely the workup protocol, we can better understand how it could be the case for this market. Recall that the workup protocol gives
market participants the ability to workup order sizes if and when desired, whereas iceberg orders can be adversely executed when the market is moving so fast that traders cannot cancel soon enough. Empirically, workups tend to be used more frequently in more volatile times, undermining the popularity of iceberg orders. Likewise, hidden orders are used less often around the release of key macroeconomic reports, FOMC rate decision announcements, and Treasury auctions. These are moments when the market is eagerly waiting for and trading on the newly released announcements, so priority in the order queues seems to be an important consideration.

Overall, our paper highlights how the electronic market for trading in U.S. Treasury securities differs from its voice-assisted precedent and from other markets studied in the literature. Comparing with the voice-assisted trading system, the electronic market facilitates a much greater 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. Comparing with other market setups, the high level of market liquidity and the presence of the more preferred workup protocol to manage order exposure in this market are likely related to the lower usage of iceberg orders and the seemingly greater importance of execution probability in traders’ decisions.
References


The table reports daily averages of trading volume, trade frequency, and average trade size for on-the-run Treasury coupon securities on the BrokerTec platform, for the period 2010-2011. Volume and trade size are reported in millions of dollars. Multiple order matchings (including during workups) associated with the arrival of an aggressive order are aggregated as a single trade.

Table 1: Trading Activity

<table>
<thead>
<tr>
<th>Maturity</th>
<th>Trading Volume</th>
<th>Trade Frequency</th>
<th>Average Trade Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Year</td>
<td>26,354</td>
<td>934</td>
<td>28.2</td>
</tr>
<tr>
<td>3-Year</td>
<td>16,204</td>
<td>1,297</td>
<td>12.5</td>
</tr>
<tr>
<td>5-Year</td>
<td>36,262</td>
<td>3,052</td>
<td>11.9</td>
</tr>
<tr>
<td>7-Year</td>
<td>9,640</td>
<td>1,500</td>
<td>6.4</td>
</tr>
<tr>
<td>10-Year</td>
<td>31,462</td>
<td>3,066</td>
<td>10.3</td>
</tr>
<tr>
<td>30-Year</td>
<td>5,705</td>
<td>1,921</td>
<td>3.0</td>
</tr>
</tbody>
</table>
The table reports the average price distance between adjacent price levels on each side of the book, and the average bid-ask spread. 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 1/128th of one percent of par, and that for the 7-, 10- and 30-year maturities is 1/64th of one percent of par. The numbers are computed from five-minute snapshots of BrokerTec’s limit order book for the respective securities for the hours 07:00-17:30 over the period 2010-2011.
<table>
<thead>
<tr>
<th></th>
<th>First Tier</th>
<th>First 5 Tiers</th>
<th>All Tiers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bid</td>
<td>Ask</td>
<td>Bid</td>
</tr>
<tr>
<td>2-Year</td>
<td>308</td>
<td>300</td>
<td>1,561</td>
</tr>
<tr>
<td>3-Year</td>
<td>82</td>
<td>81</td>
<td>474</td>
</tr>
<tr>
<td>5-Year</td>
<td>31</td>
<td>31</td>
<td>278</td>
</tr>
<tr>
<td>7-Year</td>
<td>37</td>
<td>36</td>
<td>236</td>
</tr>
<tr>
<td>10-Year</td>
<td>26</td>
<td>26</td>
<td>213</td>
</tr>
<tr>
<td>30-Year</td>
<td>3</td>
<td>3</td>
<td>28</td>
</tr>
</tbody>
</table>

The table reports average depth on BrokerTec at the first tier, the first five tiers, and across all tiers. The statistics are computed from five-minute snapshots of the limit order book for the respective securities for the hours 07:00-17:30 over the period 2010-2011. Depth is reported in millions of dollars.
The table reports the percentage of depth that is hidden at the first tier (panel A) and across all tiers (panel B). Column “Full Sample” shows the percentage of hidden depth based on all observations, while column “Hidden > 0” shows the percentage of hidden depth based on observations with positive hidden depth only. The percentage of observations with positive hidden depth is reported in column “% of Obs”. The statistics are computed from five-minute snapshots of BrokerTec’s limit order book for the respective securities for the hours 07:00-17:30 over the period 2010-2011.
<table>
<thead>
<tr>
<th></th>
<th>Trade Direction</th>
<th>Signed Trade Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Year</td>
<td>0.357</td>
<td>0.006</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.486</td>
<td>0.017</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.708</td>
<td>0.028</td>
</tr>
<tr>
<td>7-Year</td>
<td>1.302</td>
<td>0.078</td>
</tr>
<tr>
<td>10-Year</td>
<td>1.340</td>
<td>0.066</td>
</tr>
<tr>
<td>30-Year</td>
<td>2.921</td>
<td>0.450</td>
</tr>
</tbody>
</table>

The table reports 50-tick cumulative price impact of trades using a bivariate VAR(5) model of trade and return (based on the best bid-ask midpoint), with two alternative measures for the trade variable: 1) trade direction (1 for buys and -1 for sells), and 2) signed trade volume (positive for buys and negative for sells). Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the period 2010-2011.
Table 6: Separate Price Impact of Trade Direction and Size

<table>
<thead>
<tr>
<th>Trade Direction</th>
<th>$1M Increment</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Year</td>
<td>0.271</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.390</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.571</td>
</tr>
<tr>
<td>7-Year</td>
<td>1.132</td>
</tr>
<tr>
<td>10-Year</td>
<td>1.033</td>
</tr>
<tr>
<td>30-Year</td>
<td>2.738</td>
</tr>
</tbody>
</table>

The table reports 50-tick cumulative price impact of trade direction (buy) and size separately, using a trivariate VAR(5) model of return (based on the best bid-ask midpoint), trade direction and signed trade volume. Trade direction is 1 for buys and -1 for sells. Signed trade volume is the volume of trade, signed positive for buys and negative for sells. Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the period 2010-2011.
<table>
<thead>
<tr>
<th>Buy</th>
<th>Sell</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Year</td>
<td>0.006</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.017</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.028</td>
</tr>
<tr>
<td>7-Year</td>
<td>0.081</td>
</tr>
<tr>
<td>10-Year</td>
<td>0.066</td>
</tr>
<tr>
<td>30-Year</td>
<td>0.435</td>
</tr>
</tbody>
</table>

The table reports 50-tick cumulative price impact of buyer-initiated versus seller-initiated trades using a VAR(5) model of buy trade volume, sell trade volume and return (based on the best bid-ask midpoint). Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the period 2010-2011.
The table reports 50-tick cumulative bid and ask price impact of buyer-initiated versus seller-initiated trades using a VECM(5) model of bid and ask price revisions, buy trade volume and sell trade volume, with the bid-ask spread as the error correction term. Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the period 2010-2011.
Table 9: Price Impact of Trades and Limit Orders

<table>
<thead>
<tr>
<th></th>
<th>Buy Trade</th>
<th>Sell Trade</th>
<th>Bid Limit Order</th>
<th>Ask Limit Order</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Year</td>
<td>0.0052</td>
<td>-0.0049</td>
<td>0.0011</td>
<td>-0.0011</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.0132</td>
<td>-0.0131</td>
<td>0.0078</td>
<td>-0.0053</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.0245</td>
<td>-0.0236</td>
<td>0.0139</td>
<td>-0.0119</td>
</tr>
<tr>
<td>7-Year</td>
<td>0.0592</td>
<td>-0.0544</td>
<td>0.0285</td>
<td>-0.0275</td>
</tr>
<tr>
<td>10-Year</td>
<td>0.0579</td>
<td>-0.0570</td>
<td>0.0353</td>
<td>-0.0341</td>
</tr>
<tr>
<td>30-Year</td>
<td>0.3986</td>
<td>-0.4258</td>
<td>0.3491</td>
<td>-0.2801</td>
</tr>
</tbody>
</table>

The table reports 50-tick cumulative price impact of trades and limit orders using 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). 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. Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the period 2010-2011.
Table 10: Price Impact of Trades After FOMC Announcements

<table>
<thead>
<tr>
<th></th>
<th>Buy Trade</th>
<th>Sell Trade</th>
<th>Bid Limit Order</th>
<th>Ask Limit Order</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A: On FOMC Days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Year</td>
<td>0.0049</td>
<td>-0.0069</td>
<td>0.0018</td>
<td>-0.0024</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.0153</td>
<td>-0.0264</td>
<td>0.0176</td>
<td>-0.0083</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.0258</td>
<td>-0.0283</td>
<td>0.0150</td>
<td>-0.0248</td>
</tr>
<tr>
<td>7-Year</td>
<td>0.0749</td>
<td>-0.0592</td>
<td>0.0567</td>
<td>-0.0281</td>
</tr>
<tr>
<td>10-Year</td>
<td>0.0504</td>
<td>-0.0702</td>
<td>0.0587</td>
<td>-0.0508</td>
</tr>
<tr>
<td>30-Year</td>
<td>0.1925</td>
<td>-0.5242</td>
<td>0.5640</td>
<td>-0.4224</td>
</tr>
<tr>
<td><strong>B: On Non-FOMC Days</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Year</td>
<td>0.0037</td>
<td>-0.0042</td>
<td>0.0006</td>
<td>-0.0005</td>
</tr>
<tr>
<td>3-Year</td>
<td>0.0123</td>
<td>-0.0121</td>
<td>0.0058</td>
<td>-0.0032</td>
</tr>
<tr>
<td>5-Year</td>
<td>0.0210</td>
<td>-0.0237</td>
<td>0.0096</td>
<td>-0.0121</td>
</tr>
<tr>
<td>7-Year</td>
<td>0.0512</td>
<td>-0.0564</td>
<td>0.0276</td>
<td>-0.0289</td>
</tr>
<tr>
<td>10-Year</td>
<td>0.0541</td>
<td>-0.0576</td>
<td>0.0300</td>
<td>-0.0285</td>
</tr>
<tr>
<td>30-Year</td>
<td>0.2134</td>
<td>-0.2732</td>
<td>0.2828</td>
<td>-0.2976</td>
</tr>
</tbody>
</table>

The table reports 50-tick cumulative price impact of trade and limit order flow after 16 scheduled FOMC announcements over the period 2010-2011 (Panel A), and compare with similarly calculated price impact of trade and limit order flow over the same time interval on 5 days preceding and 5 days following these announcements (Panel B). The price impact estimates are based on a VAR(5) model of return (based on the best bid-ask midpoint), buy volume, sell volume, net limit order flow to the inside bid, and net limit order flow to the inside ask. Cumulative price impact is in 256ths of one percent of par. Estimation is based on BrokerTec data for the 90-minute window that begins 2 minutes after the announcement time of each FOMC announcement. The announcement times are collected from Bloomberg.
Table 11: Descriptive Statistics of Normal versus Iceberg Orders

<table>
<thead>
<tr>
<th></th>
<th>2-Year</th>
<th></th>
<th>3-Year</th>
<th></th>
<th>5-Year</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal</td>
<td>Iceberg</td>
<td>Normal</td>
<td>Iceberg</td>
<td>Normal</td>
<td>Iceberg</td>
</tr>
<tr>
<td>Percent Placed Inside Spread</td>
<td>1.18</td>
<td>2.57</td>
<td>2.40</td>
<td>4.58</td>
<td>2.74</td>
<td>10.25</td>
</tr>
<tr>
<td>Total Size ($M)</td>
<td>4.4</td>
<td>13.5</td>
<td>2.5</td>
<td>8.8</td>
<td>1.6</td>
<td>8.8</td>
</tr>
<tr>
<td>Hidden Size ($M)</td>
<td>0.0</td>
<td>9.4</td>
<td>0.0</td>
<td>6.1</td>
<td>0.0</td>
<td>6.7</td>
</tr>
<tr>
<td>Spread (cents/$100)</td>
<td>0.8</td>
<td>0.9</td>
<td>0.9</td>
<td>1.0</td>
<td>0.9</td>
<td>1.0</td>
</tr>
<tr>
<td>Same Size Depth ($M)</td>
<td>246</td>
<td>227</td>
<td>65</td>
<td>66</td>
<td>36</td>
<td>34</td>
</tr>
<tr>
<td>Opposite Size Depth ($M)</td>
<td>264</td>
<td>210</td>
<td>88</td>
<td>59</td>
<td>32</td>
<td>29</td>
</tr>
<tr>
<td>Inter-Order Duration (secs)</td>
<td>2.4</td>
<td>5.0</td>
<td>2.1</td>
<td>5.2</td>
<td>0.9</td>
<td>2.3</td>
</tr>
<tr>
<td>Past Realized Vol. (ann.)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.06</td>
<td>0.05</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>Past Trading Rate (#Trades/5min)</td>
<td>8</td>
<td>7</td>
<td>12</td>
<td>10</td>
<td>24</td>
<td>21</td>
</tr>
<tr>
<td>Past Trading Volume ($M/5min)</td>
<td>292</td>
<td>228</td>
<td>183</td>
<td>141</td>
<td>369</td>
<td>323</td>
</tr>
<tr>
<td>No. of Orders Per Day</td>
<td>62,497</td>
<td>1,244</td>
<td>69,159</td>
<td>1,018</td>
<td>172,152</td>
<td>1,454</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>7-Year</th>
<th></th>
<th>10-Year</th>
<th></th>
<th>30-Year</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal</td>
<td>Iceberg</td>
<td>Normal</td>
<td>Iceberg</td>
<td>Normal</td>
<td>Iceberg</td>
</tr>
<tr>
<td>Percent Placed Inside Spread</td>
<td>2.04</td>
<td>8.91</td>
<td>2.93</td>
<td>15.98</td>
<td>16.83</td>
<td>53.26</td>
</tr>
<tr>
<td>Total Size ($M)</td>
<td>1.5</td>
<td>5.3</td>
<td>1.4</td>
<td>11.6</td>
<td>1.2</td>
<td>7.1</td>
</tr>
<tr>
<td>Hidden Size ($M)</td>
<td>0.0</td>
<td>3.7</td>
<td>0.0</td>
<td>9.3</td>
<td>0.0</td>
<td>5.8</td>
</tr>
<tr>
<td>Spread (cents/$100)</td>
<td>1.9</td>
<td>2.2</td>
<td>1.8</td>
<td>2.0</td>
<td>4.6</td>
<td>4.8</td>
</tr>
<tr>
<td>Same Size Depth ($M)</td>
<td>39</td>
<td>38</td>
<td>29</td>
<td>27</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Opposite Size Depth ($M)</td>
<td>34</td>
<td>34</td>
<td>26</td>
<td>25</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Inter-Order Duration (secs)</td>
<td>1.0</td>
<td>3.0</td>
<td>1.0</td>
<td>3.4</td>
<td>3.9</td>
<td>11.7</td>
</tr>
<tr>
<td>Past Realized Vol. (ann.)</td>
<td>0.14</td>
<td>0.13</td>
<td>0.18</td>
<td>0.16</td>
<td>0.30</td>
<td>0.27</td>
</tr>
<tr>
<td>Past Trading Rate (#Trades/5min)</td>
<td>13</td>
<td>12</td>
<td>23</td>
<td>20</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td>Past Trading Volume ($M/5min)</td>
<td>92</td>
<td>89</td>
<td>311</td>
<td>262</td>
<td>57</td>
<td>52</td>
</tr>
<tr>
<td>No. of Orders Per Day</td>
<td>145,062</td>
<td>759</td>
<td>151,719</td>
<td>767</td>
<td>38,211</td>
<td>432</td>
</tr>
</tbody>
</table>

The table reports descriptive statistics based on limit orders submitted to the first tier of the order book on the BrokerTec platform on 100 days randomly selected from the 500 trading days spanning the sample period 2010-2011. Past realized volatility, trading rate and trading volume are calculated over the five minute interval before each order submission. Inter-order duration is the prevailing average wait time between orders on the same side, measured in seconds and averaged over the previous three orders on the same side. Past realized volatility is the square root of the past five-minute realized variance computed as the five-minute sum of squared one-second log midquote returns and annualized by a factor of $288 \times 250$ (288 five-minute intervals per day and 250 trading days per year).
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CONST</strong></td>
<td>-4.38*</td>
<td>-4.91*</td>
<td>-5.46*</td>
<td>-5.79*</td>
<td>-6.22*</td>
<td>-5.94*</td>
</tr>
<tr>
<td><strong>IMP</strong></td>
<td>-0.26*</td>
<td>0.77</td>
<td>-0.64*</td>
<td>0.53</td>
<td>-0.44*</td>
<td>0.64</td>
</tr>
<tr>
<td><strong>SIZE</strong></td>
<td>0.82*</td>
<td>2.27</td>
<td>0.89*</td>
<td>2.44</td>
<td>0.85*</td>
<td>2.34</td>
</tr>
<tr>
<td><strong>SPR</strong></td>
<td>0.09*</td>
<td>1.09</td>
<td>0.17*</td>
<td>1.19</td>
<td>0.14*</td>
<td>1.15</td>
</tr>
<tr>
<td><strong>DSAME</strong></td>
<td>0.01*</td>
<td>1.01</td>
<td>0.01*</td>
<td>0.99</td>
<td>0.16*</td>
<td>0.85</td>
</tr>
<tr>
<td><strong>DOPP</strong></td>
<td>-0.21*</td>
<td>0.81</td>
<td>-0.29*</td>
<td>0.75</td>
<td>-0.05*</td>
<td>0.95</td>
</tr>
<tr>
<td><strong>VOLA</strong></td>
<td>-0.11*</td>
<td>0.90</td>
<td>-0.20*</td>
<td>0.82</td>
<td>-0.17*</td>
<td>0.84</td>
</tr>
<tr>
<td><strong>NTRANS</strong></td>
<td>-0.01*</td>
<td>0.99</td>
<td>0.02*</td>
<td>1.02</td>
<td>0.01*</td>
<td>0.99</td>
</tr>
<tr>
<td><strong>WAIT</strong></td>
<td>0.04*</td>
<td>1.04</td>
<td>0.01*</td>
<td>1.01</td>
<td>0.04*</td>
<td>1.04</td>
</tr>
<tr>
<td><strong>PRENEWS</strong></td>
<td>-0.37*</td>
<td>0.69</td>
<td>-0.37*</td>
<td>0.69</td>
<td>-0.30*</td>
<td>0.74</td>
</tr>
<tr>
<td><strong>POSTNEWS</strong></td>
<td>-1.15*</td>
<td>0.32</td>
<td>-0.99*</td>
<td>0.37</td>
<td>-1.06*</td>
<td>0.35</td>
</tr>
<tr>
<td><strong>OFFHR</strong></td>
<td>0.24*</td>
<td>1.27</td>
<td>0.44*</td>
<td>1.55</td>
<td>0.08*</td>
<td>1.08</td>
</tr>
</tbody>
</table>

This table reports the result of the logistic regression: \[ ICE_i = f(\beta_0 + \beta_1 IMP_i + \beta_2 SIZE_i + \beta_3 SPR_i + \beta_4 DSAME_i + \beta_5 DOPP_i + \beta_6 VOLA_i + \beta_7 NTRANS_i + \beta_8 WAIT_i + \beta_9 PRENEWS_i + \beta_10 POSTNEWS_i + \beta_11 OFFHR_i) \], where \( ICE_i \) is equal to 1 if the newly submitted limit order \( i \) contains some hidden depth, and 0 otherwise. \( IMP \) is equal to 1 if the order is placed inside the prevailing spread, and 0 otherwise. \( SIZE \) is the total order size (logged). \( SPR \) is the prevailing bid-ask spread, measured in basis points of the inside mid quote. \( DSAME \) is the prevailing inside depth on the same side as the order, \( DOPP \) is the prevailing inside depth on the opposite side of the order. \( VOLA \) is the prevailing five-minute realized volatility based on one-second mid-quote log return. \( NTRANS \) is the number of transactions over the preceding five minutes. \( WAIT \) is the average wait time in seconds between limit order submissions on the same side, averaged over the preceding three same-side limit orders. \( PRENEWS \) and \( POSTNEWS \) are indicator variables with a value of 1 if the order is within the five-minute window before and after an announcement respectively (see Appendix A for the list of announcements considered). \( OFFHR \) is equal to 1 if the order is submitted outside New York trading hours (7:00-17:30 ET). To ensure comparability across days, \( SIZE, SPR, DSAME, DOPP, VOLA, WAIT, NTRANS \) are standardized by the corresponding daily mean and variance. The model is estimated based on limit orders submitted to the first tier of the order book on the BrokerTec platform on 100 days randomly selected from the 500 trading days spanning the sample period 2010-2011. Asterisk * indicates statistical significance at 5% level.
### Table 13: Determinants of Hidden Size Conditional on Hidden Order Choice

<table>
<thead>
<tr>
<th></th>
<th>2-Year $\beta$</th>
<th>3-Year $\beta$</th>
<th>5-Year $\beta$</th>
<th>7-Year $\beta$</th>
<th>10-Year $\beta$</th>
<th>30-Year $\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$e^\beta$</td>
<td>$e^\beta$</td>
<td>$e^\beta$</td>
<td>$e^\beta$</td>
<td>$e^\beta$</td>
<td>$e^\beta$</td>
</tr>
<tr>
<td><strong>CONST</strong></td>
<td>0.400*</td>
<td>0.93</td>
<td>-0.456*</td>
<td>-0.399*</td>
<td>-0.537*</td>
<td>-0.593*</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.49</td>
<td>1.10</td>
<td>1.09</td>
<td>1.09</td>
<td>1.04</td>
<td>1.03</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.93</td>
<td>0.63</td>
<td>0.67</td>
<td>0.58</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td><strong>IMP</strong></td>
<td>0.041*</td>
<td>0.96</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.04</td>
<td>1.10</td>
<td>1.09</td>
<td>1.09</td>
<td>1.04</td>
<td>1.04</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.96</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>SIZE</strong></td>
<td>0.875*</td>
<td>2.40</td>
<td>2.10</td>
<td>1.73</td>
<td>1.66</td>
<td>1.63</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.744*</td>
<td>2.10</td>
<td>1.78</td>
<td>1.66</td>
<td>1.63</td>
<td>1.47</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.744</td>
<td>2.10</td>
<td>1.78</td>
<td>1.66</td>
<td>1.63</td>
<td></td>
</tr>
<tr>
<td><strong>SPR</strong></td>
<td>-0.003*</td>
<td>1.00</td>
<td>-0.002</td>
<td>1.00</td>
<td>-0.002</td>
<td>-0.007</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.00</td>
<td>0.98</td>
<td>0.98</td>
<td>0.96</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.98</td>
<td>0.96</td>
<td>0.96</td>
<td>0.96</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>DSAME</strong></td>
<td>0.005*</td>
<td>1.00</td>
<td>-0.018*</td>
<td>1.00</td>
<td>-0.017*</td>
<td>-0.013*</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.00</td>
<td>0.98</td>
<td>0.98</td>
<td>0.96</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.98</td>
<td>0.96</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>DOPP</strong></td>
<td>-0.002*</td>
<td>0.99</td>
<td>-0.010*</td>
<td>0.99</td>
<td>-0.005*</td>
<td>-0.019*</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.00</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td><strong>VOLA</strong></td>
<td>0.008*</td>
<td>1.00</td>
<td>0.009*</td>
<td>1.00</td>
<td>0.003*</td>
<td>0.018*</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.01</td>
<td>1.01</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.01</td>
<td>1.01</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>NTRANS</strong></td>
<td>-0.006*</td>
<td>1.00</td>
<td>0.001</td>
<td>1.00</td>
<td>0.003*</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>WAIT</strong></td>
<td>-0.019</td>
<td>0.98</td>
<td>-0.049*</td>
<td>0.95</td>
<td>0.006</td>
<td>-0.070*</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td><strong>PRENEWS</strong></td>
<td>-0.046*</td>
<td>0.96</td>
<td>-0.027*</td>
<td>0.97</td>
<td>-0.000</td>
<td>-0.014</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.97</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.97</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>POSTNEWS</strong></td>
<td>-0.033*</td>
<td>0.97</td>
<td>0.011*</td>
<td>1.00</td>
<td>-0.005</td>
<td>-0.047</td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.97</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td><strong>$\beta$</strong></td>
<td>0.97</td>
<td>1.01</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

This table reports the result of the regression: $HSIZE_i = \beta_0 + \beta_1 IMP_i + \beta_2 SIZE_i + \beta_3 SPR_i + \beta_4 DSAME_i + \beta_5 DOPP_i + \beta_6 VOLA_i + \beta_7 TRADE_i + \beta_8 WAIT_i + \beta_9 PRENEWS_i + \beta_10 POSTNEWS_i + \beta_11 OFFHR_i$, where $HSIZE_i$ is the hidden size of order $i$ (logged). $IMP$ is equal to 1 if the order is placed inside the prevailing spread, and 0 otherwise. $SIZE$ is the total order size (logged). $SPR$ is the prevailing bid-ask spread, measured in basis points of the inside mid quote. $DSAME$ is the prevailing inside depth on the same side as the order, $DOPP$ is the prevailing inside depth on the opposite side of the order. $VOLA$ is the prevailing five-minute realized volatility based on one-second mid-quote log return. $NTRANS$ is the number of transactions over the preceding five minutes. $WAIT$ is the average wait time in seconds between limit order submissions on the same side, averaged over the preceding three same-side limit orders. $PRENEWS$ and $POSTNEWS$ are indicator variables with a value of 1 if the order is within the five-minute window before and after an announcement respectively (see Appendix A for the list of announcements considered). $OFFHR$ is equal to 1 if the order is submitted outside New York trading hours (7:00-17:30 ET). To ensure comparability across days, $SIZE$, $SPR$, $DSAME$, $DOPP$, $VOLA$, $WAIT$, $NTRANS$ are standardized by the corresponding daily mean and variance. The model is estimated based on limit orders submitted to the first tier of the order book on the BrokerTec platform on 100 days randomly selected from the 500 trading days spanning the sample period 2010-2011. Asterisk * indicates statistical significance at 5% level.
The figure shows average daily trading volume by year in billions of dollars 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.
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, based on data for the period 2010-2011. Times are Eastern time and indicate start of half-hour interval.
Figure 3: Frequency Distribution of Inside Spread

The figure shows the frequency distribution of the inside spread (measured in number of ticks) on BrokerTec. The tick size for the 2-, 3- and 5-year maturities is $1/128$ of one percent of par, and that for the 7-, 10- and 30-year maturities is $1/64$ of one percent of par. The numbers are computed from five-minute snapshots of BrokerTec’s limit order book for the respective securities for the hours 07:00-17:30 over the period 2010-2011.
The figure depicts the average displayed depth (blue) and hidden depth (red) 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 07:00-17:30 over the period 2010-2011. Depth is reported in millions of dollars.
The figure plots the permanent price impact (y-axis) for different buyer-initiated trade sizes (x-axis). The permanent price impact of a given trade size is the cumulative price change (measured in 256ths of one percent of par) over a 50-tick horizon following the trade. This is based on a VAR(5) model of return (based on the best bid-ask midpoint), trade direction, signed trade volume and signed trade volume squared. Trade direction is 1 for buys and -1 for sells. Signed trade volume is the volume of trade, signed positive for buys and negative for sells. Signed trade volume squared is the squared volume of trade, signed positive for buys and negative for sell. Estimation is based on BrokerTec trade data for the period 2010-2011.