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Price impact of informed trades in the U.S. treasury markets

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ABSTRACT

According to a review of the literature, there is no study that examines how the price impact of informed trades is related to liquidity levels in the U.S. Treasury markets. Using variance decomposition and regime-switching methodologies, we find that the price impact of informed trades is higher in more liquid markets. In the case of on-the-run and off-the-run spot markets, the price impact of informed trades is higher in 2-year and 5-year T-notes markets. In the case of T-notes futures markets, the price impact of informed trades is higher in 10-year futures market. We find that the price impact of uninformed (informed) individual trades decreases (increases) as the time scale increases. The results indicate that the price impact of informed trades is greater between 8:00 am and 3:00 pm when the market is more liquid, and smaller between 3:00 pm and 5:00 pm when the market is less liquid.

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1.0 Introduction

The goal of this paper is to examine how the price impact of informed trades is related to liquidity in the U.S. Treasury markets. We hypothesize that the price impact of informed trades will be greater when the market is more liquid. This hypothesis is based on the predictions of Admati and Pfleiderer's (1988) theory that informed traders prefer to trade in more liquid markets. According to a review of the literature, there is no study that examines how the price impact of informed trades is related to liquidity levels. This paper intends to fill this gap in the literature.

We examine the role of liquidity on price impact of informed trades in two dimensions. The first dimension is that we examine how the informed trade's price impact differs between less liquid and more liquid Treasury markets. We hypothesize that the price impact of informed trades is higher in more liquid Treasury markets. The current market microstructure literature supports our hypothesis. In the U.S. Treasury spot market, Li, Wang, Wu, and He (2009) found that bonds with higher liquidity, greater depth, and lower spread tend to have a higher probability of information-based trading (PIN).[1] In a related study in the equity market, Chung, Li, and McInish (2005) showed that the price impact of trades and PIN are positively and significantly related.[2] Hence, we expect to find that, in the case of the U.S. Treasury spot markets (on-the-run and off-the-run), the price impact of informed trades will be greater in the 2-year and 5-year T-notes markets (more liquid markets) and smaller in the 10-year T-notes

[1] Li et al. (2009) used the PIN measure developed by Easley, Hvidkjaer, and O'Hara (2002).
[2] Chung et al. (2005) used the models of Easley, Kiefer and O'Hara (1997), and Hasbrouck (1991).

market (less liquid market).[3] In the case of T-notes futures markets, we expect the price impact of informed trades to be greater in the 10-year futures market.[4]

We also examine the effect of time scale on price impact and how our findings change with different time scales in on-the-run T-notes spot markets. To our knowledge, other than this present study, Farmer and Zamani's (2007) study is the only one that examines how time scale and price impact of an individual trade are related. Using simulations, they measured the total price impact and transitory impact, and calculated the informational impact as the difference between the total and transitory impacts in the London Stock Exchange. They found that the average mechanical (uninformed) impact decays to zero monotonically in time. In contrast, the informational impact grows with time and approaches a constant value. Their results imply that prices do not adjust immediately to information revealed by trades in the London Stock Exchange. The regime-switching model employed in this present study will allow us to examine this issue more directly.

The second dimension is that we examine how intraday pattern of liquidity[5] and price impact of informed trades are related in each Treasury market. It is possible that the price impact of informed trades is larger in the morning than the rest of the day since macroeconomic indicators are released in the morning and market participants usually trade for hedging and funding purposes early in the morning.[6] However, if informed traders trade in large volume, then they may be identified as informed traders. Hence, informed traders may break up their large orders to hide their identity. In this case, there may be many informed trades in smaller volumes throughout the day, which means there would be similar price impacts throughout the day. To examine what the actual intraday pattern is, we divide the day into three periods (8:00 am - 10:00 am; 10:00 am - 3:00 pm; and 3:00 pm - 5:00 pm) and estimate the price impact of informed trades for each period.

The general (unconditional) liquidity measure of Kyle lambda, which is usually estimated by regressing price changes on the net volume for fixed intervals of time, is the average price impact of informed and uninformed order flows. A low (high) unconditional impact indicates high (low) liquidity. However, our focus in this study is the price impact of informed trades only. Relating trades to private information is a challenging task for an econometrician because when both liquidity and informed traders buy (sell), prices move up (down). This study uses two methodologies to examine the impact of order flow on price changes when order flow is related to private information. First, we use the vector autoregression (VAR) model. Hasbrouck (1988) states that private information from a trade should be inferred from the unexpected portion of a trade (i.e., trade innovation), not from the total trade. A useful statistics from the VAR model is the variance decomposition. Variance decompositions are used to measure the relative importance of the variables driving price changes. Since trade innovations are used in the estimation of variance decompositions, the impact of private information on price changes can be measured with this approach. Second, this study uses the regime-switching model developed by Nyholm (2002) to identify and examine the impact of informed trades on price changes. Nyholm formulated a regime-switching expansion of the well-known trade-indicator model and estimated it by applying the technique developed by Hamilton (1994). An advantage of this model is that it analyses the process by which new private information is processed and incorporated into the Treasury market on a quote-by-quote basis. The model allows us to examine the price impacts of trades during normal information and private information states. The source of private information in the treasury market is a better interpretation of the public news (Kim and Verrecchia 1994; and Green 2004). Investors observe the same public information; however, they differ in their abilities to analyze the information.

The informational role of order flow has been extensively studied in the U.S. Treasury market. For example, Fleming (2003), using T-bills and T-notes, examined various liquidity measures and the response of yields to order flows, and argued that yield changes in the absence of public information releases are due to inventory effects. Brandt and Kavajecz (2004) examined the contemporaneous relationships between order flow, liquidity, and yield curve to investigate price discovery in the U.S. Treasury market. They found that the effect of order flows on yields is permanent and strongest when liquidity is low.

As expected, we found that the price impact of informed trades is higher in more liquid markets. In the case of on-the-run and off-the-run spot markets, the price impact of informed trades is higher in 2-year and 5-year T-notes markets, while in the case of T-notes futures markets, the price impact of informed trades is higher in 10-year futures market. To our knowledge, this is the first study that directly estimates the uninformed and informed components of an individual trade's price impact. This is a new finding that informed trades have a greater impact

[3] Fleming (2003) found that 2-year and 5-year T-notes are more liquid and 10-year T-notes are less liquid.
[4] Unlike the spot market, liquidity in the U.S. Treasury futures market increases with maturity (Mizrach and Neely, 2008).
[5] Fleming (1997) found that bid-ask spread, which is a measure of liquidity, is lower between 8:00 am and 3:00 pm, and higher between 3:00 pm and 5:30 pm in the U.S. Treasury market.
[6] The Treasury market is more active in the morning since market participants use Treasuries for the purpose of hedging and funding through the REPO market. Market participants implement their trades early in the day to prepare for the trading activity later in the day.

on prices in more liquid markets; however, it supports Admati and Pfleiderer's (1988) theory that informed traders prefer to trade in more liquid markets. The variance decompositions from the VAR model indicate that trade innovations in 2-year and 5-year T-notes markets can explain approximately 36 percent of the price changes, while trade innovations in 10-year T-notes market can explain 29 percent of the price changes. The finding that unexpected order flow explains price changes more in 2-year and 5-year T-notes markets implies that the impact of an informed trade is higher in more liquid shorter term Treasuries. Using the regime-switching model, we find that a buy (sell) order in the 2-year on-the-run notes market increases (decreases) the mid-quote by 0.414 times the half spread during a normal information state, while the change is 2.671 times the half spread in a private information state. Consistent with the current literature, the results from Nyholm's (2002) model indicate that the probability of informed trading (PI) is higher in more liquid on-the-run spot markets, off-the-run spot markets, and futures markets. For example, we found that the PI measures are 0.0669, 0.0589, and 0.0531 in 2-year, 5-year, and 10-year on-the-run spot markets, respectively. The results in this study support Chung et al. (2005) findings.

Consistent with Farmer and Zamani (2007), we found that the price impact of uninformed individual trades decreases as the time scale increases, and that the price impact of individual informed trades increases as the time scale increases. This result confirms that our regime-switching model correctly classifies high-impact trades as informed and low-impact trades as uninformed. Our results indicate that the prices in different markets exhibit similar reactions to informed and uninformed trades. For example, in the case of 2-year notes, the price impact of informed trades increases from 3.845 to 12.732 times the half spread for five and sixty minute scales, respectively. The positive relationship between the time scale and price impact of informed trades implies that prices do not fully and immediately adjust to the information revealed by speculators' trades in the U.S. Treasury market. The results indicate that the difference in the individual trade's price impact between markets becomes larger as the time scale increases. For example, in the case of a sixty minute scale, the total impacts of individual informed trades for 2-year and 5-year T-notes are 12.732 and 16.526, respectively, while the total impact of an informed trade for a 10-year T-note is 10.443, in terms of half spread.

We estimate the price impact of an individual informed trade for three different periods (8:00 am - 10:00 am, 10:00 am - 3:00 pm, and 3:00 pm - 5:00 pm) and time scales (transaction by transaction, 5 minutes, and 10 minutes) between 8:00 am and 5:00 pm. The results indicate that the price impact of an informed trade is largest between 8:00 am and 3:00 pm when the market is more liquid, and smallest between 3:00 pm and 5:00 pm when the market is less liquid. Consistent with the previous results in this paper, more liquid markets (2-year and 5-year T-notes) lead to an informed trade that has a greater price impact for the three periods and time scales. The results indicate that as the time scale increases from the transaction by transaction level to the 10-minute level, the price impact of an informed trade increases; however, the increase is smaller as the estimation period moves from the morning to the afternoon period. For example, in the case of 2-year notes, the difference in price impact is 3.12 (5.73 - 2.61) for the 8:00 am - 10:00 am period, and 0.75 (3.21-2.46) for the 3:00 pm - 5:00 pm period. The results imply that time scale becomes a more important factor in measuring the price impact of an informed trade during information arrivals.

To summarize, this paper provides three main contributions. First, we show that the price impact of informed trades is higher in more liquid Treasury markets. Second, our results indicate that the price impact of uninformed (informed) individual trades decreases (increases) as the time scale increases. Third, we document the intraday pattern of informed trades' price impact. The price impact of informed trades is greater between 8:00 am and 3:00 pm when the market is more liquid, and smaller between 3:00 pm and 5:00 pm when the market is less liquid. The result implies that informed traders do not break up their large orders to hide their identity, and try to take advantage of their information as soon as possible.

The remainder of the paper is arranged as follows. Section 2 presents a brief description of the U.S. Treasury securities market and data. Section 3 describes the methodology. Section 4 presents the empirical results from our models. The paper concludes with Section 5.

2.0 Intraday data for U.S. treasuries

Treasury securities can be traded twenty-two hours daily on U.S. weekdays. Trading takes place in Tokyo between 7:30 pm ET and 3:00 am ET. Then trading begins in London at 3:00 am ET and continues until 7:30 am ET. Trading in New York begins at 7:30 am ET and continues until 5:30 pm ET. Although there is round-the-clock trading in Treasury securities, approximately 95% of the trading occurs during New York trading hours (Fleming, 1997).

Players in the Treasury markets include a small number of primary dealers and a large number of non-primary dealers, all of whom trade on their own accounts and for their clients. Primary dealers facilitate the majority of trades and act like informed investors in terms of their trading activity and the way they execute trade (Fleming and Remolona, 1999). The trading system is devised so that dealers trade amongst themselves anonymously through six inter-dealer brokers. Anonymous trading protects dealers from revealing their private information by way of the act of trading.[7] GovPX, Inc. transmits the best bid and ask quotes, the transaction price with an indication of whether the transaction is buyer- or seller-initiated, and the size of each trade from the inter-dealer brokers to subscribers in real time through online vendors.

This study uses intraday data, purchased from GovPX, Inc., for *on-the-run* and *off-the-run* 2-year, 5-year, and 10-year Treasury notes for the period from November 1, 1997, to October 31, 2000.[8] The data contain best bid and ask quotes, transaction prices, sizes, and signs (i.e., whether a transaction price is a hit or a take). This study excludes the 'when-issued' period from the analysis. We follow the data cleaning procedures presented in the appendix of Fleming (2003). As explained by Fleming (2003), identifying each trade accurately and uniquely is challenging during the work-up process. However, completed trades can be accurately and uniquely identified by increases in the aggregate volume. The number of auctions during our sample period were the same for every year for 2-year (once every month) and 10-year (once in February, May, August, and November) T-notes; however, the number of auctions for 5-year notes decreased from once every month in 1997 to once in February, May, August, and November in 2000.[9]

The 2-year, 5-year, and 10-year Treasury notes futures data are from the Futures Industry Institute. The data show the time and price of every trade involving a price change. At any given time, there are three to four contracts traded on the market. Since the nearby contract is most liquid at any point in time, it is used to construct the futures price series up to the expiration month. On the first day of the expiration month, the contract with the second shortest maturity is used.[10] The data set used in this study runs from November 1, 1997, to October 31, 2000. We have excluded the outliers from the analysis in this study.

3.0 Methodology

The following sections explain the preliminary regressions, VAR, and Markov switching models that we use to examine the information content of the order flow in 2-year, 5-year, and 10-year Treasury notes markets.

3.01 Preliminary regressions and vector autoregression (VAR) model

As discussed in Fleming (2003), a popular measure of general (unconditional) liquidity is Kyle lambda, which is usually estimated by regressing price changes on the net volume for fixed intervals of time. Kyle lambda measures the impact of order flow on price changes. A low impact indicates high liquidity. Following previous studies (Chordia et al., 2008), we focus on five-minute intervals in order to examine the relationship between price changes and order imbalance. Before 8:00 am and after 5:00 pm, non-trading becomes an issue. Therefore, trading hours from 8:00 am ET to 5:00 pm ET are divided into 108 five-minute intervals. The price changes are computed by using the midpoints of the quotes prevailing at the end of each five-minute interval. Then a single price change series ΔP_t is created by stacking up the price changes for every interval and day. Models (1) and (2) below are estimated based on this data arrangement for on-the-run T-notes.[11]

Our goal in this section is to examine the relationship between order imbalance (OIB) and price changes. OIB is defined in four different ways (OIBNUM, OIBSH, RELOIBNUM, and RELOIBSH). OIBNUM is the number of buyer-initiated bonds transacted minus the number of seller-initiated bonds transacted. OIBSH is the number of bonds bought minus the number of bonds sold. RELOIBSH is the number of bonds bought minus the number of bonds sold, divided by the number of bonds traded. RELOIBNUM is the number of buyer-initiated bonds transacted minus the number of seller-initiated bonds transacted, divided by the total number of trades.
For our preliminary analysis, first we examine the general (unconditional) liquidity of each market by estimating the price impact of order flow using the following simple linear regression for each definition of OIB.

$$\Delta P_t = intercept + \phi OIB_t + \varepsilon_t \qquad (1)$$

[7] Like the Deutsche Bank's purchase or sale of the Deutsche mark prior to German Central Bank interventions (Peiers, 1997), a respected dealer's purchase of Treasury bonds reveals the private information possessed by that dealer.
[8] We do not examine the 30-year Treasury bond since the GovPX data only includes a small fraction of the aggregate market activity for this bond.
[9] In the case of 5-year notes, once every month in 1997, eight times in 1998 (in the 1st, 2nd, 3rd, 4th, 5th, 6th, 8th, and 11th months), and four times in 1999 and 2000 (in the 2nd, 5th, 8th, and 11th months).
[10] Ederington and Lee (1993) use the contract with the highest trading volume. One pitfall is that by using trading volume as a selection criterion, the nearby contract may be selected on one day and another contract may be selected on another day, which can contaminate the data series. Harvey and Huang (1991) use the nearby contract until the day before the expiration day. A major concern is the low trading volume on the days close to expiration. Leng (1996) uses the nearby contract up to the expiration month as a compromise. We adopt Leng's (1996) approach.
[11] Off-the-run spot and futures (2-year and 5-year notes) markets are not liquid enough to conduct this type of analysis.

Where the coefficient ϕ measures the price impact of order flow on price changes.

To examine the dynamic relationship between price changes and OIB, we use vector autoregression (VAR). The following VAR model is estimated for different definitions of order imbalance.

$$\Delta P_t = \sum_{i=1}^{5} a_i \Delta P_{t-i} + \sum_{i=1}^{5} b_i OIB_{t-i} + \varepsilon_{1t}$$
$$OIB_t = \sum_{i=1}^{5} c_i \Delta P_{t-i} + \sum_{i=1}^{5} d_i OIB_{t-i} + \varepsilon_{2t} \qquad (2)$$

The variance decompositions are estimated from the VAR model. Following Hasbrouck (1991), we assume that quote revision follows the trade and, therefore, the Choleski factorization is based on the ordering of first OIB and then price changes. Variance decomposition will tell us the role of each type of order imbalance in explaining the price changes for each market.

3.02 Markov-Switching models

Liquidity traders and informed traders are assumed to be the two groups of traders in financial markets. It is the trades by informed traders that lead to permanent revisions of quotes to reflect the new information. A Markov switching model developed by Nyholm (2002) suggests this categorization of trades. Market events (quote revisions and transactions) are defined as a sequence of event times rather than wall-clock times. The notation and sequencing conventions in the model are as follows. A trade occurs at the prevailing quotes at time t-1. The dealer evaluates the information content of that trade and quotes bid and ask prices at time t. The model separates trades into high and low price impact, and classifies the high-impact trades as informed and low-impact trades as uninformed. As discussed in Nyholm (2002), this categorization is consistent with the trade-indicator regression framework (e.g., Glosten 1987; Glosten and Harris 1988; Huang and Stoll 1997) and the mixture of distribution approach as formulated by Easley and O'Hara (1987). In both of these general modeling approaches the quoted spread is related to the asymmetric distribution of private information among the market participants. Easley and O'Hara (1987) assume that asymmetric information is the sole source of the quoted spreads.

Let P_t be the midpoint of the quotes at time t. Price changes are defined as $\Delta P_t = P_t - P_{t-1}$. Low price impact trades (state 1) and high-price impact trades (state 2) can be modeled as follows.

For state 1: $\Delta P_t = \theta \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{1t}$

For state 2: $\Delta P_t = (\theta + \psi) \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{2t}$ (3)

Where S_{t-1} is the quoted spread at time t-1 and Q_{t-1} is the trade indicator variable equal to 1 (-1) if the trade was transacted at the ask (bid) at time t-1. The coefficient θ captures the reaction of quotes to trades that are not related to private information. The coefficient ψ captures the additional adjustments in the midpoint of quotes when the trades are related to private information.[12] The coefficients θ and ψ measure the size of dealers' mid-quote revisions normalized by the size of half the quoted spread. The normalization will allow us to compare the results across different markets. Note that the model in state 1 is the general one-state trade indicator model.

For each observation, the log-likelihood function is calculated as a weighted average of two densities from the equations in model (3). The weights are determined endogenously by the Markov-switching algorithm and represent the conditional regime probabilities for each trade.[13] An advantage of this estimation method is that both the parameters that explain the quote revisions and the regime categorization of each trade are endogenously determined. The unconditional probability of informed trading for each T-note can be calculated from the transition probabilities that the model estimates:

$$PI = (1 - P_{11})/(2 - P_{11} - P_{22}) \qquad (4)$$

Where $P_{11}(P_{22})$ denotes the probability of being in regime one (two), given that the system was in regime one (two) during the previous period. To be consistent with the previous section, observations taken between 8:00 am and 5:00 pm are used in the estimation.

For the futures market, we modify our regime-switching model since futures data does not include quotes and trade direction (i.e., whether a trade was buyer or seller initiated). We apply the Tick test[14] to infer the trade

[12] See Nyholm (2002) for more information about the model.
[13] RATS software is used in the estimation of the regime-switching model.
[14] The current trade is classified as buyer (seller) initiated if the price of the preceding trade is lower (higher) than the price of the current trade. If the price is the same for both trades, then the last recorded price change will be used to determine the direction.

direction.[15] Let W_t be the transaction price at time t. Returns are defined as $R_t = 10000 * \log(\frac{w_t}{w_{t-1}})$ and can be modeled as follows.

For state 1: $R_t = \theta Z_{t-1} + \varepsilon_t$

For state 2: $R_t = (\theta + \psi) Z_{t-1} + \varepsilon_t$ (5)

Where Z_t is a trade indicator variable at time t, equaling 1 if the transaction is buyer initiated and -1 if the transaction is seller initiated. Since the characteristics of the data and models are different for the spot and futures markets, the results will not be comparable between the two markets.

4.0 Results

4.01 Preliminary analysis

Fleming (2003) evaluated various liquidity measures (bid-ask spread, price impact, quote size, trade size, and yield spread) for the U.S. Treasury and concluded that bid-ask spread and price impact measures are better proxies for general (unconditional) market liquidity. Hence, for the preliminary analysis, we examine the price impact of order flow in on-the-run T-notes markets using the simple linear regression defined in equation (1).

Table 01: Price impact by different definitions of order imbalance

The results are for 2-year, 5-year, and 10-year Treasury notes for the period from November 1, 1997, to October 31, 2000, during U.S. trading hours. The model examines the relationship between order imbalance (OIB) and price changes. OIB is defined in four different ways (OIBNUM, OIBSH, RELOIBNUM, and RELOIBSH). OIBNUM is the number of buyer-initiated bonds transacted minus the number of seller-initiated bonds transacted. OIBSH is the number of bonds bought minus the number of bonds sold. RELOIBNUM is the number of buyer-initiated bonds transacted minus the number of seller-initiated bonds transacted, divided by the total number trades. RELOIBSH is the number of bonds bought minus the number of bonds sold, divided by the number of bonds traded. The values in the parenthesis are p-values. The model is defined as follows: $\Delta P_t = intercept + \phi OIB_t + \varepsilon_t$

	2-year T-notes	5-year T-notes	10-year T-notes
Panel A: OIB is defined as OIBNUM			
Intercept	-0.000389 (.000)	-0.000611 (.000)	-0.000544 (.000)
ϕ	0.001491 (.000)	0.003107 (.000)	0.005572 (.000)
$\bar{R}^2$	0.333	0.332	0.254
Panel B: OIB is defined as OIBSH			
Intercept	-0.000079 (.002)	-0.000195 (.003)	-0.000159 (.163)
ϕ	0.000049 (.000)	0.000223 (.000)	0.000395 (.000)
$\bar{R}^2$	0.148	0.181	0.117
Panel C: OIB is defined as RELOIBNUM			
Intercept	-0.000178 (.000)	-0.000313 (.000)	-0.000235 (.029)
ϕ	0.005627 (.000)	0.013795 (.000)	0.021534 (.000)
$\bar{R}^2$	0.234	0.229	0.198
Panel D: OIB is defined as RELOIBSH			
Intercept	-0.000105 (.000)	-0.000212 (.000)	-0.000183 (.096)
ϕ	0.004812 (.000)	0.012233 (.000)	0.018381 (.000)
$\bar{R}^2$	0.1888	0.214	0.171

The results in Table 1 indicate that the impact of trades on price changes is positive as expected. Panel A of Table 1 presents the results for OIBNUM, which correspond to Model 1 of Table 8 in Fleming (2003). The coefficient of 0.001491 and adjusted R^2 statistic of 0.333 of the 2-year note in this study are almost identical to the coefficient and adjusted R^2 statistic that Fleming (2003) found in his study. Consistent with his findings, we found that the coefficient of the 2-year note is the smallest and the coefficient of the 10-year note is the largest, which indicates that the 2-year note is the most liquid and the 10-year note is the least liquid among 2-year, 5-year, and 10-year on-the-run Treasury notes.

In addition to defining order imbalance as OIBNUM, this study examines the relationship between price changes and the different definitions of order imbalances, which are presented in Panels B, C, and D. In each panel, the

[15] Finucane (2000) and Theissen (2001) found that the tick test did not underperform compared with the Lee and Ready (1991) test, while Ellis, Michaely, and O'Hara (2000) found that the Lee and Ready test improved the classification by some five percent of observations over the tick test.

coefficient of the 2-year note is the smallest and the coefficient of the 10-year note is the largest, regardless of the definition of order imbalance. The adjusted R^2 statistic in Panel A is the largest out of all four panels, which implies that the OIBNUM definition of order imbalance has the highest explanatory power for price changes.

The results in Table 1 are consistent with the findings of Brandt and Kavajecz (2004). Brandt and Kavajecz (2004) measured the contribution of order flow imbalance to explain the day-to-day changes in U.S. Treasury yields using an *incremental* adjusted R^2. They found that the response of yields to order flow is the strongest in the 2-5 year maturity range.

4.02 The VAR model

In order to examine the extent to which unexpected order imbalance impacts price changes, we estimate the variance decompositions using model (2) for each definition of order imbalance. The results in Table 2 indicate that 36.41 percent (35.34 percent and 29.32 percent) of the variation in prices is explained by unexpected OIBNUM in the 2-year (5-year and 10-year, respectively) T-note market. The results in Table 2 indicate that order imbalance, defined in terms of number of trades (OIBNUM and RELOIBNUM), has higher explanatory power, and that a shock to order imbalance in 2-year and 5-year T-notes markets has more impact on the variation in price changes. The results from Table 2 show that order imbalance in more liquid Treasuries has a stronger impact on price changes.

Table 02: Relative contribution of order imbalance to the variance of returns

The results are for 2-year, 5-year, and 10-year Treasury notes for the period from November 1, 1997, to October 31, 2000 during the U.S. trading hours. The variance decomposition is based on different definitions of order imbalance (OIBNUM, OIBSH, RELOIBNUM, and RELOIBSH). OIBNUM is the number of buyer initiated trades minus the number of seller initiated trades. OIBSH is the number of bonds bought minus the number of bonds sold. RELOIBSH is the number of bonds bought minus the number of bonds sold, divided by the number of bonds traded. RELOIBNUM is the number of buyer-initiated bonds transacted minus the number of seller-initiated bonds transacted, divided by the total number trades. For example, 26.58% implies that RELOIBNUM explains 26.58% of the variation in returns in 2-year T-notes market.

	OIBNUM	OIBSH	RELOIBNUM	RELOIBSH
2-year note returns	36.41	15.85	26.58	22.31
5-year note returns	35.34	19.17	25.42	22.68
10-year note returns	29.32	13.38	22.99	19.83

4.03 Markov-switching models

We estimate the regime-switching model for the on-the-run, off-the-run, and futures markets, and the results are presented in Panels A, B, and C of Table 3, respectively. An advantage of this model is that it allows us to examine the price impacts of trades during normal information and private information states. The results in Panel A of Table 3 indicate that order flow is positively related to price changes, and during a normal information state (θ), the price impact of order flow is the smallest in 2-year T-notes and largest in 10-year T-notes markets, which is consistent with the results in Table 1. The θ coefficient represents the average mid-quote change in terms of half spread given a buy or sell order. For example, θ in Panel A of Table 3 is equal to 0.414 for 2-year T-notes, which implies that a buy (sell) order increases (decreases) the mid-quote by 0.414 times the half spread.

The results in Panel A indicate that, during a private information state (ψ), the additional revision of the quote midpoint due to private information is the largest in 2-year T-notes and smallest in 10-year T-notes markets. For example, ψ is equal to 2.257 for 2-year T-notes, which implies that a buy (sell) order increases (decreases) the mid-quote by 2.257 times the half spread, in addition to the average adjustment of 0.414 times the half spread in a normal information state, when an order is believed to be coming from an informed trader. The total adjustment in the quote midpoint during a private information state is the sum of the θ and ψ coefficients. The total adjustments for 2-year and 5-year notes are very similar and are greater than the total adjustment in the 10-year notes market. For 2-year T-notes, the total adjustment is equal to 2.671 times the half spread in a private information state.

The findings of this study for the Treasury market are comparable to Nyholm's (2003) findings in the equity market. Nyholm found average values of 0.065 and 1.773 for the θ and ψ coefficients, respectively (Table II, p. 463). The fact that Nyholm's findings are smaller than the findings in this study might be related to the differences in the regulations between the two markets. Unlike the NYSE and the AMEX, the interdealer broker Treasury market is not subject to market presence or price continuity rules that limit bid-ask spreads or price changes to specified minimums or maximums. The absence of market presence rules means that bid-ask spreads as wide as 1/16 of a point are common. Likewise, the absence of price continuity rules indicates that trade-to-trade price changes as large as 1/4 of a point occur (Fleming and Remolona, 1999).

Table 03: Price impact of order flow in the U.S. Treasury spot and futures markets

For the spot market, we estimate the following Markov-switching model:

For state 1: $\Delta P_t = \theta \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{1t}$; For state 2: $\Delta P_t = (\theta + \psi) \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{2t}$

For the futures market, we estimate the following Markov-switching model:

For state 1: $R_t = \theta Z_{t-1} + \varepsilon_t$; For state 2: $R_t = (\theta + \psi) Z_{t-1} + \varepsilon_t$

Where $R_t = 10000 * \log(\frac{W_t}{W_{t-1}})$. Q_t is a trade indicator variable at time t, equaling 1 if the transaction is buyer initiated and -1 if the transaction is seller initiated. P_t is the midpoint of the quotes at time t. W_t is the transaction price at time t. The probability of informed trading for each T-note can be calculated from the transition probabilities: $PI = (1 - P_{11})/(2 - P_{11} - P_{22})$. The results are for 2-year, 5-year, and 10-year on-the-run spot, off-the-run spot, and futures T-notes for the period from November 1, 1997, to October 31, 2000, during U.S. trading hours. The values in the parenthesis are p-values.

	θ	ψ	$\theta + \psi$	PI
Panel A: On-the-run spot market				
2 year	0.414 (.000)	2.257 (.000)	2.671	6.69%
5 year	0.440 (.000)	2.133 (.000)	2.573	5.89%
10 year	0.476 (.000)	1.871 (.000)	2.347	5.31%
Panel B: Off-the-run spot market				
2 year	0.576 (.000)	6.418 (.000)	6.994	5.88%
5 year	0.591 (.000)	5.783 (.000)	6.374	4.33%
10 year	0.707 (.000)	4.991 (.000)	5.698	3.71%
Panel C: Futures market				
2 year	-1.096 (.000)	2.459 (.000)	1.363	4.16%
5 year	-1.469 (.000)	2.917 (.000)	1.448	4.67%
10 year	-2.233 (.000)	4.172 (.000)	1.939	4.95%

Panel A indicates that the probability of informed trading (PI) is 6.69, 5.89, and 5.31 percent for 2-year, 5-year, and 10-year notes, respectively. In the case of the 2-year notes, only 6.69 percent of all trades convey private information. As expected, PI is higher for 2-year and 5-year notes (more liquid markets) and lower for 10-year notes (less liquid market). Our results, based on Nyholm's (2002) regime-switching model, confirm the findings of Li et al. (2009). Using the PIN measure of Easley, Hvidkjaer, and O'Hara (2002), Li et al. (2009) found that the U.S. Treasury bonds with higher liquidity, greater depth, and lower spread tend to have a higher PIN measure. The average PI of 9.205 percent that Nyholm (2003) found in the equity market is higher than this study's finding in the Treasury market. Unlike equity markets, the only source of private information in the Treasury market is the differences in the interpretation of public news. Hence, it is expected that PI is lower in the Treasury market.

Panel B of Table 3 presents the results for off-the-run T-notes. The results in Panel B are consistent with the ones in Panel A. Price impact during a normal information state (θ) is smaller in more liquid treasury markets (2-year and 5-year T-notes) and larger in less liquid markets (10-year T-notes). However, during a private information state, the total adjustment ($\theta + \psi$) is larger in more liquid T-notes markets. In Panel B of Table 3, consistent with the findings of Li et al. (2009), we find that PI is lower in off-the-run markets than on-the-run markets. The results in Panel B indicate that PI and the price impact of an informed trade are positively related. When Panels A and B are compared, we can see that the price impact during a private information state is higher in an off-the-run market. This may seem inconsistent with our argument that in more liquid markets, the price impact of informed trades is higher.[16] However, this finding might be related to the time between each transaction. As shown in Table 4, the price impact of informed trades is larger when there is more time between the trades. We will discuss this issue in more detail when we present the results in Table 4.

Panel C of Table 3 presents the results for the futures market. Since our futures data does not include quotes, we use model (5) to investigate the price impact during normal and private information states in the futures market. In model (5), returns are based on transaction prices. Unlike the U.S. Treasury spot market, liquidity improves

[16] On-the-run treasuries are more liquid than off-the-run treasuries.

with maturity in the U.S. Treasury futures market (i.e., 10-year futures are more liquid than 2-year futures). The sign of the normal information state coefficient (θ) is negative since trades without private information lead to bid and ask bounce. However, when trades contain private information, then prices adjust to the information in the direction of the trades. The positive sign of ψ confirms the adjustment of prices to private information. Consistent with Panels A and B, the results in Panel C indicate that the total price adjustment ($\theta + \psi$) to an informed trade is greater in more liquid markets and that PI is also greater in more liquid markets. These results support Admati and Pfleiderer's (1988) theory as well as the findings of Li et al. (2009) and Chung et al. (2005). Since the characteristics of the data and models are different for the spot and futures markets, the results will not be comparable between the two markets.

Table 04: Maximum likelihood estimates of the Markov-switching model: On-the-run Treasuries

For state 1: $\Delta P_t = \theta \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{1t}$; For state 2: $\Delta P_t = (\theta + \psi) \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{2t}$

P_t is the midpoint of the quotes at time t. Q_t is a trade indicator variable at time t, equaling 1 if the transaction is at the ask and -1 if the transaction is at the bid. The results are for 2-year, 5-year, and 10-year on-the-run Treasury notes for the period from November 1, 1997, to October 31, 2000, during U.S. trading hours. The price changes in the regime-switching model are based on 5-minute, 10-minute, and 60-minute intervals. Trading hours from 8:00 am ET to 5:00 pm ET are divided into 5-minute, 10-minute, and 60-minute intervals. The price changes are computed by using the midpoints of the quotes prevailing at the end of each interval. The values in the parenthesis are p-values.

	2 year			5 year			10 year		
	5 min	10 min	60 min	5 min	10 min	60 min	5 min	10 min	60 min
θ	0.531	0.485	0.08	0.584	0.573	0.04	0.596	0.581	0.007
	(.000)	(.000)	(.377)	(.000)	(.000)	(.632)	(.000)	(.000)	(.9464)
ψ	3.314	4.887	12.732	3.463	4.965	16.526	2.857	4.213	10.443
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
$\theta + \psi$	3.845	5.372	12.732	4.047	5.538	16.526	3.453	4.794	10.443

In Table 4, we examine how time scale affects the price impact of an individual trade in on-the-run treasury spot markets. The price changes in the regime-switching model are based on 5-minute, 10-minute, and 60-minute intervals. Trading hours from 8:00 am ET to 5:00 pm ET are divided into 5-minute, 10-minute, and 60-minute intervals. The price changes are computed by using the midpoints of the quotes prevailing at the end of each interval. Then, a single price change series ΔP_t is created by stacking up the price changes for every interval and day. For the first interval, the price change is based on the first and last prices within the interval. Q_t is a trade indicator variable for the last observation at the end of each interval.

Table 4 presents the price impact during a normal information state (θ), the additional adjustment during a private information state (ψ), and the total adjustment during a private information state ($\theta + \psi$). The results indicate that the price impact of liquidity trades decreases as the time scale increases and that the price impact of informed trades increases as the time scale increases. For example, in the case of 2-year notes, the price impact of informed trades increases from 3.845 to 12.732 times the half spread for 5- and 60-minute intervals, respectively. The fact that the price impact of liquidity trades becomes smaller is intuitive since the trades of liquidity traders should not have a permanent impact on prices. The positive relationship between time scale and the price impact of informed trades (trades by skilled traders) implies that it takes time for prices to fully adjust to the information revealed by the trades of skilled traders. Our results in Table 4 are consistent with the findings of Farmer and Zamani (2007). As mentioned earlier, they find that the average mechanical (uninformed) impact decays to zero monotonically in time. In contrast, the informational impact grows with time and approaches a constant value. They also find that, on average, the initial mechanical impact is about half the asymptotic informational impact. Our results indicate that prices in different markets exhibit similar reactions to informed and uninformed trades.

The results in Table 4 indicate that the difference in the price impact of informed trades between the markets becomes larger as the time scale increases. For example, in the case of a 60-minute scale, the total impact of informed trades for 2-year and 5-year T-notes is 12.732 and 16.526, respectively, while the total impact of an informed trade for 10-year T-notes is 10.443, in terms of half spread.

Our results from Tables 3 and 4 seem to suggest that the private information content of a trade and the time scale in estimating the price impact of a trade are the two factors affecting the price impact of an informed trade. When the price changes are based on event time, the time scale of off-the-run treasuries is much longer than that of on-the-run treasuries[17] and, therefore, it seems natural to observe that informed trades have a larger price impact for off-the-run than on-the-run treasuries in Table 3, even though the PI is bigger for on-the-run treasuries.

Next, we estimate the total price impact of an informed trade ($\theta + \psi$) for three different periods (8:00 am - 10:00 am, 10:00 am -3:00 pm, and 3:00 pm -5:00 pm) and time scales (transaction by transaction, 5 minutes, and 10 minutes) between 8:00 am and 5:00 pm to examine the intraday relationship between liquidity and price impacts. The results in Table 5 indicate that the price impact of an informed trade is largest between 8:00 am and 3:00 pm when the market is more liquid. Consistent with the previous results in this paper, more liquid markets (2-year and 5-year T-notes) lead to an informed trade having a greater price impact for the three periods and time scales.

As in Table 4, the results in Table 5 indicate that as the time scale increases from the transaction by transaction level to the 10-minute level, the price impact of an informed trade increases. However, the increase is smaller as the estimation period moves from the morning to afternoon period. For example, in the case of 2-year notes, the difference in price impact is 3.12 (5.73 - 2.61) for the 8:00 am - 10:00 am period, and 0.75 (3.21-2.46) for the 3:00 pm - 5:00 pm period. The results imply that time scale becomes a more important factor in measuring the price impact of an informed trade during information arrivals.

Table 05: Maximum likelihood estimates of the Markov-switching model: On-the-run Treasuries

For state 1: $\Delta P_t = \theta \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{1t}$; For state 2: $\Delta P_t = (\theta + \psi) \frac{S_{t-1}}{2} Q_{t-1} + \varepsilon_{2t}$

P_t is the midpoint of the quotes at time t. Q_t is a trade indicator variable at time t, equaling 1 if the transaction is at the ask and -1 if the transaction is at the bid. The results ($\theta + \psi$) are for 2-year, 5-year, and 10-year on-the-run Treasury notes for the period from November 1, 1997, to October 31, 2000, during U.S. trading hours. The price changes in the regime-switching model are based on transactions level, 5-minute and 10-minute intervals. For the 5-minute and 10-minute intervals, trading hours from 8:00 am ET to 5:00 pm ET are divided into 5-minute and 10-minute intervals, and the price changes are computed by using the midpoints of the quotes prevailing at the end of each interval. The values in the parenthesis are p-values.

	8:00 am - 10:00 am			10:00 am - 3:00 pm			3:00 pm - 5:00 pm		
	transaction	5 min	10 min	transaction	5 min	10 min	transaction	5 min	10 min
2 year	2.61 (.000)	4.56 (.000)	5.73 (.000)	2.83 (.000)	3.87 (.000)	5.57 (.000)	2.46 (.000)	2.68 (.000)	3.21 (.000)
5 year	2.49 (.000)	4.51 (.000)	5.98 (.000)	2.66 (.000)	3.93 (.000)	5.65 (.000)	2.48 (.000)	2.76 (.000)	3.27 (.000)
10 year	2.23 (.000)	3.68 (.000)	4.65 (.000)	2.38 (.000)	2.86 (.000)	4.29 (.000)	2.05 (.000)	2.74 (.000)	3.14 (.000)

5.0 Conclusions

This paper examines how the price impact of informed trades is related to liquidity in the 2-year, 5-year, and 10-year U.S. Treasury on-the-run, off-the-run, and futures markets. We find that the price impact of informed trades is higher in more liquid markets. The variance decompositions from the VAR model indicate that trade innovations in 2-year and 5-year T-notes markets can explain approximately 36 percent of the price changes, while trade innovations in the 10-year T-notes market can explain 29 percent of the price changes. The results from the regime-switching model show that, in the case of on-the-run and off-the-run spot markets, the price impact of an informed trade is higher in the 2-year and 5-year T-notes markets. In the case of T-notes futures markets, the price impact of an informed trade is higher in the 10-year futures market. Our finding that informed trades have more impact on prices in more liquid markets is new.

Consistent with the finding of Farmer and Zamani (2007) regarding the London Stock Exchange, we find that the price impact of uninformed individual trades decreases as the time scale increases and that the price impact of individual informed trades increases as the time scale increases. The positive relationship between time scale and the price impact of informed trades implies that prices do not fully and immediately adjust to the information revealed by speculators' trades in the U.S. Treasury market.

We estimate the price impact of an individual informed trade for three different periods (8:00 am - 10:00 am, 10:00 am - 3:00 pm, and 3:00 pm -5:00 pm) and time scales (transaction by transaction, 5 minutes, and 10 minutes) between 8:00 am and 5:00 pm. The results indicate that the price impact of an informed trade is largest between 8:00 am and 3:00 pm when the market is more liquid and smallest between 3:00 pm and 5:00 pm when

[17] Our estimations in Table 3 are based on event time. On-the-run treasuries are much more frequently traded than off-the-run treasuries.

the market is less liquid. The results indicate that as the time scale increases from the transaction by transaction level to the 10-minute level, the price impact of an informed trade increases. However, the increase is smaller as the estimation period moves from the morning to the afternoon period. The results imply that time scale becomes a more important factor in measuring the price impact of an informed trade during information arrivals.

Our findings have policy implications for high-frequency traders. The finding that, following economic news, informed traders do not break up their large orders to hide their identity implies that high-frequency traders should trade very quickly to take advantage of their information.

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