Effects of Search Frictions on Quality and Integration of Markets: Evidence from Treasury Securities Going Off the Run

Kasing Man, Xinyuan Stacie Tao, and Chunchi Wu*

January 28, 2016

ABSTRACT

When a new security goes off the run, search frictions increase and matching of trades becomes less efficient. We assess this effect on market quality by following trades of individual Treasuries through different stages of off-the-run. When a Treasury security goes off-the-run, it dramatically reduces liquidity, increases volatility and price impacts of trades, and affects the volatility-volume relation. Search frictions also reduce informativeness of trades and speed of price adjustment to information shocks, thereby impeding price discovery and inducing significant price discount. Despite the short-term adverse effects, we find no evidence that search frictions cause segmentation in the Treasury market.

JEL classification: G12; G13

Keywords: Search frictions; Market quality; Price discovery; Treasury market; Informativeness of trades; Cointegration

*Kasing Man is at College of Business and Technology Western Illinois University (Email: ks-man@wiu.edu); and Xinyuan Stacie Tao (Email: xinyuant@buffalo.edu) and Chunchi Wu are at School of Management, State University of New York at Buffalo. Address correspondence to Chunchi Wu, 335A Jacobs Management Center, School of Management, State University of New York at Buffalo, Buffalo, NY 14260-4000, Tel: 716-645-0448; Email: chunchiw@buffalo.edu.

Search problems are prevalent in financial markets. In a typical negotiated market, an investor who wants to trade must search for counterparties. During the search process, investors incur monetary or nonmonetary costs (e.g., time for waiting), which depends on the ease of meeting counterparties and externalities in the order matching process (e.g., automation or human-assisted systems). While an investor's search efficiency can improve by a canvass of intermediaries, contact with these intermediaries is not always immediate and often must be done sequentially. To trade with an intermediary, an investor needs to have an account and credit clearance, along with other requirements. The number of accounts that an investor can establish dictates their access to services of intermediation and available search options. An investor's outside options also depend on how easily s/he can locate a counterparty. All else equal, investors with fewer search options are expected to receive less favorable prices.

Liquidity and price discovery are perhaps the two most important functions of financial markets. Intermediaries play a crucial role in facilitating these functions in their capacity of matching buyers and sellers and providing liquidity. A number of studies have shown that search frictions affect bid-ask spreads, risk premia, and price dynamics. The importance of search frictions has been increasingly recognized in financial research. Recent attempts to incorporate search frictions into financial models have yielded considerable insights into asset pricing, liquidity and market efficiency (see, for example, Duffie, Gârleanu, and Pedersen, 2005, 2007; Vayanos and Wang, 2007; Vayanos and Weill, 2008; Brunnermeier and Pedersen, 2009; Duffie, 2010; Feldhütter, 2012; He and Milbradt, 2014; Duffie, Dworczak, and Zhu, 2015). By delving into the effects of trading frictions and search-and-bargaining on intermediation and asset prices, these models have generated a wealth of implications for market microstructure and the pricing of assets in a frictional world.

This paper expands the current literature by investigating the role of search frictions in affecting liquidity and price discovery of Treasury markets. Liquidity and adverse selection often reinforce each other. As an example, smaller stocks or bonds are less liquid and more opaque, and these securities tend to have lower trading volume, higher information asymmetry, and greater adverse selection. The greater adverse selection discourages participation by liquidity traders and makes the market for these securities even less liquid. In such circumstance, it is difficult to disentangle the effects of liquidity and adverse selection. In our paper, we overcome this difficulty by taking advantage of the unique auction process in the U.S. Treasury market to identify the impact of search frictions on liquidity and to isolate their effects on market quality and price discovery.

In the Treasury market, the newly issued security is referred to as “on the run”, and when a new security is auctioned, the previously issued security of a similar maturity goes “off the run”. The on-the-run issue is actively traded but immediately after it goes off the run, it becomes much less active. Because there are no discernable difference in the payoff-related information, whatever the differences between on- and just off-the-run issues are attributable to the liquidity differential between these two types of securities. This control experiment granted by periodic auctions permits us to isolate the effects of search frictions on market microstructure and the pricing of Treasury securities.

The on-the-run security is nearly identical to the just off-the-run security in payoff structure and maturity. However, immediately after the security goes off the run, trading volume drops substantially. The significant decline in trading volume makes it difficult to match buyers and sellers of off-the-run securities. In other words, search frictions, in terms of difficulty of finding a match, increase dramatically after a Treasury security goes off the run. We exploit this unique feature associated with the auction event to have better controls on information-related factors and to focus on the effects of search frictions on liquidity and price discovery of the Treasury market.

By focusing on the effects of search frictions, we document a number of unique findings that contribute to the current literature. First, we find that market quality deteriorates significantly after a Treasury security goes off the run. Liquidity declines dramatically, bid-ask spreads widen, prices become more volatile, and order imbalance increases. Results show that the auction event has drastic impacts on the microstructure of the off-the-run market. Second, we find a strong negative relation between return volatility and trading volume for highly liquid on-the-run Treasury issue but a positive relation for illiquid off-the-runs. This finding is in stark contrast to the literature of microstructure which prescribes a positive volatility-volume relation in a liquid market that attracts informed traders (e.g., Jones, Kaul, and Lipson, 1994; Andersen, 1996; Dufour and Engle, 2000; Downing and Zhang, 2004; Xu, Chen, and Wu, 2006). We show that the positive volatility-volume relation for off-the-run bonds is attributed to liquidity frictions, consistent with predictions of the search-based theory of Duffie, Gârleanu, and Pedersen (2005, 2007).[1] Similarly, we find a positive (negative) relation of bid-ask spreads to trading volume for off-the-run (on-the-run) securities, which has little to do with asymmetric information. Instead, this bid-ask spread behavior is driven predominantly by illiquidity associated with search and trading frictions in an inactive market.

Third, price impacts of trades are much higher for off-the-run securities. The higher price impacts are due to higher search frictions when a security goes off the run, rather than adverse selection. We find that the magnitude of price changes associated with trades or volume is much larger for illiquid off-the-runs than for liquid on-the-runs. This finding is robust to controls of different trading intervals, bid-ask bounce, time duration between trades, and order imbalance.

Fourth, we document strong evidence that search frictions affect price discovery and Treasury price dynamics. We show that the adjustment speed of prices to the new equilibrium is slower for off-the-run securities when there is an information shock. There is evidence to suggest that investors of off-the-runs are less attentive to macroeconomic news. Prices of off-the-runs do not converge to the fundamental value promptly and consequently, causes greater price deviations from on-the-runs in the short run. This effect is more pronounced surrounding the macroeconomic information announcement. Investors' inattentiveness to news contributes to the slow adjustment of prices to information shocks and affects price dynamics in a manner portrayed by Duffie (2010). Moreover, search frictions affect the information efficiency in the Treasury market. We find that both asymmetric information component of transaction prices and informativeness of trades are much lower for securities with higher search frictions associated with going off the run.

Finally, despite higher yields and lower liquidity for off-the-run securities, there is no evidence that the on- and off-the-run markets are segmented. The analysis of cointegration shows that these markets are integrated and suggests that the spread between on- and off-the-run notes is an equilibrium phenomenon consistent with the prediction of the dynamic equilibrium asset pricing model that assets with higher search frictions are priced with a greater discount.

Our paper is related to a number of studies on the information of trades, order flow, trading venue, liquidity, volatility and pricing in the Treasury market (Green, 2004; Brandt and Kavajecz, 2004; Goldreich, Hanke, and Nath, 2005; Barclay, Hendershott, and Kotz, 2006; Pasquariello and Vega, 2007, 2009; Li et al., 2009; Engle et al., 2012; Liu et al., 2014; Jiang, Lo,

[1] Wang and Wu (2015) take a similar approach to study the effects of search frictions in the corporate bond market.

and Valente, 2014; Fleming, Mizrach, and Nguyen, 2014; Fleming and Nguyen, 2015). Our work complements these studies by documenting the effects of search frictions in the Treasury market. The paper closest to our work is Barclay, Hendershott, and Kotz (2006). This paper examines the choice of trading venue by dealers in U.S. Treasury securities to determine when services provided by human intermediaries are difficult to replicate in fully automated trading systems. It finds that human intermediaries can uncover hidden liquidity and facilitate better matching of customer orders in less active markets such as off-the-runs. Unlike this paper which investigates the roles of electronic and human-assisted trading systems and market shares, our study focuses on the effects of search frictions on market quality, price discovery and the equilibrium relationship between on- and off-the-run markets.

Our focus on the on-/off-the-run phenomenon is related to a number of important studies on this issue (e.g., Vayanos and Weill, 2008; Pasquariello and Vega, 2009; Fontaine and Garcia, 2012; Shen and Yan, 2015). Our paper is differentiated from these studies by investigating the implications of search frictions for market quality and price discovery surrounding the event when a security goes off the run. Our work is also related to past studies on price discovery and asset returns in different markets (e.g., Barclay and Hendershott, 2003; He et al., 2009; Ghysels et al., 2015). Recent studies have shown illiquidity associated with search frictions can strain capital markets and affect asset pricing and market liquidity (see Brunnermeier and Pedersen, 2009; Duffie, 2010; Gârleanu and Pedersen, 2011; He and Milbradt, 2014). Building on theoretical constructs of search-based models, we provide empirical evidence that search frictions affect liquidity and asset pricing in the Treasury market.

More importantly, we find that illiquidity associated with search frictions significantly affect price discovery and market quality. To our knowledge, this paper represents the first effort to test the implications of search-based models using Treasury transaction data. We show that search frictions not only affects the efficiency of trade matches, bid-ask spreads and asset pricing as predicted by search-based theories but also have important consequences for price discovery and market quality. Treasury yields provide important information for risk-free rates, which are essential for pricing all other financial assets. Our findings for the effects of search frictions on the pricing of securities and price discovery in the Treasury market thus have relevant implications for asset pricing and microstructure of other assets.

The remainder of the paper is organized as follows. Section I discusses the data and highlights important effects of the event when a security goes off the run on the microstructure of the Treasury market. Section II presents empirical results associated with the effects of search frictions on market quality and price discovery. Section III conducts cointegration analysis to examine whether on- and off-the-run markets are integrated. Finally, Section IV summarizes main findings and concludes the paper.

I. Data

The primary source of our transaction data for U.S. Treasury securities is the GovPX. This is the main database providing publicly accessible data for off-the-run issues traded in the interdealer market. Another data source is BrokerTek which covers interdealer transactions on the electronic trading system. However, BrokerTek only provides transaction data for on-the-runs. To avoid the confounding effects due to different trading platforms, we focus on the GovPX data set which covers both on- and off-the-run transactions. Using the GovPX data also allows us to compare the results of the previous studies, which were used by most previous research.

GovPX consolidates quote and trade data from major brokers in the interdealer market, and records quote and trade information in the time unit of seconds. The dataset contains the best bid and ask quotes and associated quote size and yields, transaction prices and associated trading size and yields, and the buy-/sell-indicator, i.e., a “take” (buyer-initiated) or “hit” (seller-initiated) order. The dataset also includes security information such as CUSIP, type, coupon, maturity date, and on- and off-the-run indicators. GovPX identifies a newly issued security as on-the-run until another new issue with the same maturity is auctioned.

Trades in GovPX can be identified by changes in accumulated volume. However, GovPX stopped reporting this data item after March 2001. We identify trades using the method of Man, Wang, and Wu (2013). This method suggests that trades can be identified based on changes in trade sign (hit or take), price and size. If there is a change in any of these three items: trade sign, price, or size, it will be treated as a new trade. According to Man et al. (2013), the accuracy of this method for identifying actual trades is very high.[2]

We select securities with maturity of 2, 5 and 10 years because they are most liquid and issued regularly. Our sample contains transaction data during the daytime trading hours, from

[2] Man et al. (2013) show that the accuracy of identifying actual trades using this procedure is about 97%.

7:30 a.m. to 5:00 p.m. Eastern Time (ET), over the period from January 1992 to December 2008. Unlike corporate bond and stock markets, trading in the Treasury market is round the clock. Nevertheless, trading volume and frequency are much higher and the market is much more liquid during the New York daytime trading hours.

To have tighter control on external factors, we focus on the auction event window surrounding the day when a security goes off the run. The typical auction cycle is monthly for 2-year note, and quarterly for 5- and 10-year notes. We define the off-the-run day (t = 0) as the day after the auction for the subsequent note with the same maturity. The auction event window is (-20, +19) for 2-year note and (-60, +59) for 5- and 10-year notes. We denote the newly issued note as on-the-run, the issue just one auction away (within the event window) as the just-off-the-run, and older issues with multiple auctions away as off-the-runs or more off-the-runs.

Table I summarizes average daily trading data for on- and just-off-the-run 2-, 5- and 10-year notes. Mean trading frequency, volume, size, and depth are much higher, and bid-ask spreads, order imbalance and standard deviation of price changes are much lower for on-the-runs than for just-off-the-runs. Results show that liquidity for on-the-run notes is much higher than for just-off-the-runs.

[Insert Table I here]

Figure 1 portrays the daily trading activity for 2-year, 5-year and 10-year Treasury notes over the auction event window. Trading data are averaged daily across securities with the same maturity on a given day relative to the off-the-run day. The horizontal axis denotes the days in relation to the off-the-run day. As shown, on the day of going off the run, average daily trading frequency, volume, and depth drop dramatically[3] and continue to decline thereafter. Off-the-run issues farther away from the auction day trade less frequently and have lower trading volume. Average trade size also decreases while order imbalance and bid-ask spreads increase and prices become more volatile after a security goes off the run. Larger order imbalance and price volatility reflect higher search and trading frictions as it becomes more difficult for traders to locate counterparties for off-the-runs due to the less active market.

[Insert Figure 1 here]

Results show that the off-the-run event has dramatic impacts on the microstructure of the Treasury market. After a security goes off the run, liquidity dissipates rapidly. Although the drop

[3] Barclay, Hendershott, and Kotz (2006) report a pattern of trading volume similar to ours.

in trading volume for off-the-runs has been noted previously, we show that many other microstructure variables are also significantly affected. Participants in the on- and off-the-run markets and investor clienteles are quite different between the two markets (Duffie et al., 2007). In the on-the-run market, participants are predominantly short-term sophisticated traders, such as hedgers, speculators and dealers. By contrast, in the off-the-run market, participants are typically buy-and-hold investors who have little incentive to trade in the short run. Illiquidity and inactive investors contribute to higher search frictions and lower liquidity, making it more difficult to locate counterparties in the off-the-run market.

II. Empirical Results

We begin our analysis by examining how search frictions affect the price and trading dynamics of Treasury securities. The Treasury auction market provides an ideal laboratory to study the effects of search frictions. Immediately after an issue goes off the run, liquidity drops and trading patterns change dramatically while there is no significant change in the payoff-relevant information. This unique setting allows us to isolate the effect of liquidity frictions on price and trading dynamics of Treasury securities. We show that traders in the on-the-run market are more attentive to new information by comparing price movements on days with and without news announcements. Moreover, trades of on-the-run notes contain more information than those of off-the-run notes. Finally, despite the differences in trading and price behaviors in the short run, we show that the on- and off-the-run markets are cointegrated with each other in the long run.

A. The Relation between Volatility and Volume

Return volatility and its relation with trading volume are widely studied in the literature. Standard market microstructure theory suggests that information is incorporated into prices through trading activities. According to this theory, the arrival of new information induces trades and moves prices, thereby leading to higher price volatility. This results in a positive relation between price volatility and volume (e.g., Admati and Pfleiderer, 1988). In sharp contrast, the liquidity-based theory predicts a negative relation between volatility and volume in the presence of search frictions (e.g., Duffie, Gârleanu, and Pedersen, 2005, 2007). The search-based theory suggests that when trading volume is high, search frictions are low. Lower frictions reduce price fluctuations or volatility, leading to a negative relation between volume and volatility. Thus, information- and search-based theories generate dramatically different predictions for the volatility-volume relation. An important question is which theory better explains the volatility and volume behaviors in the Treasury market.

To test the competing hypotheses, we regress return volatility of bond *i* at time *t* against trading volume with an interactive off-the-run dummy variable over the auction event window:

$$Volatility_{i,t} = \alpha + \beta_1 Volume_{i,t} + \beta_2 \left(Volume_{i,t} * D_{i,t}^{off}\right) + \varepsilon_{i,t} \quad (1)$$

where D^{off} is the dummy variable which takes value 1 for just-off-the-run notes and 0 for on-the-run notes. Volatility is measured by standard deviation of transaction price changes (in bps) and volume is total trading volume (in $billion) in a given day. β_1 captures the volatility-volume relation when the note is on the run whereas β_2 captures the incremental effect of volume when the note is just off the run.

The null hypothesis is that $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_1 + \beta_2 > 0$. These sign restrictions are consistent with the predictions of the search-based theory. Because just-off-the-run securities are illiquid, search cost is high and investors need to give more price concessions to attract counterparties. Prices thus deviate more often from the fundamental value and volatility of transaction prices is higher as trades and volume increase. This results in higher susceptibility of price volatility to trading volume. On the contrary, liquidity is high for on-the-runs. As it is much easier to match trades, prices will not fluctuate much from the fundamental value. A large number of orders from both buy and sell sides balance each other and smooth the price. Higher volume is thus accompanied by lower price volatility, leading to a negative relation between volatility and volume.

Table II reports the results of the panel regression with control for bond-specific fixed effect. Consistent with the prediction of the search-based theory, β_1 is negative and β_2 is positive. The value of β_2 in absolute terms is much larger than β_1, rendering a positive volatility-volume relation for just-off-the-runs. These findings are at odds with the prediction of the information-based theory. Studies in the Treasury market have shown that informed traders concentrate on the on-the-run market (see Green, 2004; Brandt and Kavajecz, 2004). According to the information-based theory (Jones, Kaul, and Lipson, 1994), trades of liquid on-the-run securities should carry more information and hence exhibit a positive volatility-volume relation. Nevertheless, against this prediction, we find a significant negative relation between volatility and volume for on-the-run securities. This finding is however consistent with the prediction of the search-based theory and suggests that search frictions, rather than information frictions, shape the unique volatility-volume behavior in the Treasury market.

B. The Relation between Bid-Ask Spreads and Volume

We next examine the behavior of bid-ask spreads. A number of models have been proposed to explain the bid-ask spread.[4] The information-based theory suggests that trading volume contains private information which has a positive impact on the bid-ask spread. On the other hand, the search-based theory suggests that under symmetric information, high search frictions are associated with large bid-ask spreads (Duffie, Gârleanu, and Pedersen, 2005). When trading volume and frequency are high, search frictions are low and it is easier to match trades. The lower participation rate for market makers reduces the bid-ask spread as dealers can lower their inventory holdings and associated costs.

In the U.S. Treasury market, positions in on-the-run securities are plenty and it is easy to find counterparties to match their trades. For these securities, trading volume is high and search frictions are low, and according to the search-based theory, bid-ask spreads would tend to be low when search frictions are low. By contrast, for just-off-the-run securities, volume is thin, search frictions are high, and it is more difficult to locate counterparties to trade. Investors have to rely more on intermediaries to complete their transactions and it is more difficult for individual traders to compete with dealers through limit orders or find a direct counterparty to trade. As a result, bid-ask spreads would tend to be higher.

To see whether the information- or search-based theory has higher explanatory power, we regress bid-ask spreads on trading volume with a dummy variable for just-off-the-runs:

$$Spreads_{i,t} = a + b_1 Volume_{i,t} + b_2\left(Volume_{i,t} * D_{i,t}^{off}\right) + \epsilon_{i,t} \quad (2)$$

The null hypothesis is $b_1 < 0$, $b_2 > 0$, and $b_1 + b_2 > 0$ where b_1 measures the effect of volume on bid-ask spreads for on-the-run securities and $b_1 + b_2$ is the effect for just-off-the-run securities. Again, we run panel regressions with control for bond-specific fixed effect.

The right panel of Table II reports the results of bid-ask spread regressions. As shown, b_1 is significantly negative and b_2 is significantly positive. The sum of b_1 and b_2 is positive, suggesting that volume has a positive effect on bid-ask spreads for just-off-the-run securities. The positive effect of volume for just off-the-run securities cannot be attributed to asymmetric

[4] See, for example, Glosten and Milgrom (1985), Stoll (1989), Easley et al. (1996), Huang and Stoll (1997), and Madhavan, Richardson, and Roomans (1997).

information as the literature has shown that informed traders avoid these illiquid Treasury securities (see Brandt and Kavajecz, 2004). Instead, the differential volume effect is largely due to the difference in search frictions between on- and just-off-the-runs. Results strongly support the prediction of search-based models that higher search frictions for off-the-runs increase bid-ask spreads.

[Insert Table II here]

C. Price Impacts

The search-based and information-based theories also yield distinct predictions for price impacts. The search-based theory suggests that price impacts are higher for securities with higher search frictions. When search frictions are high, it is more difficult to find counterparties to trade. A seller needs to give price concessions to attract a buyer whereas a buyer needs to pay a premium to attract a seller. These deviations from the fundamental value are expected to be larger when search frictions are higher. Thus, price impacts of trades tend to be high when search frictions are high for securities such as off-the-runs. This suggests that price impacts of trades will be higher for off-the-runs than for on-the-runs. On the other hand, the information-based theory suggests that informed trading concentrates on liquid securities. On-the-run and just-off-the-run securities are very similar in terms of payoff. The information-based theory predicts that informed traders will choose the venue with higher liquidity to trade when two securities are similar. Trades of on-the-run securities should therefore carry more information and their impacts on prices are greater. Conversely, as informed traders avoid illiquid off-the-run securities to minimize transaction cost, price impacts are expected to be low for these illiquid securities because their trades do not contain information. Hence, contrary to the search-based theory, the information-based theory predicts that price impacts are higher for on-the-run trades than for off-the-run trades.

We test the implications of alternative theories by examining the price impacts of trades using different model specifications. We first regress log absolute midquote changes on trading volume (size) using trade-by-trade data. Using midquotes instead of trading prices mitigates the bid-ask bounce effect. We estimate the following regression for on- and just-off-the-runs jointly by including an off-the-run dummy variable:

$$Midquote\ Change_{i,t} = \alpha + \beta_1 Volume_{i,t} + \beta_2\left(Volume_{i,t} * D_{i,t}^{off}\right) + \varepsilon_{i,t} \tag{3}$$

where volume is equal to trade size in this trade-by-trade regression and $D_{i,t}^{off}$ takes value one for an off-the-run trade. By construction, the coefficient of trade size for just-off-the-run notes is $\beta_1 + \beta_2$. The search-based theory predicts that β_2 and $\beta_1 + \beta_2$ are both positive.

Panel A of Table III shows estimation of price impacts of trades. In column 1, the coefficient of trade size (or volume) is negative for on-the-run notes but positive for just-off-the-run notes. This implies that for liquid on-the-run securities, price impact is lower when trade size is larger. The result is consistent with the finding in bond markets that trading cost is lower for large size of trades (see Edwards, Harris, and Piwowar, 2007). On the other hand, for illiquid off-the-run securities, results show that price impacts are positively related to trade size. This finding is consistent with the search-based model prediction. For illiquid securities, it is more difficult to find counterparties who are willing to trade at a large amount. To attract counterparties, investors thus have to give more price concessions. Also, from the perspective of liquidity providers, liquidity is more valuable when trading illiquid securities and so they charge more for providing liquidity. This explains the positive coefficient of trade size for just-off-the-runs.

Hasbrouck (1991a) shows that trading activity has persistent impacts on prices. To account for this effect, we next include lagged variables up to five periods in column 2. Results show that controlling for the effects of lagged variables reduces the coefficient of contemporaneous trade size for on-the-runs but the sign of the coefficient remains negative in most cases. For just off-the-run securities, the coefficient of current trade size remains positive and highly significant across all notes.

Trade-by-trade data can be noisy, which may lead to imprecise coefficient estimates. To mitigate this effect, we use data at 5- and 30-minute trading intervals to obtain more precise estimates of price impacts (see also Fleming, 2003). Unlike the trade-by-trade case, trading activity now can be represented by volume, number of trades, and average trade size. The price impact is measured by log absolute midquote changes, $|\log\left(\frac{midquote_t}{midquote_{t-1}}\right)|$, where $midquote_t$ is the midquote at interval *t*. Panel B of Table III reports the results of regressions at the 5- and 30-minute intervals. To investigate the role of each trading variable, we estimate the regression with a single trading variable (columns 1-3) and with combination of trading variables (columns 4-5).

Results show that the coefficients of trading frequency and volume are positive and greater for just-off-the-run bonds in all cases, consistent with the prediction of search-based models. The coefficient of trade size is negative for on-the-runs and positive for off-the-runs similar to the results in the trade-by-trade regressions. Controlling for the effect of trading frequency, the sign of volume and trade size becomes negative for on-the-runs. In the off-the-run market, trading frequency is low and volume is thin. Also, trades often come from the same side in a short trading window and fewer liquidity providers are willing to take large positions. These factors tend to increase the impacts of trading variables on prices.

[Insert Table III here]

As a robust check, we also use both midquote changes without taking the absolute value and absolute transaction price changes (with no log transformation) as the dependent variable and find similar results in terms of sign and significance of coefficients. In addition, we run the midquote changes on net trading activities, including net trading frequency (buy-initiated minus sell-initiated), net trading volume, proportion of buy-initiated frequency (net frequency divided by total frequency) and buy-/sell-initiated trading frequency. Unreported results show similar patterns. The price impacts of these trading variables are significantly positive and greater for just-off-the-runs across all regressions.

We further run regressions using signed trade (volume) and controlling the effects of other trading variables, including time interval between two consecutive trades and order imbalance. Chordia, Roll, and Subrahmanyam (2002) suggest that order imbalance is an important indicator of one-side trading pressure that impacts prices. Dufour and Engle (2000) show that time duration between trades contains information for asset prices and the price impact increases as time duration shortens. To account for these effects, we run the following regressions on signed trade (volume) with an off-the-run dummy and control variables by pooling on- and just-off-the-run data:

$$\begin{aligned} \mathrm{y}_{i,t} &= \alpha + \beta_1 x_{i,t} + \beta_2\left(D_{i,t}^{off} * x_{i,t}\right) \\ &\quad + \beta_3 TI_{i,t} + \beta_4 OI_{i,t} + \sum_{k=1}^{5} \rho_k\, \mathrm{y}_{i,t-k} + \sum_{k=1}^{5} \theta_k\, x_{i,t-k}, \end{aligned} \tag{4}$$

where $y_{i,t} = \log\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$, p can be midquotes or trading prices, $x_{i,t}$ is either signed trade or signed volume (in \$mil.), $TI_{i,t}$ is square root of the time interval between two consecutive trades (in hours), and $OI_{i,t}$ is logarithm of absolute cumulative order imbalance (in \$mil.).

Results in Table IV show that the relation between midquote (price) changes and signed trade (signed volume) is positive, and this relation is more positive for just-off-the-run bonds. All coefficients are highly significant. The adjusted R^2 values are much higher than those reported in Table III, suggesting that the model specification with signed trades (volume) and other trading variables (order imbalance and time interval between trades) has higher explanatory power for transaction price changes.

[Insert Table IV here]

Overall, empirical evidence strongly supports the prediction of search-based models that the impacts of trading activity on prices are larger for illiquid just-off-the-run bonds. This finding is robust to different model specifications and controls for various microstructure variables.

D. The Effect of News Announcement

Macroeconomic news plays an important role in moving prices in the Treasury market (see Balduzzi, Elton and Green, 2001; Green, 2004). To examine the effect of search frictions in different information environments, we divide whole sample into two subgroups by days with and without macroeconomic announcement. The news announcement information is collected from Bloomberg. We focus on news announcements at 8:30 a.m. ET and the same types of news announcement as in Green (2004).

[Insert Figure 2 here]

Figure 2 plots the intraday pattern of trading frequency, trading volume, bid-ask spreads, and return volatility over the interval of 8:00-9:30 a.m. ET. For just-off-the-runs, all four variables show a similar pattern for news and no-news days. However, for on-the-runs, there are notable differences between news (solid lines) and no-news days (dash lines). Trading frequency and volume jump right after 8:30 a.m. and then gradually taper off, indicating that trades in the on-the-run market respond strongly to macroeconomic news. In addition, there is a spike for bid-ask spreads and return volatility around 8:30 a.m. on news days.

We report t tests for the differences in trading volume on news and no-news days in Table IV. For on-the-run notes, the volume difference is most significant at the interval of 8:30-9:00, followed by the interval between 9:00-9:30, but it is insignificant at the interval of 8:00-8:30. On the other hand, we find no significant differences in trading volume for just off-the-run notes across all time intervals. Thus, there is no evidence that volume is significantly higher on news day than on other days for off-the-runs.

To see if the effect of news announcement on volume differs by security type, we perform the difference-in-difference tests. That is, we test whether the difference between news and no-news volume is significantly different between on- and just-off-the-run notes or not. Results show significant differences between on- and just-off-the-run notes at the 8:30-9:00 and 9:00-9:30 intervals. Unreported results show a similar differential pattern between on- and just-off-the-runs for trading frequency, return volatility, bid-ask spreads, and market depth. Results suggest that trading variables of on-the-run securities respond more to news announcements.

[Insert Table V here]

An important issue is how prices respond to new information. A market has better price discovery if information is impounded into prices through trades in a more efficient and timely fashion. To estimate the information component of Treasury trades, we apply the model of Madhavan, Richardson, and Roomans (1997, hereafter MRR),[5] which provides a framework to measure different components of security price changes associated with private and public information, liquidity, and market microstructure noise. In this model, the information component of price changes reflects revisions in beliefs when new information arrives. New information comes from two sources: innovations in order flows and unanticipated public information. Specifically, price changes are characterized by the following process (see MRR, 1997):

$$\Delta P_t = P_t - P_{t-1} = (\phi + \theta)x_t + (\phi + \rho\theta)x_{t-1} + e_t \tag{5}$$

where ΔP_t is the price change between two consecutive transactions at time t and t-1, x_t is order flow with value equal to 1 if the trade is buy-initiated and -1 if sell-initiated, ϕ represents the compensation for providing liquidity, θ captures the permanent price change associated with asymmetric information, and ρ is the autocorrelation coefficient of order flows x_t and x_{t-1}. We estimate θ at half-hour trading intervals surrounding 8:30 a.m. for news and no-news days, that is,

$$\Delta P_t = P_t - P_{t-1} = \left(\phi_k + \theta_k\right)D_{k,t}x_t - \left(\phi_k + \rho_k\theta_k\right)D_{k,t-1}x_{t-1} + e_t \tag{6}$$

where k can be N (No news), B (days with news at half-hour interval before news release, i.e., 8:00-8:30a.m.), A_1 (days with news at half-hour interval after news release, i.e., 8:30-9:00), and A_2 (days with news and one hour after news release, i.e., 9:00-9:30). $D_k = 1$ if a trade-type is k

[5] Green (2004) uses the same model to examine the information content of trades.

and $D_k = 0$, otherwise.

Let

$$\mathrm{v}_t = x_t - \rho_k D_{k,t} x_{t-1}, \tag{7}$$

$$\mu_t = \Delta P_t - (\phi_k + \theta_k) D_k x_t + (\phi_k + \rho_k \theta_k) D_k x_{t-1}, \tag{8}$$

and α be a constant vector; then the moment conditions used for GMM estimation can be written as

$$E\begin{bmatrix} \mathrm{v}_t D_{k,t-1} x_{t-1} \\ \mu_t - \alpha \\ (\mu_t - \alpha) D_{k,t-1} x_{t-1} \\ (\mu_t - \alpha) D_{k,t} x_t \end{bmatrix} = 0. \tag{9}$$

From Figure 2 and Table V, one would expect that news announcement has a greater impact on the information component of on-the-run trades than that of just-off-the-runs. The news announcement has a powerful effect on trading frequency, volume, bid-ask spreads, and return volatility of on-the-runs but has little impact on those of off-the-runs. This pattern suggests that trading variables of on-the-run should contain more information.

The result of GMM estimation in Table VI confirms this conjecture. When there is no news announcement, θ is flat or decreases slightly from 8:00 to 9:30 for on-the-run notes. For just-off-the-runs, we only estimate the θ value for the whole 8:00-9:30 interval as observations are not sufficient to obtain reliable estimates for each half-hour interval. On news days, θ at the 8:00-8:30 interval before the morning news announcement is similar to that on no-news days. However, immediately after the news announcement, the θ value jumps for on-the-run issues at the 8:30-9:00 interval. The difference in the θ values between news and no-new days at the 8:30-9:00 interval is 0.13 for 2-year, 0.17 for 5-year, and 0.14 for 10-year on-the-run notes, all significant at the one percent level. By contrast, θ is relatively flat for just-off-the-run issues over the trading intervals on news days. The difference in the θ values between news and no-news days is insignificant for all just-off-the-run notes. This discrepancy suggests that off-the-run bond investors do not respond to macroeconomic announcements or they are inattentive to news.

Another interesting finding is that the differences in the θ values between news and no-news days are quite small and statistically insignificant at the 8:00-8:30 and 9:00-9:30 intervals even for on-the-run issues. Results suggest that the information-based trading occurs primarily at the new announcement interval, 8:30-9:00 a.m. For just-off-the-runs, there are no significant differences in the θ values across all trading intervals. This finding is consistent with previous studies that information-based trading concentrates in the on-the-run segment of the Treasury market.

[Insert Table VI here]

E. Speed of Adjustment to New Equilibrium

The intraday pattern in Figure 2 suggests that trading responds more quickly to macroeconomic movements in the on-the-run market than in the off-the-run market. High volume and trading frequency of on-the-run securities is expected to enhance efficacy of price discovery. The sensitivity of trading to announcements also implies that when new information is released, prices of on-the-run notes are likely to converge to the new equilibrium value more quickly than those of just-off-the-run notes. To investigate this possibility, we employ the following partial adjustment model to measure the price-adjustment speed for on- and just-off-the-run bonds:

$$p_{i,t} - p_{i,t-1} = \lambda\left(p^*_{i,t} - p_{i,t-1}\right), 0 < \lambda \leq 1, \tag{10}$$

where

$p_{i,t}$ = the close price of bond *i* on day *t*,

$p^*_{i,t}$ = the latent equilibrium value of bond *i* on day *t*,

λ is the speed-of-adjustment coefficient and the term in parentheses captures the deviation from the equilibrium. The value of adjustment coefficient is between zero and one, indicating that the change in observed prices is generally only a fraction of the change in the equilibrium value. When λ is equal to zero, prices are not responding to changes in fundamentals at all, and when λ is equal to one, the price response to the change in the equilibrium value is instantaneous.

As the latent equilibrium price $p^*_{i,t}$ is not observed, we estimate it from observable instrumental variables,

$$p^*_{i,t} = \alpha + \textstyle\sum_{k=1}^{n} \beta_k \, x_{k,i,t} + \varepsilon_{i,t}, \tag{11}$$

where x_k, $k = 1, 2 \ldots n$, denotes k^{th} instrumental variable for the equilibrium value of bonds. Combining (10) and (11), we have

$$p_{i,t} = \alpha\lambda + (1-\lambda)p_{i,t-1} + \sum_{k=1}^{n} (\beta_k \lambda) \, x_{k,i,t} + \xi_{i,t}. \tag{12}$$

Based on the term structure model, we employ coupon rates, matched Treasury market yields at time t from the Federal Reserve Bank, and time to maturity as the instrumental variables for the latent fundamental value. Microstructure theory suggests that information is assimilated into prices through trading, and since informed traders focus on liquid on-the-run securities (see Brandt and Kavajecz, 2004), the speed of adjustment (λ) to information should be higher for on-the-runs when new information arrives.

Using (12), we examine the difference in the speed of price adjustment between on- and just-off-the-runs. For each just-off-the-run note, we match the trading observations over the auction event window by an on-the-run note with the same maturity to construct two price series over the same horizon. We employ the Newton-Gauss nonlinear regression to estimate λ for on- and off-the-runs, respectively.

Table VII reports the results of nonlinear regressions. As shown, the speed of adjustment for on-the-runs is greater than that for just-off-the-runs across all notes. The differences are all significant at the 5% level. Results show that on-the-run prices respond more quickly to changes in the equilibrium value of the bond than off-the-run prices. Moreover, the speed-of-adjustment coefficient of on-the-runs is higher on news announcement days. On the days with macroeconomic announcement, the price of on-the-runs responds to news much more quickly than that of off-the-runs. As shown in Table VII, the difference in the speed of adjustment widens on news days between the two types of securities. These differences are again significant at the 5% level. The adjustment coefficients for on-the-runs are economically close to one and have relatively small t-statistics associated with the deviation from unity. Test statistics (omitted for brevity) show that the adjustment coefficients are insignificantly different from one for 2- and 5-year on-the-runs whereas they are all significantly less than one for off-the-runs. Results show that prices of on-the-run securities respond very quickly to changes in fundamentals associated with macroeconomic announcement while off-the-run prices adjust sluggishly. This finding suggests that trading and search frictions slow the adjustment of off-the-run prices to new information. It also implies that frictions likely impede price discovery and lower information efficiency in the off-the-run market.

[Insert Table VII here]

F. Informativeness of Trades

The preceding analysis shows that the differential price dynamics between on- and just-off-the-runs are driven mainly by the difference in search and trading frictions between two markets.

The impact of macroeconomic news announcement on prices is much stronger for on-the-run securities than off-the-runs, and trading in the on-the-run market reacts more quickly to news. These findings imply that trades of on-the-runs will be more informative than those of off-the-runs. As such, the efficacy of price discovery process is expected to be higher for the on-the-run market.

To see if this is indeed the case, we use the method suggested by Hasbrouck (1991b) (see Appendix) to calculate a measure of information content of trades, denoted as R_w^2. For convenience, we refer to this informativeness measure as the information share which measures the proportion of the variance in the random walk component of the bond price that is attributable to trades. Consider $Y_t = [r_t, x_t^1, x_t^0, x_t^2]'$ where r_t = Treasury returns, x_t^0= trade sign, x_t^1= signed volume, and x_t^2= signed volume-square. Let Y_t follow a VAR(p) model $(A_0 - A_1 L - A_2 L^2 - \cdots A_p L^p)Y_t = \eta_t$ where A_i is the autoregressive (AR) coefficient at lag i (see Appendix for details). For $\eta_t = [v_{1t}, v_{2t}]'$, v_{1t} is the return innovation and v_{2t} is a 3 by 1 vector corresponding to trade-related innovations. The variance of v_{1t} is σ_1^2, the covariance matrix of v_{2t} is Ω, and v_{1t} and v_{2t} are uncorrelated. Under the stationarity assumption, Y_t has an VMA(∞) representation:

$$Y_t = (I + \Theta_1 L + \Theta_2 L^2 + \Theta_3 L^3 + \cdots)A_0^{-1}\eta_t = (\Theta_0^* + \Theta_1^* L + \Theta_2^* L^2 + \Theta_3^* L^3 + \cdots)\eta_t \quad (13)$$

where $\Theta_0^* = A_0^{-1}$ and $\Theta_i^* = \Theta_i A_0^{-1}$. The (1,1)th element in Θ_i^* gives a_i^*, and the (1, i=2,3,4)th elements in Θ_i^* give the vector b_i^*. The information share is measured by R_w^2 from Hasbrouck's (1991b) Proposition 1. Specifically, $R_w^2 = \frac{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime})}{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime}) + (1+\sum_{i=1}^{\infty} a_i^*)^2\sigma_1^2}$, where the numerator $(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime})$ captures the contribution of trades to total return variance, or the ultimate effect (cumulative impulse responses) of a trade shock on returns.

Table VIII reports the estimate of R_w^2 for the same note which started as the on-the-run issue, went off the run (or just off the run), and then became more off the run. Results clearly indicate that the information content of trades is highest for on-the-runs. As shown, the information share measure R_w^2 drops markedly immediately after a Treasury issue goes off the run, at least by 70 percent for all cases. It continues to decline as the issue becomes more off the run.[6] More

[6] Just-off-the-run notes are defined as 1-auction period away from issuance and more-off-the-run notes are i-auction period away where i ranges from 2 to 5.

specifically, the information share is 31% for 2- notes, 36% for 5-year notes and 27% for 10-year notes when they are on the run. Immediately after going off the run, the information share reduces to 9%, 4%, and 2% for 2-, 5-, and 10-year notes, respectively and eventually it drops to 6%, 3%, and 0.4% when these notes are more off the run or farther away from the original auction day.

The information share estimates are for the same note which goes through different stages in the auction cycle. Since the only change is the note's seasonedness, the differences in the information share are attributed to the increase in search frictions as a Treasury issue goes off the run. Results show that search and trading frictions significantly reduce the informativeness of trades and lower the efficacy of price discovery.

[Insert Table VIII here]

III. Market Cointegration

The analysis above shows that when a Treasury note goes off the run, search frictions increase, liquidity decreases, and price discovery becomes less efficacious. An important question that naturally arises is whether the markets for on-the-runs and off-the-runs are segmented in the presence of search frictions. To answer the question, we construct the time-series data for on-the-run notes and period(i)-off-the-run notes, where i = 1, 2,…5, represents the number of auctions away. A higher i indicates that a Treasury note is more off the run. The six time series for notes with different auction periods are lined up by the dates surrounding the auction event.

We first regress yields of on-the-run notes (Y_{on}) on yields of period(i)-off-the-run notes ($\mathrm{Y}_{\mathrm{off}(i)}$), i.e., $Y_{on} = b_0 + b_1 Y_{off(i)}$, to provide a generic picture for the relation between the two yield series.[7] On a given trading day, if the price of on-the-run notes is exactly same as that of period(i)-off-the-run note, b_0 will be zero and b_1 will be equal to one. Alternatively, if $\mathrm{Y}_{\mathrm{off}(i)}$ behaves different from Y_{on}, b_1 will deviate from one. In the special case that b_1 is equal to one, minus b_0 represents average on-/off-the-run yield spreads, i.e., yields of period(i)-off-the-runs

[7] Yields of on-the-runs are adjusted to make their time to maturity same as that of period(i)-off-the-runs. Longer maturity of on-the-runs comes up with maturity premium and therefore, there are two components of yield spreads, liquidity premium and maturity premium. To better study the liquidity effects, we deduct maturity premium from yields of on-the-runs by fitting yield curves with quasi-cubic hermite spline function, which is the methodology used by U.S. Department of The Treasury.

minus those of on-the-runs.

Panel A of Table IX reports results of the ordinary least squares (OLS) regression. Results show that b_1 is very close to 1 in all cases and b_0 becomes more negative as the period(i) increases. This finding suggests that prices of on-the-run and period(i)-off-the-run notes comove with each other but the on-/off-the-run spread increases when a note becomes more off the run.

We next present formal tests for market cointegration. In cointegration analysis, the unit root test, Johansen's maximum eigenvalue test for the number of cointegration vector, and the vector error-correction model (VECM) estimation are applied sequentially. Since cointegration analysis concerns if a linear combination of Y_{on} and $\mathrm{Y}_{\mathrm{off}(i)}$ is stationary, we apply the unit root (UR) test and Johansen's max eigenvalue test first. A large p-value in the unit root test indicates that the null hypothesis of unit root cannot be rejected, which means the time-series data are non-stationary. Having established that both Y_{on} and $\mathrm{Y}_{\mathrm{off}(i)}$ are I(1) non-stationary, we then check the number of cointegration vectors between them.

The Johansen's max eigenvalue test is a sequential test. First, we test the null hypothesis H(0) that there is no cointegration vector versus the alternative hypothesis that there is at least one. Failure to reject H(0) means there is no common implicit equilibrium yield (price) between on-the-run and period(i)-off-the-run markets. If H(0) is rejected, we next test the null hypothesis H(1) that there is one cointegration vector versus the alternative that there are more than one. In our empirical analysis, H(0) is rejected at 1% for on-the-runs and all period(i)-off-the-runs, and H(1) cannot be rejected under all cases. This finding suggests that there is only one shared common equilibrium yield between on-the-run and period(i)-off-the-run markets, or there exists only one cointegration vector.

After establishing that Y_{on} and $\mathrm{Y}_{\mathrm{off}(i)}$ are cointegrated, we use VECM to examine the price dynamics of the on-the-run and period(i)-off-the-run markets. Consider the two markets with bond yields denoted as two series $Z_t = (Y_{on,t}, Y_{off(i),t})'$ where both series are cointegrated I(1) sharing a common equilibrium yield. The error-correction term of the cointegrated I(1) yields series is $z_t = c + \beta' Z_t = c + Y_{on,t} + \beta_2 Y_{off(i),t}$ with the normalized cointegration vector $\beta = (1, \beta_2)'$ where c is a constant introduced to capture the equilibrium spread between on- and off-the-run yields due to illiquidity associated with search frictions in the off-the-run market that induces a price discount. The VECM then is expressed as

$$\Delta Z_t = \alpha\left(c + Y_{on,t-1} + \beta_2 Y_{off(i),t-1}\right) + B_1 \Delta Z_{t-1} + B_2 \Delta Z_{t-2} + \cdots + B_{r-1}\Delta Z_{t-r+1} + e_t \ , \tag{14}$$

where $= (\alpha_{on}, \alpha_{off(i)})'$, B_i is the AR coefficient, and Δ is the first difference operator. The error term e_t is a zero-mean vector of serially uncorrelated innovations with a variance-covariance matrix $\Omega = \begin{pmatrix} \sigma_{on}^2 & \sigma_{on,off(i)} \\ \sigma_{off(i),on} & \sigma_{off(i)}^2 \end{pmatrix}$. Specifically, σ_{on}^2 and $\sigma_{off(i)}^2$ are the innovation variances of two yield series for on- and off-the-runs, and $\sigma_{on,off(i)} = \sigma_{off(i),on} = \rho\sigma_{on}\sigma_{off(i)}$ is the covariance where ρ is the correlation of innovations between the two markets.

Intuitively, c is like -b_0 and β_2 is like -b_1 in the OLS regression of on-the-run yields against period(i)-off-the-run yields. After taking the yield spread c into account, the error correction term $c + Y_{on,t-1} + \beta_2 Y_{off(i),t-1}$ is supposed to be close to zero. If this term differs from zero at time t-1, yield correction will take place and the correction usually occurs in the opposite direction at time t. For example, if $c + Y_{on,t-1} + \beta_2 Y_{off(i),t-1} > 0$ at t-1, i.e., $Y_{on,t-1}$ is higher than expected (the price of on-the-runs is too low) or $Y_{off(i),t-1}$ is lower than expected (the price of period(i)-off-the-runs is too high), the yield in the on-the-run market will go down, represented by negative α_{on} and that in period(i)-off-the-run markets will go up, with positive $\alpha_{off(i)}$, and vice versa. Consequently, two yields will correct for the disequilibrium and converge to the common equilibrium yield. Moreover, the magnitude of α_{on} ($\alpha_{off(i)}$) in (14) captures the speed of yield correction when there exists a deviation from the equilibrium. A smaller absolute value of the speed not only means a slower correction but more importantly, suggests that the market has more price discovery. In the extreme case that $\alpha_{on} = 0$ and $\alpha_{off(i)} \neq 0$, only period(i)-off-the-run market corrects for the yields while the on-the-run market is considered as full reflection of information. In this case, the on-the-run market is credited for the entire amount of price discovery and the off-the-run market has no contribution to price discovery in the Treasury market.

Panel B of Table IX reports the results of VECM estimation. As shown, -β_2 is very close to one and c becomes larger as i increases (i.e., more off the run), consistent with the results from the OLS regression. As Treasury notes become more off the run, the on-/off-the-run spread increases. This result is in line with the expectation that on-the-runs (off-the-runs) are priced higher (lower). However, the two markets are not segmented because bonds traded at these two markets are tied to the implicit equilibrium price. This phenomenon is consistent with the equilibrium of the dynamic asset pricing model of Duffie, Gârleanu, and Pedersen (2005, 2007) with search frictions. This model suggests that in a steady-state equilibrium, assets with higher search frictions will be priced at a larger illiquidity discount that represents the present value of illiquidity risk premiums due to search frictions. The asset with no search frictions has an equilibrium price close to the perfect (frictionless) market price. In our case, the on-the-run note has almost no search frictions and its price is close to the perfect market equilibrium price. By contrast, the off-the-run note has search frictions, and its equilibrium price (yield) is lower (higher) than the on-the-run price by an illiquidity discount. As a Treasury note becomes more off the run, search frictions of the note are higher and its equilibrium price will be even lower or further deviates from the frictionless market equilibrium price.

The correction parameter α_{on} is mostly negative and $\alpha_{off(i)}$ is all positive. Moreover, the magnitude of negative α_{on} is small and mostly insignificant, which suggests that prices of on-the-runs are close to the equilibrium value and does not need much correction. On the contrary, $\alpha_{off(i)}$ is all significantly positive, suggesting that yields (prices) of period(i)-off-the-runs go up (down) to approach to the equilibrium yield (price). In addition, $\alpha_{off(i)}$ is much larger than α_{on} in absolute terms, suggesting that price correction takes place mostly in the off-the-run market and so price discovery is lower in this market.

Overall, results strongly suggest that the on- and off-the-run markets are integrated. The on-the-run market plays the price leadership role and its price reflects most information while it is mainly the off-the-run market that corrects for disequilibrium errors. In the dynamic equilibrium, prices are synchronous and the off-the-run security is priced below the on-the-run security with an illiquidity discount consistent with the prediction of the search-based model of Duffie, Gârleanu, and Pedersen (2007).

[Insert Table IX here]

IV. Conclusion

Recent development in dynamic asset pricing modeling has shown that search frictions can significantly affect the temporal behavior and equilibrium of asset prices. Search frictions are particularly important for OTC markets without central market makers. This paper uses transaction data from the Treasury market to examine some of the important implications of the search-based model. By exploiting the unique feature of Treasury auctions, we overcome the difficulty to separate the effects of liquidity and adverse selection.

We find that in a market with search frictions, the relations of both volatility and bid-ask spreads with trading volume are positive and price impacts of trades are larger for illiquid off-the-run Treasury notes. Macroeconomics announcement has little impact on the trading activity in the off-the-run market and the asymmetric information component of prices and the speed of price adjustment to the new equilibrium value are much lower for off-the-runs. These findings suggest that investors in the off-the-run market respond slowly or are less attentive to news. Moreover, we find that trades are more informative for on-the-run notes than for off-the-run notes and the former plays a price leadership role in the price discovery of the U.S. Treasury market.

Despite high search frictions in the off-the-run market, we find strong evidence supporting the hypothesis that on- and off-the-run markets are integrated. However, in equilibrium, there is a positive yield spread between on- and off-the-run notes. The on-/off-the-run spread widens as a note becomes more off the run. This finding supports the prediction of the search-based model that the price discount of bonds is positively related to search frictions. As a bond is farther away from the auction day, it becomes less liquid and has greater search frictions. The price differences between on- and off-the-run notes reflect the discount of illiquidity associated with search and trading frictions in a frictional market.

Our findings improve the understanding for the role of search frictions in asset pricing and price dynamics. We show that search frictions not only have an effect on asset prices but also affect market quality and price discovery in financial markets. Search frictions reduce the efficacy of price discovery and lower market quality in terms of liquidity and volatility. While search frictions increase trading costs and result in asset price discount, it does not appear to cause disintegration in the Treasury bond market. Empirical evidence shows that even though search frictions have profound effects on the microstructure of the Treasury market and pricing of securities with different seasonedness, the markets of on- and off-the-runs remain integrated.

Appendix

Computation of Hasbrouck's (1991b) information share measure R_w^2

In this appendix, we first discuss the procedure for computing Hasbrouck's (1991b) information share measure R_w^2 for the bivariate case with return and signed volume, and then the extension to four variables case with return, signed volume, signed trade, and signed volume square.

Let $Y_t = (r_t, x_t)$ be a bivariate vector consists of return r_t and signed volume x_t. Following Hasbrouck's (1991) equation (4), let Y_t follows a vector autoregressive (VAR) model of order *p* in the form:

$$(A_0 - A_1 L - A_2 L^2 - \cdots A_p L^p)Y_t = \eta_t \tag{A1}$$

where $A_0 = \begin{bmatrix} 1 & -b_0 \\ 0 & 1 \end{bmatrix}$ which implies r_t is related to the contemporaneous x_t but not the other way around. The AR coefficients are $A_i = \begin{bmatrix} a_i & b_i \\ c_i & d_i \end{bmatrix}$, and L is the back-shift operator. The error terms $\eta_t = \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix}$ has diagonal covariance matrix with the diagonal elements being σ_1^2 and σ_2^2. Such orthogonal structure is possible due to the contemporaneous structure A_0.

Denote $A(L) = A_0 - A_1 L - A_2 L^2 - \cdots A_p L^p$ as the AR polynomial, which is a 2 by 2 matrix with diagonal elements $A_{11}(L) = 1 - \sum_{i=1}^{p} a_i L^i$, $A_{22}(L) = 1 - \sum_{i=1}^{p} d_i L^i$ and off-diagonal elements $A_{12}(L) = -b_0 - \sum_{i=1}^{p} b_i L^i$, and $A_{21}(L) = -\sum_{i=1}^{p} c_i L^i$. Under the stationarity assumption, it follows that the VAR(*p*) in (A1) has a vector moving-average (VMA) representation:

$$Y_t = A^{-1}(L)\eta_t \tag{A2}$$

Or alternatively,

$$det(L)Y_t = \begin{bmatrix} A_{22}(L) & -A_{12}(L) \\ -A_{21}(L) & A_{11}(L) \end{bmatrix} \eta_t \tag{A3}$$

where $det(L) = A_{11}(L) * A_{22}(L) - A_{12}(L) * A_{21}(L)$ is the determinant of *A(L)*, and note that it admits an AR(*2p*) model form. This implies that the first element r_t follows:

$$r_t = \frac{(1-\sum_{i=1}^{p} d_i L^i)}{\det(L)} v_{1t} + \frac{(b_0+\sum_{i=1}^{p} b_i L^i)}{\det(L)} v_{2t} \tag{A4}$$

$$= (1 + \sum_{i=1}^{\infty} a_i^* L^i)v_{1,t} + (b_0^* + \sum_{i=1}^{\infty} b_i^* L^i)v_{2,t} \tag{A5}$$

The first term corresponds to v_{1t} in (A4) has an ARMA(*2p, p*) form and hence has a MA(∞) representation under the stationarity assumption for the AR(*2p*) term; and we can derive the corresponding MA(∞) coefficients a_i^* from the ARMA (*2p, p*) coefficients in the first term in (A4). Also, we can derive b_i^*. Equation (A5) above is the Hasbrouck's (1991b) equation (5).

Similarly, the second element x_t follows:

$$x_t \ = \frac{\sum_{i=1}^{p} c_i \ L^i}{\det(L)} v_{1t} \ + \frac{(1-\sum_{i=1}^{p} a_i \ L^i \ )}{\det(L)} v_{2t} \tag{A6}$$

$$= (\sum_{i=1}^{\infty} c_i^* \, L^i) v_{1,t} \ + (1 + \sum_{i=1}^{\infty} d_i^* \, L^i) v_{2,t} \tag{A7}$$

Equation (A7) is Hasbrouck's (1991b) equation (5), and we can derive the corresponding MA(∞) coefficients c_i^* and d_i^* from their respective ARMA (*2p, p*) coefficients in (A6).

Finally, Hasbrouck's R_w^2 is given in Hasbrouck's (1991b) Proposition 1 as:

$$R_w^2 = \frac{(\sum_{i=o}^{\infty} b_i^*)^2 \sigma_2^2}{(\sum_{i=o}^{\infty} b_i^*)^2 \sigma_2^2 + (1+\sum_{i=1}^{\infty} a_i^*)^2 \sigma_1^2} \tag{A8}$$

It is important to note that equation (A5) expresses how return is being related to its own shock and the trade volume's shock. This representation is the key to derive the impulse response function and the forecast error variance decomposition in structural analysis of VAR model. For Hasbrouck's R_w^2 , the numerator in (A8) captures the variance of the cumulative effect (sum of all impulse responses) on returns upon a unit shock in trading volume. As such, R_w^2 measures the contribution of trades to the total return variance, or the ultimate effect of a trade shock on returns.

In empirical analysis, we use a VAR model of order 3 and use 20 terms in the MA(∞) to compute the R_w^2. We also try VAR(5) and 30 terms in the MA representation, and the conclusion remains broadly the same. Furthermore, to better measure the impact of trade, we follow Hasbrouck (1991b) to introduce trade sign and signed volume-squared in addition to signed volume alone to estimate R_w^2.

Specifically, in the above setting, r_t remains to be the return, and x_t is now a 3 by 1 vector $[x_t^1, x_t^0, x_t^2]'$ where x_t^0= trade sign, x_t^1= signed volume, and x_t^2= signed volume-square. The AR coefficient A_i becomes a 4 by 4 matrix with the dimensions of its elements changed accordingly, and σ_2^2 becomes a 3 by 3 covariance matrix Ω. The R_w^2 is now in the form of equation (7) in Hasbrouck's (1991b) Proposition 1:

$$R_w^2 = \frac{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime})}{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime})+(1+\sum_{i=1}^{\infty} a_i^*)^2\sigma_1^2} \quad \text{(A9)}$$

In principle, one can derive the MA form for r_t just like the 2 variable case. However, the derivation of the inverse of a 4 by 4 matrix $A(L)$, with each element being a polynomial in L^i where i = 0, 1, …, p is very tedious. Rather than taking this approach, we use simulation to compute the R_w^2.

First, recall the VAR model of $Y_t = [r_t, x_t^1, x_t^0, x_t^2]'$ is $(A_0 - A_1 L - A_2 L^2 - \cdots A_p L^p)Y_t = \eta_t$. For the error term $\eta_t = \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix}$, v_{1t} and v_{2t} are uncorrelated where v_{1t} has variance σ_1^2 and v_{2t} has covariance Ω. Since v_{1t} and v_{2t} are uncorrelated, we can estimate the coefficient A_i separately by first running a regression of r_t on r_{t-j} (j = 1, 2,…, p) and $x_{t-i}^1, x_{t-i}^0, x_{t-i}^2$ (i = 0, 1, 2,…, p) and then running a VAR(p) for $[x_t^1, x_t^0, x_t^2]'$. The resulting coefficients of these models give the corresponding elements of A_i, and their residual variances give σ_1^2 and Ω, respectively.

Then, we can express the VAR model in the usual form:

$$(I - A_0^{-1}A_1 L - A_0^{-1}A_2 L^2 - \cdots - A_0^{-1}A_p L^p)Y_t = A_0^{-1}\eta_t \quad \text{(A10)}$$

Under the stationarity assumption, Y_t has an VMA(∞) representation:

$$\begin{aligned} Y_t &= (I + \Theta_1 L + \Theta_2 L^2 + \Theta_3 L^3 + \cdots)\ A_0^{-1}\eta_t \\ &= (\Theta_0^* + \Theta_1^* L + \Theta_2^* L^2 + \Theta_3^* L^3 + \cdots)\ \eta_t \end{aligned} \quad \text{(A11)}$$

where $\Theta_0^* = A_0^{-1}$ and $\Theta_i^* = \Theta_i\ A_0^{-1}$. Thus, the (1,1)th elements in Θ_i^* gives the a_i^*, and the (1, i=2,3,4)*th* elements in Θ_i^* give the vector b_i^*.

In empirical investigation, we simulate Y_t according to (A10) with p = 3 and based on the estimated coefficients we obtain the VMA coefficients Θ_i and in turn the Θ_i^* in (A11), and finally, Hasbrouck's R_w^2 in (A9). In our simulations, we simulate 1.2 million observations, and the simulation is repeated 3 times. The computed R_w^2 displays high similarity, and the average R_w^2 is reported in Table VIII.

REFERENCES

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday trading patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Andersen, Torben G., 1996, Return volatility and trading volume: An information flow interpretation of stochastic volatility, *Journal of Finance* 51, 169-204.

Balduzzi, Pierluigi, Elton, Edwin J., Green, T. Clifton, 2001, Economic news and bond prices: Evidence from the U.S. Treasury market. Journal of Financial and Quantitative Analysis 36, 523-544.

Barclay, Michael J., and Terrence Hendershott, 2003, Price discovery and trading after hours, *Review of Financial Studies* 16, 1041-1073.

Barclay, Michael J., and Terrence Hendershott, and Kenneth Kotz, 2006, Automation versus intermediation: Evidence from Treasuries going off the run, *Journal of Finance* 61, 2395-2414.

Brandt, Michael W., and Kenneth A. Kavajecz, 2004, Price discovery in the U.S. Treasury market: The impact of order flow and liquidity, *Journal of Finance* 59, 2623-2654.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201-2238.

Chordia, Tarun, Richard Roll, and Avandhar Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, *Journal of Financial Economics* 65, 111–130.

Downing, Chris, and Frank Zhang, 2004, Trading activity and price volatility in the municipal bond market, *Journal of Finance* 59, 899-931.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, Over-the-counter markets, *Econometrica* 73, 1815–1847.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2007, Valuation in over-the-counter markets, *Review of Financial Studies* 20, 1865-1900.

Duffie, Darrell, 2010, Presidential address: asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237-1267.

Duffie, Darrell, Piotr Dworczak, and Haoxiang Zhu, 2015, Benchmarks in Search Markets, Working Paper, Stanford University.

Dufour, Alfonso, and Robert F. Engle, 2000, Time and the price impact of a trade, *Journal of Finance* 55, 2467-2498.

Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph Paperman, 1996, Liquidity, information, and less-frequently traded stocks, *Journal of Finance* 51, 1405-1436.

Edwards, Amy, Lawrence Harris, and Michael Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance* 62, 1421-1451.

Engle, Robert, Michael J. Fleming, Eric Gyhsels, and Giang Nguyen, 2012, Liquidity, volatility, and flights to safety in the U.S. Treasury market: Evidence from a new class of dynamic order book models, Staff report, Federal Reserve Bank of New York.

Feldhütter, Peter, 2012, The same bond at different prices: Identifying search frictions and sell pressures, *Review of Financial Studies* 25, 1155-1206.

Fleming, Michael J., 2003, Measuring Treasury market liquidity, *Economic Policy Review* 9, 83-108.

Fleming, Michael J., Bruce Mizrach, and Giang Nguyen, 2014, The microstructure of a U.S. Treasury ECN: The BrokerTec platform, Staff report, Federal Reserve Bank of New York.

Fleming, Michael J., and Giang Nguyen, 2015, Order flow segmentation and the role of dark pool trading in the price discovery of U.S. Treasury securities, Working paper, Federal Reserve Bank of New York.

Fontaine, Jean-Sébastien, and Réne Garcia, 2012, Bond liquidity premia, *Review of Financial Studies* 25, 1207-1254.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2011, Margin-based asset pricing and deviations from the law of one price, *Review of Financial Studies* 24, 1980-2022.

Ghysels, Eric, Anh Le, Sunjin Park, and Haoxiang Zhu, 2015, Risk return trade-off in the U.S. Treasury market, Working paper, MIT Sloan School of Management.

Glosten, Larry R. and Paul R. Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed trades, *Journal of Financial Economics* 13, 71-100.

Goldreich, David, Bernd Hanke, and Purnendu Nath, 2005, The price of future liquidity: Time-varying liquidity in the U.S. Treasury market, *Review of Finance* 9, 1-32.

Green, T. Clifton, 2004, Economic news and the impact of trading on bond prices, *Journal of Finance* 59, 1201-1234.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *Journal of Finance* 46, 179–207.

Hasbrouck, Joel, 1991b, The summary informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571-595.

He, Zhiguo, and Konstantin Milbradt, 2014, Endogenous liquidity and defaultable bonds, *Econometrica* 82, 1443-1508.

He, Yan, Hai Lin, Junbo Wang, and Chunchi Wu, 2009, Price discovery in the round-the-clock U.S. Treasury market, *Journal of Financial Intermediation* 18, 464-490.

Huang, Roger D. and Hans R. Stoll. 1997, The components of the bid-ask spread: A general approach, *Review of Financial Studies* 10, 995–1034.

Jiang, George J., Ingrid Lo and Giorgio Valente, 2014, High-frequency trading around macroeconomic news announcements: Evidence from the U.S. Treasury market, Working paper, City University of Hong Kong.

Jones, Charles M., Gautman Kaul, and Mark L. Lipson, 1994, Transactions, volume, and volatility, *Review of Financial Studies* 7, 631-651.

Li, Haitao, Junbo Wang, Chunchi Wu, and Yan He, 2009, Are liquidity and information risks priced in the Treasury bond market? *Journal of Finance* 64, 467-503.

Liu, Xiaoquan, Ingrid Lo, Minh Nguyen, and Giorgio Valente, 2014, Computer-based trading, institutional investors and Treasury bond returns, Working paper, City University of Hong Kong.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035-1064.

Man, Kasing, Junbo Wang, and Chunchi Wu, 2013, Price discovery in the U.S. Treasury market: Automation vs. intermediation, *Management Science* 59, 695-714.

Pasquariello, Paolo, and Clara Vega, 2007, Informed and strategic order flow in the bond markets, *Review of Financial Studies* 20, 1975-2019.

Pasquariello, Paolo, and Clara Vega, 2009, The on-the-run liquidity phenomenon, *Journal of Financial Economics* 92, 1-24.

Shen, Ji, and Hongjun Yan, 2015, A search model of the aggregate demand for safe and liquid assets, Working paper, Yale School of Management.

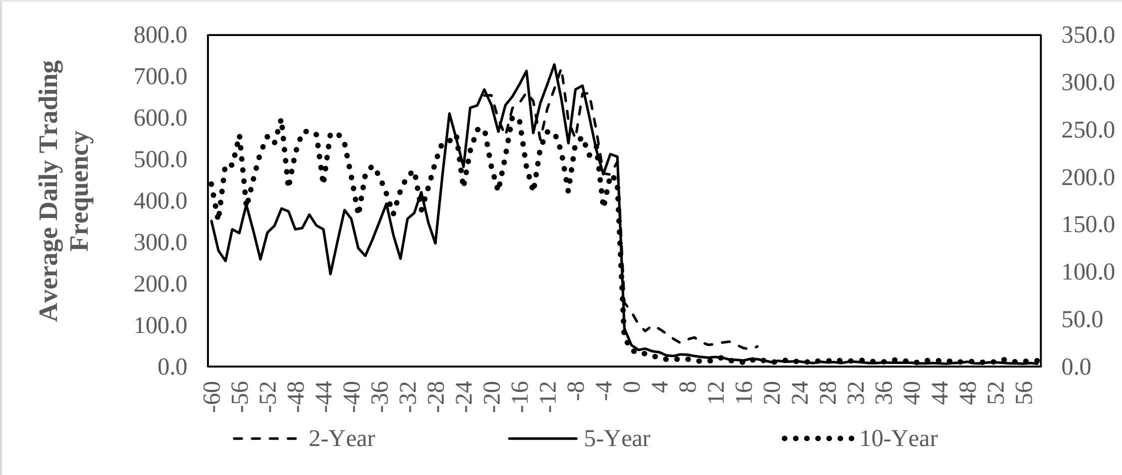
Stoll, Hans R., 1989, Inferring the components of the bid-ask spread: Theory and empirical tests, *Journal of Finance* 44,115–134.

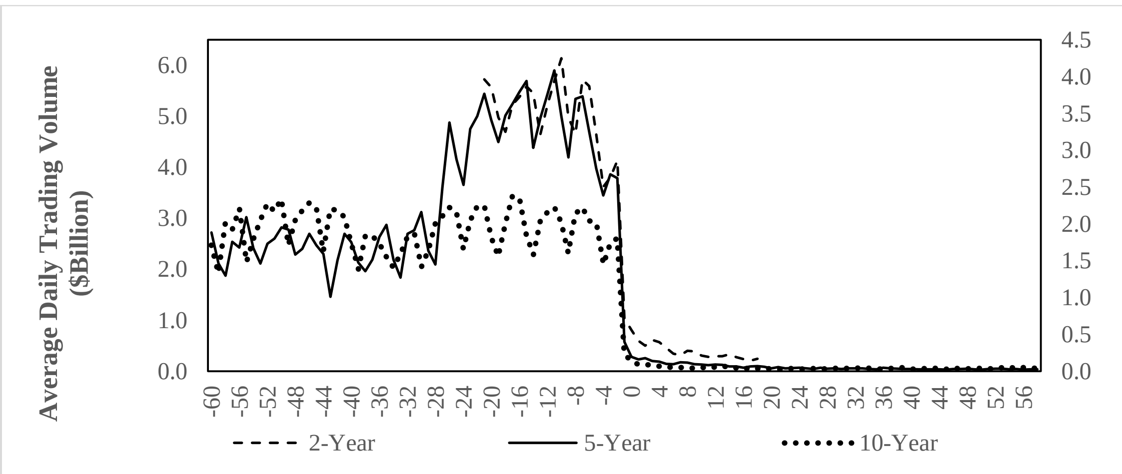
Vayanos, Dimitri, and Tan Wang, 2007, Search and endogenous concentration of liquidity in asset markets, *Journal of Economic Theory* 136, 66-104.

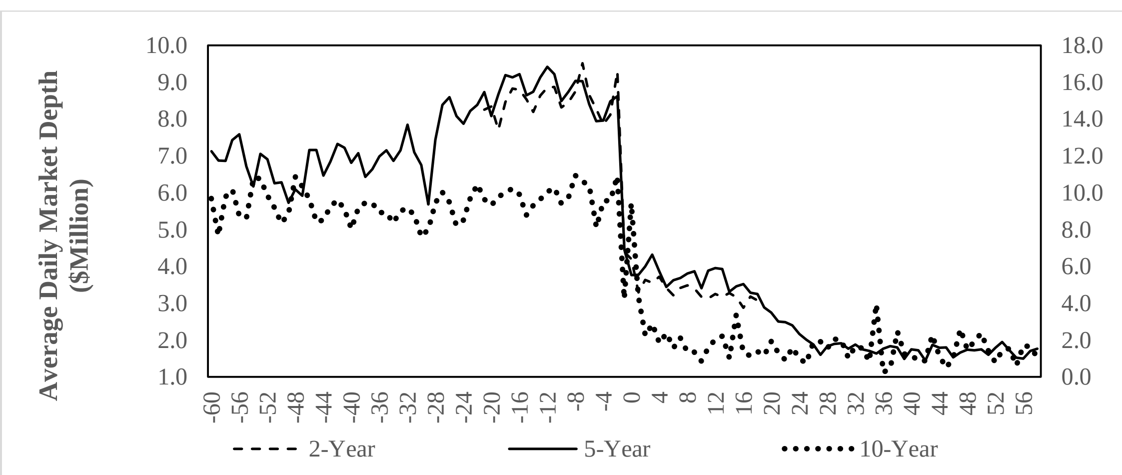
Vayanos, Dimitri, and Pierre-Olivier Weill, 2008, A search-based theory of the on-the-run phenomenon, *Journal of Finance* 63, 1361-1398.

Wang, Junbo, and Chunchi Wu, 2015, Liquidity, credit quality, and the relation between volatility and trading activity: Evidence from the corporate bond market, *Journal of Banking and Finance* 50, 183-203.

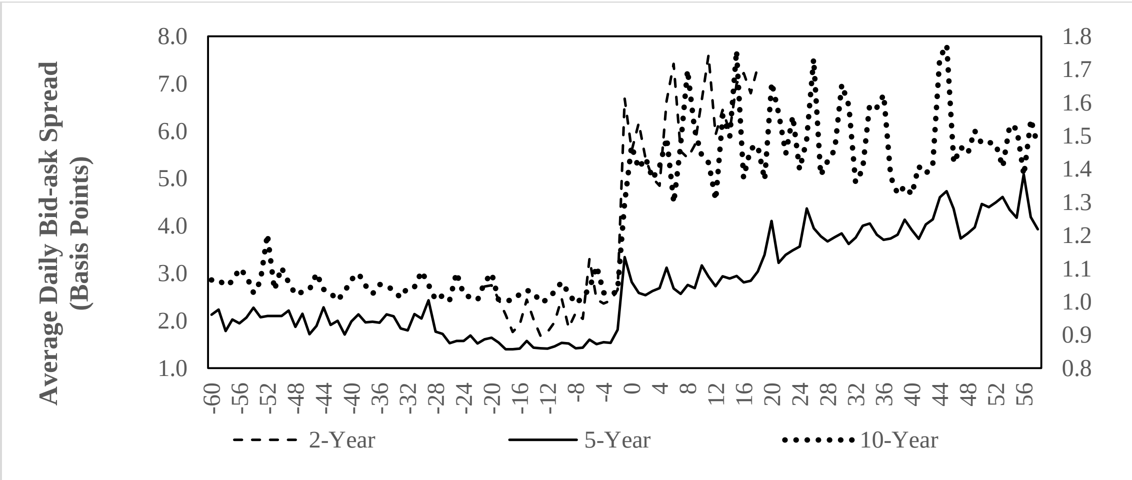
Xu, Xiaoqing Eleanor, Peter Chen, and Chunchi Wu, 2006, Time and dynamic volume–volatility relation, *Journal of Banking and Finance* 30, 1535-1558.

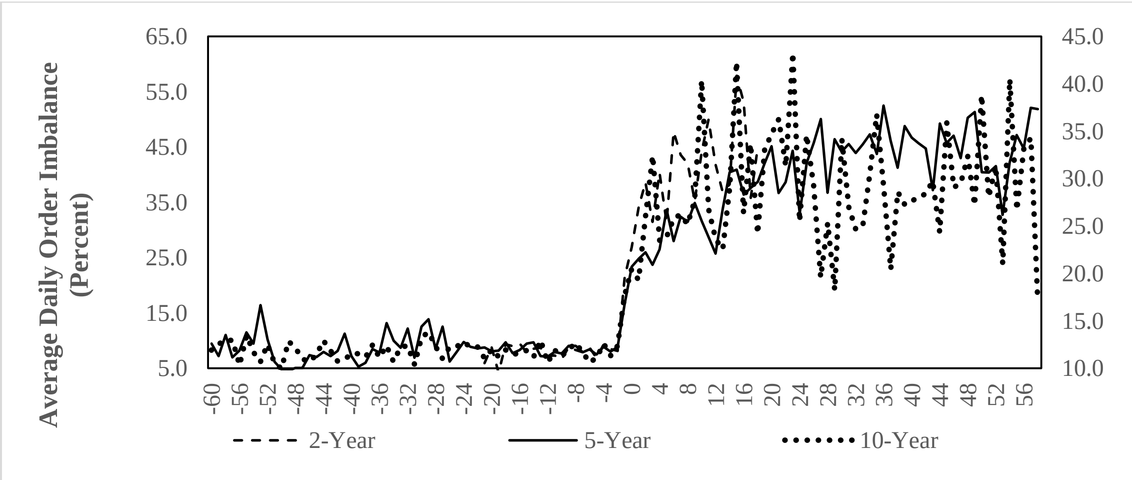

Average Daily Trading Frequency
2-Year
5-Year
10-Year


Average Daily Trading Volume ($Billion)
2-Year
5-Year
10-Year


Average Daily Market Depth ($Million)
2-Year
5-Year
10-Year


Average Daily Size
($Million)
8.5
7.5
6.5
5.5
4.5
3.5
2.5
18.0
16.0
14.0
12.0
10.0
8.0
6.0
-60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4 0 4 8 12 16 20 24 28 32 36 40 44 48 52 56
2-Year
5-Year
10-Year


Average Daily Bid-ask Spread
(Basis Points)
8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
-60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4 0 4 8 12 16 20 24 28 32 36 40 44 48 52 56
2-Year
5-Year
10-Year


Average Daily Order Imbalance
(Percent)
65.0
55.0
45.0
35.0
25.0
15.0
5.0
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
-60 -56 -52 -48 -44 -40 -36 -32 -28 -24 -20 -16 -12 -8 -4 0 4 8 12 16 20 24 28 32 36 40 44 48 52 56
2-Year
5-Year
10-Year

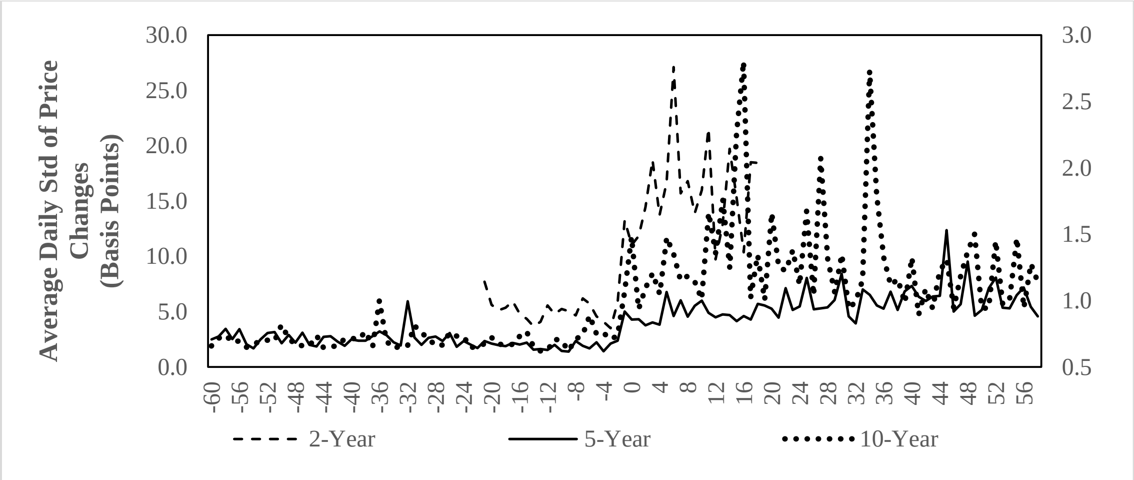
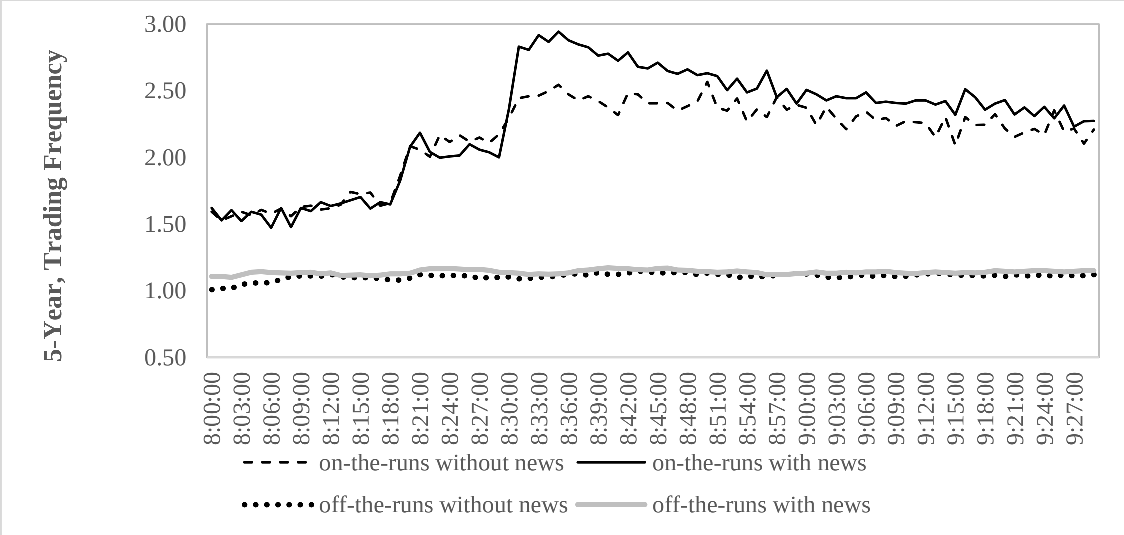
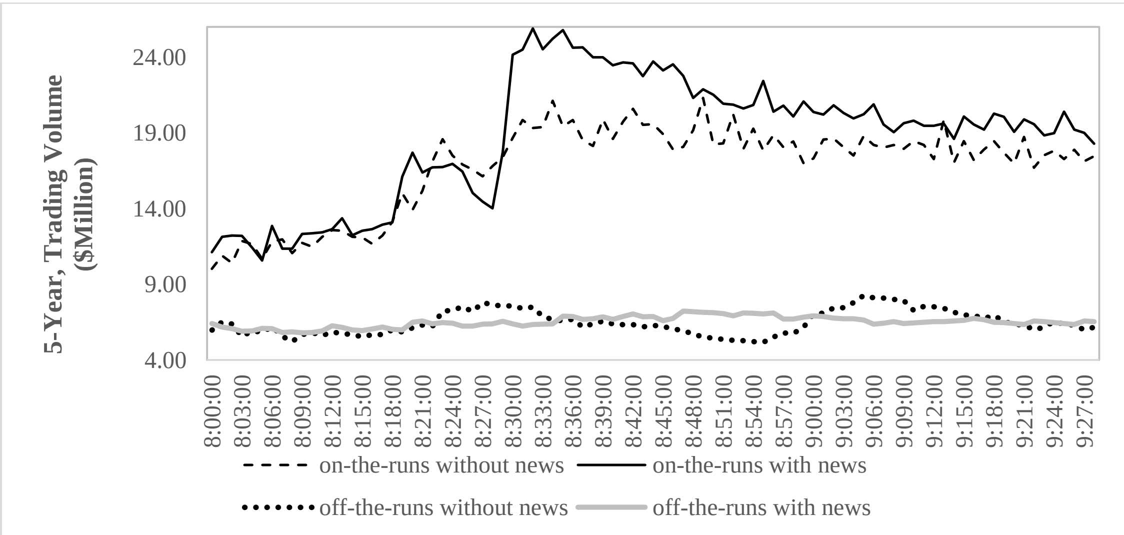
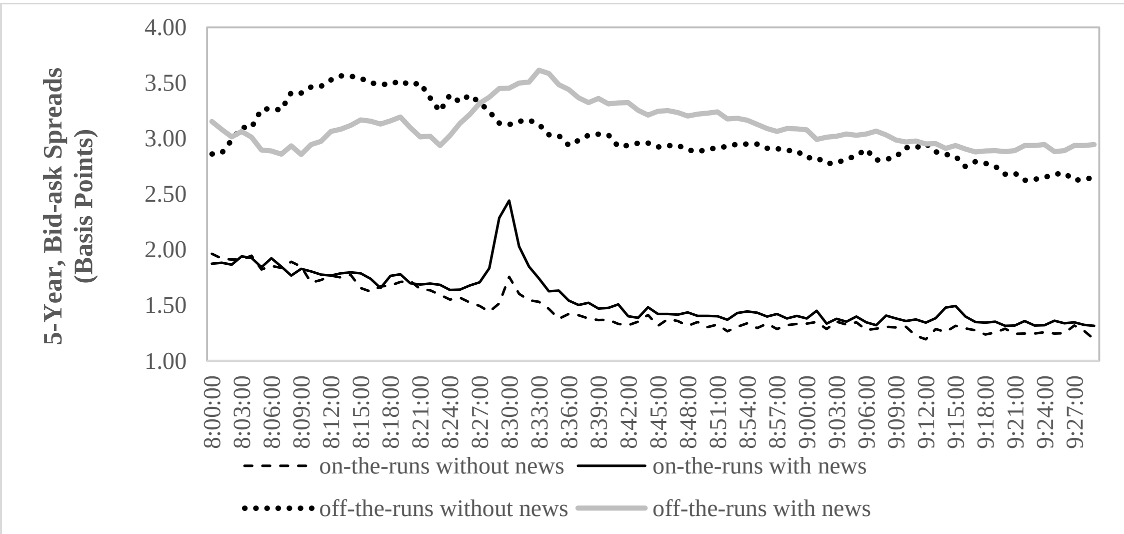


Figure 1. **Daily trading activity for 2-, 5-, and 10-year notes over the auction event window.** This figure shows trading activity of Treasury notes within the auction event window, i.e., (-20, 19) for 2-year notes and (-60, 59) for 5- and 10-year notes. The horizontal-axis denotes the date relative to the day of going off the run, where the negative number denotes days before going off the run, positive number denotes days after, and time 0 denotes one day after the auction. The vertical-axis denotes different trading variables. In all charts, the left vertical axis indicates value for 5- and 10-year notes while the right vertical axis indicates value for 2-year notes. Frequency and volume are the daily number of trades and daily total volume. Size is the daily average size of transactions. Bid-ask spreads are calculated as quoted ask price minus quoted bid price divided by midquote. Depth equals to the sum of quoted ask size and bid size divided by 2. Order imbalance (OI) is the absolute value of net trading volume (buy-initiated volume minus sell-initiated volume) scaled by total volume. Standard deviation (Std) is calculated using log transaction price changes.


5-Year, Trading Frequency
3.00
2.50
2.00
1.50
1.00
0.50
8:00:00
8:03:00
8:06:00
8:09:00
8:12:00
8:15:00
8:18:00
8:21:00
8:24:00
8:27:00
8:30:00
8:33:00
8:36:00
8:39:00
8:42:00
8:45:00
8:48:00
8:51:00
8:54:00
8:57:00
9:00:00
9:03:00
9:06:00
9:09:00
9:12:00
9:15:00
9:18:00
9:21:00
9:24:00
9:27:00
on-the-runs without news
on-the-runs with news
off-the-runs without news
off-the-runs with news


5-Year, Trading Volume ($Million)
24.00
19.00
14.00
9.00
4.00
8:00:00
8:03:00
8:06:00
8:09:00
8:12:00
8:15:00
8:18:00
8:21:00
8:24:00
8:27:00
8:30:00
8:33:00
8:36:00
8:39:00
8:42:00
8:45:00
8:48:00
8:51:00
8:54:00
8:57:00
9:00:00
9:03:00
9:06:00
9:09:00
9:12:00
9:15:00
9:18:00
9:21:00
9:24:00
9:27:00
on-the-runs without news
on-the-runs with news
off-the-runs without news
off-the-runs with news


5-Year, Bid-ask Spreads (Basis Points)
4.00
3.50
3.00
2.50
2.00
1.50
1.00
8:00:00
8:03:00
8:06:00
8:09:00
8:12:00
8:15:00
8:18:00
8:21:00
8:24:00
8:27:00
8:30:00
8:33:00
8:36:00
8:39:00
8:42:00
8:45:00
8:48:00
8:51:00
8:54:00
8:57:00
9:00:00
9:03:00
9:06:00
9:09:00
9:12:00
9:15:00
9:18:00
9:21:00
9:24:00
9:27:00
on-the-runs without news
on-the-runs with news
off-the-runs without news
off-the-runs with news

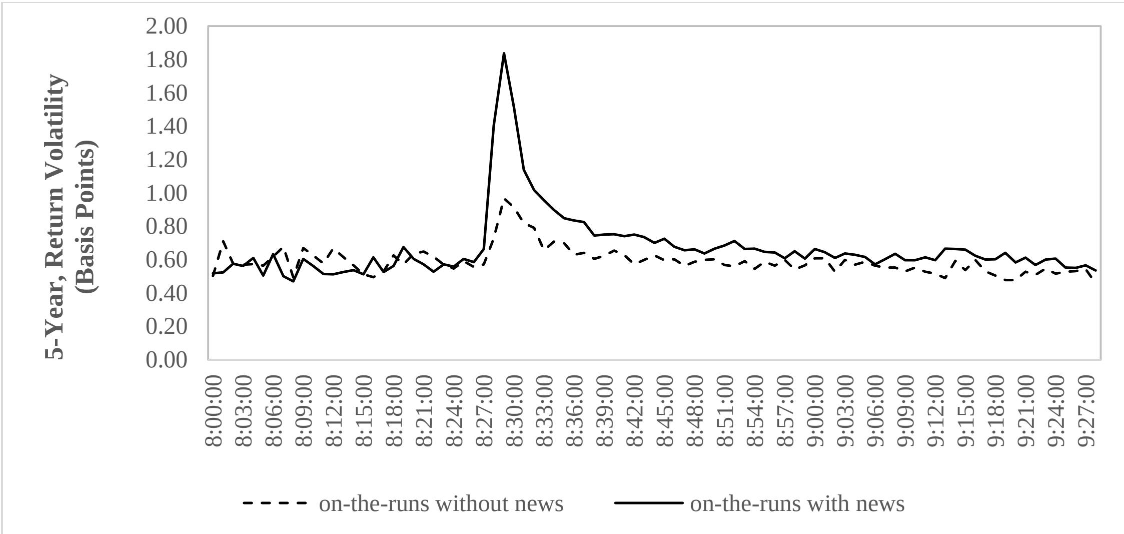


Figure 2. Intraday patterns on news and no-news days. This figure plots average trading frequency, trading volume ($mil), bid-ask spreads (bps), and return volatility (bps) for 5-year notes by minute from 8:00 to 9:30 a.m. The sample period is from January 1992 to February 2008. Figures for off-the-run notes are plotted using a 10-minute moving average, except for return volatility which cannot be calculated by minute due to low frequency of trades.

Table I

Descriptive statistics of on- and off-the-run U.S. Treasury notes

This table provides descriptive statistics for 2-, 5- and 10-year notes based on daily data. A Treasury note is said to be "on-the-run" until the next note with the same maturity is issued. All variables are computed from trading data between 7:30-17:00 (Eastern Time) and averaged to obtain daily measures over the event window, i.e., (-20, 19) for 2-year notes and (-60, 59) for 5- and 10-year notes. The sample covers the period from January 1992 to December 2008. Frequency and volume are the daily number of trades and total volume. Size is the average size of transactions over the day. Bid-ask spreads are calculated as quoted ask price minus quoted bid price divided by the midquote. Depth equals to quoted ask size plus quoted bid size divided by two. Order imbalance is the absolute value of net trading volume (buy-initiated volume minus sell-initiated volume) divided by total volume. Standard deviation of price changes is based on log transaction price changes. Standard errors of mean are in parentheses.

	Frequency	Volume	Size	Spreads	Depth	Order Imbalance	Std
		($billion)	($million)	(bps)	($million)	(%)	(bps)
All notes							
On-the-runs	419.48	3.64	10.41	1.59	10.72	13.80	1.46
	(271.65)	(2.32)	(6.40)	(1.14)	(6.03)	(15.90)	(2.64)
Just-off-the-runs	23.49	0.17	6.01	3.10	3.36	44.21	4.80
	(24.46)	(0.23)	(4.65)	(2.31)	(2.82)	(32.05)	(8.15)
2-Year							
On-the-runs	263.45	3.51	15.40	0.98	15.09	16.56	0.92
	(184.16)	(2.48)	(6.82)	(0.69)	(6.23)	(16.55)	(1.54)
Just-off-the-runs	33.57	0.31	8.75	1.55	4.87	37.56	1.82
	(27.18)	(0.31)	(5.71)	(0.81)	(3.74)	(29.05)	(3.33)
5-Year							
On-the-runs	571.09	4.46	7.55	1.59	8.39	9.89	1.42
	(268.25)	(2.28)	(1.38)	(0.89)	(2.40)	(8.97)	(1.86)
Just-off-the-runs	19.00	0.10	4.89	3.47	2.71	46.91	5.55
	(21.42)	(0.14)	(3.16)	(2.12)	(1.61)	(32.54)	(8.40)
10-Year							
On-the-runs	495.65	2.79	5.34	2.70	5.72	14.09	2.47
	(259.96)	(1.61)	(1.38)	(1.26)	(2.15)	(20.27)	(4.30)
Just-off-the-runs	17.91	0.08	4.13	5.68	1.98	48.95	9.31
	(21.91)	(0.11)	(4.06)	(2.91)	(2.29)	(34.31)	(12.11)

Table II

Daily regressions of volatility and bid-ask spreads on volume

The dependent variable in Panel A, volatility (in bps), is measured by intraday standard deviation of transaction price changes in each day *t* for bond *i*, and the dependent variable in Panel B, bid-ask spreads (in bps), is measured by quoted ask price minus quoted bid price divided by matched midquote averaged for each day. The independent variable is daily trading volume (in $bil). Both regressions include an interactive term with off-the-run dummy (denoted as D^{off}), controlling for the bond-specific fixed effect,

$$\text{Volatility}_{i,t} = \alpha + \beta_1 Volume_{i,t} + \beta_2 \left(Volume_{i,t} * D_{i,t}^{off}\right) + \varepsilon_{i,t}$$

$$\text{Spreads}_{i,t} = a + b_1 Volume_{i,t} + b_2 \left(Volume_{i,t} * D_{i,t}^{off}\right) + \epsilon_{i,t}$$

The coefficient of off-the-run bonds is the sum of β_1 and β_2 or b_1 and b_2. Heteroskedasticity-consistent *t*-value is in parentheses. The data observations are over the event window of going off-the-run, which is (-20, 19) for 2-year notes, and (-60, 59) for 5- and 10-year notes from January 1992 to December 2008.

	Volatility			Bid-ask spreads		
	2-Year	5-Year	10-Year	2-Year	5-Year	10-Year
Volume	-0.162	-0.505	-1.756	-0.122	-0.197	-0.727
	(-9.354)	(-15.970)	(-16.195)	(-27.168)	(-20.166)	(-26.095)
Volume*D^{off}	0.348	2.765	2.912	0.186	1.396	1.784
	(2.102)	(4.454)	(1.055)	(4.309)	(6.833)	(2.625)
Adj. R^2	0.029	0.112	0.117	0.185	0.180	0.279

Table III

Impacts of trading activity on absolute midquote changes

This table presents trades impacts on absolute midquote changes, trade-by-trade (Panel A) and over 5- and 30-minute intervals (Panel B). The dependent variable is log absolute midquote changes (in bps), i.e., $y_{i,t} = \left|\log(\frac{Mid_{i,t}}{Mid_{i,t-1}})\right|$, where t denotes t^{th} interval and $Mid_{i,t}$ denotes the midquote at interval t for bond i. The independent variable in Panel A is trading size of each transaction (in $mil). The independent variables in Panel B are total trading frequency (Freq), total trading volume (Volume, in $10mil), and average trade size (Size, in $mil) at 5- and 30-minute intervals, respectively. All regressions include an interactive term with off-the-run dummy (denoted as D^{off}). The coefficient of off-the-run bonds is the sum of coefficients of the independent variable and the interactive term. Heteroskedasticity-consistent t-value is in parentheses. The data observations are within the auction event window, which is (-20, 19) for 2-year notes, and (-60, 59) for 5- and 10-year notes from January 1992 to December 2008. In panel A, column 1 reports results of estimation for the contemporaneous relation and column 2 includes 5 lagged variables in the regression.

Panel A: Trade-by-trade

	Absolute midquote changes					
	2-Year		5-Year		10-Year	
	(1)	(2)	(1)	(2)	(1)	(2)
Trade size	-0.001	-0.001	-0.005	-0.002	-0.003	0.000
	(-16.221)	(-6.351)	(-40.694)	(-2.525)	(-12.934)	(0.004)
Trade size*D^{off}	0.013	0.005	0.097	0.040	0.123	0.052
	(28.941)	(9.478)	(25.496)	(12.188)	(11.757)	(6.657)
Adj. R^2	0.004	0.132	0.017	0.103	0.005	0.065
Control for Lagged effect	No	Yes	No	Yes	No	Yes

Panel B: 5- and 30-minute intervals

		5-minute intervals					30-minute intervals				
		(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
2-Year	Freq	0.015			0.017	0.015	0.010			0.008	0.010
		(40.271)			(36.405)	(41.167)	(26.473)			(19.006)	(26.860)
	Freq*D^{off}	0.069			0.083	0.062	0.037			0.038	0.032
		(29.056)			(27.872)	(22.810)	(17.136)			(18.067)	(13.010)
	Volume		0.003		-0.001			0.005		0.001	
			(15.107)		(-6.102)			(18.914)		(2.335)	
	Volume*D^{off}		0.018		-0.014			0.015		-0.009	
			(12.470)		(-8.091)			(9.866)		(-4.710)	
	Size			-0.001		-0.001			-0.001		-0.002
				(-19.565)		(-13.341)			(-4.874)		(-5.335)
	Size*D^{off}			0.004		0.001			0.002		0.003
				(18.463)		(5.479)			(3.826)		(4.482)
	Adj. R^2	0.012	0.002	0.003	0.013	0.013	0.055	0.038	0.000	0.056	0.056
5-Year	Freq	0.022			0.035	0.025	0.012			0.009	0.019
		(2.270)			(2.179)	(2.328)	(21.848)			(11.530)	(29.262)
	Freq*D^{off}	0.288			0.320	0.225	0.120			0.138	0.045
		(4.265)			(3.917)	(3.736)	(20.606)			(28.506)	(6.262)
	Volume		0.003		-0.016			0.010		0.004	
			(0.540)		(-1.424)			(17.123)		(4.740)	
	Volume*D^{off}		0.151		-0.056			0.089		-0.055	
			(3.508)		(-1.273)			(10.729)		(-9.191)	
	Size			-0.016		-0.012			-0.030		-0.074
				(-3.972)		(-2.559)			(-11.161)		(-16.457)
	Size*D^{off}			0.036		0.019			0.037		0.087
				(4.376)		(2.306)			(13.947)		(18.870)
	Adj. R^2	0.012	0.004	0.002	0.005	0.006	0.043	0.029	0.005	0.044	0.065
10-Year	Freq	0.054			0.063	0.055	0.031			0.034	0.036
		(50.998)			(45.459)	(52.349)	(26.412)			(23.229)	(29.611)
	Freq*D^{off}	0.460			0.556	0.395	0.244			0.246	0.133
		(17.660)			(16.521)	(13.012)	(10.620)			(9.675)	(5.129)
	Volume		0.036		-0.015			0.036		-0.010	
			(29.769)		(-10.421)			(21.476)		(-4.497)	
	Volume*D^{off}		0.291		-0.201			0.220		-0.113	
			(9.074)		(-5.988)			(6.861)		(-2.518)	
	Size			-0.012		-0.011			-0.036		-0.101
				(-16.630)		(-15.817)			(-5.779)		(-15.105)
	Size*D^{off}			0.065		0.028			0.056		0.145
				(11.337)		(4.505)			(5.179)		(10.627)
	Adj. R^2	0.037	0.010	0.006	0.038	0.038	0.099	0.063	0.002	0.101	0.113

Table IV
Impacts of signed trade and volume on midquote and price changes

This table summarizes trade-by-trade impacts of signed trade and volume on midquote changes. The dependent variable is log midquote changes (in bps), i.e., $y_{i,t} = \log(\frac{Mid_{i,t}}{Mid_{i,t-1}})$, where $Mid_{i,t}$ denotes matched midquote at t for bond i. The independent variable is signed trade (+1/-1 denotes buy-/sell-initiated trade) or signed volume (sign times volume, in $mil) with control variables, including time interval between trades (in hours), order imbalance (in $mil) and five lagged variables. Time interval is square root of time interval between two consecutive trades and order imbalance is logarithm value of absolute cumulative volume difference between buy- and sell-initiated trades. All regressions include an interactive term with off-the-run dummy (denoted as D^{off}). The coefficient of off-the-run bonds is the sum of coefficients of the independent variable and the interactive term. Heteroskedasticity-consistent t-value is in parentheses. The data observations are within the auction window, which is (-20, 19) for 2-year notes, and (-60, 59) for 5- and 10-year notes from January 1992 to December 2008.

		Signed trade as regressor				Signed volume as regressor			
		Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
		Midquote		Trading price		Midquote		Trading price	
2-Year	Sign	0.122	0.123	0.149	0.150	0.004	0.004	0.003	0.003
		(88.845)	(89.478)	(69.848)	(70.067)	(70.450)	(70.502)	(37.319)	(37.298)
	Sign*D^{off}	0.133	0.130	0.157	0.156	0.004	0.004	0.004	0.004
		(15.119)	(14.748)	(11.420)	(11.233)	(9.894)	(9.753)	(4.436)	(4.372)
	Time Interval		0.142		0.154		0.117		0.130
			(8.123)		(5.917)		(6.640)		(4.970)
	Order Imbalance		0.003		0.013		0.003		0.015
			(3.329)		(9.360)		(3.728)		(9.750)
	Adj.R^2	0.171	0.172	0.187	0.187	0.133	0.133	0.169	0.169
5-Year	Sign	0.292	0.292	0.384	0.387	0.016	0.016	0.019	0.019
		(147.766)	(149.289)	(139.786)	(140.164)	(58.276)	(58.019)	(55.531)	(56.066)
	Sign*D^{off}	0.424	0.417	0.495	0.506	0.021	0.021	0.034	0.034
		(12.141)	(11.850)	(13.842)	(14.162)	(3.094)	(3.017)	(7.790)	(7.773)
	Time Interval		0.239		0.266		0.203		0.229
			(4.025)		(3.824)		(3.401)		(3.291)
	Order Imbalance		0.001		0.001		0.002		0.002
			(0.307)		(0.387)		(0.771)		(0.850)
	Adj.R^2	0.163	0.164	0.208	0.209	0.133	0.134	0.184	0.185
10-Year	Sign	0.479	0.480	0.543	0.544	0.031	0.031	0.032	0.032
		(142.408)	(142.123)	(99.219)	(99.153)	(87.522)	(87.437)	(41.487)	(41.438)
	Sign*D^{off}	0.242	0.239	0.739	0.731	0.019	0.019	0.051	0.050
		(2.412)	(2.364)	(8.221)	(8.050)	(2.301)	(2.331)	(4.375)	(4.299)
	Time Interval		0.335		0.330		0.213		0.243
			(5.780)		(2.706)		(3.673)		(1.975)
	Order Imbalance		0.001		0.004		0.001		0.004
			(0.602)		(1.817)		(0.348)		(1.862)
	Adj.R^2	0.172	0.172	0.140	0.141	0.093	0.093	0.100	0.101

Table V

Trading volume surrounding macroeconomics news announcement

The table shows the average volume difference between days with and without news for on- and off-the-run notes at each half-hour interval. The mean difference is reported and *t*-value is in parentheses. The null hypothesis (H_0) of *t*-test is that the difference between two means of trading volume is equal to zero. *, **, *** indicate the significance of rejecting H_0 at the 10%, 5% and 1% levels, respectively.

		Volume (news) vs. Volume (no-news)		
		8:00-8:30	8:30-9:00	9:00-9:30
		Difference	Difference	Difference
All notes	On-the-runs	17.727	260.893***	156.171***
		(1.378)	(12.337)	(10.681)
	Just-off-the-runs	39.935	8.536	-17.561
		(1.207)	(0.218)	(-0.411)
	On - Off	-27.335	249.046***	173.732***
		(-0.789)	(5.650)	(3.784)
2-Year	On-the-runs	0.557	89.847***	70.800***
		(0.057)	(6.016)	(6.318)
	Just-off-the-runs	38.983	14.235	3.392
		(1.376)	(0.704)	(0.171)
	On - Off	-38.426	75.612***	67.408**
		(-1.331)	(2.829)	(2.859)
5-Year	On-the-runs	10.462	106.742***	56.121***
		(1.756)	(9.245)	(12.585)
	Just-off-the-runs	4.619	12.356	-14.624
		(0.376)	(0.949)	(-1.179)
	On - Off	5.844	94.386***	70.745***
		(0.430)	(5.917)	(5.747)
10-Year	On-the-runs	6.707	64.304***	29.250***
		(1.128)	(7.704)	(4.480)
	Just-off-the-runs	-3.667	-18.055	-6.329
		(-0.312)	(-0.578)	(-0.175)
	On - Off	5.247	79.048***	35.579
		(0.402)	(2.481)	(0.943)

Table VI

The asymmetric information component of trades surrounding macroeconomic news announcement

This table reports GMM estimates of the asymmetric information component of trades (θ) of the MRR model for 5-year on- and just-off-the-run notes between 8:00 and 9:30 am ET. We report estimates for days with and without news. For no-news days, the first column shows the asymmetric information component of on- and just-off-the-run notes during the 90-minute interval of 8:00-9:30 and the next three columns report estimates for on-the-run notes for three intervals: 8:00-8:30, 8:30-9:00, and 9:00-9:30, respectively. For news days, we report estimates for each 30-minute interval. Diff is the difference in θ for each 30-minute interval on news days and the θ reported in the first column (8:00-9:30 intreval). The θ estimate of just-off-the-runs is scaled by average price changes to make it comparable with the estimate of on-the-runs. *t*-value is in parentheses. *** indicates that the θ difference between days with and without news is significant at the 1% level.

		No-news days				News days					
		Overall 8:00-9:30	8:00-8:30	8:30-9:00	9:00-9:30	8:00-8:30	Diff (News – No-news)	8:30-9:00	Diff (News – No-news)	9:00-9:30	Diff (News – No-news)
2-Year	On-the-runs	0.31	0.33	0.33	0.27	0.28	-0.03	0.45	0.13***	0.31	0.00
		(51.61)	(24.61)	(29.48)	(36.51)	(17.62)	(-1.84)	(41.11)	(14.26)	(38.66)	(-0.56)
	Just-off-the-runs	0.18				0.15	-0.03	0.21	0.03	0.19	0.01
		(5.89)				(8.15)	(-0.72)	(15.46)	(0.91)	(16.86)	(0.25)
5-Year	On-the-runs	0.63	0.70	0.65	0.56	0.61	-0.02	0.80	0.17***	0.63	0.00
		(63.42)	(29.37)	(39.35)	(38.92)	(35.94)	(-0.97)	(58.62)	(13.03)	(65.21)	(-0.21)
	Just-off-the-runs	0.32				0.29	-0.04	0.34	0.02	0.33	0.00
		(5.05)				(1.96)	(-0.23)	(12.54)	(0.30)	(15.46)	(0.03)
10-Year	On-the-runs	0.94	1.08	0.94	0.87	0.97	0.02	1.08	0.14***	0.91	-0.03
		(68.82)	(38.80)	(39.93)	(42.42)	(36.91)	(0.71)	(47.18)	(6.91)	(59.53)	(-1.93)
	Just-off-the-runs	0.64				0.60	-0.04	0.62	-0.02	0.38	-0.27
		(3.34)				(2.99)	(-0.16)	(5.43)	(-0.12)	(6.09)	(-1.37)

Table VII

Speed of adjustment in daily U.S. Treasury prices

This table reports estimates of the speed of adjustment to the new equilibrium price for on- and just-off-the-run notes. To estimate the adjustment speed (λ), we use the partial adjustment model $p_{i,t} - p_{i,t-1} = \lambda(p^*_{i,t} - p_{i,t-1}), 0 < \lambda \leq 1$, where $p_{i,t}$= close price of bond *i* on day *t* and $p^*_{i,t}$ = latent true value of bond *i* on day *t*. As $p^*_{i,t}$ is unobserved, we estimate it as a function of three observable variables: bond coupon, yield to maturity, and time to maturity, i.e., $p^*_{i,t} = \alpha + \sum_{k=1}^{n} \beta_k \, x_{k,i,t} + \varepsilon_{i,t}$,. Combining two equations, we have $p_{i,t} = \alpha\lambda + (1-\lambda)p_{i,t-1} + \sum_{k=1}^{n}(\beta_k \lambda) \, x_{k,i,t} + \xi_{i,t}$. Newton-Gauss nonlinear regression is used to estimate λ, and *t*-value is in parentheses. We use the data within the auction event window, which is (-20, 19) for 2-year notes, and (-60, 59) for 5- and 10-year notes in the regression. The sample period is from January 1992 to December 2008.

	2-Year		5-Year		10-Year	
	On-the-runs	Just-off-the-runs	On-the-runs	Just-off-the-runs	On-the-runs	Just-off-the-runs
Panel A: Full sample						
Speed of Adjustment	0.973	0.725	0.970	0.911	0.888	0.825
	(107.474)	(48.750)	(104.045)	(82.926)	(51.697)	(44.653)
Adj.R^2	0.990	0.985	0.990	0.996	0.997	0.998
Panel B: Days with news announcement						
Speed of Adjustment	0.982	0.761	0.980	0.913	0.907	0.819
	(87.339)	(47.017)	(77.547)	(66.868)	(43.637)	(33.249)
Adj.R^2	0.990	0.988	0.989	0.996	0.997	0.998

Table VIII
Informativeness of Trades

This table summarizes the estimates of informativeness of trades for on-the-runs, just-off-the-runs, and more off-the-runs, respectively. Consider $Y_t = [r_t, x_t^1, x_t^0, x_t^2]'$ where r_t = returns, x_t^0= trade sign, x_t^1= signed volume, and x_t^2= signed volume-square. Let Y_t follows a VAR(p) model $(A_0 - A_1 L - A_2 L^2 - \cdots A_p L^p)Y_t = \eta_t$. For the error term $\eta_t = [v_{1t}, v_{2t}]'$, v_{1t} corresponds to the return's innovation and v_{2t} is a 3 by 1 vector corresponds to trade related innovations. v_{1t} has variance σ_1^2 and v_{2t} has covariance Ω, and v_{1t} and v_{2t} are uncorrelated. Under stationary assumption, Y_t has an VMA(∞) representation $Y_t = (I + \Theta_1 L + \Theta_2 L^2 + \Theta_3 L^3 + \cdots)\ A_0^{-1}\eta_t$ or $= (\Theta_0^* + \Theta_1^* L + \Theta_2^* L^2 + \Theta_3^* L^3 + \cdots)\ \eta_t$ where $\Theta_0^* = A_0^{-1}$ and $\Theta_i^* = \Theta_i\ A_0^{-1}$. The (1,1)th element in Θ_i^* gives the a_i^* and the (1, i=2,3,4)th elements in Θ_i^* give the vector b_i^*. The informativeness of trades is presented by R_w^2 from Hasbrouck's (1991b) Proposition 1. Specifically, $R_w^2 = \frac{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime})}{(\sum_{i=o}^{\infty} b_i^*)\Omega(\sum_{i=o}^{\infty} b_i^{*\prime}) + (1+\sum_{i=1}^{\infty} a_i^*)^2\sigma_1^2}$ where the numerator $(\sum_{i=o}^{\infty} b_i^*)\Omega\ (\sum_{i=o}^{\infty} b_i^{*\prime})$ captures the contribution of trades to the total return variance. The computation details are given in the Appendix.

R_w^2	2-Year	5-Year	10-Year
On-the-runs	0.312	0.358	0.265
Just-off-the-runs	0.090	0.041	0.021
More off-the-runs	0.063	0.035	0.004

Table IX

Cointegration Analysis

This table reports the results of cointegration analysis between on-the-run and period(i)-off-the-run markets, where i denotes the number of auctions away from issuance, ranging from 1 to 5. Time-series data of daily close yields for three notes with different auction periods are constructed. The OLS regression in Panel A is $Y_{on} = b_0 + b_1 * Y_{off(i)}$ and t-value is given in parentheses. The UR Test in Panel B is the augmented Dickey-Fuller unit root test with null hypothesis (H(0)) of the existence of unit root. p-value of the on-the-runs (upper value) and period(i)-off-the-runs (lower value) is reported. Max eigenvalue test is Johansen's maximum eigenvalue test for the number of cointegration vector. This is a sequential test. First, we test the null hypothesis H(0) that there is no cointegration vector versus the alternative that there is at least one. Failure to reject H(0) means there is no common implicit equilibrium yield between on-the-run and period(i) off-the-run markets. If H(0) is rejected, we test the null hypothesis H(1) that there is one cointegration vector versus the alternative that there are two vectors. ** means rejecting the null hypothesis at 1% significance level.

Panel A: Least squares regression of on-the-run yields on period(i)-off-the-run yields

Period (i)	2-Year		5-Year		10-Year	
	b_0	b_1	b_0	b_1	b_0	b_1
1	-0.033	1.001	-0.060	1.008	-0.076	1.004
	(-6.287)	(1049.038)	(-10.397)	(1059.018)	(-5.934)	(520.727)
2	-0.053	1.002	-0.025	1.002	-0.064	0.997
	(-8.680)	(903.771)	(-3.703)	(902.662)	(-2.883)	(296.438)
3	-0.066	1.001	-0.026	1.001	-0.062	0.994
	(-9.370)	(779.368)	(-2.982)	(706.290)	(-2.343)	(248.981)
4	-0.073	0.999	-0.022	1.000	-0.126	1.003
	(-7.957)	(597.104)	(-2.377)	(659.323)	(-7.068)	(373.942)
5	-0.096	1.000	-0.063	1.006	-0.175	1.009
	(-10.360)	(586.867)	(-5.875)	(569.091)	(-9.414)	(359.322)

Panel B: VECM estimation

	Period (i)	c	β_2	α_{on}	$\alpha_{off(i)}$	UR test	Max eigenvalue test
2-Year	1	0.044	-1.004	-0.170	0.229	0.488	H(0)**
		(3.627)	(-462.592)	(-3.829)	(4.777)	0.597	H(1)
	2	0.064	-1.004	-0.097	0.069	0.498	H(0)**
		(2.504)	(-217.546)	(-2.692)	(1.929)	0.544	H(1)
	3	0.081	-1.004	-0.084	0.058	0.551	H(0)**
		(2.648)	(-180.222)	(-2.928)	(2.060)	0.568	H(1)
	4	0.103	-1.005	-0.045	0.111	0.554	H(0)**
		(2.683)	(-143.360)	(-1.996)	(4.711)	0.578	H(1)
	5	0.100	-1.001	-0.038	0.040	0.557	H(0)**
		(1.619)	(-88.051)	(-1.821)	(2.062)	0.644	H(1)
5-Year	1	-0.025	-0.996	-0.033	0.242	0.724	H(0)**
		(-1.602)	(-387.778)	(-0.295)	(2.115)	0.667	H(1)
	2	0.013	-1.000	-0.050	0.306	0.682	H(0)**
		(0.834)	(-394.086)	(-0.603)	(3.790)	0.680	H(1)
	3	0.017	-1.000	-0.112	0.237	0.660	H(0)**
		(0.747)	(-275.561)	(-1.567)	(3.442)	0.653	H(1)
	4	0.017	-1.000	-0.092	0.313	0.674	H(0)**
		(0.776)	(-273.841)	(-1.651)	(5.441)	0.737	H(1)
	5	0.058	-1.005	-0.142	0.104	0.640	H(0)**
		(1.852)	(-194.863)	(-2.652)	(2.132)	0.697	H(1)
10-Year	1	0.134	-1.011	-0.059	0.054	0.656	H(0)**
		(2.048)	(-104.078)	(-0.960)	(0.913)	0.590	H(1)
	2	0.109	-1.004	-0.021	0.131	0.568	H(0)**
		(1.783)	(-110.224)	(-0.504)	(3.303)	0.578	H(1)
	3	0.108	-1.002	-0.006	0.143	0.588	H(0)**
		(1.881)	(-116.727)	(-0.162)	(4.010)	0.582	H(1)
	4	0.177	-1.011	0.005	0.163	0.565	H(0)**
		(3.290)	(-125.493)	(0.146)	(4.907)	0.567	H(1)
	5	0.201	-1.013	-0.007	0.128	0.615	H(0)**
		(3.465)	(-115.978)	(-0.242)	(4.380)	0.614	H(1)