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The Evolution of Treasury Market Liquidity: Evidence from 30 Years of Limit Order Book Data

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Abstract

This paper uses order book and transactions data from the U.S. Treasury securities market to calculate daily liquidity measures for a nearly thirty-year sample period (1991-2020). We then construct a daily index of liquidity from bid-ask spreads, quoted depth, and price impact, reflecting the fact that the varying measures capture different aspects of market liquidity. The index is highly correlated with liquidity proxies proposed in the literature, but is more sensitive to short-term drivers of liquidity, suggesting that it better measures contemporaneous liquidity (as opposed to expected future liquidity). In March 2020, in particular, the index peaks at a level commensurate with that seen during the 2007-09 global financial crisis, whereas the liquidity proxies peak at much lower levels. Significant drivers of market liquidity include announcements, implied volatility, and the extent to which high-frequency traders are present in the market.

Key words: Treasury securities, market liquidity, index, low latency, electronification

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1 Introduction

U.S. Treasury securities occupy a central role in global financial markets by virtue of their exceptional liquidity. Treasuries are used to manage interest rate risk, price offerings by other issuers, collateralize financing transactions, implement monetary policy, and as a reserve asset to foreign central banks, and all of these uses depend on the securities' liquidity. Moreover, investors are willing to pay a premium for the securities' high liquidity, resulting in lower yields and hence lower government borrowing costs (e.g., Amihud and Mendelson (1991), Longstaff (2004), and Krishnamurthy and Vissing-Jorgensen (2012)). Liquidity is a key attribute that is inextricably linked to the pricing and widespread use of U.S. Treasuries.

Even before the pandemic, Treasury market liquidity was attracting increased interest because of its behavior during the 2007-09 global financial crisis (GFC), because of post-crisis regulatory changes, and because of the increasing role of high-frequency trading firms (HFTs) in the market. Nguyen, Engle, Fleming, and Ghysels (2020) document the liquidity disruptions in the most actively traded Treasury securities during the crisis and Musto, Nini, and Schwarz (2018) explore the unusual pricing discrepancies that arose among less actively traded securities. Adrian, Fleming, Shachar, and Vogt (2017) describe the post-crisis regulatory changes and how they may have affected liquidity in dealer-intermediated markets such as the Treasury market. The Joint Staff Report (2015) examines the October 15, 2014 flash rally in the Treasury market and shows that HFTs now account for the majority of activity in the so-called interdealer market.

There was again a marked disruption to market functioning in March 2020 when massive customer selling of Treasuries triggered by the COVID-19 pandemic overwhelmed dealers' capacity to intermediate trades (Duffie (2020)). Treasury market liquidity deteriorated to its worst level since the GFC with wide bid-ask spreads, low market depth, and a high price impact of trades (Fleming (2020) and Fleming and Ruela (2020)). The disruptions led the Federal Reserve to initiate Treasury security purchases at an unprecedented speed and scale to support market functioning (Fleming, Liu, Podjasek, and Schurmeier (2022)) and to discussion of ways in which the market could be made more resilient (e.g., Duffie (2020), Liang and Parkinson (2020), and Group of Thirty (2021)).

Despite its importance, no studies have used order book and transactions data to assess Treasury market liquidity over an extended period. Some studies have examined liquidity using order book data over relatively short time spans (e.g., Fleming (2003), Chordia, Sarkar, and Subrahmanyam (2005), Nguyen, Engle, Fleming, and Ghysels (2020), and Adrian, Fleming, Shachar, and Vogt (2017)). Other studies have taken a longer-term focus relying on liquidity proxies, such as the yields on RefCorp bonds relative to Treasuries (Longstaff (2004)) or the dispersion of Treasury security yields around a smooth yield curve (Hu, Pan, and Wang (2013)). Still other studies, such as Goyenko and Ukhov (2009), Goyenko, Subrahmanyam, and Ukhov (2011), and Goyenko and Sarkissian (2014), have used bid-ask spread data from the Center for Research in Security Prices (CRSP). As explained in Duffee (1996) (also see Elton and Green (1998)), CRSP bid-ask spreads have at times been based on a maturity-dependent "spread curve" that does not change from day to day, calling into question the information content of such spreads.

In this paper, we assess Treasury market liquidity over a nearly 30-year sample period using order book and transactions data from the interdealer market. In particular, we look at GovPX data from the voice-assisted interdealer brokers for the 1991 to 2000 period and data from the BrokerTec electronic trading platform for the 2001 to 2020 period. The measures we focus on are bid-ask spreads, quoted depth, and price impact, although we also examine trading volume, trade frequency, and trade size.

Interestingly, we find little correlation between our bid-ask spread series and those of CRSP. Moreover, the CRSP series remain unchanged for years at a time, including through the depths of the GFC and the COVID-19 related disruptions of March 2020. Further investigation reveals that CRSP relied on indicative quotations, even after switching its pricing source in 1996, whereas our bid-ask spreads are based on actual order book data. The evidence suggests that the CRSP bid-ask spreads have little informational value (in the time series) over our sample period.

The paper also develops a daily index of Treasury market liquidity. We do this by combining our bid-ask spread, depth, and price impact measures, reflecting the fact that the measures capture different aspects of market liquidity. The index, and the underlying measures, point to poor liquidity around the near-failure of Long-Term Capital Management (LTCM) in 1998, after September 11, amidst the GFC, and during the COVID-related disruptions of March 2020.

We find that the index is correlated with proxies for liquidity developed in the literature, but also exhibits important differences. In terms of levels, daily changes, and monthly changes, for example, the index is consistently and positively correlated with the on-the-run/off-the-run spread and with Hu, Pan, and Wang (2013)'s noise measure, but only weakly correlated with the RefCorp spread (Longstaff (2004)). Interestingly, day-of-week patterns, and effects from announcements known to affect liquidity, such as the employment report (Fleming and Remolona (1999)) and Federal Open Market Committee (FOMC) announcements (Fleming and Piazzesi (2005)), are present in our liquidity index, but not the on-the-run/off-the-run or RefCorp measures. These differences are likely explained by the fact that our index actually measures liquidity, whereas the on-the-run/off-the-run and RefCorp spreads measure the value of expected future liquidity differences.[1]

The disparate behavior of the various measures is perhaps most notable in March 2020 when the liquidity index rose to a level commensurate with that seen during the GFC, but the other measures increased much more modestly. One possible reason is that the March 2020 liquidity disruptions may have been expected to be short-lived (which turned out to be the case) and so were not capitalized into prices to the same extent as during the GFC. This may have been because the disruptions did not emanate from the financial sector, as during the GFC, and/or because policy actions to address the disruptions were expected. It is also possible that the other measures were less affected by the "dash-for-cash" nature of the March 2020 disruptions, as opposed to a more common flight to liquidity, which tends to disproportionately benefit Treasuries and on-the-run securities in particular. An additional factor is that the indicative prices relied on to construct some of the other measures may have been less reliable during March 2020 because of the market disruptions, perhaps biasing the measures downward.

The last part of the paper explores the drivers of market liquidity. We are especially

[1] We find that Hu, Pan, and Wang (2013)'s noise measure exhibits modest day-of-week patterns, but not announcement effects, likely reflecting the short-term nature of announcement effects and that Hu, Pan, and Wang measure noise at the end of the trading day (and not over the trading day as we do with our index).

interested in how changes in market structure affect liquidity given the introduction of the first electronic interdealer platform in the Treasury market in 1999 and the opening of these platforms to HFTs in the mid 2000s. Moreover, we know from other markets that electronic trading, algorithmic trading, and high-frequency trading reduce transaction costs (e.g., Domowitz (2002) and Hendershott, Jones, and Menkveld (2011)). Our regression analysis in particular seeks to measure the effects of algorithmic and high-frequency trading using measures similar to those in Hendershott, Jones, and Menkveld (2011) and Hasbrouck and Saar (2013).

We find that market structure changes help explain the variation in liquidity over time. Not only is the market more liquid in the electronic era than in the voice-assisted era that preceded it, but the growth of high-frequency trading, in particular, is associated with improved liquidity and helps explain the overall improvement in liquidity over time. In contrast, we do not find evidence of algorithmic trading leading to improved liquidity. Aside from market structure changes, and earlier mentioned announcement and day-of-week effects, we find that liquidity is strongly and negatively correlated with implied volatility. Not only does volatility increase the inventory holding costs from making markets, but there is a close link between volatility, funding liquidity, and market liquidity (Brunnermeier and Pedersen (2009)).

The paper proceeds as follows. Section 2 describes the structure of the secondary Treasury market, focusing on the interdealer market, in which dealers trade with one another. Section 3 discusses the order book and transactions data used in the study. Section 4 presents our main empirical findings, including time series measures of market liquidity, our Treasury liquidity index, comparisons of GovPX/BrokerTec bid-ask spreads to CRSP bid-ask spreads and our index to market liquidity proxies, and an analysis of the determinants of market liquidity. Section 5 concludes.

2 Treasury Market Structure

U.S. Treasury securities trade in a multiple dealer, over-the-counter secondary market. Traditionally, the predominant market makers were the primary government securities dealers, those dealers with a trading relationship with the Federal Reserve Bank of New York. The dealers trade with the Fed, their customers, and one another. The core of the market is the interdealer broker (IDB) market, which accounts for nearly all interdealer trading. Trading in the IDB market takes place 22-23 hours per day during the week, although the vast majority of trading occurs during New York hours, roughly 07:00 to 17:30 Eastern time (Fleming (1997)).

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

Most previous research on the microstructure of the Treasury market has used data from voice-assisted brokers, as reported by GovPX, Inc. (e.g., Fleming and Remolona (1999), Brandt and Kavajecz (2004), and Pasquariello and Vega (2007)). GovPX receives market information from IDBs and re-disseminates the information in real time via the internet and data vendors. 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. 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.[2] In June 2000, BrokerTec Global LLC, a rival electronic trading platform, began operations.[3] As trading of on-the-run securities migrated to these two electronic platforms, and the number of brokers declined due to mergers, GovPX's data coverage dwindled. By the end of 2004,

[2] Cantor spun eSpeed off in a December 1999 public offering. The platform was sold to NASDAQ OMX Group in July 2013, becoming Nasdaq Fixed Income, and then sold to Tradeweb Markets Inc. in June 2021, becoming part of the firm's Dealerweb unit.

[3] 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. ICAP changed its name to NEX Group PLC in December 2016. NEX Group was acquired by the CME Group in November 2018.

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

BrokerTec and eSpeed are fully automated electronic trading platforms on which buyers are matched to sellers without human intervention. Both brokers provide electronic screens that display the best bid and offer prices and associated quantities. On BrokerTec, 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 is available. Traders enter limit orders (minimum order size is $1 million par value) or hit/take existing orders electronically, with priority of execution of limit orders based on price and time. As with the voice-assisted brokers, the electronic brokers ensure trader anonymity, even after a trade, and charge a small fee for their services.

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

Beside iceberg orders, the electronic brokers retained a workup feature, similar to the expandable limit order protocol of the voice-assisted brokers, but with some important modifications.[4] On BrokerTec, the most important difference is that the right-of-first-refusal previously given to the original parties to the transaction was eliminated, giving all market participants immediate access to workups.[5]

When BrokerTec began operations, platform participants were limited to government securities dealers. However, in 2004, BrokerTec opened access to non-dealer participants, including

[4]Boni and Leach (2004) provide a thorough explanation of this feature in the voice-assisted trading system. The protocol 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.

[5]For a detailed analysis of workup activity on the BrokerTec platform, see Fleming and Nguyen (2019).

hedge funds and HFTs. Table 3.3 (p. 59) in the Joint Staff Report (2015) on the U.S. Treasury market shows that HFTs account for 56% of trading volume in the on-the-run 10-year note, compared to bank-dealers' share of 35%. The remaining 9% is split among non-bank dealers and hedge funds.[6] These statistics show that the interdealer market for U.S. Treasury securities, despite the name, is no longer solely for dealers.

3 Order Book and Transactions Data

We rely on order book and transactions data from GovPX and BrokerTec to analyze Treasury market liquidity. The GovPX database contains information for when-issued, on-the-run, and off-the-run Treasury bills, notes, and bonds, whereas the BrokerTec database contains information for on-the-run Treasury notes and bonds only. The GovPX database, which starts June 17, 1991, contains information on prices and (since August 1994) depth at the inside tier of the limit order book, as well as trade prices and (until April 2001) volume. In contrast, our BrokerTec database, which starts January 2, 2001, contains a complete record of every order placed on the platform. We generate prices and depth at the inside tier by fully reconstructing the limit order book.

We limit our analysis to the on-the-run 2-, 5-, and 10-year notes. On-the-run securities are the most recently auctioned securities of a given maturity. As mentioned, we only have access to BrokerTec data for the on-the-run notes and bonds, and the 2-, 5-, and 10-year notes are the only coupon-bearing securities that were continuously issued over our sample period.[7]

Because trading activity has migrated in recent years from the voice-assisted brokers to the electronic platforms, the representativeness of the databases changes over time. In particular, GovPX coverage is high early in the sample, but falls sharply in 1999 and 2000. Fleming (2003) thus finds that GovPX coverage of the interdealer market is 57% in 1998, but 52% in 1999,

[6] The mentioned statistics are based on trading activity on the BrokerTec platform from April 2-17, 2014.

[7] While the Treasury currently also issues 3-, 7-, 20- and 30-year coupon securities, issuance of the 3-year note was suspended between May 2007 and November 2008, issuance of the 7-year note was suspended between April 1993 and February 2009, issuance of the 20-year bond was suspended between January 1986 and May 2020, and issuance of the 30-year bond was suspended between August 2001 and February 2006.

and just 42% in the first quarter of 2000. In contrast, BrokerTec coverage starts modestly in 2001, but has high coverage for recent years. Fleming and Nguyen (2019) compare BrokerTec trading activity with that of eSpeed reported in Luo (2010) and Dungey, Henry, and McKenzie (2013) and find that BrokerTec accounts for 57-60% of electronic interdealer trading in the on-the-run 2-, 5-, and 10-year notes over the January 2005 to May 2008 sample period.

In our analysis, we use GovPX data from June 1991 to December 2000 and BrokerTec data from January 2001 to June 2020. This provides good coverage of the interdealer market for most of our nearly 30-year sample period, but limited coverage for roughly the 1999 to 2004 period, first when GovPX coverage was declining, and then when BrokerTec activity was increasing. The limited coverage for the 1999 to 2004 period would tend to bias our liquidity measures and suggest historically poor liquidity at that time despite the absence of financial crises. It is for this reason that we choose to adjust the liquidity measures over this period.[8]

Daily trading activity over time is plotted in Figure 1, and daily trading activity summary statistics are reported in Table 1, with statistics for the GovPX sample period in Panel A, the BrokerTec sample period in Panel B, and the full sample period in Panel C. For the full sample period, daily trading volume averages roughly $17-24 billion per note, average number of trades per day ranges from about 670 to 1,650, and average trade size ranges from about $10.8 million to $24.9 million.[9]

[8]Specifically, we adjust our raw liquidity measures, discussed in the next section, by scaling them to the roughly 57-60% coverage levels of 1998 and 2005. For the 1998 to 2000 sample period, in which we rely on GovPX data, we first regress each of our liquidity measures on the Merrill Lynch Option Volatility Estimate index (MOVE Index), the Chicago Board Options Exchange Volatility Index (VIX Index), and the share of weekly interdealer trading accounted for by GovPX for the 2-, 5-, and 10-year notes (overall interdealer trading is reported weekly by the Federal Reserve Bank of New York via its FR 2004 statistical release). We use the trade volume share coefficient from the regression results to scale the measures for 1999 and 2000 to the 1998 level of coverage. A similar approach is followed with the BrokerTec data, in which the measures for 2001 to 2004 are scaled to the 2005 level of coverage. The trading activity measures are not adjusted (because our analysis of those is mostly descriptive) and the liquidity measures are not adjusted outside of the 1999 to 2004 period.

[9]In calculating the number of trades per day and trade size, every order match within a given workup is counted as part of the same trade. This is the most reliable way to calculate trade size using GovPX data because the volume field in the dataset, which is used to uniquely identify trades, only changes when a workup is complete (and reflects the full size of the workup). We follow the same trade definition with the BrokerTec data for consistency. However, the workup protocol was only introduced to the BrokerTec platform on April 8, 2002, making it impossible to precisely implement our workup-delineated trade definition from January 2, 2001 to April 5, 2002. Instead, over our early BrokerTec sample, we calculate an alternate trade frequency measure that defines a trade as a single instance of trading (a precise timestamp when one aggressive order is matched to one or more passive orders) for

Figure 1 and Table 1 further show a significant upward trend in trading activity over time. For the GovPX sample period, daily trading volume averages about $3-5 billion per note. This average grows to about $22-33 billion in the BrokerTec sample, or about a four- to eight-fold increase, with the greatest proportional increase occurring in the 10-year note. Trade frequency also rapidly expands in the BrokerTec period: for instance, trading in the 10-year note increases from roughly 570 trades per day to nearly 2,200 trades per day. Meanwhile, the average trade size more than doubles, showing a discrete jump at the start of the BrokerTec period. In March 2020, trading volume and trading frequency jump to record levels as average trade size plunges.

4 Empirical Results

4.1 Liquidity Measures

To assess Treasury market liquidity, we calculate bid-ask spreads, quoted depth, and price impact. The bid-ask spread is one of the most direct measures of market liquidity as it directly measures the cost of trade execution (albeit only a single trade of limited size). The bid-ask spread is calculated for each security and day as the average spread between the best bid and the best offer in the limit order book, as reported by GovPX or BrokerTec, divided by the bid-ask midpoint. In calculating the average, we limit our analysis to New York trading hours (07:30 to 17:00 Eastern time) and weight all ticks (changes in the order book) equally, implicitly giving greater weight to more active times of day.

Average daily bid-ask spreads are plotted in the top panel of Figure 2, and summary statistics are reported in Table 2. Spreads are quite narrow, with full sample averages of 0.8 basis points for the 2-year note, 1.0 basis points for the 5-year note, and 2.0 basis points for the 10-year note. The spreads are relatively wide and variable over the GovPX and early BrokerTec periods and narrow and stable since 2005, except for widenings during the GFC and in March 2020. There is also a marked narrowing of the 2-year spread in November 2018,

the same security. Over the first several quarters when both this measure and the workup-delineated measure are available (April 8, 2002 - December 31, 2003), we calculate the average ratio of the two measures for each security. For January 2, 2001 - April 5, 2002, the daily trade frequency measure (also used to calculate trade size) is the trade instance measure, scaled down by this average ratio.

when BrokerTec halved the note's tick size.[10]

While the bid-ask spread directly measures transaction costs and hence liquidity, it does not account for the depth of the market and hence how costs might vary for multiple trades or trades larger than the minimum size. Another limitation of the measure is that the minimum tick size is frequently constraining, which may explain the limited variation in the spread after 2005. For example,Fleming, Mizrach, and Nguyen (2018) find that 97% of inside spreads for the on-the-run 2-year note equal the minimum tick size (using BrokerTec tick data for 2010-2011).

The quantity of securities that can be traded at the various bid and offer prices helps account for the depth of the market and complements the bid-ask spread as a measure of market liquidity. Depth is calculated for each security and day as the average quantity sought at the best bid price plus the average quantity offered at the best ask price. The quantities only include shown amounts in the limit order book and hence exclude quantities hidden through iceberg orders as well as latent depth that gets revealed through the workup process.[11] As with the bid-ask spread, we limit our analysis to New York trading hours and weight all ticks equally. Moreover, because of the long time span covered by the study, we inflation-adjust depth to 2020 dollars using the gross domestic product implicit price deflator.

Average daily depths are plotted in the second panel in Figure 2, and summary statistics are reported in Table 2. Average depth at the inside tier (bid plus offer side) is far and away greatest for the 2-year note, averaging $512 million for the full sample period, versus $90 million for the 5-year note and $77 million for the 10-year note. Depth is much greater on BrokerTec than it was on GovPX, with the 2-year note showing a nearly ten-fold increase. Moreover, depth shows tremendous variation on BrokerTec, plunging during the GFC and again dropping during the 2013 taper tantrum, around the time of the October 2014 flash

[10] The minimum tick size is 1/2 of a 32nd of a point for the 10-year note (where a point equals one percent of par), 1/4 of a 32nd for the 5-year note, and 1/8 of a 32nd for the 2-year note (it was 1/4 of a 32nd until November 19, 2018). Fleming, Nguyen, and Ruela (2022) analyze the effects of the tick size change on market liquidity and price discovery.

[11] Fleming, Mizrach, and Nguyen (2018) show that about 10% of depth at the inside tier is hidden via iceberg orders for the 2-, 5- and 10-year notes, and Fleming and Nguyen (2019) find that workups happen in roughly half of transactions for these notes, with depth on the passive side accounting for about 15-25% of the size of such transactions.

rally, and in March 2020. By contrast, bid-ask spreads show a more muted response to at least some of these episodes. Inside depth for the 2-year also drops sharply in November 2018 when the note's tick size was halved.

One limitation of quoted depth is that it does not consider the spread between quoted price tiers, including the inside bid-ask spread, and as such does not directly capture the cost aspect of liquidity. Another drawback is that market participants often do not reveal the full quantities they are willing to transact at a given price (as mentioned earlier), so that quoted depth may underestimate true depth. Conversely, because of the speed with which orders can be withdrawn from the market, actual depth may effectively be lower than what is posted in the limit order book.

A popular liquidity measure, suggested by Kyle (1985) considers the rise (fall) in price that typically occurs with a buyer-initiated (seller-initiated) trade. The "Kyle lambda", or price impact, is defined as the slope of the line that relates the price change to trade size and is often estimated by regressing price changes on net signed trading volume (positive for buyer-initiated volume and negative for seller-initiated volume) for intervals of fixed time. The measure is relevant to those executing large trades or a series of trades and, together with the bid-ask spread and depth measures, provides a fairly complete picture of market liquidity.

We calculate price impact for each security and day as the coefficient from a regression of one-minute price changes on contemporaneous net order flow. Price changes are calculated using the midpoint of the last bid and offer quotes posted in a one-minute interval and net order flow is calculated as the number of buyer-initiated trades less the number of seller-initiated trades during that interval.[12] Since trade direction is included in the GovPX and BrokerTec databases, we can sign trades unambiguously.[13] As with the bid-ask spreads and depth, the

[12] The regressions using net trading frequency tend to have greater explanatory power than those using net trading volume. This may reflect the fact that trade size is exogenous – depending on trading conditions – and that the informativeness of amounts executed during workups tends to be less than that of initial trades, as shown in Fleming and Nguyen (2019).

[13] Two factors complicate this process for BrokerTec data before April 8, 2002. First, before this date, our BrokerTec data does not indicate the aggressive side of each trade. Over this period, we sign trades by comparing the trade price to the state of our derived BrokerTec order book just before the trade. If the trade price matches the best ask (bid) price at that time, then the trade is signed as an aggressive buy (sell). For trades where this method does not yield a definitive aggressive side, we look to see which side of the order book had quantity removed as part of the trade, then label the opposite side as aggressive. Second, the issue described in footnote 9 means that net trade frequency

measure is calculated for New York trading hours only.

Daily price impact coefficients are plotted in the bottom panel of Figure 2, and summary statistics are reported in Table 2. Average price impact coefficients for the full sample are 12.0 basis points per 100 hundred net trades for the 2-year note, 25.2 for the 5-year note, and 44.0 for the 10-year note. Price impact tends to be higher during the GovPX sample period than during the BrokerTec sample period, especially in 1999 and 2000 when GovPX data coverage is limited. For the BrokerTec period, price impact rises sharply during the GFC and in March 2020, and to a lesser extent during the 2013 taper tantrum and around the October 2014 flash rally.

We report the correlation coefficients of each liquidity measure across the 2-, 5-, and 10-year notes in Table 3. The table shows that better liquidity in one security tends to be associated with better liquidity in another. The association is strongest between the 5- and 10-year notes, with correlations ranging from 77-89% for bid-ask spreads, depth, and price impact. By contrast, the correlations between the 2- and 5-year notes range from 56-78% and those between the 2- and 10-year notes range from 49-62%. Liquidity dynamics for the 2-year note are thus somewhat different from those for the longer maturities. A similar relationship holds for trading frequency and volume.

We also report correlations across our various liquidity measures in Table 4. The correlations are of daily averages across the 2-, 5-, and 10-year notes. The analysis reveals that better liquidity by one measure tends to be associated with better liquidity in another, so bid-ask spreads and price impact are positively correlated with one another, and both negatively correlated with depth. Increases in the trading activity measures, and especially trade size, also tend to be associated with better liquidity. Interestingly, the correlations between bid-ask spreads and the depth and price impact measures are smaller in magnitude in the latter part

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before April 8, 2002 cannot be calculated in a manner consistent with that done since that date. As in our trade frequency adjustments, we calculate an alternate price impact measure over our BrokerTec sample that defines a single trade in a security as any instance of trading. For the period April 8, 2002 - December 31, 2003, when both this measure and the measure based on workup-delineated trades can be computed, we calculate the average daily ratio of the two measures for each security. For January 2, 2001 - April 5, 2002, the daily price impact measure becomes the price impact from the trade instance definition, scaled up by this average ratio. Note that this adjustment is made prior to the market coverage adjustments of footnote 8.

of the sample, perhaps reflecting the spread's limited variation over this period.

4.2 Liquidity Index

To summarize the evolution of Treasury market liquidity from 1991 to 2020, we construct a liquidity index, combining the bid-ask spread, depth, and price impact measures. The rationale for combining the measures is that no single measure suitably measures liquidity by itself because each captures a different aspect of liquidity. Bid-ask spreads thus measure the cost aspect of liquidity (for single trades of limited size), order book depth the quantity of securities that can be transacted (at the inside spread), and price impact the extent to which prices move in response to trades, thereby measuring both cost and quantity aspects of liquidity.

To facilitate combining the measures into a single index, we first take the negative of the natural log of depth. The log depth measure has better statistical properties. Moreover, in periods of illiquidity, bid-ask spreads, price impact, and negative depth all tend to rise, which allows us to use positive index weights for all index components.

Before creating the index, we impute the measures for dates they are missing because of data limitations, primarily depth before August 1994, but also occasional days for any of the measures. To do this, for each security (2-, 5-, and 10-year note) and sub-sample (GovPX and BrokerTec), we first project each measure onto the MOVE Index and the VIX Index, excluding the 1999-2004 period of limited data coverage. With three securities, two subsamples, and three liquidity measures, this amounts to running 18 separate regressions. Then, for any dates with missing values, we use the predicted values from the aforementioned regression models.

The next step in index construction is to standardize each of the liquidity measures for each security to have mean zero and variance one. We then construct an index for each measure, through a simple averaging across the three notes, as well as an index for each note, through a simple averaging across the three measures. We also create an overall Treasury liquidity index by averaging across the three measures for each of the notes.[14] As a last step, the indexes

[14] We also calculate the index as the first principal component of the nine underlying series, and get very similar results, but prefer the simple averaging. With averaging, the weights on the series, and hence past values of the index, do not change as the sample is extended. This is especially relevant

themselves are standardized to have mean zero and variance one.

The indexes for the various measures are plotted in the top panel of Figure 3 and the indexes for the 2-, 5-, and 10-year notes are plotted in the middle panel of Figure 3. The indexes, which are highly correlated across both measures and securities, tend to be lower during the BrokerTec sample period, likely reflecting the liquidity benefits of electronic trading and expanded competition from HFTs in the interdealer market. Aside from some spikes in the early 1990s, the indexes are marked by sharp increases in the fall of 1998 around the near-failure of LTCM, after the September 11 attacks, in late 2008 after the bankruptcy of Lehman Brothers, and in March 2020 amidst the COVID-19 related disruptions. The indexes also point to increased illiquidity during the 2013 taper tantrum and around the October 2014 flash rally.

The high correlations across the measure- and security-specific indexes suggest a common factor structure, which we aim to capture by simple averaging. The bottom panel of Figure 3 plots the resulting aggregate liquidity index. Over the 1991 to 2020 sample period, the overall index reveals a downward trend, reflecting the combined compression of bid-ask spreads, price impact, and negative log depth over the last 30 years. The data suggest that liquidity at the end of our sample period in December 2020 was good by historical standards.

4.3 Comparison with CRSP Bid-Ask Spreads

Existing longer-term studies of Treasury transaction costs have relied on CRSP bid-ask spreads. Until 1996, CRSP's source for Treasury price quotes was the "Composite 3:30 P.M. Quotations for US Government Securities" compiled by the Federal Reserve Bank of New York. Starting in October of 1996, CRSP's source for Treasury price quotes switched to GovPX, which provides a daily 5 p.m. aggregation of intra-day bids, offers, and transactions.[15]

Figure 4 plots CRSP bid-ask spreads for the 2-, 5-, and 10-year notes against those from GovPX and BrokerTec.[16] Each panel in the figure shows that the GovPX/BrokerTec and

when there are structural changes, such as the November 2018 tick size halving for the 2-year note. The sharp narrowing of the 2-year spread at that time causes the influence of the spread on the first principal component to decline as the sample is extended and more of the post-change period enters the index.

[15]See http://www.crsp.com/files/treasury_guide_0.pdf.

[16]We plot the raw spreads, and not the proportional ones, so as to make it easier to see the raw

CRSP bid-ask spread series have very little in common. For the period from late June 1998 through January 2009, the CRSP series are nearly constant. The CRSP series actually narrow in late June 1998, right before liquidity worsened with the near-failure of LTCM. The spreads then remained steady through the LTCM episode, the September 11 attacks, and the late 2008 depths of the GFC. There is some variation in the CRSP spreads between February 2009 and June 2015, but the spreads are then close to constant for the next several years, including through the COVID-19 related disruptions of 2020.

Table 5 confirms the lack of correlation between our GovPX/BrokerTec bid-ask spreads and the CRSP spreads. Not only are the correlations not close to one, but they are frequently close to zero or negative, with 13 of the 27 coefficients in the table less than zero. The weak correlations occur regardless of estimation approach, be it daily levels, daily changes, or monthly changes.

In terms of magnitudes, the CRSP bid-ask spreads imply significantly higher costs to execute trades. The 2-, 5-, and 10-year notes all show CRSP spreads to frequently be two 32nds of a point in the early- to mid-1990s, roughly 2-6 times wider than the average spreads we record from the intraday GovPX data over the same period. CRSP spreads during the BrokerTec era are somewhat narrower, albeit still multiples of the BrokerTec spreads, on average. That said, spreads may vary across different parts of the market (be it the interdealer market or the dealer-to-customer market), so it is really the lack of positive correlation in the spreads that is most surprising.

It turns out that an important reason for the spread differences is that CRSP relied on indicative bid-ask spreads from GovPX after switching to that source in 1996, whereas our analysis relies on market spreads. The GovPX database contains both market quotes, which reflect actual quotes submitted by market participants, and indicative quotes, which reflect model-based estimates of prices (Jordan and Kuipers (2005)). When we instead pull end-of-day (5 p.m.) indicative quotes from GovPX, our series matches the CRSP series perfectly for much of the sample.[17]

spreads' lack of variation over time.

[17] Specifically, the quotes match on nearly every day from October 1996 to May 2005. After May 2005, there is variation in the CRSP series that does not match the indicative GovPX quotes.

Another possible reason for the divergences in the spread series could be time-of-day differences. CRSP reports end-of-day spreads, whereas we report averages based on quotes throughout the day. However, when we instead pull end-of-day market quotes from GovPX and BrokerTec, we essentially get a noisier and more discrete version of our average series and not anything looking like the CRSP series. Overall, our findings cast doubt on the value of the information contained in CRSP bid-ask spreads over our sample period.

When CRSP's pricing source was the Federal Reserve Bank of New York, Duffee (1996) reported that CRSP bid-ask spreads have at times been based on a maturity-dependent "spread curve" that does not change from day to day. Similarly, Elton and Green (1998) concluded that "the bid-ask spreads listed in the CRSP data are not market data but are merely representative spreads." Our findings show that the CRSP spreads remained indicative after CRSP switched its pricing source to GovPX in October 1996.[18]

4.4 Comparison with Liquidity Proxies

In the absence of data with which to measure Treasury market liquidity directly, several liquidity proxies have been constructed, including Hu, Pan, and Wang (2013)'s noise measure, the on-the-run/off-the-run spread (e.g.Furfine and Remolona (2002), and the RefCorp spread (Longstaff (2004)). These measures share some common features with our liquidity index, but also exhibit some notable differences.

Hu, Pan, and Wang (2013)'s noise measure captures the dispersion of market yields around a smoothed yield curve (also see Fleming (2000) for a similar measure).[19] The idea is that the abundance of arbitrage capital during normal times should smooth out the Treasury yield curve and keep the average dispersion low. In contrast, during liquidity crises, the shortage of arbitrage capital limits relative value trades, allowing yields to move more freely and resulting in more noise in the curve.

[18] Jordan and Kuipers (2005) compare the Federal Reserve Bank of New York data with the end-of-day GovPX data between May 1, 1996 and October 15, 1996 and similarly conclude that "bid-ask spreads in both sources appear to be largely artificial and contain limited information."

[19] Specifically, it is calculated as the root mean squared error of the deviations between market yields and the model yields from a smooth zero-coupon yield curve. Hu, Pan, and Wang (2013) examine data through 2011, but we obtained their measure through December 2020 from Jun Pan's website.

The on-the-run/off-the-run spread measures the yield difference between an on-the-run security and an off-the-run security with similar cash flows. It is calculated here (using parameters from the Nelson-Siegel-Svensson model of Gurkaynak, Sack, and Wright (2007)) as the yield of a hypothetical security with the same cash flows as the on-the-run 10-year note less the actual yield of the note.[20] The spread captures the yield investors forego in order to hold the most recently auctioned 10-year Treasury note and reflects the higher liquidity of the on-the-run issue as well as any differences in security borrowing costs (e.g., Krishnamurthy (2002), Vayanos and Weill (2008), and Pasquariello and Vega (2009)).

The RefCorp spread is measured as the yield of a 10-year Resolution Funding Corporation zero-coupon bond less the yield a 10-year zero-coupon Treasury bond.[21] RefCorp is a government-sponsored enterprise that provided funds to the Resolution Trust Corporation, which was established to finance the bailout of savings and loan associations in the wake of the savings and loan crisis of the 1980s. Longstaff (2004) argues that since RefCorp bonds and Treasury securities are equally creditworthy, but RefCorp bonds are much less liquid, the RefCorp spread solely reflects the value of the liquidity difference.

Figure 5 plots each of the three liquidity proxies against our liquidity index. The series all exhibit some common variation with, most strikingly, all rising sharply during the GFC. Consistent with these patterns, the correlations of the series are generally positive, as shown in Table 6, whether assessed in terms of daily levels, daily changes, or monthly changes. That said, there are also some notable differences in the series, reflecting the fact that they are measuring somewhat different aspects of liquidity and that there is necessarily some measurement noise in the series. Most notably, the liquidity index displays a downward trend over time, and the RefCorp spread an upward trend. This causes some of the RefCorp correlations with the other series to be negative.

The advent of electronic trading and the growth of high-frequency trading likely explain the downward trend in our liquidity index. As discussed earlier, electronic trading in the interdealer Treasury market started in 2000 (and is reflected in our data in 2001 when our

[20] Parameter values are estimated daily with data as of 3 p.m. We use actual GovPX and BrokerTec yields from the same time of day.

[21] Given differences in coupon payment dates, we look at the 10-year point on Bloomberg's fair value curves for RefCorp and Treasury zero-coupon bonds, following Longstaff (2004).

data source switches from GovPX to BrokerTec) and BrokerTec opened to HFTs in particular in 2004. Moreover, as shown in Barclay, Hendershott, and Kotz (2006), electronic trading only occurs in on-the-run securities, with trading migrating to voice-assisted brokers when securities go off the run. The decline in trading costs brought about by electronic and high-frequency trading might thereby have little effect on Hu, Pan, and Wang (2013)'s noise measure, which is mostly based on off-the-run prices, and might actually cause the on-the-run/off-the-run spread to widen if the greater liquidity of the on-the-run 10-year note increases its liquidity premium relative to off-the-run securities.

The upward trend in the RefCorp spread in particular may be explained by the shrinking size of the longer-term RefCorp market as several outstanding issues near maturity. As reported in Longstaff (2004), RefCorp issued $30.0 billion of debt securities across six issues between 1989 and 1991. Only two of the six issues, accounting for about 1/3 of outstanding debt, have maturity dates after January 2021, with both maturing in 2030. The reduced supply of longer-term RefCorp debt has likely reduced the liquidity of the RefCorp market, contributing to the widening of the RefCorp spread.

One interesting way to distinguish our liquidity index from the liquidity proxies is to regress each of the series on dummy variables for major announcement days, days of the week, and days with early market closes ahead of a holiday. The announcement days we consider are those for the employment report and FOMC announcements, both of which have been shown to have significant effects on market liquidity (e.g., Fleming and Remolona (1999) and Fleming and Piazzesi (2005)). Day-of-the-week patterns in liquidity have been found in the Treasury market using GovPX data (Chordia, Sarkar, and Subrahmanyam (2005)).

As shown in Table 7, the announcement day coefficients are only significant for the liquidity index and the day-of-week and early close coefficients are only significant for the liquidity index and the noise measure, and to a lesser extent the on-the-run/off-the-run spread. As expected, the findings point to worse liquidity on employment report and FOMC announcement days, better liquidity on Mondays through Thursdays (that is, worse liquidity on Fridays), and worse liquidity on days with early closes.

What explains the disparate results? Our liquidity index actually measures liquidity, and over the course of the trading day. The on-the-run/off-the-run spread and the RefCorp spread, in contrast, measure the value of expected future liquidity differences, and are seemingly less affected by day-to-day fluctuations in liquidity. The noise measure does appear affected by day-to-day fluctuations in liquidity, but is measured at the end of the trading day, and is seemingly not affected by short-lived intraday disruptions to liquidity caused by announcements. This is not meant to imply that our measure is inherently better, but a measure that actually tracks liquidity on a given day has particular value for certain purposes (e.g., evaluating the potential profitability of new trading strategies or deciding when to execute trades).

4.5 March 2020

The dissimilar behavior of the various measures is perhaps most notable in March 2020 when massive customer selling of U.S. Treasury securities triggered by the COVID-19 pandemic overwhelmed dealers' capacity to intermediate trades, contributing to a marked deterioration of market functioning (Duffie (2020)). The disruptions led the Federal Reserve to initiate Treasury security purchases at an unprecedented speed and scale to support market functioning (Fleming, Liu, Podjasek, and Schurmeier (2022)) and to discussion of ways in which the market could be made more resilient (e.g., Duffie (2020), Liang and Parkinson (2020), and Group of Thirty (2021)).

Consistent with evidence presented elsewhere (e.g., Fleming (2020) and Fleming and Ruela (2020)) Figure 5 shows the liquidity index worsening in March 2020 to a level similar to that seen during the GFC. In contrast, the other measures increase much more modestly. These patterns are not obscured by the 21-day averaging of the series in Figure 5 as they are just as evident in the unsmoothed daily series.

One possible explanation for the disparate results is that the March 2020 liquidity disruptions may have been expected to be short-lived (which turned out to be the case) and so were not capitalized into prices to the same extent as the poor liquidity during the GFC. This may have been because the disruptions did not emanate from the financial sector, as during the GFC, and/or because policy actions to address the disruptions were expected. The on-the-run/off-the-run and Refcorp spreads may have thus been less affected than if the disruptions were expected to last longer.

It is also possible that the on-the-run/off-the-run and Refcorp spreads were less affected by the "dash-for-cash" nature of the March 2020 disruptions, as opposed to a more common flight to liquidity. A typical flight to liquidity benefits Treasuries, and more liquid on-the-run securities in particular, driving liquidity spreads wider. In mid March 2020, in contrast, Treasury note and bond prices declined amidst massive selling by hedge funds (Schrimpf, Shin, and Sushko (2020), mutual funds (Ma, Xiao, and Zeng (2020), and central banks (Duffie (2020)), as customers sought the liquidity of Treasury bills and cash.

An additional factor is that the indicative prices relied on to construct some of the other measures may have been less reliable during March 2020 because of the market disruptions. End-of-day prices for off-the-run securities are necessarily indicative because off-the-runs are much less less actively traded than on-the-runs and because there is no active central limit order book for off-the-runs. It is presumably harder to generate indicative prices that are reflective of market conditions amidst high volatility and illiquidity. It therefore seems plausible that measures that rely on such prices, such as Hu, Pan, and Wang (2013)'s noise measure (which uses data from CRSP) may have been biased down at the time because of their indicative nature.

An interesting feature of the Fed's purchases of Treasuries during the pandemic is that their pace and distribution were informed by observable measures of market functioning, reflecting the particular motivation for the purchases (Logan (2020), Federal Reserve Bank of New York (2021), p. 25, and Fleming, Liu, Podjasek, and Schurmeier (2022)). In particular, the purchases relied on both direct measures of liquidity, including the three components of the liquidity index constructed here, as well as measures of relative value including spline errors (similar to Hu, Pan, and Wang (2013)'s noise measure) and on-the-run/off-the-run spreads. The central bank thus seemingly thought that both sets of measures – those examined in this paper, as well as measures of relative value, which are often used as liquidity proxies – are important indicators of market functioning.

4.6 Explaining Liquidity Variation

Market liquidity is a function of the market structure that allows buyers and sellers of securities to come to a market clearing price. Dealers and HFTs play a crucial role, as these institutions intermediate between buyers and sellers. The ability of the market making sector to intermediate in turn depends on its ability to obtain funding. For example, during times of market turmoil or crisis, one would expect market makers to have difficulty raising funds, which in turn affects their ability to make markets.

In fact, theory suggests a close link between market liquidity, volatility, and funding liquidity (Brunnermeier and Pedersen (2009)). When a volatility shock occurs, lenders may tighten their terms of funding via higher haircuts and repo rates. As funding becomes scarce, market makers find it more difficult to finance their inventories. Market liquidity can therefore decline, which leads to higher volatility (e.g. through higher price impact). There is therefore a self reinforcing feedback mechanism linking volatility shocks, funding liquidity, and market liquidity.

Changes in market structure could also be expected to affect market liquidity. We know from other markets that electronic trading, algorithmic trading, and high-frequency trading reduce transaction costs (e.g., Domowitz (2002) and Hendershott, Jones, and Menkveld (2011)). Electronic IDB platforms were launched in the Treasury market in 1999 and 2000, as discussed earlier, and now account for roughly 90% of IDB trading volume in the on-the-run coupon securities (Brain, Pooter, Dobrev, Fleming, et al. (2018)). Moreover, these platforms opened to HFTs in the mid 2000s, with HFTs now accounting for most activity in this key segment of the market.

We investigate the drivers of market liquidity by relating our market liquidity index to various measures of credit risk, funding liquidity, and market structure. The particular measures we consider are the Baa-Aaa spread, the Treasury-eurodollar (TED) spread, the VIX Index, the MOVE Index, a measure of the extent of algorithmic trading, and a proxy for the share of high-frequency trading.

The Baa-Aaa spread is calculated as the yield on Moody's Baa corporate bond index less the yield on Moody's Baa corporate bond index. It measures the relative default risk and risk premium of lower and higher grade corporate bonds (e.g., Krishnamurthy and Vissing-Jorgensen (2012) and Hu, Pan, and Wang (2013)).

The TED spread is calculated as the spread between 3-month LIBOR and the 3-month Treasury bill rate. The LIBOR rate is a Aa rate that reflects uncollateralized lending in the interbank market, whereas the Treasury bill rate is considered to be a risk-free rate given its U.S. government backing. Brunnermeier, Nagel, and Pedersen (2008) employ the TED spread as a measures of funding liquidity, noting that it typically increases when banks face liquidity problems (also see Hu, Pan, and Wang (2013)).

The VIX Index is a measure of U.S. stock market volatility implied by the prices of options on the S&P 500 index, and is also used as a measure of funding liquidity in Brunnermeier, Nagel, and Pedersen (2008) and Hu, Pan, and Wang (2013).

The MOVE Index is a measure of U.S. Treasury yield volatility implied by the prices of one-month options on 2-, 5-, 10-, and 30-year Treasury futures. The index provides another measure of funding liquidity, and one that is presumably more closely tied to risk appetite in the U.S. Treasury market in particular.

While our datasets do not identify those trades that are algorithmic, we know that common algorithmic strategies involve the rapid submission and cancelation of limit orders. Hendershott, Jones, and Menkveld (2011) thereby propose the number of order book updates divided by trading volume as a proxy for algorithmic trading. We construct such a measure, defined as the number of order book updates at the inside tier divided by trading volume. We calculate the measure for each of the 2-, 5-, and 10-year notes, for each day, for the same trading hours used to construct our liquidity measures. We average across the notes to get a single measure for each day.

We also do not have access to data on the extent of high-frequency trading in the Treasury market over time, but can proxy for the percent of trading volume accounted for by HFTs by the percent of trading volume that appears to be low latency. We define a trade as low latency if it occurs within 0.01 seconds of the preceding trade, too short of an interval to reflect human reaction. Our measure is motivated by Hasbrouck and Saar (2013)'s definition of low latency activity as strategies that respond to market events in the millisecond environment and is similar to the approach used by Salem, Younger, and St John (2018), who also examine data from BrokerTec.

Figure 6 plots our liquidity index against each of the independent variables. The most striking feature of the credit and funding liquidity variables is the sharp increase during the GFC, coninciding with the increase in illiquidity at the time. More recently, the four series jump higher in March 2020 when liquidity deteriorated abruptly. In contrast to the first four series, the most prominent feature of the last two is their upward trend, from near-zero or zero early in the sample period when algorithmic trading was much less common and high-frequency trading nonexistent (as defined).[22]

4.7 Evidence from Regressions

We formally investigate the relationships between market liquidity and the independent variables through regression analysis. Specifically, we regress our market liquidity index on the credit spread, funding liquidity, and market structure variables, both by themselves and altogether. We employ as control variables the same announcement, day-of-week, and early close dummy variables considered earlier. The results are reported in Table 8.

Coefficients in the univariate models are all of the expected sign, and most are significantly different from zero. Liquidity therefore worsens with the credit spread and funding liquidity variables, but improves with the market structure changes that have led to increased high-frequency trading. The MOVE Index and the low latency variable have the highest explanatory power among the independent variables, whereas the algorithmic variable has little explanatory power and is not statistically significant.

Turning to the multivariate models, the MOVE Index and low latency variables remain highly significant, albeit with coefficients somewhat closer to zero. In contrast, the Baa/Aaa spread, TED spread, and VIX Index coefficients move much closer to zero and mostly lose their statistical significance. The algorithmic variable remains statistically insignificant in the multivariate models.

[22]We can and do calculate our algorithmic measure over the part of our sample period covered by GovPX data. In contrast, we set our low latency measure to equal zero for this part of our sample because low latency trading as we define it was not possible through the voice-assisted brokers that reported to GovPX.

In Table 9, we report the results from regressions of our various liquidity sub indexes on our independent variables. This analysis serves as a robustness check, while also allowing us to explore differences in the relationships by tenor and liquidity measure. The results for the different liquidity measures are especially important as they exclude the observations for depth imputed from the MOVE and VIX indexes before August 1994 and thus show that the significant results for the implied volatility variables are not circular. Overall, the results are highly consistent across tenor and measure.

Lastly, in Table 10 we report the results from regressions of our liquidity index and the liquidity proxies on our independent variables. Some findings are broadly consistent across series, with the MOVE Index, in particular, positive for all four series and statistically significant for all but the Refcorp series. Perhaps the most notable difference in the results is that the low latency variable is not significant for any series other than our liquidity index.

The differential effects of the low latency variable likely reflect differences in what exactly the dependent variable is measuring. High-frequency trading is concentrated in the benchmark coupon securities, which we examine with our liquidity index. In contrast, the noise measure is largely based on prices of off-the-run securities, which may be little affected by the improved liquidity in the on-the-run securities. Similarly, the Refcorp spread is based on a zero-coupon Treasury yield, which may be little affected by on-the-run liquidity. The on-the-run/off-the-run spread should be affected by improved liquidity of the on-the-run, but the spread may be driven more by changes in the value of the liquidity differences than by changes in on-the-run liquidity.

5 Conclusion

This paper uses order book and transactions data to assess U.S. Treasury market liquidity over a nearly 30-year sample period (1991-2020). We calculate bid-ask spreads, quoted depth, and price impact for the on-the-run 2-, 5-, and 10-year notes, and we combine the measures into a daily index of Treasury market liquidity. We compare our measures to one another and those used in the extant literature, and we explore the drivers of market liquidity, including macroeconomics announcements, funding liquidity, and high-frequency trading.

Interestingly, we find little correlation between our bid ask spread series and those of CRSP. Moreover, the CRSP series remained unchanged for years at a time, including through the depths of the 2007-09 global financial crisis and the COVID-19 related disruptions of March 2020. Earlier research concluded that CRSP bid-ask spreads are not market data but indicative. Our analysis reveals that CRSP spreads remained indicative after CRSP switched its pricing source in 1996. The evidence suggests that the CRSP spreads have little informational value (in the time series) over our sample period.

We find that our liquidity index is correlated with proxies for liquidity developed in the literature, but also exhibits important differences. Like other measures, our index rises sharply during the 1998 LTCM episode and the GFC. In contrast to other measures, however, day-of-week patterns, and effects from announcements known to affect liquidity, are present in our liquidity index, but not consistently in the liquidity proxies. Moreover, our index suggests illiquidity in March 2020 commensurate with that seen during the GFC, whereas the proxies suggest a much more muted worsening of liquidity. These differences are likely explained by the fact that our index actually measures liquidity, whereas some of the proxies measure the value of expected future liquidity differences.

Lastly, we explore the drivers of market liquidity. Aside from announcement and day-of-week effects, we find that liquidity is strongly and negatively correlated with implied volatility, consistent with the well-documented liquidity-volatility relationship. We also find that market structure changes help explain the variation in liquidity over time. The electronic market is more liquid than the voice-assisted market that preceded it, and the growth of high-frequency trading is associated with improved liquidity and helps explain the overall improvement in Treasury market liquidity over time.

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Table 1: Trading Activity Summary Statistics

Panel A: GovPX Sample (June 1991-December 2000)			
	2-Year	5-Year	10-Year
Trading volume	5.12	5.07	3.31
	(2.53)	(2.42)	(1.62)
Trade frequency	386.78	637.78	567.15
	(162.37)	(267.60)	(232.61)
Trade size	12.99	7.82	5.67
	(2.55)	(1.34)	(1.11)

Panel B: BrokerTec Sample (January 2001-December 2020)			
	2-Year	5-Year	10-Year
Trading volume	22.11	33.20	28.59
	(14.14)	(18.79)	(16.11)
Trade frequency	808.20	2103.90	2169.38
	(638.80)	(1194.88)	(1203.79)
Trade size	30.52	16.31	13.25
	(10.54)	(5.41)	(4.20)

Panel C: Full Sample (June 1991-December 2020)			
	2-Year	5-Year	10-Year
Trading volume	16.63	24.13	20.43
	(14.16)	(20.35)	(17.79)
Trade frequency	672.29	1631.09	1652.19
	(569.00)	(1208.33)	(1249.00)
Trade size	24.87	13.57	10.80
	(12.02)	(6.02)	(4.99)

Source: Authors' calculations, based on data from BrokerTec and GovPX.
Notes: The table reports means and standard deviations (in parentheses) of daily trading volume, daily trade frequency, and average daily trade size for the on-the-run 2-, 5-, and 10-year Treasury notes from June 17, 1991 to December 31, 2020. Trading volume is in billions of dollars (par value) and trade size is in millions of dollars (par value).

Table 2: Liquidity Summary Statistics

Panel A: GovPX Sample (June 1991-December 2000)			
	2-Year	5-Year	10-Year
Bid-ask spread	0.78	1.32	2.44
	(0.25)	(0.37)	(0.60)
Depth	67.13	31.39	22.58
	(23.66)	(7.71)	(6.96)
Price Impact	16.27	30.46	53.75
	(5.73)	(9.35)	(16.15)
Panel B: BrokerTec Sample (January 2001-December 2020)			
	2-Year	5-Year	10-Year
Bid-ask spread	0.79	0.89	1.78
	(0.19)	(0.22)	(0.46)
Depth	652.60	109.07	93.93
	(550.54)	(53.98)	(42.92)
Price Impact	9.92	22.62	39.28
	(5.39)	(11.35)	(16.19)
Panel C: Full Sample (June 1991-December 2020)			
	2-Year	5-Year	10-Year
Bid-ask spread	0.78	1.03	1.99
	(0.21)	(0.34)	(0.59)
Depth	511.51	90.34	76.71
	(541.19)	(57.71)	(48.39)
Price Impact	11.96	25.15	43.96
	(6.25)	(11.35)	(17.53)

Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, GovPX, and Haver.
Notes: The table reports means and standard deviations (in parentheses) of average daily bid-ask spread, average daily order book depth at the inside spread (bid plus offer side), and daily price impact for the on-the-run 2-, 5-, and 10-year Treasury notes from June 17, 1991 (August 22, 1994 for depth) to December 31, 2020. Price impact is estimated as the slope coefficient from a regression of one-minute price changes on the net number of trades over the same one-minute interval. Bid-ask spread is in basis points in return space, so one basis point equals one one hundredth of a percent of price (with price measured as the bid-ask midpoint), depth is in millions of dollars (par value, inflation adjusted to the 2020 price level); and price impact is in basis points per 100 net trades.

Table 3: Correlations of Individual Liquidity/Activity Measures Across Securities

Panel A: Bid-Ask Spread			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.564	1.000	
10-Year	0.490	0.869	1.000
Panel B: Depth			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.775	1.000	
10-Year	0.616	0.894	1.000
Panel C: Price Impact			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.750	1.000	
10-Year	0.591	0.770	1.000
Panel D: Trading Volume			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.690	1.000	
10-Year	0.655	0.973	1.000
Panel E: Trade Frequency			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.752	1.000	
10-Year	0.678	0.977	1.000
Panel F: Trade Size			
	2-Year	5-Year	10-Year
2-Year	1.000		
5-Year	0.771	1.000	
10-Year	0.792	0.934	1.000

Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, GovPX, and Haver.
Notes: The table reports correlation coefficients of the levels of daily liquidity/activity measures across securities for the on-the-run 2-, 5-, and 10-year Treasury notes from June 17, 1991 (August 22, 1994 for depth) to December 31, 2020.

Table 4: Correlations Across Liquidity/Activity Measures

Panel A: GovPX Sample (June 1991-December 2000)						
	Bid-Ask Spread	Depth	Price Impact	Trading Volume	Trade Frequency	Trade Size
Bid-ask spread	1.000					
Depth	-0.701	1.000				
Price Impact	0.861	-0.591	1.000			
Trade Volume	-0.050	0.115	-0.000	1.000		
Trade Frequency	0.005	-0.041	0.018	0.941	1.000	
Trade Size	-0.346	0.571	-0.263	0.544	0.280	1.000
Panel B: BrokerTec Sample (January 2001-December 2020)						
	Bid-Ask Spread	Depth	Price Impact	Trading Volume	Trade Frequency	Trade Size
Bid-ask spread	1.000					
Depth	-0.205	1.000				
Price Impact	0.629	-0.472	1.000			
Trade Volume	-0.324	0.088	-0.011	1.000		
Trade Frequency	-0.226	-0.127	0.225	0.786	1.000	
Trade Size	-0.144	0.557	-0.345	0.337	-0.198	1.000
Panel C: Full Sample (June 1991-December 2020)						
	Bid-Ask Spread	Depth	Price Impact	Trading Volume	Trade Frequency	Trade Size
Bid-ask spread	1.000					
Depth	-0.316	1.000				
Price Impact	0.723	-0.523	1.000			
Trade Volume	-0.406	0.371	-0.226	1.000		
Trade Frequency	-0.319	0.160	-0.018	0.845	1.000	
Trade Size	-0.322	0.694	-0.459	0.612	0.215	1.000

Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, GovPX, and Haver.

Notes: The table reports correlation coefficients across the levels of daily liquidity/activity measures from June 17, 1991 (August 22, 1994 for depth) to December 31, 2020. Daily liquidity/activity measures are averages of those for the on-the-run 2-, 5-, and 10-year notes.

Table 5: Correlations of GovPX/BrokerTec Bid-Ask Spreads with CRSP Bid-Ask Spreads

Panel A: GovPX Sample (June 1991-December 2000)			
	2-Year	5-Year	10-Year
Daily level	0.428	0.295	-0.159
Daily change	0.166	0.129	0.016
Monthly change	-0.010	0.004	-0.026
Panel B: BrokerTec Sample (January 2001-December 2020)			
	2-Year	5-Year	10-Year
Daily level	-0.344	-0.264	-0.252
Daily change	0.000	-0.003	-0.002
Monthly change	-0.003	0.012	-0.069
Panel C: Full Sample (June 1991-December 2020)			
	2-Year	5-Year	10-Year
Daily level	0.049	0.175	-0.110
Daily change	0.097	0.071	0.005
Monthly change	-0.004	0.009	-0.045

Source: Authors' calculations, based on data from from BrokerTec, CRSP, the Federal Reserve Bank of New York, GovPX, and Haver.

Notes: The table reports correlation coefficients of average daily bid-ask spreads from GovPX/BrokerTec and end-of-day bid-ask spreads from CRSP for each of the on-the-run 2-, 5-, and 10-year notes from June 17, 1991 to December 31, 2020. Correlation coefficients are reported for the daily levels of the spreads, daily changes in the spreads, and monthly changes (measured as of the middle of each month).

Table 6: Correlations of Liquidity Index with Other Liquidity Series

	Liquidity Index	Noise Measure	On-the-run Spread	Refcorp Spread
Panel A: Daily Levels				
Liquidity index	1.000			
Noise measure	0.477	1.000		
On-the-run spread	0.623	0.760	1.000	
Refcorp spread	-0.328	0.254	-0.111	1.000
Panel B: Daily Changes				
Liquidity index	1.000			
Noise measure	0.225	1.000		
On-the-run spread	0.045	0.015	1.000	
Refcorp spread	-0.033	-0.014	0.020	1.000
Panel C: Monthly Changes				
Liquidity index	1.000			
Noise measure	0.193	1.000		
On-the-run spread	0.313	0.326	1.000	
Refcorp spread	0.047	0.182	0.123	1.000

Source: Authors' calculations, based on data from from Bloomberg, the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, GovPX, Haver, and Hu, Pan, and Wang (2013).
Notes: The table reports correlation coefficients between the liquidity index and other measures of liquidity from June 17, 1991 to December 31, 2020. Correlation coefficients are reported for daily levels of the measures, daily changes, and monthly changes (measured as of the middle of each month).

Table 7: Announcement and Day-of-Week Effects in Liquidity Series

	(1) Liquidity Measure	(2) Noise Measure	(3) On-the-Run Spread	(4) Refcorp Spread
Employment	0.33***	0.01	-0.00	-0.02*
	(0.02)	(0.01)	(0.01)	(0.01)
FOMC	0.35***	0.02	-0.00	-0.01
	(0.03)	(0.01)	(0.01)	(0.01)
Monday	-0.22***	-0.06***	-0.01**	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Tuesday	-0.22***	-0.05***	-0.01**	0.00
	(0.02)	(0.01)	(0.00)	(0.00)
Wednesday	-0.18***	-0.05***	-0.01*	0.00
	(0.02)	(0.01)	(0.00)	(0.00)
Thursday	-0.09***	-0.04***	0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.00)
Early close	0.25***	0.05***	-0.01	-0.00
	(0.04)	(0.01)	(0.01)	(0.01)
Constant	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	7376	7368	7349	7370
Adjusted R^2	0.219	0.068	0.003	0.001

Source: Authors' calculations, based on data from Bloomberg, the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, GovPX, Haver, and Hu, Pan, and Wang (2013).

Notes: The table reports time series regressions of the market liquidity index and other market liquidity measures onto various dummy variables from June 17, 1991 to December 31, 2020. Dependent variables are standardized and the reported regressions are in daily changes. Newey-West standard errors are in parentheses, with lag length $T^{1/3}$, where T is the indicated sample size.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Credit, Funding Liquidity, and Market Structure Effects on Market Liquidity Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Baa/Aaa spread	0.38*						-0.09	-0.06
	(0.15)						(0.15)	(0.17)
TED spread		0.50***					-0.06	-0.11
		(0.08)					(0.08)	(0.07)
VIX index/100			3.27***				0.47	0.80*
			(0.47)				(0.38)	(0.39)
MOVE index/100				2.03***			1.64***	1.68***
				(0.20)			(0.20)	(0.20)
Algorithmic trades/100					0.17		-0.21	-0.09
					(1.83)		(0.84)	(0.85)
Low latency share						-7.98***	-4.75***	-3.80***
						(0.75)	(0.61)	(0.63)
Constant	-0.01	-0.01	-0.01	-0.00	-0.01	0.01	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Announcements	No	No	No	No	No	No	No	Yes
Days of week	No	No	No	No	No	No	No	Yes
Early close	No	No	No	No	No	No	No	Yes
Observations	7350	7356	7334	7283	7356	7356	7261	7261
Adjusted R^2	0.005	0.029	0.071	0.216	-0.000	0.136	0.260	0.367

Source: Authors' calculations, based on data from the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, the Federal Reserve Bank of St. Louis, GovPX, and Haver.
Notes: The table reports time series regressions of the market liquidity index onto various independent variables from June 17, 1991 to December 31, 2020. The reported regressions are in 21-day changes. Hansen-Hodrick standard errors are in parentheses, with a bandwidth of 21.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Effects on Security-Specific and Measure-Specific Indexes

	(1) 2-Year	(2) 5-Year	(3) 10-Year	(4) Bid-Ask Spread	(5) Depth	(6) Price Impact
Baa/Aaa spread	-0.05	-0.06	0.03	0.10	0.05	-0.31
	(0.18)	(0.17)	(0.17)	(0.18)	(0.07)	(0.26)
TED spread	0.01	-0.14*	-0.11	-0.15	0.02	-0.18**
	(0.06)	(0.07)	(0.08)	(0.12)	(0.05)	(0.06)
VIX index/100	0.63	0.74	1.22*	-0.43	0.93***	1.62***
	(0.42)	(0.38)	(0.54)	(0.59)	(0.26)	(0.48)
MOVE index/100	1.65***	1.66***	1.62***	1.69***	0.65***	2.08***
	(0.19)	(0.20)	(0.21)	(0.30)	(0.11)	(0.22)
Algorithmic trades/100	0.15	0.55	0.17	-0.29	-2.19*	2.27*
	(0.75)	(0.72)	(0.75)	(1.17)	(0.89)	(1.15)
Low latency share	-0.91	-3.16***	-2.99***	-2.58*	-5.45***	-1.80*
	(0.50)	(0.48)	(0.81)	(1.19)	(0.47)	(0.80)
Constant	-0.00	0.00	0.00	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Announcements	Yes	Yes	Yes	Yes	Yes	Yes
Days of week	Yes	Yes	Yes	Yes	Yes	Yes
Early close	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7261	7261	7261	7261	6489	7261
Adjusted R^2	0.227	0.322	0.337	0.196	0.474	0.283

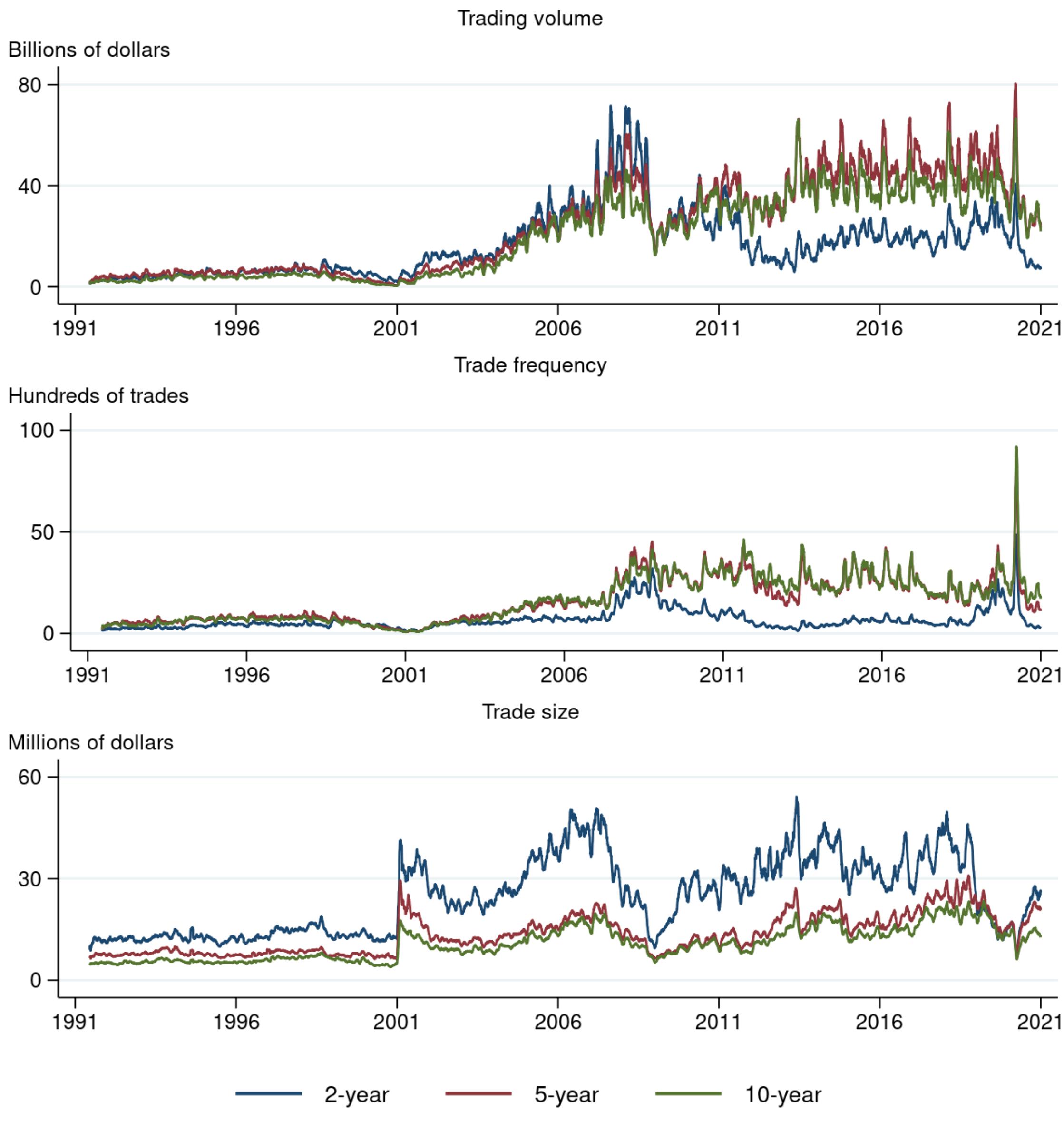
Source: Authors' calculations, based on data from Bloomberg, the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, the Federal Reserve Bank of St. Louis, GovPX, and Haver.
Notes: The table reports time series regressions of security-specific and measure-specific market liquidity indexes onto various independent variables from June 17, 1991 (August 22, 1994 for depth) to December 31, 2020. The reported regressions are in 21-day changes. Hansen-Hodrick standard errors are in parentheses, with a bandwidth of 21.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Credit, Funding Liquidity, and Market Structure Effects on Market Liquidity Series

	(1) Liquidity Measure	(2) Noise Measure	(3) On-the-Run Spread	(4) Refcorp Spread
Baa/Aaa spread	-0.06	0.91	0.58	0.80***
	(0.17)	(0.47)	(0.39)	(0.24)
TED spread	-0.11	0.04	-0.05	-0.08
	(0.07)	(0.25)	(0.09)	(0.15)
VIX index/100	0.80*	0.68	0.37	-0.09
	(0.39)	(0.39)	(0.36)	(0.39)
MOVE index/100	1.68***	0.51**	0.78***	0.10
	(0.20)	(0.16)	(0.13)	(0.13)
Algorithmic trades/100	-0.09	-0.02	0.18	0.64
	(0.85)	(0.78)	(0.58)	(0.91)
Low latency share	-3.80***	-0.85	0.64	-0.20
	(0.63)	(0.45)	(0.50)	(0.76)
Constant	0.00	-0.00	-0.00	0.00
	(0.01)	(0.02)	(0.02)	(0.02)
Announcements	Yes	Yes	Yes	Yes
Days of week	Yes	Yes	Yes	Yes
Early close	Yes	Yes	Yes	Yes
Observations	7261	7253	7211	7249
Adjusted R^2	0.367	0.234	0.141	0.065

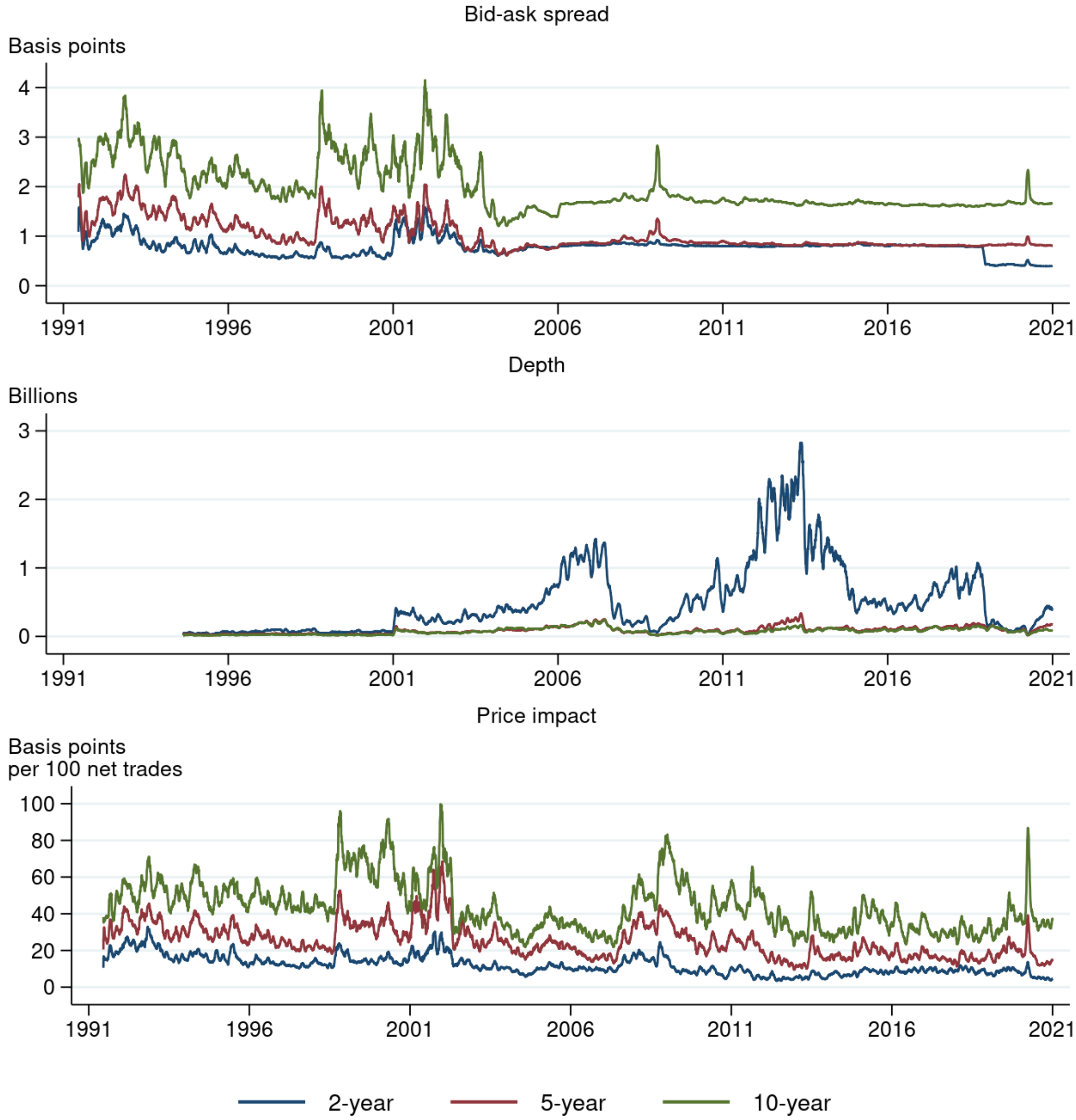
Source: Authors' calculations, based on data from Bloomberg, the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, the Federal Reserve Bank of St. Louis, GovPX, Haver, and Hu, Pan, and Wang (2013).
Notes: The table reports time series regressions of the market liquidity index and other market liquidity measures onto various independent variables from June 17, 1991 to December 31, 2020. All dependent variables are standardized and the reported regressions are in 21-day changes. Hansen-Hodrick standard errors are in parentheses, with a bandwidth of 21.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Trading Activity Metrics



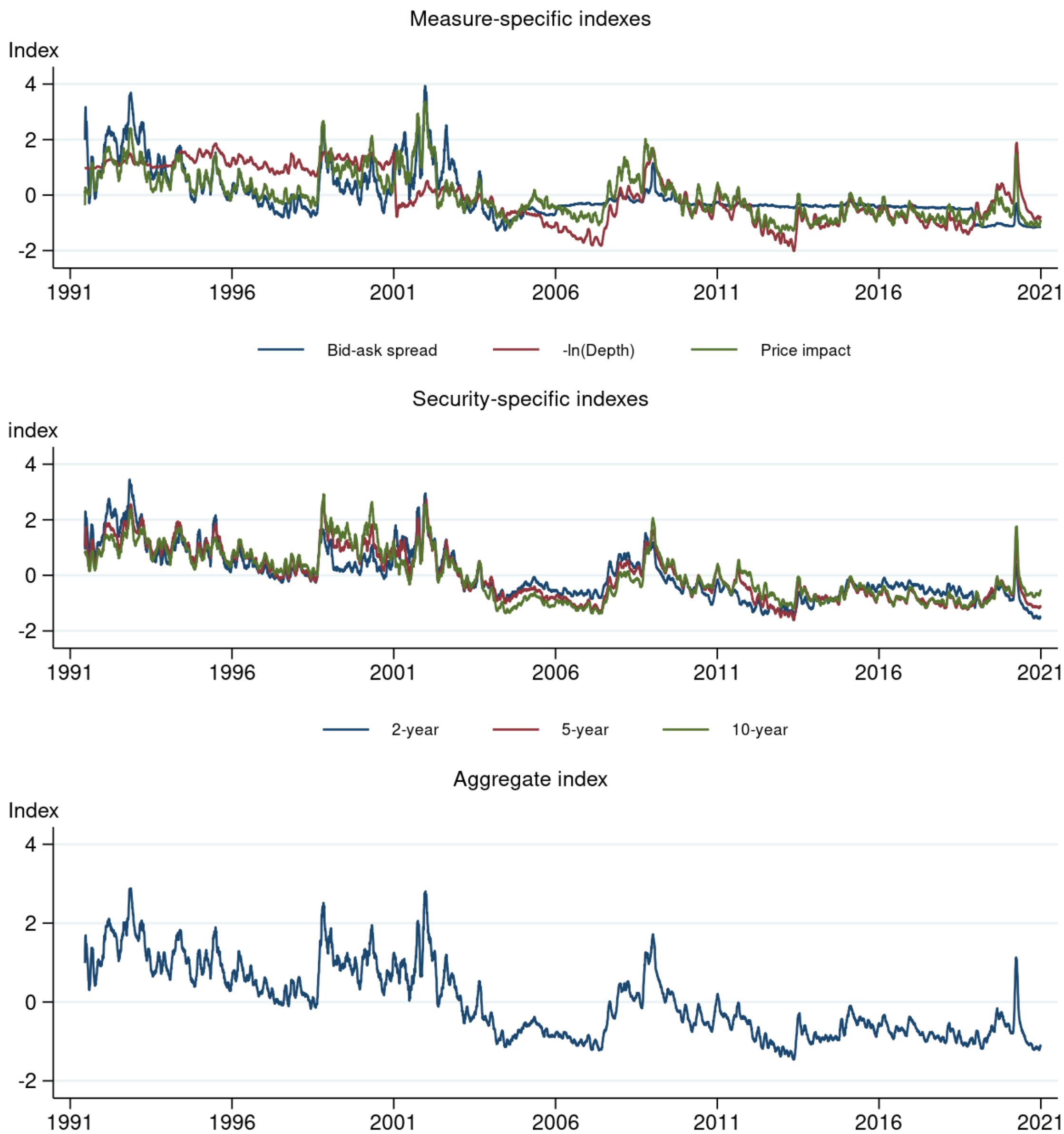
Source: Authors' calculations, based on data from BrokerTec and GovPX.
Notes: The figure plots trading volume, trade frequency, and average trade size by day from June 17, 1991 to December 31, 2020. Plotted lines are 21-day moving averages.

Figure 2: Liquidity Metrics



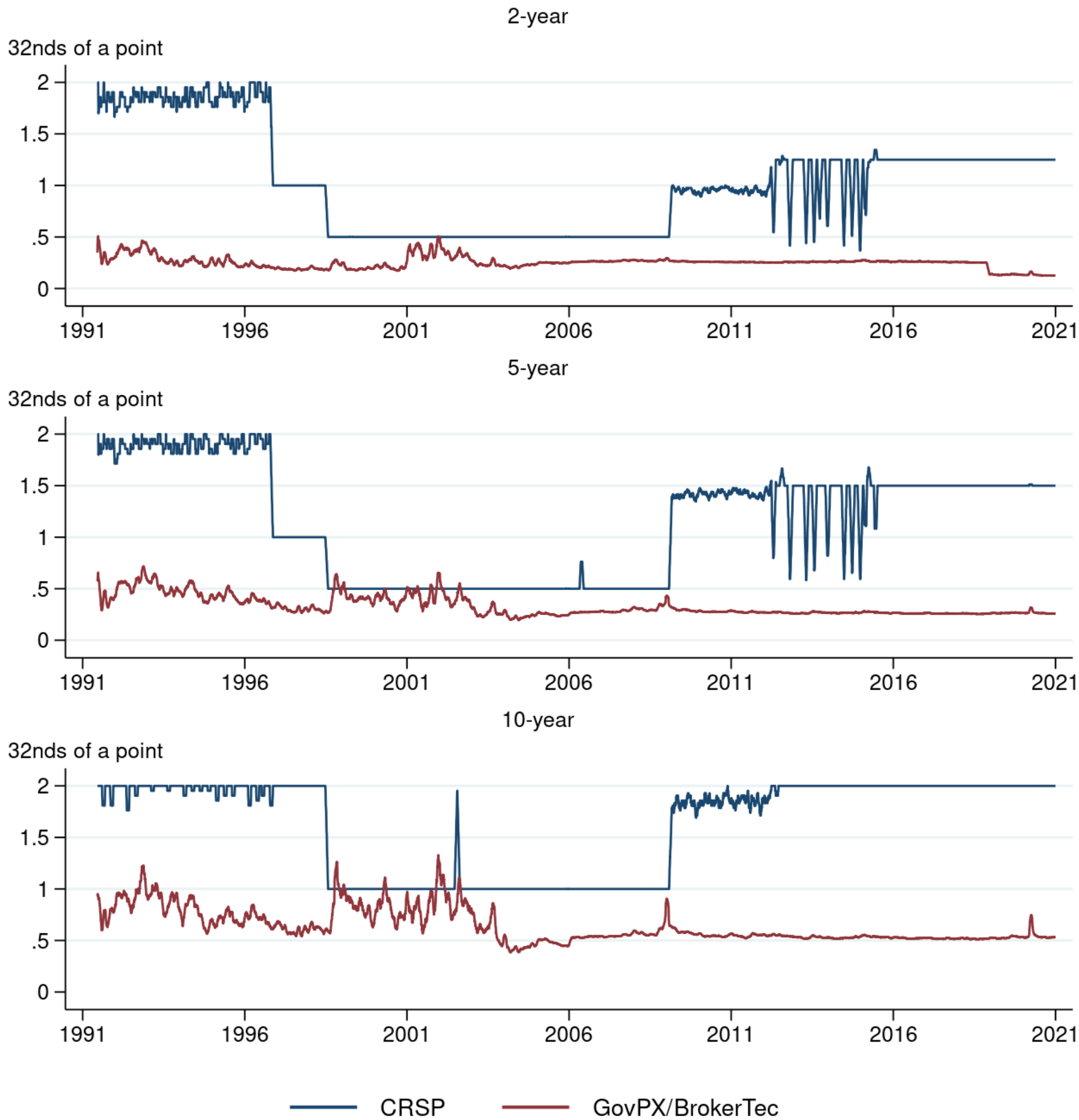
Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, GovPX, and Haver.
Notes: The figure plots average bid-ask spread, average order book depth at the inside spread (bid plus offer side), and price impact by day from June 17, 1991 (August 22, 1994 for depth) to December 31, 2020. Price impact is estimated as the slope coefficient from a regression of one-minute price changes on the net number of trades over the same one-minute interval. Basis points are measured in return space, so one basis point equals one one hundredth of a percent of price (with price measured as the bid-ask midpoint). Plotted lines are 21-day moving averages.

Figure 3: Liquidity Index



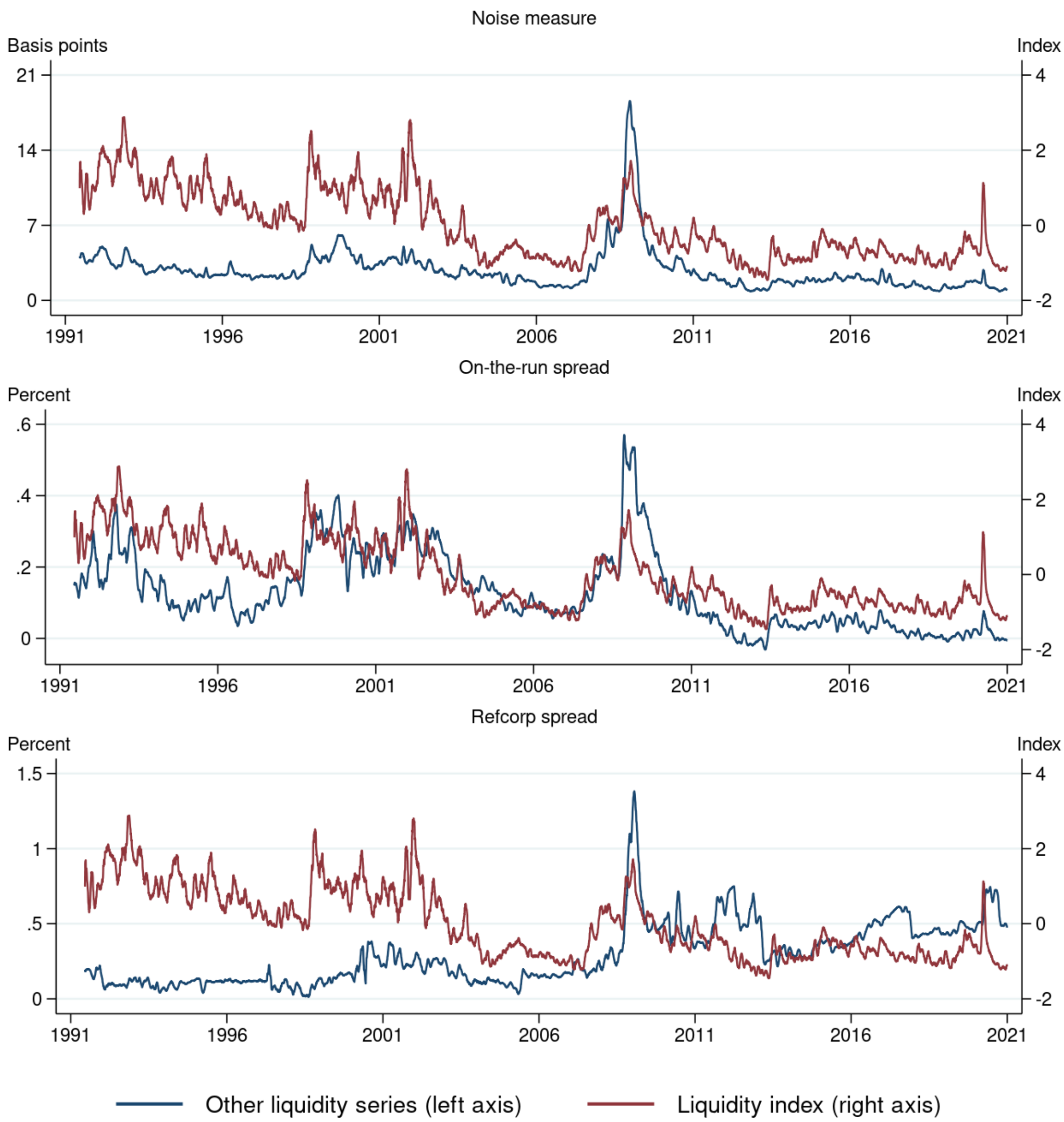
Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, GovPX, and Haver.
Notes: The figure plots measure-specific and security-specific liquidity indexes and the aggregate liquidity index by day from June 17, 1991 to December 31, 2020. The measure-specific indexes are the average of the indicated standardized liquidity series across the 2-, 5-, and 10-year securities. The security-specific indexes are averages of the standardized bid-ask spread, negative natural log of depth, and price impact series. The aggregate index is the average of the specific indexes. Plotted lines are 21-day moving averages.

Figure 4: GovPX/BrokerTec vs. CRSP Bid-Ask Spreads



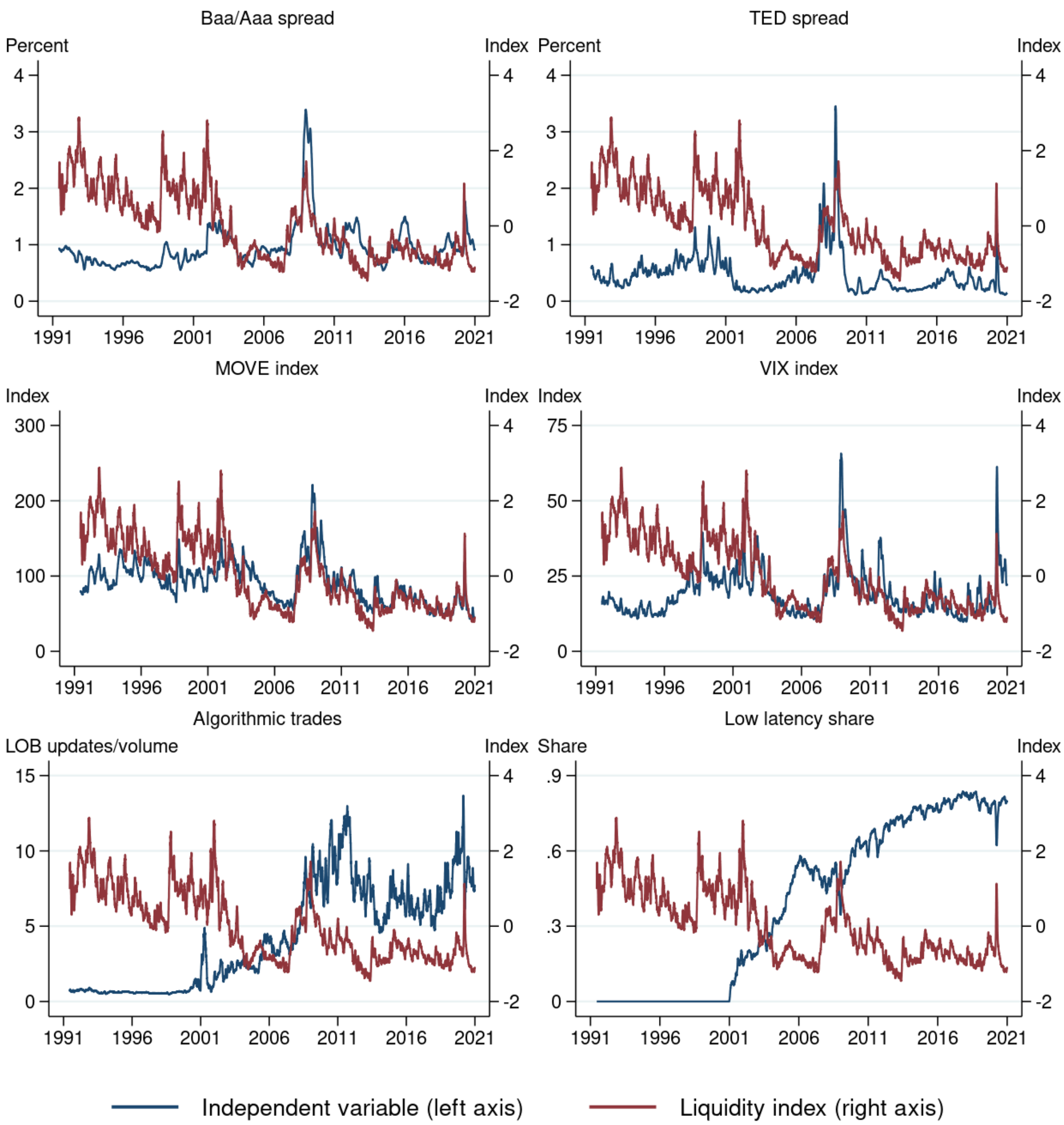
Source: Authors' calculations, based on data from BrokerTec, CRSP, the Federal Reserve Bank of New York, GovPX, and Haver.
Notes: The figure plots average daily bid-ask spreads from GovPX/BrokerTec and end-of-day spreads from CRSP from June 17, 1991 to December 31, 2020. Spreads are measured in 32nds of a point, where a point equals one percent of par. Plotted lines are 21-day moving averages.

Figure 5: Liquidity Index vs. Other Liquidity Series



Source: Authors' calculations, based on data from Bloomberg, the Board of Governors of the Federal Reserve System, BrokerTec, the Federal Reserve Bank of New York, GovPX, Haver, and Hu, Pan, and Wang (2013).
Notes: The figure plots the market liquidity index against various other market liquidity measures by day from June 17, 1991 to December 31, 2020. Plotted lines are 21-day moving averages.

Figure 6: Liquidity Index vs. Independent Variables



Source: Authors' calculations, based on data from BrokerTec, the Federal Reserve Bank of New York, the Federal Reserve Bank of St. Louis, GovPx, Haver, and TreasuryDirect.

Notes: The figure plots the market liquidity index against various independent variables by day from June 17, 1991 to December 31, 2020. Plotted lines are 21-day moving averages.