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Tick Size, Competition for Liquidity Provision, and Price Discovery: Evidence from the U.S. Treasury Market

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Abstract

This paper studies how a tick size change affects market quality, price discovery, and the competition for liquidity provision by dealers and high-frequency trading firms (HFTs) in the U.S. Treasury market. Employing difference-in-differences regressions around the November 19, 2018 tick size reduction in the two-year Treasury note and a similar change for the two-year futures eight weeks later, we find significantly improved market quality. Moreover, dealers become more competitive in liquidity provision and price improvement, consistent with the hypothesis that HFTs find liquidity provision less profitable in the lower tick size environment. Lastly, we find a significant shift in price discovery toward the cash market, which then reverses when the futures market tick size is reduced, suggesting that the finer pricing grid in the cash market allows traders to act on small information signals that are not profitable to exploit in the coarser pricing grid of the futures market. Our findings suggest that reducing the tick size in tick-constrained and highly liquid markets like the Treasury market is on balance beneficial.

Key words: tick size, bid-ask spread, market liquidity, price efficiency, price discovery, liquidity provision, Treasury securities, dealers, principal trading firms

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1 Introduction

This paper exploits a recent tick size change in the U.S. Treasury securities market to shed light on the role of tick size in market quality, price discovery, and the competition for liquidity provision. The U.S. Treasury securities market is the "single most important financial market in the world" (Group of Thirty, 2021), with $20.9 trillion in debt outstanding as of the end of 2020. Aside from financing the U.S. government, 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. All of these uses depend on a highly liquid and well-functioning market. Changes in market design that might affect market quality, price discovery, or the competition for liquidity provision are therefore of great importance to a wide range of stakeholders.

At the core of the Treasury market is the electronic interdealer broker (IDB) market for on-the-run coupon securities. With an average daily trading volume of roughly $190 billion, the electronic IDB market accounts for 52% of all trading in on-the-run coupon securities (Brain et al., 2018). Participants in the IDB market were traditionally limited to government securities dealers, but expanded to include high-frequency trading (HFT) firms in the mid 2000s (Joint Staff Report, 2015).[1] The more diverse participant base contributes to improved market liquidity, but may also expose liquidity to greater fragility due to the voluntary nature of liquidity provision. As a result, the question of how different types of market participants contribute to liquidity provision has taken on increasing importance in analyses of the changing structure of the Treasury market (e.g., Joint Staff Report, 2015; Inter-Agency Working Group, 2021).

The tick size change in the Treasury market presents a valuable opportunity to examine how the minimum price increment influences market participants' trading strategies and market outcomes. Starting with the November 19, 2018 trading day, the largest electronic IDB platforms halved the tick size on the benchmark 2-year note, from 1/4 to 1/8 of a 32nd of a point (where a point equals

[1]The HFT firms in the Treasury IDB market are often referred to as "principal trading firms" or PTFs. Because low latency is the main characteristic that we use to differentiate dealers and PTFs, we use the HFT and PTF terminology interchangeably in the paper.

one percent of par).[2] That the tick size reduction applies only to the 2-year note provides a natural experiment to identify the role of tick size in determining market quality, price discovery, and liquidity provision.[3]

Furthermore, a similar tick size change in the parallel market for 2-year Treasury note futures (from 1/4 to 1/8 of a 32nd of a point) did not occur until eight weeks later, starting with the January 14, 2019 trading day.[4] The staggered tick size reductions in the cash and then futures markets allow us to disentangle effects that are due to the granularity of a given market's pricing grid from effects that are due to the mismatch in tick size of the parallel markets. The latter effects should reverse upon the futures tick size reduction, whereas the former effects should not. The established literature on equity tick size changes provide a plethora of evidence on the effects of a tick size change in a given market, but the effects of mismatched pricing grids in parallel markets have not been previously explored. This feature is unique to the U.S. Treasury market, where cash and futures instruments are highly substitutable and cross-market trading (e.g., cash/futures basis arbitrage and hedging) is highly active. Mismatched pricing grids could present impediments to cross-market trading and influence traders' venue choice, affecting market outcomes in both venues.

We employ differences-in-differences (DD) regressions to identify the effects of the aforementioned tick size changes. Our data for the cash market are from the BrokerTec platform, while our data for the futures market are from the CME, accessed through Refinitiv. We find an almost one-for-one change in the bid-ask spread of the 2-year note, with it narrowing by 0.967/256 when the tick size is reduced by 1/256. This translates to a saving in transaction costs (half spread) of roughly \$94 million per year for market participants on the BrokerTec platform alone, or about \$118 million for the entire electronic interdealer cash market. The futures market's bid-ask spread is not affected by the cash market tick size reduction, because its tick size at the time was constraining

[2] Electronic IDB platforms with central limit order books that trade on-the-run Treasury securities are BrokerTec, Nasdaq Fixed Income (formerly eSpeed and now part of Dealerweb), FENICS, and LiquidityEdge. To put the new tick size in perspective, 1/8 of a 32nd is equivalent to a tick size of 0.390625 cents per \$100 par. In the current penny tick size environment in the U.S. equity markets, this is equivalent to a one-cent tick size on a \$256 stock.

[3] Prior to this event, the tick size had been 1/4 of a 32nd on the 2-, 3-, and 5-year notes since electronic trading began in 1999, and 1/2 of a 32nd on the longer maturity securities (7, 10, and 30 years).

[4] The tick size on other Treasury futures contracts remained the same: 1/4 of a 32nd for the 5-year note futures, 1/2 of a 32nd for the 10-year and ultra 10-year note futures, and one 32nd for the bond and ultra bond futures.

(leaving little scope for the spread to narrow further), but drops by 0.951/256 when the futures market tick size is subsequently reduced by 1/256, bringing an additional $594 million transaction costs saving per year to futures market participants.

Similar to the prior literature on equity market tick size changes, we find that trading activity increases, as the smaller tick size benefits liquidity demanders, while there is some weak evidence of decreased market depth. However, different from the equity market literature in which tick size reductions are often found to benefit smaller trades at the expense of large trades (e.g., Goldstein and Kavajecz, 2000), we find that transaction costs for large trades also decline significantly, and cumulative depth within 2/256 (the old tick) of the bid-ask midpoint continues to be many times higher than the size of most trades. Accordingly, the decrease in market depth does not seem to adversely affect transaction costs for trades, large and small, in this market.

We next examine the liquidity provision behavior of two key groups of participants in the Treasury IDB market: technologically sophisticated HFTs and traditional dealers. We distinguish HFTs from dealers based on their differential speed of response to market signals. Even though both HFTs and dealers use algorithms, differences in their business models give rise to differences in their latency. An important reason dealers trade in the wholesale IDB market is to facilitate customer trades in the dealer-to-customer market. In contrast, HFTs, which only trade on their own account and have little capital for carrying positions overnight or longer, trade in the market to exploit short-term price dislocations using high-frequency trading strategies. As such, it is critical for HFTs to invest in the fastest technologies to generate a speed advantage.

It is commonly believed that a smaller tick size benefits fast traders in the competition for liquidity provision given their speed advantage (e.g., Harris, 1997). However, recent work by Yao and Ye (2018) and O'Hara et al. (2019) finds that a smaller tick size could enhance slow traders' competitiveness. The intuition is that HFTs find liquidity provision less appealing/profitable in the smaller tick size environment. At the same time, as Li et al. (2021) posit, slow traders who have lower opportunity costs and can offer a more competitive spread now find it easier to compete. We ask whether dealers, the slow traders, compete better in providing liquidity and improving prices after the tick size becomes smaller.

To separate activities of HFTs from those of dealers without trader identity data, we consider a number of latency thresholds and find that 10 millisecond (ms) is a reasonable choice. Moreover, Salem et al. (2018) analyze the distribution of trade flows on BrokerTec by time since the last trade and find that HFT trades in recent years have a latency of 10 ms or less. Using this threshold, we construct two measures of liquidity provision and price competition by HFTs and non-HFTs. The first, labeled "$FirstLO$", attributes the fraction of limit orders submitted within 10 ms from a change in the best bid-ask midpoint to HFTs, and the fraction of limit orders submitted between 10 ms and one second of the change to slow traders. The second, labeled "$SprTight$", attributes the fraction of price-improving limit orders submitted within 10 ms of a widening bid-ask spread to HFTs, and those submitted more than 10 ms after the change (but still within one second) to slow traders. Thus, $FirstLO$ reflects the extent to which each of these trader types provides liquidity to the limit order book, while $SprTight$ focuses on each type's price competitiveness.

Indeed, we find that a smaller tick size seems to benefit slow traders, with such traders more likely to restore the spread to its minimum level and to be the first to respond to price changes. Our evidence is consistent with the interpretation that slow traders in this market are dealers who, due to inventory pressures resulting from market making activities in the dealer-to-customer market, can offer more competitive pricing and now can better compete. Meanwhile, HFTs cut back their liquidity provision due to lower profitability.

We also examine the impact of tick size on price discovery, an exercise possible due to the tight link between the cash and futures markets and the staggered tick size reductions. Mizrach and Neely (2008) show that the cash and futures markets are tightly linked through the no-arbitrage principle, and Dobrev and Schaumburg (2018) find that this is even more so in recent years given the rise in high frequency trading. Thus, the two markets are increasingly viewed as one, sharing a common fundamental process. The variance of this process reflects the aggregate information affecting Treasury benchmark rates. The contribution of each market to this variance in turn indicates its share of the aggregate information. The staggered tick size reductions result in an eight-week period during which the cash market has a smaller tick size than the futures market, thereby allowing us to identify the effects of tick size on price discovery.

We measure the informational role of the market for the 2-year note relative to its futures counterpart using Hasbrouck (1995)'s information share. We find a significant shift in price discovery toward the cash market after its tick size is halved. This shift then reverses when the futures market tick size catches up. In addition, the informational advantage of the smaller tick size in the cash market is present only at very high frequencies (less than one minute). These findings suggest that the finer pricing grid in the cash market allows traders to act on small information signals that are not profitable in the coarser pricing grid of the futures market and contributes to the cash market leading the futures market in price discovery.

A potential concern with our empirical setup is that the tick size reduction in the 2-year note was not random. It is possible that the change was a response to improvement in the note's liquidity, leading to a concern over possible reverse causality. That said, there are several reasons to believe our results reflect the effects of the tick size change. First, the decision to change the tick size was made and announced far in advance.[5] In addition, we adopt a short window around the event so that any immediate changes following the tick size change are more likely to be due to the event and less likely to be due to longer-term trends. The DD regressions further help us control for market movements around the change for cleaner identification of effects.[6] Lastly, the reversal of the effects on price discovery when the futures market's tick size is subsequently reduced to the same level as the cash market provides strong support for attributing the initial increase in price discovery to the smaller tick size in the cash market.

Studying the effects of a tick size change using the Treasury market as a laboratory has additional advantages beyond those discussed earlier. First, the market is quite concentrated, with BrokerTec

[5]The CME announced the January 14, 2019 tick size change in the 2-year futures on May 18, 2018 (`https://www.cmegroup.com/content/dam/cmegroup/notices/clearing/2018/05/Chadv18-192.pdf`).

[6]We use other Treasury securities as controls in our empirical analysis but acknowledge that these are not perfect. Even though these securities are highly related, they differ in their duration and clientele. This issue could also happen with a randomized experiment, but would be mitigated by a large number of treatment and control securities. We do not have a large cross section of Treasuries to completely address this issue. Nevertheless, the small number of benchmark Treasuries that trade in the electronic IDB market should not hinder studies of this important market. Furthermore, the small number of securities reduces statistical power of tests, biasing us against finding significant results.

(the platform studied) accounting for roughly 80% of electronic interdealer market activity in on-the-run Treasury securities. Second, there is no separate dark pool trading venue. Third, the fee structure on BrokerTec (during our sample period) does not discriminate between liquidity consumption and provision. Therefore, the impact of a tick size change can manifest itself in market outcome variables in a straightforward fashion, allowing us to cleanly quantify the effects and test relevant theories which are often built on assumptions of minimal market frictions.

Our paper relates to several strands of literature. First and foremost, our analysis of the tick size change in the Treasury market fits in the rich literature on tick size and market quality. This literature is heavily based on previous tick size changes in the U.S. equity markets. Studies of tick size changes in 1997 (from eighth to sixteenth) and 2001 (from sixteenth to decimal) include Harris (1994), Bessembinder (2003), Goldstein and Kavajecz (2000), Jones and Lipson (2001), Ronen and Weaver (2001), and others as surveyed in Biais et al. (2005). Studies of the SEC Tick Size Pilot Program in 2016-2017 include Rindi and Werner (2019), Griffith and Roseman (2019), Albuquerque et al. (2020), Comerton-Forde et al. (2019), Chung et al. (2020), and Lee and Watts (2021), among others.

We add to this literature novel results related to the role of tick size on price discovery and the competition between dealers and HFTs for liquidity provision in the much less studied, but highly important, U.S. Treasury market. While some of our findings are consistent with prior evidence (narrower bid-ask spread, increased trading activity, improved price efficiency), we provide many new results, including those that arise from unique features of the Treasury market structure. Specifically, in a marketplace where fast and slow "machines" (HFTs and dealers, respectively) compete, we find that a reduction in tick size enhances dealers' competition for liquidity provision even though they do not have a speed advantage. We also find that the temporary mismatch in the pricing grids between the cash and futures markets shifts price discovery toward the finer-grid market, supporting the idea that the finer grid allows traders to transact at prices closer to true values and act on small information signals otherwise unprofitable to exploit in a larger tick environment. Our evidence from the highly liquid Treasury market provides an interesting contrast to recent evidence from the equity market's Tick Size Pilot Program. Chung et al. (2020) find that a tick size increase improves liquidity especially for small and illiquid stocks and affects small and large trades differentially. The divergence of conclusions implies that the impact of a tick size change depends on the characteristics of the security and market where the change occurs.

Most related to our work in a non-equity market setting is Chaboud et al. (2019).[7] They study a tick size reduction and subsequent reversal in the spot foreign exchange market and find that a smaller tick size reduces long-run price discovery. They show that the tick size reduction results in increased trading demand from HFTs, whose order flow contains less long-term fundamental information. Thus, a smaller tick size does not benefit long-run price discovery. Complementing their findings, we show that a smaller tick size is beneficial for short-run price discovery.

Our paper also belongs to the literature on U.S. Treasury market microstructure. The Joint Staff Report (2015) analyzes the October 2014 Treasury flash rally and documents the increased role of HFTs on electronic IDB platforms. Fleming et al. (2018) examine price discovery in the market and document a significant informational role of liquidity providers. Dobrev and Schaumburg (2018) study high-frequency trading in both cash and futures markets. Adrian et al. (2020) examine intraday market making and inventory patterns, especially by non-bank PTFs, and highlight key differences in how dealers and PTFs operate with respect to liquidity provision. We contribute to this literature evidence on how tick size affects the competition for liquidity provision between dealers and HFTs and the information share of the cash market relative to the futures market. Overall, we find that reducing the tick size is on balance beneficial, especially in regard to price discovery, and provides a useful preview of the potential effects of any future tick size reductions in other Treasury securities.

The paper proceeds as follows. Section 2 provides key institutional details and describes the data and methodology. Section 3 describes how key market quality metrics change after the cash market tick size reduction. We investigate the effects of a smaller tick size on the competition for liquidity provision in Section 4, and on price discovery in Section 5. Section 6 presents additional analysis of the effects on other Treasury securities and Treasury futures. We discuss our robustness

[7] A narrowly related study in a non-equity setting is Martinez and Tse (2019), who examine the impact of tick size reductions on market quality in the FX futures markets for the Mexican peso, the Japanese yen, and the euro.

checks in Section 7. Section 8 summarizes our key findings and concludes.

2 Institutional Details, Data, and Methodology

2.1 Institutional details

U.S. Treasury securities are debt instruments of the U.S. government issued through public auctions and subsequently traded in the secondary market. The secondary market is structured as a multiple dealer, over-the-counter market, in which the dealers trade with their customers and one another. Interdealer trading prior to 1999 was based on a network of voice-assisted brokers. Fully electronic trading began in 1999 with the introduction of the eSpeed platform, followed by the BrokerTec platform in 2000. Nearly all interdealer trading of on-the-run U.S. coupon securities occurs via electronic platforms among which BrokerTec has a roughly 80% share.[8]

Historically, participation on the electronic platforms was limited to dealers. However, as the platforms opened to other professional traders in the mid 2000s, the presence of non-dealer participants—the HFTs—increased significantly. According to the Joint Staff Report (2015) on the October 15, 2014 flash rally in the Treasury market, HFTs account for 56% of trading volume in the on-the-run 10-year note on BrokerTec, compared to bank-dealers' share of 35%.[9] HFTs' share of trading volume has likely increased since 2014.

The tick size reduction from 1/4 to 1/8 of a 32nd in the 2-year note on BrokerTec and Nasdaq Fixed Income starting with the November 19, 2018 trading day is the first such change since the beginning of electronic trading in Treasuries in 1999. Prior to this, the tick size had been 1/4 of a 32nd for the the on-the-run 2-, 3-, and 5-year notes, and 1/2 of a 32nd for the longer maturity securities (7, 10, and 30 years). Most noteworthy about this change is that it applies only to the 2-year note and only in the cash market. A similar tick size change from 1/4 to 1/8 of a 32nd in the companion market for the 2-year Treasury futures does not occur until eight weeks later, starting

[8]Electronic brokers account for 87% of trading in on-the-run coupon securities that occurs through interdealer brokers (Brain et al., 2018). Further, according to Greenwich Associates, based on 2017 Q4 data, BrokerTec's market share in the electronic interdealer market is 80%, that of Nasdaq Fixed Income (which is now part of Dealerweb) is 11%, and the rest of the market is split among Dealerweb, LiquidityEdge, FENICS, and dealer-owned internalization/crossing platforms (McPartland, 2018).

[9]The remaining 9% is split among non-bank dealers and hedge funds; shares are based on data for April 2-17, 2014.

with the January 14, 2019 trading day.[10] The staggered reductions of tick size in the cash and futures markets, and only for the 2-year maturity segment, presents a clean setting to identify how tick size affects market quality and price discovery. In particular, the temporary mismatch in tick size between the cash and futures markets between November 19, 2018 and January 14, 2019 provides a unique opportunity to assess the cash market's contribution to price discovery while it is on a finer pricing grid than the futures market.

2.2 Data

Our sample for the cash market analysis consists of the five on-the-run Treasury notes, with the 2-year note being the treatment security and the 3-, 5-, 7-, and 10-year notes the control securities. We exclude the 30-year bond due to the vast difference in duration and clientele from the 2-year note. The sample used in the futures market analysis consists of the 2-, 5-, 10-, and ultra 10-year note futures. Our sample period covers 24 weeks (112 trading days) between September 24, 2018 and March 9, 2019, divided into three eight-week sub-periods.[11] The first sub-sample period (SS1) runs from Monday, September 24, 2018 to Friday, November 16, 2018 (38 trading days), covering the eight-week period before the tick size change in the 2-year note. The second sub-sample period (SS2) runs from Monday, November 19, 2018 to Friday, January 11, 2019, covering the eight-week period from the tick size change in the 2-year note to just before the tick size change in the 2-year futures. The third sub-sample period (SS3) runs from Monday, January 14, 2019 to Friday, March 9, 2019, covering the eight-week period from the tick size change in the 2-year futures.

For the cash market, we rely on order message data from the BrokerTec platform, which accounts for roughly 80% of the electronic IDB market (McPartland, 2018).[12] We reconstruct the tick-by-tick limit order book for each of the notes by accumulating order changes at the appropriate price tiers

[10]The CME, which operates the marketplace for Treasury futures, also owns the BrokerTec platform. Thus, the subsequent tick size change in the futures market is not likely due to venue competition in response to the cash market tick size change. Moreover, as previously mentioned, the futures tick size change decision was announced prior to the cash tick size change and therefore unlikely made based on what was learned from the cash market change.

[11]The bond market was closed on the other eight weekdays during our sample period, including seven holidays and December 5, 2018 on which financial markets were closed in honor of former President George H.W. Bush; see `https://www.sifma.org/resources/general/holiday-schedule/`

[12]We do not have data for the other electronic IDB platforms nor interest rate swap trading venues. Thus, our data coverage is incomplete, but nonetheless accounts for the majority of IDB market activity in benchmark Treasuries.

from the beginning of each trading day.[13] We also extract the complete trade history for each security. The data clearly indicate which side initiates a given trade, the traded quantity and price, and whether a trade is executed during a workup.

Data for the futures market are from the CME (accessed through Refinitiv). The data are at the one-second frequency, and include last trade price, number of trades, trading volume, best bid and ask prices, and market depth for the top 25 price tiers. In analyses of cash-futures pairs, we couple the 10-year cash instrument with the ultra 10-year futures, because the deliverable maturity range into the latter (9 years 5 months to 10 years) more precisely matches the maturity of the 10-year note. The regular 10-year futures is instead paired with the 7-year note because its deliverable maturity ranges from 6.5 years to 10 years and because the average maturity of the CTD underlying the 10-year future contract during the two-year period enclosing our sample period (2018–2019) is 6.95 years. Treasury futures contracts covering the 3-year tenor do not exist during our sample period. As is standard in the literature, we use the front-month contract (i.e., the one with the closest maturity) until its trading volume is overtaken by the next maturity contract, at which point we switch to using data on the next maturity contract.[14]

From these data, we construct key market quality metrics, the details of which are provided in Table 1. These metrics are computed from intraday data from 7:30 to 17:00 ET (mostly at the 1-minute frequency unless otherwise noted) and then aggregated to the daily level.[15] The aggregation is by simple averaging for stock variables (such as spreads and depths) and by summing for flow

[13]BrokerTec operates as a central limit order book market. Trading spans 22-23 hours per day during the week, commencing around the start of the trading day in Tokyo (at 18:30 EST or 19:30 EDT the previous day in the U.S.) and concluding with the end of the trading day in New York (at 17:30 ET; see Fleming 1997). All order messages sent to the platform are captured and time-stamped to the microsecond. Each order specifies a quantity and a price, and whether it is for purchase or sale. Aggressive orders are typically priced at the prevailing best price on the opposite side and are immediately executed. Aggressive orders are rarely priced beyond the best price on the opposite side because of the quoted depth typically available at the inside tier and because of the availability of the workup protocol. The workup protocol allows market participants to transact additional quantities at an existing trade price (see Fleming and Nguyen, 2019 for further details on the workup protocol).

[14]Front-month contracts are typically the most liquid contracts until one or two trading days before the first day of the delivery month when traders roll over their interests to the next maturity contracts.

[15]Although the cash and futures markets both operate almost round the clock, the majority of activity occurs during New York trading hours. Thus, to avoid the effects of potential overnight hour irregularities, our analyses use data from 7:30 to 17:00 ET (while the cash market trading continues until 17:30 ET, we use data only through 17:00 ET because Treasury futures trading ends at that time). For the three early market close days in our sample period (November 23, December 24, and December 31, 2018), we truncate the data at the earlier closing time of the two markets.

variables (such as trading volume) unless otherwise noted. Because market depths are highly variable, we winsorize intraday depth observations at the 2.5 and 97.5 percentiles before taking the average for the day to reduce the effects of outliers. Several price efficiency measures (e.g., return autocorrelation, variance ratio, and pricing errors) are computed from 1-second midpoint returns.

Figure 1 illustrates the impact of the cash market tick size change on the level and tightness of the bid-ask spread. The upper plot shows an immediate narrowing for not just the inside bid-ask spread but also the bid-ask spread faced by a large trade. The lower plot indicates that the tick size constraint on the spread lessens: the average percent of time the bid-ask spread is at exactly one tick is 99% before the event, but drops to the low nineties after.

Table 2 reports summary statistics by security for our key market quality metrics over the three sub-sample periods previously described. The second sub-sample period contains December 2018, when the market was unusually volatile, and when there was the usual end-of-year decrease in activity and in liquidity. Thus, for most securities, the second sub-sample period is characterized by wider bid-ask spreads, higher number of trades, smaller trade sizes, reduced market depth, and increased frequency of price updates and volatility.

2.3 Empirical methodology

We employ the standard DD regression model to quantify the effects of the tick size reductions on various outcome variables as follows:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta Post_t \times Treatment_i + \epsilon_{i,t}, \tag{1}$$

where $Treatment$ is an indicator variable equal to 1 for the 2-year note and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, and α_i and γ_t are security and day fixed effects, respectively. The inclusion of day fixed effects absorbs confounding effects including those due to changing market conditions, intra-week seasonality, and low market activity around holidays and on early market close days. The coefficient of interest is β, which captures the effect of the tick size reduction on a given market outcome variable Y. For robustness, we discuss an alternative model in Section 7.2 in which, instead of day fixed effects, we control explicitly for market wide liquidity, volatility, day-of-week effects, holiday effects, and early market close effects, with security-specific coefficients. Key results are qualitatively similar.

For DD empirical designs, it is important to cluster standard errors to account for possible error correlation within clusters, as pointed out in Bertrand et al. (2004). One further complication is that when the number of clusters is small, clustered standard errors are shown to over-reject (see Cameron and Miller, 2015 for an in-depth survey on cluster-robust inference). Given the small number of clusters used in this analysis (with only five securities), we follow Cameron and Miller (2015)'s suggestion to use the wild cluster bootstrap method with the six-point weight distribution devised by Webb (2013) to obtain robust p-values for clustered t-statistics. Our inferences are then based on these bootstrapped p-values.

3 How Does Tick Size Change Affect the Treasury Market?

In this section, we discuss how key measures of market quality change as a result of the tick size reductions to provide some perspective for our main empirical results in Sections 4 and 5. We estimate the regression model in Equation (1) for each market quality metric around each of the two tick size events and report the coefficient of interest (β) in Table 3.

3.1 Trading activity and transaction costs

Panel A of Table 3 shows measures of bid-ask spreads and trading activity. The cash market's tick size reduction immediately narrows the inside bid-ask spread almost one-for-one. Based on the pre-change average daily trading volume of about \$20 billion par in the 2-year note, this spread reduction translates to a transaction cost saving (half spread) of roughly \$94 million per year for liquidity demanders on BrokerTec alone ($\frac{1}{2} \times \frac{-0.967}{256} \times 0.01\times$ \$20 billion $\times$ 250 trading days). Notably, the bid-ask spread faced by large trades (BAS_L) drops by almost as much; this differs from what is often found in studies of equity tick size reductions: reduced transaction costs for smaller trades but higher transaction costs for large trades (e.g., Goldstein and Kavajecz, 2000). The tick size change loosens the tick size constraint ($OneTick$) by about seven percentage points, but overall the bid-ask spread still remains tight around the new tick. After the subsequent tick size reduction in the futures market, the tick size constraint tightens modestly, whereas changes in the level of the spread are mixed and statistically insignificant.

Trading activity clearly increases after the tick size change, more strongly in the number of trades than in trading volume, as trade sizes are significantly smaller (by about \$2.3 million). Prior theories (e.g., Goettler et al., 2005) posit that a smaller tick size improves welfare for market order submitters at the expense of limit order submitters. Consequently, some traders who otherwise would have submitted limit orders (or would not have traded at all) are now more likely to trade, leading to higher trading volume and frequency.[16] Our evidence offers support for this view, and also indicates a change in order strategy in the smaller tick environment in which traders split their orders into smaller ones and layer into the limit order book at smaller price increments, consistent with Goldstein and Kavajecz (2000).[17] After the futures market tick size reduction, the average trade size becomes even smaller, but changes in trading volume and trading frequency are insignificant.

3.2 Price efficiency

Panel B of Table 3 shows the effects of the smaller tick size on several measures of price efficiency. Both measures of price-updating activity ($NonZeroBA$ and $NonZeroT$) show significantly decreased inertia after the tick size change, by roughly 13–20 percentage points. Importantly, the tick size reduction does not have a significant impact on volatility (we obtain similar results when we compute volatility from trade prices instead of midpoint prices). The evidence implies that the shrinking microstructure noise component of realized volatility due to lower price discreteness balances out with the increased frequency of price updates, thereby leaving realized volatility largely unchanged. This is corroborated by the significantly lower standard deviation of intraday pricing errors. While some other measures of price efficiency do not show statistically significant changes,

[16] The empirical literature generally finds consistent evidence, with a smaller tick size benefiting liquidity demanders (e.g., Harris, 1994, Bacidore, 1997, Porter and Weaver, 1997, and Bessembinder, 2000) and a larger tick size harming liquidity demanders (e.g., Albuquerque et al., 2020).

[17] We also examine whether trading activity via the workup protocol changes (see Fleming and Nguyen, 2019 for more details on the workup protocol). We find that traders are less likely to use workups in the new smaller tick environment, especially for small trades. This finding supports the interpretation that it is now less costly to trade through to the next price point, thereby disincentivizing the use of workups, particularly for smaller trading interests.

the overall evidence points to improved price efficiency as a result of the tick size change in the cash market. No further improvement is observed after the tick size change in the futures market.

3.3 Liquidity supply

With data on the full limit order book, we are able to thoroughly analyze how liquidity supply responds to a tick size change in a liquid market. We first examine depth at the inside tier ($D1$), at the best five tiers ($D5$), and across the whole book (DT).[18] Panel C of Table 3 shows that inside depth declines significantly after the tick size change, indicating that not all liquidity providers who supplied liquidity at one old tick are now willing to supply liquidity at half that tick. Although lacking in statistical significance, depth at the best five price levels and total depth also decline. Still, at the new shallower inside tier, depth is more than sufficient to absorb easily even large trades: the post-change depth at the inside tier ($D1$) averages \$237 million per Table 2, which is many times higher than the 99th percentile of the trade size distribution (\$50 million). Consequently, traders with large trading interests do not seem to be adversely affected by the reduced market depth. This is in contrast to equity market evidence whereby the combination of narrower spreads and reduced depth makes liquidity demanders with small orders better off while those with large orders worse off (e.g., Goldstein and Kavajecz, 2000). The difference highlights the high level of liquidity in the Treasury market compared to even the most liquid stocks.

Because the pricing grid changes, market depth by tier is not comparable before and after the tick size reduction. To provide a more complete picture of how liquidity supply responds to the change and to isolate the change in quantity from the effect of the increased granularity of the price grid, we examine the amount of liquidity supplied within a fixed distance from the bid-ask midpoint. Specifically, we consider the cumulative depth within one through five pre-change ticks ($D1A$–$D5A$) (corresponding to two, four, six, eight, and 10 post-change ticks for the 2-year note). Panel D of Table 3 shows that the cumulative depth changes are of mixed sign and insignificant. This is consistent with Biais et al. (2005) who predict that a tick size reduction should result in a

[18] Although market participants with API access to the platform can view the complete order book, many market participants can only see the best five tiers within the live order book.

mere redistribution of depth on a finer pricing grid. Overall, there is limited evidence of decreased market depth after the tick size reduction, and even at the significantly lower inside depth, liquidity supply still outweighs liquidity demand, resulting in lower execution costs for even large trades.

4 How Does Tick Size Affect Fast and Slow Liquidity Providers?

Even though our analysis of the limit order book in Section 3 does not find support for a significant change in liquidity supply, the tick size change might have differential effects on different types of liquidity providers. As previously discussed, from a traditional dealer-only marketplace, the Treasury electronic IDB market has became much more diverse with direct and rising participation of HFTs. Moreover, with a business model different from that of traditional dealers (principal trading to exploit price dislocations at high frequency and little capital for carrying inventory positions overnight), HFTs need to invest in the fastest trading technologies to stay competitive. Dealers also increasingly rely on sophisticated trading technologies but do not face the same pressures as the HFTs to invest in the very fastest technologies. This creates a natural separation of speed between HFTs and dealers, which we refer to as fast and slow traders. In this section, we seek to understand how the behavior of each type of liquidity provider changes with the tick size.

4.1 Liquidity provision by fast and slow traders

Prior literature suggests that the tick size can play an important role in how different types of traders compete in a limit order book market. On the one hand, Harris (1997) argues that a smaller tick size benefits fast traders in the competition for liquidity provision. A smaller tick size makes it easier for traders to exploit small information signals and should disproportionately benefit fast traders due to their speed advantage, suggesting a negative relationship between tick size and HFTs' involvement. On the other hand, Yao and Ye (2018) and O'Hara et al. (2019) find that liquidity provision by HFTs increases in tick size. They reason that fast traders exploit their speed advantage to establish time precedence when the tick size is large because it is more expensive to obtain price priority. When the tick size is small, the reward for liquidity provision shrinks, thereby disincentivizing fast traders while allowing slower traders with more competitive pricing to compete.

Li et al. (2021) provide a theoretical model to illuminate the importance of tick size on liquidity provision by HFTs and slower algorithmic traders ("EAs"). EAs provide liquidity primarily to minimize transaction costs, unlike HFTs which provide liquidity to capture bid-ask spreads. In providing liquidity, HFTs balance the reward (the spread) with the risk of being sniped when the market moves. When the tick size is large and constrains market moves, the adverse selection risk is low, thereby encouraging more liquidity provision by HFTs. In contrast, when the tick size is small, the sniping risk is greater (the market is more likely to move) while the spread is narrower, both of which discourage HFT liquidity provision. Meanwhile, the smaller tick size makes it easier for EAs to price improve, and they can do so because they have lower opportunity costs than HFTs.

The characteristics of the Treasury IDB market are quite close to those of the setup in Li et al. (2021) (a market featuring machine-to-machine interactions, in which slow traders, i.e., dealers, have lower opportunity costs in providing liquidity at better prices than HFTs due to their client market-making business). Thus, it provides an appropriate laboratory to test the model's prediction against the alternative hypothesis that a smaller tick size benefits HFTs more. Our earlier results that bid-ask spreads narrow significantly (suggesting decreased reward) and prices move more frequently (suggesting increased sniping risk) lead us to expect that HFTs will cut back on their liquidity provision and become less price competitive in the new environment.

4.2 Identification of fast traders

An important part of our analysis is the identification of liquidity provision activities by fast and slow traders. Unfortunately, the BrokerTec data, like most message-level datasets, do not provide any identification information of market participants.[19] As a result, we have to infer HFT activities based on some salient characteristics.

The prior literature on HFTs provides helpful guidance in developing our identification scheme. A seemingly natural identification method for HFT activity is measuring general market speed

[19]The only datasets with clear HFT identification flags that we are aware of are the NASDAQ October 2010 dataset covering 120 randomly selected stocks used in studies such as Yao and Ye (2018), and the EBS data for the foreign exchange market used in Chaboud et al. (2014) and Chaboud et al. (2019).

through measures like the message-to-trade ratio as in Hendershott et al. (2011). However, recent studies with access to HFT identifiers such as Yao and Ye (2018) find that these measures do not satisfactorily identify trading by HFTs. SEC (2014) further notes that general market speed proxies for HFT activity are poor because non-HFT firms also engage in algorithmic activity. Some studies, like Aquilina et al. (2022), use trader or firm identifiers to more accurately classify HFTs by analyzing trading patterns or net positions and activity on a per ID basis. However, without these identifiers (which is the case for most commercially available datasets), it is extremely difficult if not impossible to classify individual trades as HFT initiated or not.

The blurry line between HFTs and other fast traders explains the prevalence of the "algorithmic" and "low-latency" classifications used in much of the literature. For example, Brogaard et al. (2014) divide firms into "fast" and "slow" traders using subscription to colocation services as their proxy. Hasbrouck and Saar (2013) develop a measure of low-latency activity based on "strategies that respond to market events in the millisecond environment. They use quote updates as their market signal, and link submissions and cancellations within 100 ms as part of a strategic run. Chordia et al. (2018) explore activity after macroeconomic announcements and find markedly increased trading intensity within 5 ms of news releases. Dobrev and Schaumburg (2018) analyze cross-market activity between the Treasury cash and futures markets and observe a 5 ms offset between the markets, consistent with the fastest information transfer speeds currently available to HFTs. In similar spirit, we classify fast traders based on their low-latency response to market signals.

Fortunately, in the Treasury market, latency seems to provide a good separation of HFTs from dealers. Salem et al. (2018) analyze the distribution of trade flows by the time since the last trade on BrokerTec and find two clear separate masses along the latency dimension. They also find that the speed of the market has increased markedly in recent years. Co-location HFTs can respond in 5 ms or less. HFTs that trade the basis (cash/futures) can respond in under 10 ms, which is roughly the round-trip latency between New York and Chicago at the speed of light. Thus, the key to our identification is an appropriate threshold that reflects the physical limit which only sophisticated trading technologies used by HFTs can achieve.

We further validate our chosen latency threshold for categorizing fast traders using Trade Reporting and Compliance Engine (TRACE) data for U.S. Treasury securities. Effective April 1, 2019 (after the end of our sample period), the Financial Industry Regulatory Authority (FINRA) requires that large IDBs report the identity of all of their counterparties, including PTFs, in their Treasury TRACE reports. The data allow for the extent of PTF trading in the electronic IDB market to be quantified, and provide a good benchmark (albeit out of sample) to judge which latency threshold gives rise to the most accurate measure of HFT activities. We consider the following thresholds that are close to what have been used by prior researchers: 1 ms, 5 ms, 10 ms, 25 ms, 50 ms, and 100 ms. Using BrokerTec data from April 1, 2019 to December 31, 2020, we identify trades that occur within a given latency threshold following a market signal, defined as a change in the best bid or offer prices. The resultant share of daily trading volume attributable to fast traders is then compared with PTFs' share of daily trading volume on electronic IDBs as calculated from FINRA TRACE Treasury data.[20]

We report the correlations in Panel A of Internet Appendix Table A1. The correlations are quite similar but generally decreasing in latency. The average correlation, weighted by securities' average daily trading volume over the same period, indicates that the HFT trading activity identified by the 1 ms threshold is most correlated with the PTF trading volume share (0.421). However, as discussed above, adopting the 1 ms threshold would exclude HFTs that trade the cash/futures basis due to the time it takes for information to travel from New York to Chicago, resulting in these HFTs being incorrectly classified as slow traders. To assess the extent to which HFTs are misclassified as slow traders, we report in Panel B of Table A1 the correlations of the PTFs' trading volume share with the volume share of slow traders (trades occurring with a latency outside of a given threshold). The best classification threshold should have the least, or most negative, correlation with the PTF trading volume share. Along this dimension, 1 ms appears the worst, while 25 ms appears the best with the 10 ms and 50 ms thresholds coming closely behind. Overall, the analysis in Table A1 suggests that 10 ms and 25 ms may be the best thresholds overall. We feature the 10 ms threshold in our main

[20]The TRACE Treasury data is collected for regulatory use by the official sector. The PTF volume shares calculated from these data are plotted in, and provided to us by, Fleming et al. (2021).

analysis, but provide the results for other thresholds in the Internet Appendix.

After determining the appropriate latency threshold, we next measure liquidity provision by fast and slow traders using two different metrics. The first measure, denoted by $FirstLO$, captures the fraction of the first limit orders reaching the book following a market signal, defined as any change in the best bid or offer prices. If such an order arrives within 10 ms, we classify it as coming from a *fast* trader. If the order arrives more than 10 ms after the signal but still within one second, we consider it as coming from a *slow* trader. We exclude orders that arrive more than one second following a market signal because it is not clear which trader type sends such orders and whether such orders are even responses to the given market signal. For each day, we calculate the measure separately for each trader type. The denominator is the number of market signals during the day. The numerator is the number of first responding limit orders submitted by a given trader type.[21]

The second measure, denoted by $SprTight$, is the fraction of time a given trader type is the first to restore the bid-ask spread to one tick. So while $FirstLO$ captures just the general liquidity provision activities (which may or may not improve price), $SprTight$ specifically reflects price improvement in liquidity provision. We attribute the first order that restores the bid-ask spread back to one tick to either fast or slow traders again based on the latency threshold of 10 ms as previously discussed. The denominator is the number of times the bid-ask spread is greater than one tick, representing the number of opportunities for price improvement. The numerator is the number of spread-tightening limit orders submitted by a given trader type.

We plot the time series of $FirstLO$ and $SprTight$ for slow and fast traders in Figure 2. Fast traders appear to dominate the competition for liquidity provision, as indicated by the substantially higher magnitudes of both $FirstLO$ and $SprTight$ for fast traders as compared to slow traders. However, both measures increase for slow traders and decrease for fast traders following the tick size change in the cash market. Furthermore, there appears to be some reversal in the $FirstLO$ measure after the futures market's tick size change eight weeks later, but such a reversal is less evident in the $SprTight$ measure.

[21]These two fractions do not add up to 100% because of the exclusion of order activities that arrive more than one second after a market signal.

4.3 Effects of tick size on fast and slow liquidity provision

Based on the DD regression model in Equation (1), we identify the effects of tick size on the liquidity provision behavior of fast versus slow traders and report the results in Table 4. Panel A shows the effects of the cash market's tick size change. The $Post \times Treatment$ coefficient is positive for slow traders in both the $FirstLO$ and the $SprTight$ measures, with the latter being statistically significant at the 5% level. Specifically, slow traders price improve more, as reflected in an increase of 4.3 percentage points in the fraction of time such traders step in to restore a widened spread to its minimum level of one tick. Meanwhile, liquidity provision by fast traders declines significantly along both the general and the price-improvement dimensions.

Our empirical evidence supports the intuition in Yao and Ye (2018) and O'Hara et al. (2019) that a shrinking spread and decreased value of time precedence—when it is easier/cheaper to obtain price precedence—diminish the incentive for fast traders to rush to the front of the queue. To see how this intuition bears out in the Treasury market, it is helpful to revisit how fast and slow traders map into the two major participant groups in the Treasury market's electronic interdealer marketplace. HFTs utilize high speed trading technologies primarily to take advantage of very short-term price dislocations and/or provide liquidity to capture the bid-ask spreads. It is therefore critical that they have the fastest trading infrastructure. On the other hand, dealers have client-facing business outside of the interdealer trading platforms, so it is less critical for them to invest heavily in the fastest trading technologies. That is, the different business models of HFTs and dealers naturally give rise to their differential response speeds, which correspond to the "fast" and "slow" classifications. When the tick size is reduced, thereby shrinking the spread, the HFTs pull back on their liquidity provision, giving way to an increased role for dealers.

The Li et al. (2021) model also explains well our finding, especially with regard to the increased price competitiveness of dealers. Their model predicts that participants with lower (higher) opportunity costs will price improve more (less) often in a smaller tick size environment. Due to dealers' market-making business with clients, their use of liquidity provisioning limit orders in the interdealer market is more likely to economize on transaction costs rather than to collect the spreads as a major source of their revenues. Furthermore, inventory pressures from customer trading activities might allow for more competitive pricing by the dealers in the interdealer market. These features imply that dealers have lower opportunity costs to price improve on their submitted limit orders than HFTs, and therefore become more competitive in a lower tick environment.

Panel B of Table 4 shows how the competition for liquidity provision in the cash market is affected by the later tick size reduction in the futures market. The fraction of limit orders submitted ($FirstLO$) by slow traders significantly decreases, while it increases for fast traders. These changes are a reversal of the changes associated with the initial cash market's tick size reduction. A possible explanation for these findings is that some HFTs that trade the cash/futures basis do not find it profitable to respond to small market signals in the cash market when there is a tick size mismatch with the futures market, but return when the two markets' tick size equalizes. The return of cross-market trading HFTs after the futures change probably lower HFTs' opportunity costs of price improving, but perhaps not enough to significantly change the price competition behavior relative to dealers, as seen in the insignificant reversal of earlier changes in the $SprTight$ measure. Overall, our results suggest that fast traders' limit order submissions depend on the relative tick size of the cash versus the futures market whereas their propensity to improve price is tied to the absolute tick size.

4.4 Sensitivity analysis

As discussed earlier, our choice of the 10 ms latency threshold is grounded in guidance from the prior literature combined with our validation exercise using a direct measure of HFTs' share of activity available out of sample. Nevertheless, to ensure that our conclusions are not driven by this particular threshold, we repeat the analyses for other thresholds that are within the range used in earlier research and find qualitatively similar results (see Internet Appendix Table A2).

5 Effects of Tick Size on Price Discovery

In this section, we consider whether price becomes more informative with a smaller tick size. As previously discussed, we have a unique opportunity to shed light on this challenging question. The cash Treasury market operates alongside a highly liquid futures market. Mizrach and Neely (2008) establish that the cash and futures markets are tightly linked through the no-arbitrage principle, and Dobrev and Schaumburg (2018) find that this is even more so in recent years given the rise in high frequency trading. Thus, the two markets are increasingly viewed as one, sharing a common random walk fundamental process. The variance of this process reflects the aggregate information affecting Treasury benchmark rates. The contribution of each market to this variance in turn indicates its share of the aggregate information. We examine if the contribution to price discovery of each market changes with the tick size changes.

5.1 Measuring contribution to price discovery

We employ Hasbrouck (1995)'s methodology to extract the underlying efficient price process from the cash and futures prices with a vector error correction model (VECM). The variance of the efficient price changes reflects the amount of information impounded into prices. The contribution of each market to this variance indicates its role in price discovery. The model is:

$$\Delta \mathbf{P}_t = \alpha z_{t-1} + \sum_{s=1}^{k} \mathbf{A}_s \Delta \mathbf{P}_{t-s} + \epsilon_t \tag{2}$$

where $\mathbf{P}_t = \left[P_t^c, P_t^f\right]'$ is a vector of cash and futures prices (best bid-ask midpoints) at time t. In the main analysis, we sample prices at the 1-second frequency (the highest frequency available for our futures data) to capture price discovery at a reasonably granular time scale, so t indexes seconds in the trading day. z_t equals the difference between the cash and future prices and serves as the error correction term. We estimate the model with five lags and separately for each day. Daily model estimation using intraday data implies that periodic changes in the on-the-run cash security, which only occur between days, do not affect our results. Moreover, changes in the cheapest-to-deliver (CTD) security underlying the futures contract are infrequent and hence unlikely to occur within a day and affect our results.[22]

We also note that the mismatch between the on-the-run cash instrument and the CTD security

[22] In fact, over our sample period, the CTD security underlying each of the 2-, 5-, and ultra 10-year contracts remains the same throughout each contract life cycle. Only the 10-year contract sees the CTD security change within a given contract life cycle over our sample period.

(given that the CTD is rarely the on-the-run security) is not a concern for our analysis. It is absorbed by the error correction term in the model above. Furthermore, it is standard in the literature on the price discovery of Treasury cash and futures markets to pair on-the-run cash instruments with futures contracts of corresponding tenors for several reasons. First, Treasury securities in the same maturity bucket are highly correlated, with the on-the-run security being the most liquid representative of that maturity segment and hence the most responsive to new information. Second, traders who pursue strategies to arbitrage price mismatch between the cash and futures markets (basis trades) trade on-the-run Treasury securities and futures instruments, because only on-the-run Treasuries are currently traded electronically, like futures contracts, on central limit order book platforms.

Hasbrouck (1995)'s information share relies on two ingredients derived from the model. The first is the permanent impact of the shock vector on the cointegrated prices in the system (i.e., the long-run multipliers based on the moving average representation of the VECM). The second is the vector of orthogonalized shocks, which we obtain via a Cholesky decomposition of the covariance matrix of the residuals $\Omega = E[\epsilon_t \epsilon_t']$. The information share of price series j is then computed as:

$$IS_j = \frac{\left[\sum_{i=j}^{n} \gamma_i m_{ij}\right]^2}{\gamma \Omega \gamma'}, \tag{3}$$

where $\gamma = [\gamma_1,\ \gamma_2]$ is the permanent price impact of innovations in the cash and futures price series respectively, and m_{ij} is the (i, j) element of the lower triangular matrix M such that $MM' = \Omega$. The denominator is the variance of the random walk component of price changes. Thus, the information share of a given price series is the contribution of its variation to the total variation of the efficient price updates. The information share estimates depend on the ordering of the prices in the system. We estimate the information shares using both orderings and take the average.

In Figure 3, we plot the information share of the cash market over the extended sample period from September 24, 2018 to March 8, 2019, with two dashed lines marking the cash and futures tick size events (from left to right). An increase in the cash market's information share is clearly visible in the 2-year tenor after the cash tick size change, a pattern that does not exist in the other tenors with unchanged tick size. When the tick size in the futures market is halved to the same level as in the cash market, we observe a reversal of the earlier increase in the cash market's information share. Again, such a reversal is not apparent in the other tenors. The figure thus provides evidence that the tick size change plays a meaningful role in shifting price discovery to the smaller tick market.

5.2 Does a smaller tick size increase price discovery?

To formally test the effects of tick size on price discovery, we estimate the DD regression model for two outcome variables of interest: the cash market's information share and the efficient return variance $VarRW$. We first estimate these variables based on one-second returns and report the associated coefficients on $Post \times Treatment$ in the first row of Table 5, separately for the cash tick size change on November 18, 2018 and futures tick size change on January 14, 2019.[23] The period between these two events is when the cash market operates with a tick size half that of the futures market. During this period, the information share of the cash market IS_Cash increases by about 23 percentage points relative to the pre-cash-event period. Moreover, the efficient variance is significantly lower, consistent with earlier descriptive evidence of a more continuous price updating process through which small information signals get incorporated into prices quickly.

If the increased contribution of the cash market to price discovery is indeed due to its smaller tick size, this information advantage should reverse and we should observe a decrease in the cash market's information share once the futures market's tick size is reduced to the same level. The coefficient on $Post \times Treatment$ around the futures tick size event indicates exactly that: the information share of the cash market indeed decreases—by about 17 percentage points—once it loses its smaller tick size advantage. The variance of the efficient return does not change significantly, consistent with it being driven by the absolute tick size level of the cash market, which does not change through the futures tick size event.

Table 5 clearly shows that the market with a smaller tick size attracts greater price discovery, with increased price leadership by the cash market during the brief period it has a smaller tick size. The finer pricing grid makes it easier for traders to exploit their information advantage, especially

[23]There is no futures contract on the 3-year note during the sample period; thus the cash-futures analysis does not include the 3-year tenor.

small information signals that would otherwise be unprofitable to exploit in a larger tick environment. To put this finding in context, it is worth discussing in greater depth the nature of information in the Treasury market. Different from stocks, the concept of "private information" does not apply to the U.S. Treasury market. Treasury prices are driven by fundamental macroeconomic information, which is publicly available, and by differential interpretation of that information. Information advantage therefore comes from better capability to process public news or from proprietary client order flow information (e.g., Fleming and Nguyen, 2019). The latter source of information arises somewhat exogenously due to clients' trading demand whereas the former (better capability to process public news) is within the realm of traders' optimization. That said, there is little scope for additional information acquisition because Treasury market participants are highly sophisticated; it is not likely that a macroeconomic announcement remains imperceptible for an extended period of time. Thus, any information advantage tends to be small and diminish quickly. This is consistent with our evidence of traders tilting more toward the smaller-tick-size cash market—to presumably trade on these small information advantages—when the cash market tick size is narrower.

To explore this hypothesis further, we analyze the information share of the cash market at various return frequencies. The idea is that if the smaller tick size is beneficial for quickly exploiting small information signals, then the cash market's information advantage should lessen as the return measurement horizon increases. To this end, we estimate the VECM in Equation (2) using prices sampled at various frequencies, ranging from one second (used in our main analysis) to 10 minutes. We then compute the cash market's information share corresponding to these frequencies and show their time series in Internet Appendix Figure A1. The rise in the information share after the cash tick size change and the reversal after the futures tick size change are only evident for the very short-horizon returns (the 1- and 10-second frequencies). Beyond these horizons, the tick size changes have little apparent effect on information shares.

The regression results reported in Table 5 formally confirm the above observation. For returns over very short horizons (1-second and 10-second), we observe an increased information share after the cash tick size change, followed by a reversal after the tick size in the futures market catches up. This pattern weakens as the return sampling frequency increases. These results suggest that the smaller tick size is most informationally beneficial at very high frequencies when it enables traders to capture their (small) information advantage quickly.

A related study by Chaboud et al. (2019) finds that the spot foreign exchange market has a *reduced* price discovery role relative to the futures market—despite an increased trading volume—after the spot market's tick size reduction. They attribute the decreased price discovery role of the smaller-tick spot market to increased liquidity demand by HFTs. They argue that HFTs can improve very short-run price efficiency but decrease long-run price efficiency because HFTs' order flow contains less long-run fundamental information. Their findings pertain to long-run price discovery, however, while the focus of our study is on very short-run price discovery. In the extremely liquid and tick-constrained Treasury market, our evidence suggests that tick size matters most for exploiting price dislocations at very high frequencies.

6 Effects on the U.S. Treasury Complex

U.S. Treasury securities are different from stocks in that they share the same fundamentals and essentially differ only in their maturity and coupon rates. That is, Treasuries are highly substitutable, especially among those close in maturity. Furthermore, this substitutability applies not only among Treasuries, but also with Treasury futures. That said, Treasuries can also be complementary to the extent that traders seek exposure across the yield curve, or conduct basis trades involving both cash and futures instruments. It is therefore plausible that a microstructure perturbation in the market for one security (specifically, the 2-year note) might have significant effects not only in its own market, but also in the markets for other segments of the yield curve or the associated futures market. Substitutability would predict opposite-sign effects on other securities compared to the effects on the 2-year note, whereas complementarity would imply same-sign effects. In the previous sections, we use other securities as controls in the identification of the effects in the 2-year note following its tick size change. In this section, we analyze whether there are spillover effects on the other Treasury notes in order to understand better the microstructure linkages across the yield curve and to interpret our earlier results with care. We then analyze the microstructure linkages with the futures market.

6.1 Microstructure linkages across the yield curve

To assess whether market liquidity and price efficiency metrics of the other on-the-run Treasury notes change significantly in the period after the 2-year note's tick size change, we estimate the following time-series regression:

$$Y_t = \alpha + \beta_1 Post_t + \beta_2 MOVE_{t-1} + \beta_3 MKTDEPTH_{t-1} + \beta_4 MKTVOL_{t-1} + \theta' D_t + \epsilon_t, \quad (4)$$

where Y_t is a market quality metric of interest. $Post$ is an indicator variable equal to 1 for the period after the tick size reduction. $MOVE$ is a measure of aggregate bond market volatility.[24] $MKTDEPTH$ is the average total market depth across all on-the-run securities on BrokerTec. $MKTVOL$ is the total trading volume across all on-the-run securities on BrokerTec. $MKTDEPTH$ and $MKTVOL$ control for the overall Treasury market liquidity level. D_t are dummies for day-of-week effects, the holiday period, and early market closes. For this analysis, it is not possible to have a DD regression setup, because we do not have the so-called "treatment" on these other securities. Our main objective in this analysis is to see if market quality in other Treasury securities along the yield curve changes after the tick size reduction of the 2-year note, controlling for prevailing market conditions. Non results would imply that there is no spillover of treatment effects from the 2-year note to other notes, and alleviate the concern of DD results being contaminated because the control group is affected by the treatment.

We estimate the regression separately for each of the other notes and report the results in Table 6. The 3-year note seems to be most affected by the 2-year note's tick size change, whereas evidence of potential spillover effects on the 5-, 7-, and 10-year notes is far weaker. The 3-year note's liquidity slightly worsens, with wider bid-ask spreads and lower market depth at or near the top of the book. However, the 3-year note (as well as the 5-year note) seems to benefit from the increased price efficiency of the 2-year note: its return autocorrelation and variance ratio both change significantly toward the random walk benchmark. This result is consistent with the idea that traders in one security learn value-relevant information from closely related securities.

[24]The ICE BofA 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.

Another noteworthy result from Table 6 is that despite the 2-year note becoming the cheapest on-the-run instrument to trade, trading activity in other notes does not seem to be affected. There is no evidence of order flow migration nor spillover across the yield curve as a result of the 2-year note's tick size change. Likewise, the event is inconsequential to price impact in the other notes. Overall, it seems that there is little spillover of treatment effects—a concern for event studies of regulatory experiments as discussed in Boehmer et al. (2020). This provides some assurance for the identified effects we discuss in our main analysis, with two cautions. First, the 3-year note exhibits some evidence of being affected by the 2-year note's tick size event. We conduct robustness checks on our earlier results by excluding the 3-year note from the DD regressions and obtain qualitatively similar results. Second, $D1A$ and $D5A$ of other Treasury notes are significantly lower in the post period. When these other notes are used as controls in the DD regression (Equation 1), the effects on the 2-year note's market depths as reported in Table 3 might be biased upward, negating the underlying depth reduction due to a smaller tick size. Nonetheless, when we take into account the effects on all market liquidity measures, the conclusion that the tick size reduction improves liquidity remains robust.

6.2 Price discovery at the short end of the yield curve

Given the high substitutability between the 2- and 3-year notes, we next examine the 2-year note's role in price discovery at the short end of the yield curve when its tick size is halved while that of the 3-year note remains unchanged. We estimate the information share split between the two notes in a similar fashion to how we estimate the information share split between the 2-year cash and futures instruments as described in Section 5. As before, the information share estimation is done for varying return sampling frequencies. Using the 2-year note's information share (versus the 3-year note's) as the outcome variable of interest, we estimate the time-series regression model in Equation 4 for the cash tick size change on November 19, 2018 and separately for the futures tick size change on January 14, 2019.

Table 7 reports the $Post$ coefficient estimates for the 2-year note's information share at various horizons. We again find that once the 2-year note's tick size is reduced, its role in price discovery rises, in this case relative to that of the 3-year note. However, unlike the cash-futures price discovery results, this rise in price discovery does not reverse around the futures tick size change—an event that is unrelated to the mismatch in tick size between the 2- and 3-year notes. This additional evidence lends strong support to our conclusion that price discovery shifts toward the smaller-tick market. Again, such a shift occurs only at very high return sampling frequencies and dissipates at lower frequencies. It seems that the informational benefit of a smaller tick size is mainly due to timely incorporation of small and short-lived information signals. The tick size change does little to affect the balance of price discovery with respect to more fundamental, long-term information.

6.3 Microstructure linkages with the futures market

While our main focus in this paper is on the cash Treasury market, the futures market is an integral part of the U.S. Treasury complex. More importantly, the cash and futures instruments for a given tenor are highly linked through the no arbitrage principle and the high level of cross-market trading, so much so that they are often viewed as one security in multiple markets in standard price discovery analyses. Therefore, it is natural to ask if the 2-year futures is affected by the cash market's tick size change in addition to its own market tick size change. To answer this question, we estimate the same DD regression as specified in Equation (1) but in which the treatment security is the 2-year futures and the control group consists of other Treasury note futures contracts (5-year, 10-year, and ultra 10-year).

As Table 8 shows, there is no significant change in the 2-year futures' bid-ask spread associated with the cash market event (in terms of either the level or the tightness around one tick). This is not surprising, given that the futures market is also highly liquid with the bid-ask spread equaling one tick most of the time. Therefore, the tick size reduction in the cash market cannot tighten the futures' spread any further. It follows that trading volume does not increase significantly, as it does for the cash instrument. While it is plausible that the increased trading activity in the cash market around its tick size reduction could spill over to the futures market because many market participants trade in both, such a spillover effect is not sufficient to significantly change the level of trading activity in the futures market. In the same vein, the cash tick size change has no significant impact on the futures' price efficiency measures.

Only after the tick size reduction in its own market do we see the futures' bid-ask spread narrow (also almost one-for-one) and the frequency of one-tick spreads decline. The narrower spread results in significant transaction cost savings for futures market participants. Based on the average daily trading volume of roughly 640,000 contracts or \$128 billion par notional amount in the 2-year futures over the eight-week period before the futures market tick size change, a decrease of 0.951/256 in the bid-ask spread implies that liquidity demanders save \$594 million per year ($\frac{1}{2} \times \frac{-0.951}{256} \times 0.01\times$ \$128 billion $\times$ 250 trading days). Trading activity increases significantly, through the increased number of now smaller trades, and prices update more frequently.

The only futures market metric that appears to be affected by both tick size changes is market depth, which declines significantly. One caveat with the market depth results is that the order precedence rule for the 2-year futures is not first-in first-out (FIFO) like other Treasury futures, but a mix of FIFO and pro-rata, the latter of which may cause market participants to over-quote.[25] It is therefore not clear if the drop in market depth indicates decreased liquidity supply or simply a reduced need to over-quote. Considering other market quality metrics, it seems reasonable to conclude that 1) the tick size change in the cash market has minimal impact on the futures market, and 2) futures market quality improves after its own tick size change, as expected.

7 Robustness checks

7.1 Placebo tests

To check the robustness of our results, we perform placebo tests by repeating our main regressions around a date without a tick size change. To control for time-of-year effects and secular trends, we choose the placebo date as the same day of week of the relevant tick size change one year earlier. Thus, for the cash tick size reduction, the placebo event date is Monday, November 20, 2017. The 8-week window prior to this date starts on Monday, September 25, 2017. The 8-week window after

[25] Field and Large (2008) hypothesize that market participants rationally choose to over-quote under pro-rata precedence rules. Haynes and Onur (2020) examine an episode in which the order precedence rule for the 2-year futures contract temporarily changed to 100% FIFO and find that the pro-rate rule is associated with higher and more variable depth.

this date ends on Friday, January 12, 2018. For the futures tick size reduction, the placebo event date is Monday, January 15, 2018, with the before and after period running from November 20, 2017 to March 10, 2018.

The effects of the placebo tick size reductions on market quality are reported in Internet Appendix Table A3. None of the market quality metrics exhibit any significant change through the placebo events in either the cash or futures markets. Likewise, we do not observe any significant change in the liquidity provisioning behavior of fast and slow traders nor in the contribution to price discovery of the cash market, as shown in Internet Appendix Table A4. The absence of significant changes in our placebo results validates the equal-trend assumption needed for DD regression results and provides support for the effects identified around the real tick size reductions.

7.2 Alternative multivariate regression model

While the main empirical model used in the paper, based on the standard DD setup with security and day fixed effects, is clean and easy to interpret, it does not allow for possible differential responses of each security to time-varying market conditions. Many researchers, including Vayanos and Vila (2021), subscribe to the preferred-habitat view of the yield curve, which implies that Treasury securities at different maturity segments might have differential clienteles and thus might respond differently to the same market developments. To consider this possibility, we estimate the following alternative regression model in which we control explicitly for market condition variables with security-specific coefficients on those variables:

$$Y_{i,t} = \alpha_i + \beta_1 Post_t + \beta_2 Post_t \times Treatment_i + \theta' Z_t + \epsilon_{i,t}. \tag{5}$$

In this specification, $Treatment$ is an indicator variable equal to 1 for the 2-year note and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, α_i captures security fixed effects, and Z_t are variables to control for intra-week seasonality, low market activity around holidays and on early market close days, and prevailing market conditions. These market condition variables are: 1) aggregate bond market volatility (the $MOVE$ index), 2) average total market depth across all on-the-run securities on BrokerTec ($MKTDEPTH$), and 3) total trading volume across all on-the-run securities on BrokerTec ($MKTVOL$). All three variables are lagged by one day and interacted with security dummies to allow for security-specific responses. We drop $Treatment$ from the regression model to avoid multicollinearity (between the 2-year fixed effect and $Treatment$). The coefficient of interest is β_2, capturing the effect of the tick size change on a given market outcome variable.

We report the main results from this alternative specification in Tables A5 – A8 in the Internet Appendix. Our key findings are robust: 1) increased (decreased) competition for liquidity provision from slow (fast) traders following the cash tick size change, 2) an increased price discovery role for the cash market when its tick size is smaller, with this increase showing up most strongly for very high frequency returns, 3) overall improved market quality (transaction costs, trading volume, and price efficiency), and 4) minimal impact of the cash tick size change on the futures market given that the latter is constrained by its own tick size, which does not change at the same time as the cash market's tick size. The robustness of the results lends further credibility to our main conclusions.

8 Conclusion

This paper studies the role of the minimum price increment on liquidity provision and price discovery in the U.S. Treasury securities market. Exploiting a recent tick size reduction for the 2-year note, followed eight weeks later by a commensurate change for the 2-year futures contract, we observe how tick size affects market quality, price discovery, and liquidity provision by traditional dealers (slow traders) and HFTs (fast traders). Based on DD regressions, we find an almost one-for-one decrease in bid-ask spreads and increased trading activity, similar to the evidence in many earlier equity tick size studies. However, different from those studies, we find that the improvement in liquidity for small trades does not seem to come at the expense of large trades, with depth near the top of the book remaining many times higher than the size of most trades.

We also find that slow traders become more competitive relative to fast traders in liquidity provision when the tick size is halved, evidenced by the former's increased propensity to tighten spreads in response to changing market conditions. An improved ability of dealers to compete in providing liquidity at better prices is potentially beneficial to price discovery because trading in the dealer-to-customer segment likely confers dealers with fundamental information on order flow and demand for Treasury securities. Such information is not as readily available to HFTs, which do not have customer-facing businesses.

We further find that the smaller tick size unambiguously improves price quality. Prices move more frequently without raising realized volatility and can respond to smaller information shocks, resulting in greater price efficiency. Based on an analysis of the cash and futures markets' joint price discovery around the tick size change, we provide novel evidence that the smaller tick size concentrates greater price discovery in the cash market, in which a finer pricing grid enables faster capture of information rents. The cash tick size change induces increased trading in both markets, but disproportionately so in the cash market, indicating a preference for trading in the smaller tick market, consistent with the increased price discovery result.

We also use the 2-year note tick size change to study how such a market design perturbation in one security permeates through the Treasury interest rate complex given the tight connection among Treasury securities and between the cash and futures markets. Our analysis suggests that the 3-year note experiences some spillover of treatment effects from the 2-year note, whereas longer maturity notes are not significantly affected. The lack of effects on these other securities helps ease the concern of treatment spillovers often expressed for event studies of regulatory or natural experiments. We also find minimal impact of the cash market's tick size change on the 2-year futures, but significantly narrower bid-ask spreads and increased trading frequency when the future's own tick size is subsequently reduced.

Overall, we contribute to the literature new evidence from the Treasury market on the liquidity provision of two major groups of market participants—dealers and HFT firms—and how the tick size affects their competition. Our study also illuminates the role of tick size in price discovery, showing that a smaller tick size encourages more timely incorporation of information signals at high frequency, thereby improving short-term price discovery. Finally, our study suggests that reducing the tick size in tick-constrained and highly liquid markets is on balance beneficial, and provides a useful preview for the potential effects of any future tick size reductions in other Treasury securities.

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Table 1: Variable Descriptions

BAS	Difference between the best bid and the best ask price, sampled at 1-minute frequency and averaged for each day. Expressed in 256ths of a percent of par.
BAS_L	Difference between the bid and the ask price applicable for executing a large trade, defined as the 99th percentile of the trade size distribution of each security ($50, $33, $23, $13, and $20 million for the 2-, 3-, 5-, 7-, and 10-year notes respectively). Sampled at 1-minute frequency and averaged for each day. Expressed in 256ths.
$OneTick$	Fraction of time the inside bid-ask spread (sampled at 1-minute frequency) equals one tick.
$TVol$	Total volume traded, in $ billion par.
$TFreq$	Number of trades.
$TSize$	Average trade size in $ million par.
$D1$ ($D5$)	Sum of bid and ask depth at the inside tier (best five tiers), sampled at 1-minute frequency and averaged for each day. Expressed in $ million par.
DT	Sum of bid and ask total depth across the whole book, sampled at 1-minute frequency and averaged for each day. Expressed in $ million par.
DxA	Sum of bid and ask cumulative depth within x ticks of the best bid-ask midpoint, sampled at 1-minute frequency and averaged for each day. Expressed in $ million par. For the 2-year note, we use the pre-change tick size (i.e., 2/256th).
$FirstLO\_Slow$	Fraction of the first limit orders reaching the book between 10 milliseconds and 1 second after a change in the best bid or ask prices.
$FirstLO\_Fast$	Similar to $FirstLO\_Slow$ but with a response speed of below 10 milliseconds.
$SprTight\_Slow$	Fraction of the first limit order restoring the bid-ask spread to one tick between 10 milliseconds and 1 second of a spread widening.
$SprTight\_Fast$	Similar to $SprTight\_Slow$ but with a response speed of below 10 milliseconds.
$NonZeroBA$	Fraction of minutes with non-zero midpoint returns.
$NonZeroT$	Fraction of minutes with non-zero returns based on trade prices.
RV	Realized volatility based on 1-minute log midpoint returns, calculated as $RV = \sqrt{\sum_{t=1}^{N}[\ln(p_t) - \ln(p_{t-1})]^2}$ and annualized by a factor of $\sqrt{250}$. Expressed in %.
$\|AR30\|$	Absolute autocorrelation of 30-second midpoint returns.
VR	Six times the ratio of the daily variance of 10-second midpoint returns to that of 1-minute midpoint returns.
$PErr$	Hasbrouck (1993) standard deviation of intraday pricing errors based on a VAR(5) of trade-by-trade log return, trade sign, signed volume, and signed square root of volume.
IS_Cash	Hasbrouck (1995) information share of the cash market (see calculation details in Section 5.1). This is computed for return sampling frequencies of 1 second, 10 seconds, 30 seconds, 1 minute, 5 minutes, and 10 minutes. The 7-year note is paired with the 10-year futures, and the 10-year note is paired with the ultra 10-year futures.
$VarRW$	Variance of the random walk of the underlying price process, computed for various sampling frequencies as in IS_Cash (see calculation details in Section 5.1). In percent squared.

Notes: All variables are computed on a daily basis using data from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). The sample period is from September 24, 2018 to March 9, 2019.

Table 2: Summary Statistics

	2-Year			3-Year			5-Year			7-Year			10-Year		
Variable	SS1	SS2	SS3	SS1	SS2	SS3	SS1	SS2	SS3	SS1	SS2	SS3	SS1	SS2	SS3
							Panel A: Means								
BAS	2.01	1.10	1.06	2.06	2.10	2.08	2.03	2.06	2.06	4.12	4.19	4.12	4.06	4.11	4.08
BAS_L	2.08	1.39	1.32	2.22	2.43	2.31	2.19	2.36	2.24	4.38	4.59	4.33	4.34	4.70	4.31
$OneTick$	0.99	0.91	0.94	0.97	0.95	0.96	0.98	0.97	0.97	0.97	0.96	0.97	0.99	0.97	0.98
$TVol$	20	26	20	18	19	16	47	47	40	14	14	12	38	36	32
$TFreq$	2561	4722	3894	3843	4383	3548	13003	14044	10932	5721	6258	5016	12940	13582	11245
$D1$	907	236	209	302	181	190	170	122	150	115	89	120	135	101	147
$D1A$	907	793	654	302	181	190	170	122	150	115	89	120	135	101	147
$D5$	5473	2519	2179	2700	1809	1669	1302	1049	1215	797	680	799	956	748	1034
$D5A$	5473	4192	4009	2700	1810	1669	1302	1049	1215	797	681	799	956	748	1034
DT	10314	6290	6195	5819	4377	3960	3095	2751	3096	1734	1598	1840	2345	1979	2704
$NonZeroBA$	0.12	0.37	0.30	0.25	0.31	0.25	0.40	0.45	0.39	0.34	0.37	0.29	0.41	0.44	0.36
RV	0.99	0.94	0.81	1.41	1.67	1.46	2.22	2.56	2.15	3.57	3.97	3.28	4.51	4.68	3.99
$\|AR30\|$	0.22	0.15	0.16	0.21	0.17	0.19	0.15	0.12	0.14	0.20	0.17	0.18	0.16	0.15	0.15
$VR_{10s,1m}$	1.81	1.53	1.61	1.84	1.65	1.78	1.61	1.49	1.57	1.78	1.71	1.70	1.61	1.58	1.55
$PErr$	0.04	0.02	0.02	0.03	0.04	0.04	0.03	0.03	0.03	0.05	0.05	0.05	0.05	0.06	0.06
IS_Cash	0.45	0.69	0.52				0.48	0.48	0.47	0.43	0.45	0.44	0.42	0.42	0.44
$VarRW$	1.00	1.07	0.70				5.70	7.57	5.38	14.17	16.92	12.29	22.68	24.77	18.38
							Panel B: Standard deviations								
BAS	0.01	0.06	0.02	0.03	0.08	0.02	0.02	0.06	0.02	0.05	0.19	0.05	0.04	0.09	0.05
BAS_L	0.04	0.24	0.09	0.08	0.40	0.07	0.08	0.35	0.06	0.12	0.45	0.12	0.13	0.69	0.10
$OneTick$	0.01	0.05	0.02	0.01	0.03	0.01	0.01	0.02	0.01	0.01	0.03	0.01	0.01	0.02	0.01
TV	6	8	5	6	7	5	15	17	9	4	5	4	13	14	7
$Tfreq$	1009	1350	945	1245	1584	804	4599	5109	2621	1986	2146	1192	4944	5094	2434
$D1$	190	132	70	55	68	46	26	31	18	15	20	12	19	28	13
$D1A$	190	323	140	55	68	46	26	31	18	15	20	12	19	28	13
$D5$	536	866	289	244	612	204	96	222	94	54	139	44	77	177	69
$D5A$	536	1360	468	244	611	204	96	221	94	54	139	44	77	177	69
DT	713	1817	824	380	1377	408	209	519	264	100	293	123	149	419	189
$NonZeroBA$	0.04	0.09	0.06	0.08	0.08	0.04	0.10	0.10	0.06	0.08	0.09	0.06	0.08	0.09	0.06
RV	0.19	0.28	0.16	0.27	0.50	0.28	0.48	0.76	0.41	0.62	1.56	0.53	0.82	1.22	0.61
$\|AR30\|$	0.06	0.08	0.05	0.05	0.06	0.07	0.05	0.05	0.05	0.05	0.06	0.06	0.04	0.06	0.05
$VR_{10s,1m}$	0.27	0.27	0.21	0.23	0.21	0.21	0.21	0.22	0.18	0.18	0.25	0.24	0.15	0.23	0.17
$PErr$	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
IS_Cash	0.11	0.16	0.08				0.05	0.11	0.07	0.04	0.06	0.04	0.03	0.05	0.04
$VarRW$	0.49	0.52	0.29				2.66	4.23	1.91	5.46	7.21	3.93	8.73	10.66	4.71

This table reports the means (Panel A) and standard deviations (Panel B) of key variables for on-the-run Treasury notes based on data from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). Variables are as defined in Table 1. The sample period is from September 24, 2018 to March 9, 2019. SS1 is the first sub-sample period from September 24, 2018 to November 16, 2018, covering the 8-week period before the tick size reduction in the 2-year note on November 19, 2018. SS2 is the second sub-sample period from November 19, 2018 to January 11, 2019, covering the 8-week period from the tick size reduction in the 2-year note to just before the tick size reduction in the 2-year futures on January 14, 2019. SS3 is the third sub-sample period from January 14, 2019 to March 9, 2019, covering the 8-week period from the tick size reduction in the 2-year futures. Statistics for IS_Cash and $VarRW$ are not available for the 3-year note because the 3-year futures contract did not exist during our sample period.

Table 3: Effects of Tick Size Reductions on Market Quality

	Cash Tick Size Reduction		Futures Tick Size Reduction	
Outcome Variable	Coef	Adj R^2	Coef	Adj R^2
Panel A: Trading Activity and Transaction Costs				
BAS	-0.967^{***}	0.945	-0.008	0.576
BAS_L	-0.930^{**}	0.804	0.152	0.755
$OneTick$	-0.072^{**}	0.722	0.028^{*}	0.557
$LogTVol$	0.234^{*}	0.799	-0.082	0.778
$LogTfreq$	0.548^{**}	0.876	0.011	0.833
$TSize$	-2.301^{**}	0.695	-0.464^{*}	0.457
Panel B: Price Efficiency				
$NonZeroBA$	0.203^{**}	0.923	0.002	0.909
$NonZeroT$	0.133^{**}	0.897	0.011	0.913
RV	-0.344	0.668	0.369	0.680
$\|AR30\|$	-0.047	0.536	0.002	0.626
$VR_{10s,1m}$	-0.171	0.638	0.030	0.694
$PErr$	-0.023^{*}	0.445	-0.007	0.340
Panel C: Liquidity Supply within Select Price Tiers				
$LogD1$	-1.076^{**}	0.906	-0.298	0.757
$LogD5$	-0.558	0.891	-0.249	0.788
$LogDT$	-0.360	0.830	-0.109	0.730
Panel C: Liquidity Supply within Fixed Price Distances				
$LogD1A$	0.183	0.854	-0.391	0.799
$LogD2A$	0.121	0.863	-0.281	0.796
$LogD3A$	0.039	0.854	-0.218	0.781
$LogD4A$	-0.007	0.858	-0.176	0.792
$LogD5A$	-0.046	0.860	-0.149	0.795
Observations	370		370	

This table reports the effects of tick size reductions on various market quality metrics based on the regression model $Y_{i,t} = \alpha_i + \gamma_t + \beta Post_t \times Treatment_i + \epsilon_{i,t}$, where Y is the outcome variable of interest (shown in column 1 and defined in Table 1), $Treatment$ is an indicator variable equal to 1 for the 2-year note and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, and α_i and γ_t are security and day fixed effects, respectively. Columns "Coef" show the estimates of β. Columns "Adj. R^2" report the adjusted R^2 of each regression for a given outcome variable. Variables are measured at the daily frequency using data from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). The sample includes 2-, 3-, 5-, 7-, and 10-year notes. For regressions around the cash tick size reduction, the sample period is from September 24, 2018 to January 11, 2019, with the $Post$ period starting on November 19, 2018. For regressions around the futures tick size reduction, the sample period is from November 19, 2018 to March 9, 2019, with the $Post$ period starting from January 14, 2019. Standard errors are clustered by security. Statistical significance is based on wild cluster bootstrap p-values (with 9999 reps and using six-point weight distribution). $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 4: Effects of Tick Size Reductions on Competition for Liquidity Provision

	Slow Traders		Fast Traders	
	$FirstLO$	$SprTight$	$FirstLO$	$SprTight$
Panel A: Cash Tick Size Reduction				
Post × Treatment	0.044	0.043**	−0.083*	−0.112**
	(0.006)	(0.003)	(0.008)	(0.005)
Security Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.416	0.615	0.495	0.617
Observations	370	370	370	370
Panel B: Futures Tick Size Reduction				
Post × Treatment	−0.041**	−0.035	0.060**	0.018
	(0.003)	(0.010)	(0.004)	(0.016)
Security Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.475	0.399	0.481	0.344
Observations	370	370	370	370

This table reports the effects of tick size reductions on the competition for liquidity provision between fast and slow traders. The regression model is $Y_{i,t} = \alpha_i + \gamma_t + \beta Post_t \times Treatment_i + \epsilon_{i,t}$, where Y is the outcome variable of interest, $Treatment$ is an indicator variable equal to 1 for the 2-year note and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, and α_i and γ_t are security and day fixed effects, respectively. Slow and fast traders are identified by the latency of response to market signals, with longer than 10 ms for slow traders and less than 10 ms for fast traders. $FirstLO$ is the fraction of the first limit orders reaching the book submitted by a given trader type following a market price change. $SprTight$ is the fraction of time a given trader type is the first to restore the bid-ask spread to one tick. Variables are measured at the daily frequency using data from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). The sample includes 2-, 3-, 5-, 7-, and 10-year notes. For regressions around the cash tick size reduction in Panel A, the sample period is from September 24, 2018 to January 11, 2019, with the $Post$ period starting on November 19, 2018. For regressions around the futures tick size reduction in Panel B, the sample period is from November 19, 2018 to March 9, 2019, with the $Post$ period starting from January 14, 2019. Standard errors are clustered by security and reported in parentheses. Statistical significance is based on wild cluster bootstrap p-values (with 9999 reps and using 6-point weight distribution). *$p < .1$; **$p < .05$; ***$p < .01$.

Table 5: Tick Size Reductions and Term Structure of Information Share

	Cash Tick Size Reduction		Futures Tick Size Reduction	
Sampling Frequency	IS_Cash	$VarRW$	IS_Cash	$VarRW$
1 second	0.230^{**}	-2.160^{*}	-0.172^{*}	4.029
	(0.006)	(0.291)	(0.014)	(1.325)
10 seconds	0.194^{*}	-2.217^{*}	-0.155^{*}	4.150
	(0.008)	(0.279)	(0.014)	(1.384)
30 seconds	0.128^{*}	-1.871	-0.106	4.002
	(0.009)	(0.338)	(0.016)	(1.401)
1 minute	0.068^{*}	-2.244	-0.055	4.073
	(0.006)	(0.426)	(0.016)	(1.341)
5 minutes	0.035	-2.197	0.035	4.950
	(0.005)	(0.712)	(0.007)	(1.258)
10 minutes	0.078^{*}	-15.693	-0.014	17.900^{*}
	(0.004)	(3.835)	(0.006)	(2.031)

This table shows the effects of tick size reductions on price informativeness of the cash market relative to the futures market at various return horizons. The numbers reported in the table are the estimates of β from the following regression model $Y_{i,t} = \alpha_i + \gamma_t + \beta Post_t \times Treatment_i + \epsilon_{i,t}$, where Y is the outcome variable of interest, $Treatment$ is an indicator variable equal to 1 for the 2-year note and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, and α_i and γ_t are security and day fixed effects, respectively. The dependent variable is the information share of the cash market based on midpoint returns at a given sampling frequency. Information shares are computed from a VECM(5) estimated separately for each day using cash and futures prices sampled at each given horizon for the 2-, 5-, 7-, and 10-year maturities (with the 7-year note paired with the 10-year Treasury futures and the 10-year note paired with the ultra 10-year Treasury futures). Cash data are from the BrokerTec platform and futures data are from the CME. The sample includes 2-, 3-, 5-, 7-, and 10-year notes. For regressions around the cash tick size reduction, the sample period is from September 24, 2018 to January 11, 2019, with the $Post$ period starting on November 19, 2018. For regressions around the futures tick size reduction, the sample period is from November 19, 2018 to March 9, 2019, with the $Post$ period starting from January 14, 2019. Standard errors are clustered by security and reported in parentheses. Statistical significance is based on wild cluster bootstrap p-values (with 9999 reps and using six-point weight distribution). $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 6: Spillovers to Other Segments of the Yield Curve

Outcome Variable	3-Year	5-Year	7-Year	10-Year
	Panel A: Trading Activity and Transaction Costs			
BAS	0.048**	0.019	0.053	0.028
BAS_L	0.082	0.024	0.091	0.117
$OneTick$	−0.019**	−0.005	−0.010	−0.006
$LogTFreq$	0.133	0.041	0.050	0.034
$LogTVol$	0.184	0.070	0.028	0.007
	Panel B: Price Efficiency			
$NonZeroBA$	0.041	0.012	−0.016	−0.002
RV	0.223	0.192	0.023	−0.057
$\|AR30\|$	−0.053***	−0.050**	−0.030	−0.004
$\|VR_{10s,1m} - 1\|$	−0.213**	−0.138	−0.072	0.051
$PErr$	0.008	0.004	0.002	0.009
	Panel C: Liquidity Supply			
$LogD1A$	−0.253***	−0.124**	−0.142***	−0.149**
$LogD5A$	−0.133**	−0.065*	−0.045	−0.123***
$LogDT$	−0.062	0.011	−0.001	−0.063
	Panel D: Competition for Liquidity Provision			
$FirstLO\_Slow$	−0.013*	0.005	−0.002	0.009*
$SprTight\_Slow$	0.030**	0.004	0.021	0.022
$FirstLO\_Fast$	0.014	0.011	0.004	−0.005
$SprTight\_Fast$	−0.066***	−0.005	−0.028	−0.032**

This table shows the effects of the 2-year note's tick size reduction on other on-the-run Treasury notes. The regression model is $X_t = \alpha + \beta Post_t + \theta' Z_t + \epsilon_t$. $Post$ is an indicator variable equal to 1 for the period after the cash market's tick size reduction on November 19, 2018. Z_t include variables to control for aggregate bond market volatility (the $MOVE$ index), Treasury market liquidity (measured by the average total market depth $MKTDEPTH$ and aggregate trading volume $MKTVOL$ across all on-the-run securities traded on BrokerTec), day-of-week dummies, a dummy for early market close days, and a dummy for the holiday period (December 24, 2018 – December 31, 2018). The table reports the estimate of β for outcome variables indicated in the first column (see Table 1 for variable description). Variables are measured at the daily frequency using data from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). The sample period is from September 24, 2018 to January 11, 2019. *$p < .1$; **$p < .05$; ***$p < .01$.

Table 7: Tick Size Reductions and Information Share of 2-Year Note (vs. 3-Year Note)

Sampling Frequency	Cash Tick Size Reduction	Futures Tick Size Reduction
1 second	0.188^{***}	0.042
	(0.043)	(0.051)
10 seconds	0.273^{***}	0.019
	(0.063)	(0.078)
30 seconds	0.277^{***}	-0.025
	(0.076)	(0.096)
1 minute	0.244^{***}	0.022
	(0.082)	(0.098)
5 minutes	0.051	-0.054
	(0.073)	(0.081)
10 minutes	0.067	-0.015
	(0.062)	(0.058)

This table shows the effects of tick size reductions on the price informativeness of the 2-year note relative to the 3-year note. The table reports the estimate of β from the regression model $X_t = \alpha + \beta Post_t + \theta' Z_t + \epsilon_t$, where the dependent variable is the 2-year note's information share at various sampling frequencies. $Post$ is an indicator variable equal to 1 for the period following the tick size change. Z_t include variables to control for aggregate bond market volatility (the $MOVE$ index), Treasury market liquidity (measured by the average total market depth $MKTDEPTH$ and aggregate trading volume $MKTVOL$ across all on-the-run securities traded on BrokerTec), day-of-week dummies, a dummy for early market close days, and a dummy for the holiday period (December 24, 2018 – December 31, 2018). The information share is computed from a VECM(5) estimated separately for each day using the best bid-ask midpoints of the 2-year note and 3-year note at each given sampling frequency. The data are from the BrokerTec platform over New York trading hours (7:30 to 17:00 Eastern time). For regressions around the cash tick size reduction, the sample period is from September 24, 2018 to January 11, 2019, with the $Post$ period starting on November 19, 2018. For regressions around the futures tick size reduction, the sample period is from November 19, 2018 to March 9, 2019, with the $Post$ period starting from January 14, 2019. Standard errors of estimates are reported in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Table 8: Effects of Tick Size Reductions on Treasury Futures Market

	Cash Tick Size Reduction		Futures Tick Size Reduction	
Outcome Variable	Coef	Adj R^2	Coef	Adj R^2
		Panel A: Trading Activity and Transaction Costs		
BAS	-0.003	0.292	-0.951^{**}	0.982
$OneTick$	-0.011	-0.002	-0.047^{*}	0.448
$LogTVol$	0.190	0.758	0.074	0.799
$LogTFreq$	0.133	0.856	0.448^{*}	0.859
$TSize$	9.674	0.501	-16.845	0.555
		Panel B: Price Efficiency		
$NonZeroBA$	0.019	0.854	0.169^{**}	0.906
RV	0.086	0.771	0.106	0.814
$\|AR30\|$	0.003	0.402	-0.028	0.609
$VR_{10s,1m}$	0.068	0.410	-0.056	0.623
		Panel C: Liquidity Supply		
$D1$	-2.027^{**}	0.689	-1.582^{**}	0.503
$D5$	-1.059^{*}	0.721	-1.189^{**}	0.637
$D1A$	-2.022^{**}	0.688	-0.752^{*}	0.410
$D2A$	-1.499^{**}	0.707	-0.651^{*}	0.472
$D3A$	-1.268^{*}	0.712	-0.589^{*}	0.500
$D4A$	-1.141^{*}	0.716	-0.544^{*}	0.518
$D5A$	-1.055^{*}	0.720	-0.516^{**}	0.539

This table reports the effects of tick size reduction on various market quality metrics in the futures market based on the regression model $Y_{i,t} = \alpha_i + \gamma_t + \beta Post_t \times Treatment_i + \epsilon_{i,t}$, where Y is the outcome variable of interest (shown in column 1 and defined in Table 1), $Treatment$ is an indicator variable equal to 1 for the 2-year futures and 0 otherwise, $Post$ is an indicator variable equal to 1 for the period following the tick size change, i provides security indexing, t provides day indexing, and α_i and γ_t are security and day fixed effects, respectively. Columns "Coef" show the estimates of β. Columns "Adj. R^2" report the adjusted R^2 of each regression for a given outcome variable. The sample includes 2-, 5-, 10-year, and ultra 10-year Treasury futures. Variables are measured at the daily frequency using data from the CME over New York trading hours (7:30 to 17:00 Eastern time). For regressions around the cash tick size reduction, the sample period is from September 24, 2018 to January 11, 2019, with the $Post$ period starting on November 19, 2018. For regressions around the futures tick size reduction, the sample period is from November 19, 2018 to March 9, 2019, with the $Post$ period starting from January 14, 2019. Standard errors are clustered by security. Statistical significance is based on wild cluster bootstrap p-values (with 9999 reps and using six-point weight distribution). *$p < .1$; **$p < .05$; ***$p < .01$.

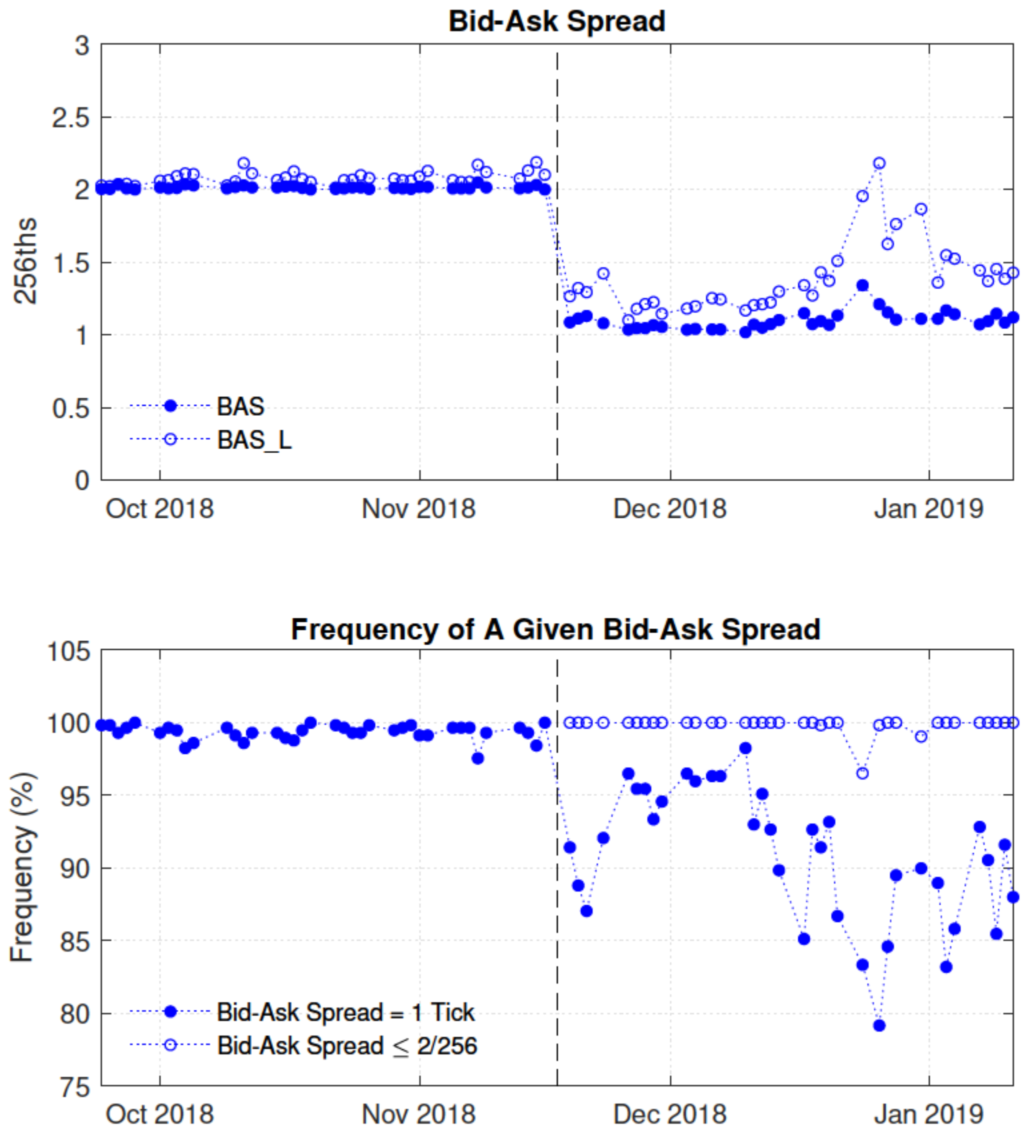

Figure 1: 2-Year Note's Bid-Ask Spreads Around Tick Size Reduction.
The top plot shows the evolution of daily average bid-ask spreads of the 2-year note on the BrokerTec platform. BAS is the difference between the best bid and best ask prices. BAS_L is the bid-ask spread for executing a large trade, defined as the 99th percentile of the trade size distribution prior to the tick size change ($50 million par). The bottom plot shows the fraction of time in a day at which the spread is at one tick (which equals 2/256 in the pre- and 1/256 in the post-change period). In the post-change period, we also plot the fraction of time at which the spread is at the pre-change tick size of 2/256 or narrower. Data are from BrokerTec. The sample period is from September 24, 2018 to January 11, 2019. The vertical line separates the pre-change period (through November 16, 2018) and the post-change period (starting November 19, 2018).

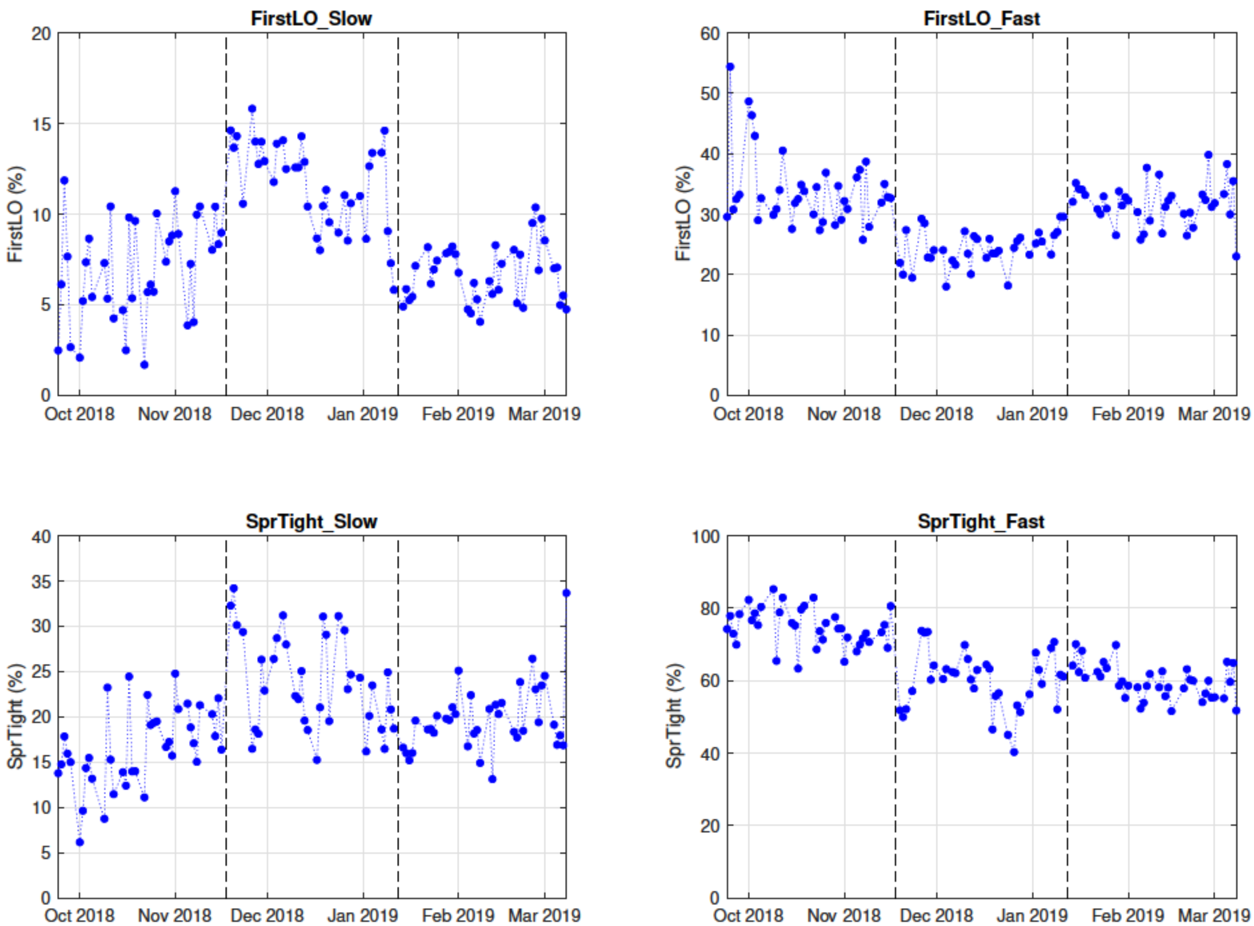

Figure 2: Competition for Liquidity Provision Around Tick Size Reductions.
This figure shows measures of competition for liquidity provision by trader type. Trader type is based on the latency of response to market information signals, with longer than 10 ms for slow traders and faster than 10 ms for fast traders. The upper plots show the fraction of first limit orders submitted in response to changes in the best bid or offer prices for slow and fast traders respectively. The lower plots show the fraction of first limit orders that restore the spread to one-tick for slow and fast traders respectively. Data are from BrokerTec. The sample period is from September 24, 2018 to March 8, 2019. The left vertical line separates the cash market's pre-change period (through November 16, 2018) and its post-change period (starting November 19, 2018). The right vertical line separates the futures market's pre-change period (through January 11, 2019) and its post-change period (starting January 14, 2019).

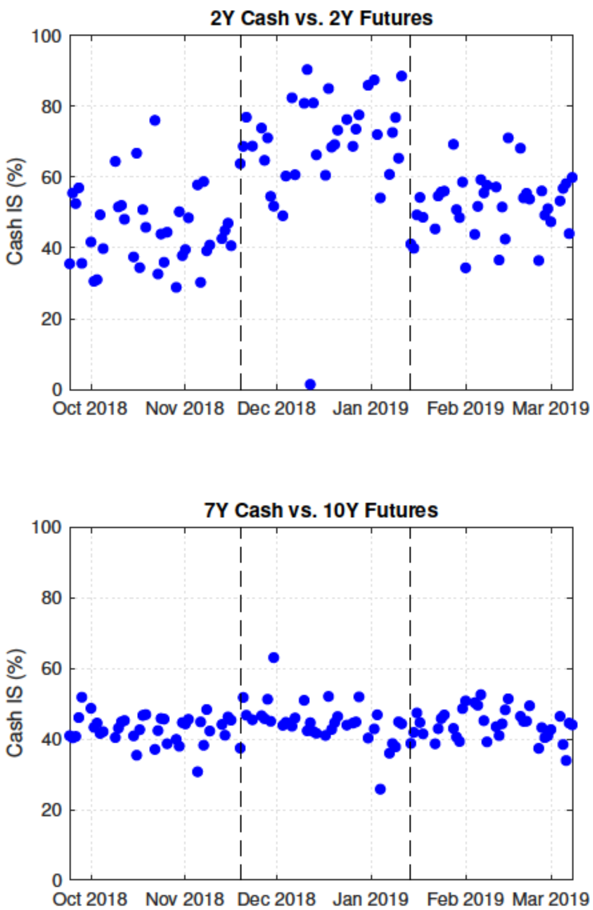

Figure 3: Information Share of Cash Market Around Tick Size Reductions.
This figure shows the information share of the cash market for each cash-futures pair. The information share is the fraction of the efficient return variance explained by the price variation in the cash market. Efficient return variance and information share are computed from a VECM (5) of cash and futures prices sampled at the one-second frequency. Data for cash instruments are from BrokerTec. Data for futures instruments are from the CME. The sample period is from September 24, 2018 to March 8, 2019. Model estimation is based on data over New York trading hours (7:30 to 17:00 Eastern time). The left vertical line separates the cash market's pre-change period (through November 16, 2018) and its post-change period (starting November 19, 2018). The right vertical line separates the futures market's pre-change period (through January 11, 2019) and its post-change period (starting January 14, 2019).