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Information-Based Trading in the Treasury Note Interdealer Broker Market[1]

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Despite its pervasive presence in world financial markets, there are few studies of interdealer broker markets. This paper examines the trading behavior of primary dealers in the 5-year Treasury note interdealer broker market. The analysis examines trading patterns, announcement effects, and volatility–volume relations. The results show that trading frequency is consistent with activity motivated by public information or dealer's private knowledge of inventory or order flow information. Additionally, although the interdealer broker market is an anonymous electronic compilation and matching system without designated market makers, trade size does not appear to have any information content. *Journal of Economic Literature* Classification Numbers: C22, G14.

Key Words: announcement effects; information; interdealer broker market; volatility.

1. INTRODUCTION

Multiple-dealership structure is prevalent in trading systems around the world. Prominent examples are the London Stock Exchange (LSE) and Nasdaq equity

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markets, the foreign exchange markets, and the U.S. debt markets.[2] A distinguishing feature of these multiple-dealer trading platforms is the presence of an interdealer market in general and an interdealer broker (IDB) market in particular, which facilitates trades between dealers. For example, Reiss and Werner (1998) report that 23.5% of the £ trading volume on the LSE is due to interdealer trading, and 21.3% of this is transacted in the IDB market. On Nasdaq, market makers have long relied on Instinet, the electronic IDB market, and an increasing number of similar alternative trading venues, known as electronic communication networks (ECNs), have appeared recently on the scene.

An analysis of IDBs is useful for understanding multiple-dealer trading mechanisms since IDBs are an integral part of a dealer environment. Trading in the interdealer market can be visualized as the second stage of a two-step process where the first stage is the transaction between the dealer and the customer. In the second stage, dealers enter the interdealer market to trade on available information or to manage their inventories. Information-based trading may also necessitate inventory adjustments. During the second stage, dealers often turn to a broker, who collects and posts bids and offers, and executes trades.

What is the information-based trading behavior of primary dealers in the 5-year U.S. Treasury note IDB market? We attempt to infer the dealers' behavior by associating it with the two components of volume, trade frequency and average trade size. Specifically, we first examine the intraday patterns and announcement effects associated with volume, volatility, and spread. Second, we analyze spread components in the immediate neighborhood of U.S. macroeconomic announcements to understand the nature of information-based trading. Third, we investigate the dynamics between volume, volatility, and spread that go beyond any intraday and announcement effects. Our analysis is based on the GovPX database, which contains intraday trade and quote data for Treasury securities traded on the IDB market.

We consider both public and private information-based trading. Public information-based trading may result from news releases that generate a greater dispersion of beliefs as modeled by Harris and Raviv (1993) and Shalen (1993). The level of information asymmetry could also increase following a public announcement. Kim and Verrecchia (1994) model an environment where some traders, such as information intermediaries, are able to generate private information from the public news releases. Another source of private information is due to the fact that not all information about the discount rate is public even if information about Treasury securities cash flows is public. As highlighted in the literature on the foreign exchange market, dealers' knowledge of their own inventory and customer order flow may convey information about fundamentals, short-term price fluctuations, or customer demand. Therefore, some dealers may possess an informational

[2] As of October 20, 1997, the LSE uses an electronic limit order book for small orders but large orders are still executed through a dealer market.

advantage over other market participants, and this advantage may be especially pronounced during public announcements.[3]

Our paper contributes to three strands of literature. First, it contributes to the literature on IDB markets. The market microstructure literature is replete with studies of multiple-dealer markets. However, there is little research on interdealer markets and even fewer analyses of IDB markets. Ho and Stoll (1983) is the classic theoretical analysis of risk sharing based on inventory considerations in a dealer market. They show that an interdealer market is unnecessary if dealers adjust their quotes in response to trades with their customers.[4] Recently, Naik *et al.* (1999) modeled the two-stage dealership mechanism. In their model, risk-averse intermediaries trade with public customers in the first stage, and in the second stage, asymmetric information and inventory risk sharing motivate trading between intermediaries. Viswanathan and Wang (1998) examine the reasons for the prevalence of interdealer trading in financial markets, including trading through IDBs in the second stage.

Empirical studies of the interdealer or IDB markets generally require data sets that identify both intraday quotes and trades by counterparties. Few such data sets are available. For example, in the foreign exchange interdealer markets, quotes from specific dealers are available but trade data are rare.[5] One well-known exception is the LSE data, which permit the identification of trades and quotes by type of individual dealer. Hansch *et al.* (1998) and Reiss and Werner (1998) exploit this data set and find that dealers primarily use interdealer trading for sharing inventory risk. Inventory risk sharing reflects interdealer trading in which dealers cover their positions and is considered liquidity-based trading. Reiss and Werner also provide evidence specifically for the LSE's IDB market. These papers focus on the dealers' inventory risk-sharing activities and ignore the information-based incentive that motivates trading in the interdealer market. This study focuses on information-based trading activities in the Treasury note IDB market. These activities constitute trading caused by differences of opinion following a news release or by access to private information.

Second, our paper contributes to the literature on Treasury securities by studying the Treasury note market. The U.S. Treasury securities market is one of the world's largest and most liquid financial markets.[6] In 1999, the supply of Treasury notes exceeded that of all other Treasury instruments combined, accounting for 57% of Treasury debt outstanding. Despite its size and importance, relatively little theoretical and empirical analysis focuses on the microstructure of this fixed income market, let alone its interdealer or IDB markets. Earlier studies of Treasury

[3] See, for example, Evans and Lyons (1999) and Lyons (2001).

[4] This would be violated in a market where dealers who are not at the inside quotes receive preferential order flows.

[5] See, for example, Huang and Masulis (1999).

[6] In 1999, the amount of Treasury debt note held by the federal government totaled about $3.6 trillion and primary dealers trade an average daily volume of $190 billion in government securities (Dupont and Sack, 1999).

issues by Garbade and Silber (1976) and Garbade and Rosey (1977) use daily data to examine the cross-sectional determinants of the bid–ask spread and price dispersion. Recently, Fleming (1997) provided the first detailed intraday analysis of the round-the-clock market for U.S. Treasury securities. With the advent of high frequency data, several studies document the impact of macroeconomic announcements on the bid–ask spread, volume, and volatility of various Treasury instruments (Fleming and Remolona (1997b, 1999) and Balduzzi *et al.* (2001).[7]

Third, our paper contributes to the vast literature on the volatility–volume relation.[8] Several theories explain the observed positive volatility–volume relation. In *mixture of distribution* models, both volatility and volume are driven by information arrival.[9] In *asymmetric information* models, trading by informed traders leads to increased volatility.[10] In *dispersion of beliefs* models, public information generates differences of opinion that in turn results in increased volume and volatility.[11] In the spirit of Jones *et al.* (1994), we decompose trade volume during a time interval into the number of trades and average trade size. We then apply the theoretical models and the structural features of the IDB market to interpret the behavior of these variables.

Our results show a surprising dichotomy in the behavior of the components of trade volume. The behavior of trade frequency is consistent with information-based trading. On the other hand, trade size does not appear to have any information content. Jones *et al.* (1994) find that, for the Nasdaq multiple dealer market, trade size has no incremental information content after controlling for trade frequency. Our result is surprising in that we find it for an environment where, unlike the Nasdaq market, trading in size by informed traders is accommodated by being an anonymous trading venue without designated market makers. The Treasury note IDB market is similar to ECNs in that both permit anonymous trading and do not have market makers.[12] Huang (2002) compares the Nasdaq market to ECNs and finds that the latter has a better price discovery mechanism than the former. This suggests that ECNs attract informed traders.

Jones *et al.* also reach their conclusion by focusing on the impact of volume on volatility. In addition to the volatility–volume relation, we reach our results based on analyses of intraday patterns and announcement effects. Their results and ours contrast with microstructure theories of stock price determination, which emphasize the role of trade size as a means of detecting informed trading.[13] However, ours is consistent with microstructure models where traders are allowed to act

[7] Ederington and Lee (1993), Becker *et al.* (1996), and Bollerslev *et al.* (2000) examine the Treasury futures market.

[8] For example, see Karpoff (1987) for an early survey and Chan and Fong (1999), and Daigler and Wiley (1999) for more recent studies.

[9] For example, see Epps and Epps (1976) and Harris (1987).

[10] For example, see Kyle (1985) and Admati and Pfleiderer (1988).

[11] For example, see Harris and Raviv (1993) and Shalen (1993).

[12] However, unlike the IDB market, ECNs are not restricted to just dealers.

[13] See, for example, Easley and O'Hara (1987).

strategically, resulting in the breakup of large orders into a smaller number of trades.[14]

Our results reveal intraday patterns and announcement effects that are consistent with the dichotomous behavior of the volume components. The intraday trade frequency pattern is similar to the intraday volatility pattern and they both peak during the period that macroeconomic news is commonly released. On the other hand, the intraday trade size pattern remains fairly uniform throughout New York trading hours. Further, trade frequency responds positively to major news announcements, whereas trade size appears to be unaffected by macroeconomic announcements. Finally, an examination of the components of the spread around announcements suggests trading based on superior inventory or order flow information. Specifically, the adverse information component of the spread continues to be elevated 30 minutes after an announcement.

Our results also show that return volatility is positively associated with number of trades but not with average trade size. The positive association between volatility and trade frequency is consistent with trading motivated by information-based trading. On the other hand, trade size is unrelated to return volatility during the more volatile morning period. This suggests that trade size has no information content and is not associated with differences of opinion or asymmetric information.

The remainder of the paper is organized as follows. Section 2 provides a description of the U.S. Treasury securities' IDB market. Section 3 describes the data. Section 4 examines the intraday patterns and announcement effects. Section 5 investigates the volatility–volume relation. Section 6 concludes the paper.

2. TREASURY SECURITIES IDB MARKET

Descriptions of the Treasury debt markets are provided by Stigum (1990), Department of Treasury, Securities and Exchange Commission, and Board of Governors of the Federal Reserve System (1992), and Dupont and Sack (1999). Trading in the secondary market for Treasury securities can be thought of as occurring in two stages. The first stage is the retail trade in which dealers interact with customers. In the second stage, dealers trade with each other directly or through a broker. The vast majority of interdealer trades have come to be executed through IDBs. Although the IDB market is open to some nonprimary dealers, most transactions are between primary dealers.[15]

Dealers accumulate short or long positions by trading with customers. Dealers then access the interdealer market, a specific example of which is the IDB market, to trade with other dealers or to manage their inventory positions. In 1998, there were six IDBs in the Treasury securities market. A dealer wishing to trade in an IDB market can either post limit orders in a brokers' screen or trade against other dealers' quotes. This can be accomplished, for example, by keying in the

[14] See, for example, Kyle (1985).

[15] Primary dealers have the obligation of "underwriting" Treasury securities offerings.

information directly on a Web-based brokerage system. In return for compiling bids and offers and for executing trades, an IDB earns a commission.

The Treasury securities IDB market is a broker-mediated alternative trading venue with some distinctive characteristics. It is used almost exclusively to execute trades between dealers. Trading on the IDB market means that dealers do not incur an obligation to reciprocate to the counterparty with a two-way quote in the future. In other words, there are no designated market makers and dealers need not be on both sides of the market. Further, trades are executed anonymously, which enables dealers to trade in size.

3. DATA DESCRIPTION

In 1990, the primary dealers and four IDBs serving the Treasury securities market founded GovPX in a private joint venture.[16] Based on October 1997 data, Boni and Leach (2001) find that GovPX covers roughly 70% of all interdealer trades. The data provide real-time information on price and volume transactions by primary dealers and cover all on-the-run, off-the-run, and when-issued securities.[17] The data aggregate depth across broker systems and limit orders across dealers. Hence, trades as reported in the GovPX data may be based on limit orders placed by one or several dealers in one system, on one or both sides. The data also do not distinguish which trading system reported the trade. The data may look like they came from a consolidated system, but in reality, they are the result of reporting from many competing systems that run parallel to each other.

Our GovPX data cover the entire 1998 tick-by-tick trading record.[18] Each tick record is an update rather than a refresh. On-the-run securities are the most recently issued securities of a given maturity and account for the majority of trading volume in the interdealer market.[19] Among the on-the-run issues of bills, notes, and bonds, we focus on the 5-year note, as it is the most actively traded security among the brokers reporting to GovPX (Fleming, 1997). Treasury notes also account for the largest market capitalization of all the Treasury debt securities outstanding and is worth $2 trillion as of the end of 1998.[20]

3.1. Filtering Procedures

Each line (record) in the data set contains the bid price, bid size, ask price, ask size, last trade side, last trade price, last trade size, and aggregate volume,

[16] IDB Cantor Fitzgerald is the lone holdout and it makes its screens available through Telerate.

[17] Off-the-run securities are securities that are no longer actively traded in the market place. When-issued securities are securities that have been announced for auction but are yet to be issued.

[18] Our data from GovPX do not include trades that go through Cantor Fitzgerald Inc. However, Cantor Fitzgerald specializes in 30-year Treasury bonds, while our study focuses on 5-year Treasury notes.

[19] Fleming (1997) reports that from April 4 to August 19, 1994, 64% of daily interdealer trading volume in the GovPX data is in on-the-run issues.

[20] The figure is from http://www.publicdebt.treas.gov/opd/opds121999.htm.

among other variables. We follow Fleming and Remolona (1997a) in screening our GovPX data. (1) Since each record is a meaningful refresh, it often happens that quote information such as bid or ask prices and sizes has changed while trade information remains the same as in the previous record. Therefore we only retain the price and volume data from the first line reporting an increase in total daily volume to count each trade only once. (2) The bid–ask quotes are screened through a multistep procedure. First, one-sided quotes (a bid or an offer but not both) are eliminated. Second, negative spreads or spreads greater than 0.5 point are dropped.[21] This is because a spread of 0.5 point seems implausible in a market where the typical spread for the on-the-run 5-year note is $1/64$ of a point. Third, quote-to-quote price changes in excess of $7/16$ point in absolute value are deleted because these price changes often revert immediately. Finally, we drop quotes with bid–ask midpoints that are more than ten standard deviations from the mean of the daily bid–ask midpoint and quotes with spreads that are more than ten standard deviations from the mean daily spread.[22]

We analyze trading activity between 8:00 and 16:00 ET, a total of 8 hours. This segment is the most active market period. Given the large number of individual quotes in the data set, we aggregate the tick-by-tick information over 10-minute intervals. This minimizes the number of intervals with no or few observations while allowing for relatively fine measurement of intraday patterns and announcement effects. There are a total of 245 trading days in 1998, each with 48 10-minute intervals, for a total of 11760 intraday observations.[23]

3.2. *Variable Definitions*

The variables used in the analysis are defined for each 10-minute interval. Volume is measured by the par value quantity of traded securities. Frequency is the number of trades. Average trade size is defined as volume divided by frequency. For returns, we use the transaction prices at the end of the immediately preceding and the current 10-minute intervals. The log of price is weighted by the inverse of its distance from the endpoint, and the return is then calculated as the difference between the weighted log-prices.[24] Volatility is measured as the

[21] A point is 1% of par value.

[22] One-sided quotes average about 53 a day over the 1-year sample period. All other criteria delete 215 quotes in total, most of which are quotes with spreads more than ten standard deviations from daily spread mean.

[23] The original tick data contain records on 250 trading days. We eliminated 5 trading days with more than 20 no trading intervals, leaving 245 trading days in the sample. Our sample still contains 148 no-trading intervals that amounts to 1.26% of all observations.

[24] To illustrate, if two transaction prices occur at the following times: 100 at 10:59 and 102 at 11:02. The price at 11:00 is calculated as $100*(120/(120+60))+102*(60/(120+60))$. The weighted price at each end point is used to calculate the return. For example for 11:00 to 11:10 return, we find the prices immediately before and after 11:00 to compute one weighted price and another pair of prices immediately before and after 11:10 to compute the other weighted price. The more common approach is to choose the last transaction price before the endpoint to calculate the return. Use of weighted returns generates more "near-zero" returns instead of "zero" returns. Our results are robust with respect to this interpolation procedure.

absolute return. Bid–ask spread is the average of the quoted spreads within each interval.

Of all the variables in the paper, alternative measures are most common for volatility. To gauge the robustness of our results we adopt the Andersen and Bollerslev (1998) procedure of constructing an alternative volatility measure: $|R_{t,n}/\hat{s}_{t,n}|$, where $\hat{s}_{t,n}$ is the normalized intraday periodic component used to filter out the intraday patterns, announcement effects, and trend over the sample period.[25] We conduct all of the empirical analyses using both measures of volatility. However, since both measures produce essentially the same results, we do not report the results using the Andersen and Bollerslev measure.

3.3. *Summary Statistics*

Table I presents the basic descriptive statistics. Panel A shows that the average 10-minute trading volume is \$115.0 million, with a median of \$99.0 million and it ranges from \$0 to \$935.0 million. The average number of trades is 13.7, with a median of 13 trades and ranges from 0 to 57 trades. The average trade size is \$8.3 million, with a median trade size of \$7.7 million, and it ranges from \$1 million to \$100 million. The minimum trade size corresponds to the mandated minimum trade size in the IDB market. The average volatility is 0.0191%, with a median of 0.0123% and it ranges from 0 to 0.7175%. The average spread is 0.0103% (of par value), with a median of 0.0091% and it ranges from 0 to 0.0946%. The low bid–ask spread reflects the extremely high liquidity in the Treasury note market and is compatible with the average spread of 0.015% in the sample studied by Fleming (1997).

As a prelude to the regression analyses below, Panel B summarizes the bivariate contemporaneous correlations between the variables. Trade volume, trade frequency, and trade size are positively correlated with one another, and the highest correlation of 0.821 is between volume and trade frequency. Return volatility is positively correlated with volume and frequency, but slightly negatively correlated with size. Bid–ask spread is negatively correlated with all three trading activity variables but positively correlated with volatility.

4. INTRADAY PATTERNS AND ANNOUNCEMENT EFFECTS

We consider three deterministic influences on our time series variables in this section. First, we examine intraday patterns for evidence of information-based trading by primary dealers in the Treasury note IDB market. There is prior evidence of strong intraday patterns in the IDB market. For example, Fleming (1997) and Fleming and Remolona (1999) find systematic volume, volatility, and spread patterns during the New York trading hours.

[25] The normalized estimate for the intraday periodic component $\hat{s}_{t,n}$ is given by $\hat{s}_{t,n} = [T \times N \times \exp(\hat{f}_{t,n}/2)]/[\sum_{t=1}^{T}\sum_{n=1}^{N} \exp(\hat{f}_{t,n}/2)]$, where $\hat{f}_{t,n}$ is given by the two-step procedure in Andersen and Bollerslev (1998) and captures the intraday patterns, announcement effects, and time series trends using the same independent variables in (1) of Section 4.1, and $\sum_{t=1}^{T}\sum_{n=1}^{N} \hat{s}_{t,n} \equiv 1$.

TABLE I
Summary Statistics and Correlations

Panel A: Summary statistics

	Mean	Median	Std. Dev.	Maximum	Minimum
Trade volume (million \$)	115.0	99.0	82.3	935.0	0.0
Trade frequency	13.7	13.0	8.0	57.0	0.0
Trade size (million \$)	8.3	7.7	4.0	100.0	1.0
Return volatility (×100,000)	19.1	12.3	24.7	717.5	0.0
Bid–ask spread (×100,000)	10.3	9.1	5.3	94.6	0.0

Panel B: Contemporaneous correlations

	Volume	Frequency	Size	Volatility	Spread
Volume (million \$)	1	0.821	0.464	0.218	−0.141
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Trade frequency		1	0.028	0.332	−0.036
			(0.0040)	(0.0001)	(0.0003)
Trade size (million \$)			1	−0.072	−0.180
				(0.0001)	(0.0001)
Return volatility (×100,000)				1	0.418
					(0.0001)
Bid–ask spread (×100,000)					1

Note. The data set contains tick-by-tick 5-year U.S. Treasury note trading activity among primary dealers in the interdealer broker market. The sample period is January 2, 1998 to December 31, 1998 for a total of 245 trading days. We construct 10-minute trade volume, trade frequency, trade size, return volatility, and bid–ask spread variables for data between 8:00 and 16:00 ET. This results in a total of 48 intraday observations per trading day. Volume is the par value quantity of securities traded within the 10-minute interval. Frequency is the number of trades within the 10-minute interval. Trade size is volume divided by frequency. Volatility is measured by the absolute 10-minute return during the interval. Bid–ask spread is the average of all quoted spread within the 10-minute interval. Panel A summarizes the mean, median, standard deviation (std. dev.), maximum, and minimum of the variables. Panel B reports the contemporaneous correlations and the corresponding p-values in parentheses.

Second, the arrival of public information in the form of scheduled announcements is observable with a high degree of accuracy in this market. This knowledge translates into behavior that introduces announcement effects into the data at predetermined times. Earlier studies by Fleming and Remolona (1997b), Ederington and Lee (1993), and others have examined the effect of announcements on volume, volatility, and spread using cash or futures market data for Treasury notes or bonds. In contrast to our analysis, the earlier research typically uses dummy variables to account for the announcement effects. The dummy variable approach essentially assumes that the response patterns are flat. Our estimates provide a more accurate measure of the gradual dissipating announcement effects, with the dissipating patterns determined by the data themselves. In the case of volatility, we also incorporate other factors such as interdaily volatility persistence captured by the GARCH models, following the method of Andersen and Bollerslev (1998) and Bollerslev *et al.* (2000). Moreover, ours is a first attempt at examining the components of trading volume in analyzing announcement effects.

Third, there may be time trends in the data during our sample period. Therefore, our analysis accounts for this possibility.

4.1. Estimation Procedure

Let $\text{vom}_{t,n}$ denote dollar trading volume during interval n on day t, $\text{frq}_{t,n}$ denote frequency or number of trades, $\text{siz}_{t,n}$ denote dollar trade size, $\text{vol}_{t,n}$ denote return volatility, and $\text{spd}_{t,n}$ denote bid–ask spread. Also let $Y_{t,n}$ denote $\text{vom}_{t,n}$, $\text{frq}_{t,n}$, $\text{siz}_{t,n}$, $\text{vol}_{t,n}$, or $\text{spd}_{t,n}$. We estimate the fixed impacts on the variables using the following specification:

$$Y_{t,n} = \sum_{n=1}^{N} \delta_n \,\text{edum}_{t,n} + \sum_{j=1}^{J} \lambda_j I_j(t,\ n) + \theta\ \text{tred}_{t,n} + \varepsilon_{t,n}. \tag{1}$$

The first term on the right side, $\text{edum}_{t,n}$, is the indicator variable that takes on the value of 1 during interval n on day t, and is 0 otherwise. It accounts for the intraday patterns. Since the sampling interval is 10 minutes, there are $n = 48$ number of intraday intervals per day. The variable $I_j(t,\ n)$ is the announcement indicator for event j that begins during interval n on day t. The details of its construction are provided below. The variable $\text{tred}_{t,n}$ takes on the value of $((t-1) \times 48 + n)/11760$, $t = 1, \ldots, 245$, $n = 1, \ldots, 48$. It captures the time series trend in the dependent variables. After examining (1) in this section, we use its residuals for analyses of volatility–volume relations in Section 5.

Estimation of the announcement effects is more complicated. This is because the dynamic response of $Y_{t,n}$ to an announcement may occur over several intervals. Estimation of this dynamic response pattern is also made difficult by the small number of specific announcements. For example, with monthly announcements there are only 12 events during 1998. We adopt the parsimonious approach of Andersen and Bollerslev (1998) to address these problems. They impose a reasonable decay structure on the response pattern and simply estimate the degree to which the event "loads onto" this pattern to capture the gradual dissipating announcement effects. We are able to represent the response pattern with a third-order polynomial:

$$\begin{gathered} I_j = c_0 \cdot [1-(i/q)^3] - c_1 \cdot [1-(i/q)^2] \cdot i + c_2 \cdot [1-i/q] \cdot i^2, \\ i = 0, 1, 2, \ldots q, \end{gathered} \tag{2}$$

where q is the response horizon. Based on some experiments, we set q to be 1 hour or six 10-minute intervals ($q = 6$), for volume, frequency, and size and 30 minutes, or three 10-minute intervals, for volatility and spread ($q = 3$). Given the small number of specific announcements, we estimate a common response pattern (c_0, c_1, c_2) for all the announcements. This is accomplished by estimating (1) without the λ_j coefficients but after substituting (2) into (1). Substitution of the estimated (c_0, c_1, c_2) coefficients into (2) then provides the common response patterns used in estimating (1). In this second estimation of (1), the λ_j coefficients that load onto the pattern are estimated for individual announcements, although we fix the response pattern. The process is repeated separately for volume, frequency, size, volatility, and spread.

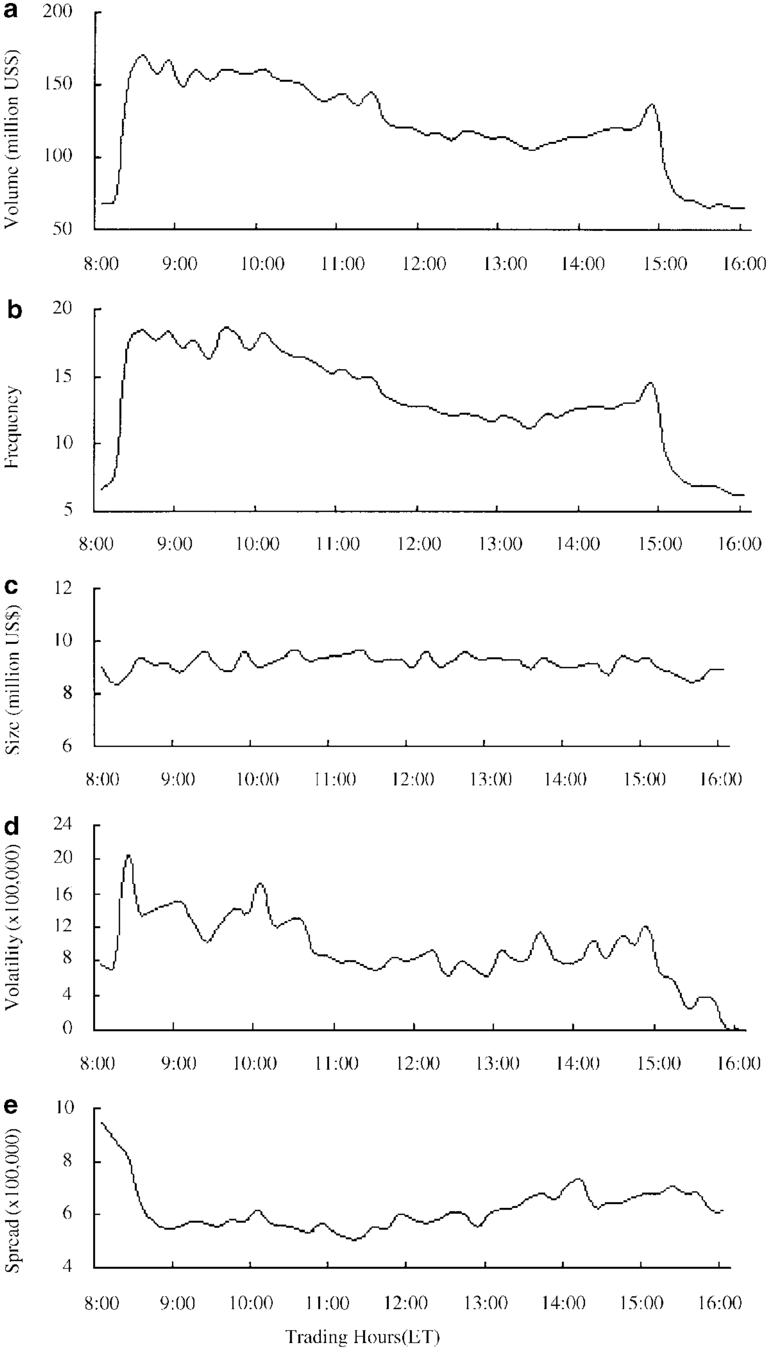
4.2. *Empirical Results*

Figure 1 plots the estimated intraday seasonal loading coefficients δ_n. Almost all of the 48 intraday dummy indicators are highly and fully significant. Figure 1a charts the trading volume pattern. Dollar volume begins to ascend steeply at the start of New York trading at 8:00 am ET and peaks soon thereafter at 8:30. At its peak, the average 10-minute volume reaches \$171 million. It then gradually declines until 15:00 when there is a small spike, after which it falls off sharply. The peaks between 8:30 and 10:00 coincide with the release of major U.S. macroeconomic announcements. Figure 1b graphs the intraday trade frequency pattern. The pattern is almost a carbon copy of Fig. 1a. Figure 1c depicts the trade size pattern, the other component of volume. It looks nothing like Fig. 1a; it fluctuates within a fairly uniform band during the trading hours. Figure 1d exhibits the return volatility pattern. It has a configuration resembling that of volume and trade frequency, although it appears to be more jagged.

Figures 1a to 1d suggest that volatility, trading volume, and number of trades are driven by the same factors and that trade size responds to a different set of factors. A comparison of Figs. 1c and 1d also suggests that the two activities are distinct from one another. Since volatility in Treasury notes is driven by public news and dealers' private information on their inventories and order flows, the figures suggest that trade frequency increases with macroeconomic announcements and decreases in their absence. In contrast, trade size does not appear to be associated with information-based trading.

Figure 1e shows the intraday bid–ask spread pattern. Bid–ask spread is a major component of transaction cost and often serves as an important indicator of market liquidity. It is highest at the start of New York trading but drops off sharply with the public release of macroeconomic news around 8:30. It then rises gradually until the end of the trading session in New York. This pattern appears to be the opposite of that observed for volume and trade frequency and seems to be unrelated to trade size.

To analyze the impact of news in the Treasury note IDB market, we examine a total of 32 announcements. Of the 32 announcements, 23 are collected from Business Week. These 23 announcements overlap to a large degree the announcements studied by Fleming and Remolona (1997b) and Balduzzi *et al.* (2001). Fleming and Remolona also provide the full title and reporting entity for these announcements. The remaining nine announcements are auto sales, current account, factory orders, FOMC meetings, housing completion, import prices, real earnings, reserve assets, and 5-year Treasury note auction results.


a
Volume (million US$)
200
150
100
50
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
b
Frequency
20
15
10
5
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
c
Size (million US$)
12
10
8
6
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
d
Volatility (x100,000)
24
20
16
12
8
4
0
8:00
9:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
e
Spread (x100,000)
10
8
6
4
8:00
9:00
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12:00
13:00
14:00
15:00
16:00
Trading Hours(ET)

We collect the dates and release times of the 32 different macroeconomic releases from Bloomberg and Reuters News Service. Most of these announcements are released widely and virtually instantaneously at a precise time. Among the 32 regularly scheduled news releases, 12 are made at 8:30 am ET. This list contains the employment report, consumer price index, durable goods orders, housing starts, leading indicators, initial jobless claims, trade balance, producer price index, retail sales, personal income, employment costs, and gross domestic product. Twelve of the announcements are made at 10:00 am ET, covering business inventories, construction spending, consumer confidence, NAPM survey, new single-family home sales, factory inventories, existing home sales, productivity and costs, current account, housing completion, import prices, and real earnings. The remaining eight announcements are industrial production (9:15), the Beige book and auto sales (12:00), 5-year Treasury note auction results (13:30), the federal budget (14:00), FOMC meetings (14:15), and consumer installment credit and reserve assets (15:00). With the following exceptions, all announcements are monthly. Current account and employment costs are released quarterly. Initial jobless claims are announced weekly. In 1998, the issuance frequency for the 5-year note was reduced from monthly to quarterly and was auctioned eight times. The Beige book is released eight times per year on the same cycle as FOMC meetings. The preliminary and final reports on productivity and costs are released each quarter, resulting in a total of eight announcements per year.

Table II.A summarizes the empirical results reported in more detail in Table II. B. Table II.A reports only the number of positive, significantly positive, negative, and significantly negative loading coefficients λ_j, as well as the three most important announcements for volume, frequency, size, volatility, and spread. There are very few significantly negative coefficients for the five variables. This is in sharp contrast to the positive coefficients. For example, 28 out of 32 announcements positively impact volume, with 10 being highly significant. Among the 32 announcements, employment report and employment costs are by far the two most important announcements for volume, frequency, volatility, and spread.

To gauge the economic significance of the macroeconomic announcements, we measure the instantaneous impact by $\lambda_j c_0$. Using the employment report as an example, the estimated loading coefficient $\hat{\lambda}$ for volume equals 6.031 and estimated c_0 equals 29.7, which translates into an immediate volume increase of (6.031)(29.7) or \$179 million in the 10-minute interval on days when an

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FIG. 1. Five-year Treasury note 10-minute intraday patterns. Estimated intraday seasonal loading coefficients δ_n in Eq. (1) are plotted for (a) trade volume, (b) trade frequency, (c) trade size, (d) return volatility, and (e) bid–ask spread. The sample period is from January 2, 1998 to December 31, 1998 for a total of 245 trading days. Ten-minute volume, frequency, size, volatility, and spread are constructed between 8:00 and 16:00 ET, resulting in 48 intraday observations per trading day. Volume is the par value quantity of securities traded in each 10-minute interval. Frequency is the number of trades. Size of trade is volume divided by frequency. Volatility is measured by the absolute 10-minute return during the interval. Bid-ask spread is the average of all quoted spread within the interval.

TABLE II.A
Macroeconomic Announcement Effects

	Positive	Significant positive	Negative	Significant negative	Three most important announcements
Trade volume	28	10	4	1	Employment report, employment costs, construction spending
Trade frequency	29	17	3	1	Employment report, employment costs, Beige book
Trade size	17	0	15	2	Reserve assets, consumer credit, factory orders
Return volatility	21	11	11	1	Employment report, employment costs, NAPM survey
Bid–ask spread	26	12	6	3	Employment report, employment costs, PPI

Note. The table reports the distribution of the estimated macroeconomic announcement effects (λ coefficients) for volume, frequency, trade size, volatility, and bid–ask spread. The sample period is from January 2 1998 to December 31, 1998. For volume, frequency, and trade size, the announcement response pattern is approximated by a third-order polynomial restricted to reach zero at the end of 1 hour response horizon or the 6th 10-minute interval. For volatility and spread, the response horizon is restricted to be 30 minutes. The λ coefficients measure the extent to which the variables load onto this pattern. A total of 32 macroeconomic news is included in the sample. They are CPI, durable goods orders, housing starts, leading indicators, initial jobless claims, trade balance, employment report, PPI, retail sales, industrial production, business inventories, construction spending, consumer confidence, NAPM survey, new single-family home sales, personal income, federal budget, consumer installment credit, auto sales, existing home sales, employment costs, productivity and costs, GDP, Beige book, current account deficit, factory orders, FOMC meetings, housing completion, import prices, real earnings, reserve assets, and 5-year Treasury note auction results.

employment report is released. Similar calculations show that the immediate increase in frequency is 19.7 trades, compared to 18.5 trades on nonannouncement days. The immediate elevation of volatility is 0.0941%, which is about seven times the level of 0.0136% on nonannouncement days. Finally, the spread widens by 0.0121%, compared to the spread of 0.0064% on nonannouncement days.

Similar to the intraday patterns, the results presented in Table II.A suggest the dichotomous nature of the two volume components. Trade frequency responds positively to 29 announcements with 17 being highly significant. In contrast, trade size responds positively to 17 announcements but none are significant. Whereas trade frequency reacts negatively to only three announcements, trade size reacts negatively to 15 announcements, only two of which are significant. Additionally, if trade size is impacted by any announcement, it should respond to the employment report most significantly. Of all the announcements, employment report is considered the "king of the kings" and affects virtually all markets. The employment report is conspicuously absent from the list of important announcements for trade size. These results indicate that public announcements have significant and positive directional influence on trade frequency but little impact on trade size.

The evidence suggests that trade frequency is associated with information-based trading, whereas trade size is not.

The observed relation between trade frequency and news releases may be affected by the difference between a trade and an order. Specifically, a trade in the GovPX data set may be an outcome of an order from one particular dealer interacting with one or several orders on the other side. The brokers that contribute to the GovPX data also allow iceberg orders, whereby the execution of a particular order can take some time as the order goes through a so-called "workup" process. This process involves bilateral negotiations between parties for additional

TABLE II.B
Effects of Individual Macroeconomic Announcements

Panel A: Macroeconomic announcement effects on trade frequency and trade size

	Trading volume		Trade frequency		Trade size	
Announcements	Coeffs.	T-stats.	Coeffs.	T-stats.	Coeffs.	T-stats.
Employment report	6.031	8.01**	4.927	14.18**	0.228	0.33
Employment costs	4.934	3.65**	3.234	5.29**	0.924	0.79
Beige book	1.512	2.72**	2.113	4.19**	−1.192	−1.48
Construction spending	2.892	2.74**	2.110	5.16**	0.782	0.44
PPI	1.794	3.50**	1.893	5.54**	−0.013	−0.02
Single-family home sale	1.487	2.83**	1.545	4.50**	−0.867	−1.10
Retail sales	1.731	3.33**	1.462	3.75**	0.570	0.73
CPI	1.844	2.72**	1.398	3.70**	−0.361	−0.49
Housing starts	0.858	1.39	1.162	3.44**	−1.047	−1.31
Federal budget	1.216	2.58**	1.089	2.75**	0.814	1.05
Current account	0.316	0.41	0.881	1.55	−1.575	−1.98**
Trade balance	0.862	1.61	0.807	2.78**	−0.009	−0.01
5-year note auctions	0.666	1.46	0.771	2.54**	−0.280	−0.30
GDP	1.373	2.39**	0.761	2.17**	0.756	1.20
NAPM survey	0.416	0.39	0.755	1.79*	−0.788	−0.46
Durable goods orders	0.767	1.49	0.736	2.03**	0.681	0.90
Housing completion	0.475	0.75	0.662	1.72*	−0.965	−1.44
FOMC meetings	0.478	0.83	0.601	1.28	0.436	0.46
Existing home sales	0.543	1.20	0.464	1.39	0.026	0.04
Initial jobless claims	0.123	0.40	0.347	1.67*	−0.566	−1.26
Productivity and costs	0.047	0.08	0.332	1.05	−0.338	−0.31
Real earnings	−0.082	−0.14	0.294	0.67	−1.730	−2.42**
Import prices	0.527	1.11	0.281	0.93	0.211	0.22
Industrial production	0.038	0.09	0.239	0.72	0.310	0.37
Personal income	0.043	0.10	0.226	0.62	0.029	0.04
Reserve assets	0.990	1.32	0.189	0.50	1.862	0.94
Factory orders	0.701	1.41	0.175	0.59	1.322	1.61
Consumer confidence	0.255	0.38	0.097	0.22	−0.559	−0.77
Business inventories	−0.662	−1.22	0.038	0.10	−1.210	−1.63
Leading indicators	0.290	0.48	−0.136	−0.35	0.037	0.04
Instalment credit	−0.224	−0.48	−0.145	−0.49	1.679	1.07
Auto sales	−1.502	−3.57**	−1.227	−4.39**	0.336	0.29

TABLE II.B—*Continued*

Panel B: Macroeconomic announcement effects on return volatility and bid–ask spread

Announcements	Return volatility		Bid–ask spread	
	Coefficients	Robust T-stats.	Coefficients	Robust T-stats.
Employment report	8.848	3.50**	6.068	6.15**
Employment costs	8.406	1.99**	5.005	3.73**
Beige book	1.392	1.84*	0.929	2.13**
Construction spending	−0.942	−0.46	0.933	0.95
PPI	2.573	2.66**	2.848	4.21**
New single-family home sales	1.973	1.67*	1.487	2.56**
Retail sales	1.323	1.42	2.528	4.40**
CPI	0.486	0.60	1.633	2.75**
Housing starts	1.127	1.67*	0.803	2.18**
Federal budget	0.246	0.52	−0.768	−1.49
Current account	−0.592	−1.21	0.336	0.36
Trade balance	1.429	2.36**	0.473	1.11
5-year Treasury note auction results	1.331	2.14**	0.610	1.24
GDP	3.400	2.56**	1.528	2.40**
NAPM survey	5.984	2.87**	1.768	1.80*
Durable goods orders	0.123	0.19	1.080	1.98**
Housing completion	0.145	0.24	0.898	0.83
FOMC meetings	−0.131	−0.34	−0.648	−1.69*
Existing home sales	0.307	0.48	0.728	1.45
Initial jobless claims	−0.545	−1.20	0.169	0.41
Productivity and costs	−0.598	−1.18	−0.026	−0.04
Real earnings	0.183	0.26	0.817	1.35
Import prices	−0.187	−0.42	0.098	0.17
Industrial production	−0.194	−0.42	0.664	1.17
Personal income	1.432	1.90*	0.516	0.89
Reserve assets	0.102	0.16	−1.135	−1.73*
Factory orders	−0.018	−0.03	0.291	0.57
Consumer confidence	−0.466	−0.76	0.522	0.98
Business inventories	1.260	1.23	0.966	1.94*
Leading indicators	−0.553	−0.74	−0.340	−0.54
Consumer installment credit	0.181	0.40	0.290	0.29
Auto sales	−0.852	−3.39**	−0.778	−2.39**

Note. The table reports the estimated macroeconomic announcement effects (λ coefficients) and robust t-statistics for trading volume, trade frequency, trade size, volatility, and bid–ask spread. The sample period is from January 2, 1998 to December 31, 1998 for a total of 11,760 obervations. The regression takes the form of Eq. (1), where the $I_j(t,n)$ regressors refer to the prespecified volatility response patterns associated with a news announcement. For trading volume, trade frequency, and trade size, the announcement response pattern is approximated by a third-order polynomial restricted to reach zero at the end of the response horizon of 1 hour, or the 6th 10-minute interval. For volatility and spread, the response horizon is restricted to be 30 minutes. A total of 32 macroeconomic announcements are included in the sample. In both Panels A and B, the macroeconomic announcements are ranked according to the estimated λ coefficients from trade frequency. * indicates significance at the 10% level; ** indicates significance at the 5% level.

liquidity. During periods of heightened information flow, such as those surrounding macroeconomic announcements, dealers involved in a trade may be reluctant to waste time negotiating workups.[26] Consistent with this view, Boni and Leach (2001) find that large trades are less likely to consist of more than one workup during the hour following macroeconomic news announcements. Therefore, order splitting may have contributed to an increase in the frequency of trades as measured by the GovPX data following news announcements. This possibility is attenuated by the fact that trade size appears to be fairly stable throughout the New York trading hours and does not appear to be materially different around news releases.

Figure 2 plots the estimated response patterns over the entire response horizon for the three most important announcements.[27] They show that the announcement effects on volume, frequency, and size dissipate gradually over the entire 1-hour horizon. In contrast, the effects on volatility and spread dissipate much faster, requiring only half as much time.

The last term in (1) is the trend term. During 1998, the trend coefficient is significantly negative for volume, frequency, and size of trade. For the same time period, it is significantly positive for volatility and spread.

4.3. Announcements Effects and Private Information-Based Trading

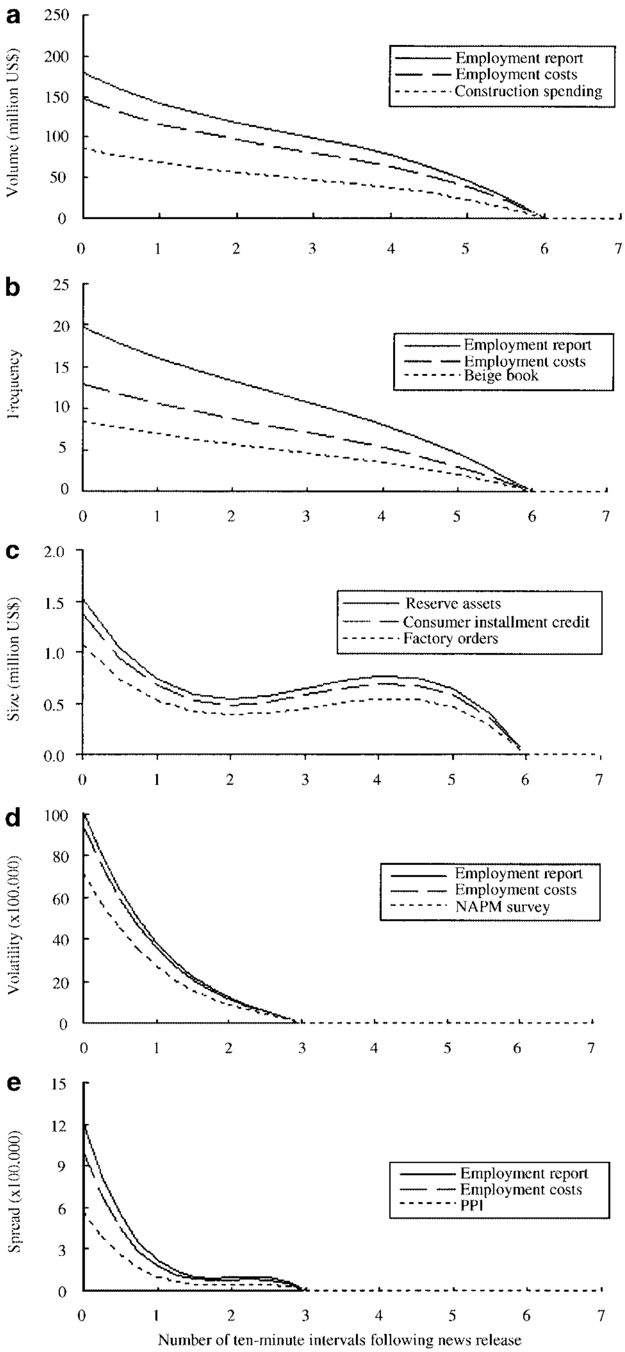
In the previous section, our analyses of announcement effects suggest that news releases are accompanied by more frequent trading. In this section, we examine two types of private information that motivate more frequent trading around announcements: Dealers knowledge of their private inventories and order flows and superior processed information stimulated by news releases. Green (2001) investigates the same two types of private information by examining spread components around economic announcements. We use a different methodology and approach by examining the duration of the spread components around macroeconomic news releases.

There is a sizable literature that examines spread components.[28] The spread is generally thought of as consisting of three components that compensate the liquidity suppliers for the costs of processing their order, of holding inventory, and of trading with informed traders. The latter is often referred to as the adverse information or adverse selection cost and measures the loss to a liquidity supplier from trading with someone with private information. Green (2001) uses a specific model of spread decomposition to arrive at the components. We apply the model-free approach of Huang and Stoll (1996) that is generally applicable. This requires

[26] Dealers who are stuck in a queue are more likely to jump to another system to get their trade done.

[27] The detailed estimates of (c_0, c_1, c_2) for volume, frequency, size, volatility, and spread used in the paper are available from the authors upon request.

[28] See, for example, Huang and Stoll (1997).


a
Volume (million US$)
Employment report
Employment costs
Construction spending
b
Frequency
Employment report
Employment costs
Beige book
c
Size (million US$)
Reserve assets
Consumer installment credit
Factory orders
d
Volatility (x100,000)
Employment report
Employment costs
NAPM survey
e
Spread (x100,000)
Employment report
Employment costs
PPI
Number of ten-minute intervals following news release

defining two additional spreads,

$$\text{Effective Half-Spread} = |p_t - q_t|$$

$$\text{Realized Half-Spread} = \begin{cases} (p_{t+\tau} - p_t) \mid (p_t = \text{bid}_t) \\ -(p_{t+\tau} - p_t) \mid (p_t = \text{ask}_t), \end{cases}$$

where p_t is the trade price at time t, q_t is the midpoint of the prevailing quotes at the time of the trade, and τ is not less than 5 minutes. The effective spread differs from quoted bid–ask spread in that it accounts for trades at the inside of the bid and ask quotes. The realized spread measures the amount earned by liquidity suppliers when prices reverse. An estimate of the adverse selection component is then the difference between the average effective spread and the average realized spread.

Following a public announcement, the level of asymmetric information may increase for two reasons. First, according to Kim and Verrecchia (1994), the release of public news enables some information processors to generate private information. Given the level of competition among information processors, the resultant informed trading tends to concentrate in the immediate aftermath of an announcement. This suggests an increase in adverse selection component that dissipates rapidly after an announcement. Second, trading induced by private knowledge of inventory and order flows following a news release may influence trading over a longer time interval as dealers trade to reach their desired inventory levels. This suggests a more sustained increase in adverse selection component after an announcement. We examine the adverse selection component 15 and 30 minutes before and after important announcements and focus on whether trading based on information of order flows and inventories is prevalent. Green (2001) also examines the same two motivations we consider and concludes that the evidence suggests trading based on private information of customer order flows and inventories rather than trading based on privately generated information asymmetry among bond dealers. His analysis focuses on relating the price effect of announcements to the adverse selection component of the spread.

Our results are presented in Table III. In Panel A, we report the effective spreads and adverse selection components 15 and 30 minutes before and after important announcements. In Panel B, we show the results for the control sample of nonannouncement days. For announcements at 8:30, 10:00, and 14:00, Panel A shows adverse selection components that are significantly higher following announcements. This is observed not only for 15 minutes but also for 30 minutes

FIG. 2. Estimated response patterns. Estimated response pattern $\hat{\lambda}_j \cdot I_j(t, n)$ in Eq. (1) is plotted from three most important announcements, respectively, for (a) trade volume, (b) trade frequency, (c) trade size, (d) return volatility, and (e) bid–ask spread. The gradual dissipating announcement effects are represented by a third-order polynomial as in Eq. (2). The response horizon q is set to be 1 hour or six 10-minute intervals ($q = 6$), for volume, frequency, and size and 30 minutes or three 10-minute intervals, for volatility and spread ($q = 3$). Given the small number of specific announcements, we estimate a common response pattern (c_0, c_1, c_2) for all the announcements.

TABLE III

Effective Spreads and Adverse Information around Announcements

	15 minutes before and after release time		30 minutes before and after release time	
	Before	After	Before	After
Panel A: Announcement Days				
Trading days with 6 most significant announcements at 8:30				
Effective spread	0.0043	0.0060**	0.0044	0.0050**
Adverse information	0.0033	0.0080**	0.0047	0.0070*
Observation	1,354	2,625	2,078	5,063
Trading days with 3 most significant announcements at 10:00				
Effective spread	0.0036	0.0049**	0.0037	0.0042**
Adverse information	0.0055	0.0094**	0.0053	0.0098**
Observation	913	1,452	2,034	2,735
Trading days with 2 most significant announcements at 14:00				
Effective spread	0.0042	0.0047	0.0041	0.0045*
Adverse information	0.0017	0.0122**	0.0060	0.0094**
Observation	429	490	899	985
Panel B: Nonannouncement Days				
Trading days without announcements at 8:30				
Effective spread	0.0041	0.0036**	0.0042	0.0035**
Adverse information	0.0051	0.0057	0.0060	0.0065
Observation	2,620	3,198	3,827	6,323
Trading days without announcements at 10:00				
Effective spread	0.0039	0.0041	0.0039	0.0040*
Adverse information	0.0078	0.0081	0.0074	0.0074
Observation	3,501	3,627	7,196	7,118
Trading days without announcements at 14:00				
Effective spread	0.0040	0.0040	0.0040	0.0041
Adverse information	0.0060	0.0064	0.0065	0.0059
Observation	3,880	4,019	7,667	8,163

Note. This table reports effective half-spreads, realized half-spreads, and adverse information components around macroeconomic announcements. The effective half-spread is defined as $|p_t - q_t|$, where p_t is the transaction price and q_t is the midpoint of the prevailing quote at the time of the trade. The realized half-spread is defined as the price change for initial trades at the bid and negative of the price change for initial trades at the ask. The realized half-spread is calculated for time horizon not less than 5 minutes. The adverse information components are calculated as the difference between the effective and realized half-spreads. To examine the changes in spreads around macroeconomic announcements, the table focuses on (1) the six most significant announcements at 8:30: employment report, employment costs, PPI, retail sales, CPI, and housing starts; (2) three significant announcements at 10:00: construction spending, new single family home sales, and NAPM survey; (3) two significant announcements at 14:00: Beige book and federal budget. These 11 announcements have the strongest impact on trade frequency as reported in Table II.B. Panel A reports the results for 15 and 30 minutes before and after the release time on announcement days. Panel B reports the corresponding numbers on nonannouncement days. The nonannouncement days exclude all announcements at a particular time (8:30 for example), including those that do not belong to the list of 14 announcements examined here. The table also reports the standard t-tests that compare the spreads and their components before and after the news release. * indicates significance at the 10% level while ** indicates significance at the 5% level.

after announcement times. For the control sample results in Panel B, none of the adverse selection components are significantly different 15 and 30 minutes before and after announcements. The persistent increase in adverse information after announcements supports the presence of trading based on private knowledge of inventory and order flow.

5. VOLATILITY AND VOLUME

This section examines whether the behavior of return volatility is consistent with an uninformative trade size and a close association between trade frequency and information-based trading. To seek evidence that goes beyond the fixed effects examined in the previous section, we use an empirical model that explicitly accounts for the presence of intraday seasonalities, announcement effects, and time trends. In addition, our setup accounts for the effects of short-run predictable components in the market.

5.1. Hypothesis

To explain the empirically documented positive volatility–volume relation in equity markets, several information-based models have been proposed. The earliest explanation states that the positive association arises when both volume and volatility are affected by information arrival (mixture of distribution models). Later explanations delve into the nature of the information. in asymmetric information models, the positive relation is observed when trading by market participants with private information occurs. In dispersion of beliefs models, the relation is induced by information arrival that causes differences of opinion. Models by Harris and Raviv (1993) and Shalen (1993) show that price volatility is positively associated with greater dispersion of beliefs. We address the role of information-based trading as highlighted in these models.

We hypothesize that the number of trades is positively related to return volatility. This is because if more frequent trading were motivated by differential access to information, it would be associated with higher volatility. If the increase in the number of trades were due to liquidity trading as opposed to information-based trading, it would not lead to an increase in dispersion of traders' beliefs or higher level of asymmetric information, and the hypothesis would be rejected. Harris (1987) and Tauchen and Pitts (1983) also relate the number of trades to the number of information events but they do so in the context of mixture of distribution models. As for trade size, if it were uninformative, it would not be associated with heightened volatility.

5.2. Estimation Procedure

For simplicity, let the residuals in (1) have the same variable names as in Y_t but without the subscript n. We use the following set of equations to capture the dynamics of volume and volatility in the IDB market:

$$\begin{aligned}\text{vom}_t &= a_{10} + \sum_{k=1}^{K} b_{1k}\text{vom}_{t-k} + \sum_{k=1}^{K} c_{1k}\text{vol}_{t-k} + e_{1t} \\ \text{vol}_t &= d_0 + d_1 E_{t-1}(\text{vom}_t) + e_{2t}.\end{aligned} \tag{3}$$

The first equation assumes that conditional expectations of volume are linear functions of lagged volume and volatility variables, vom_{t-k} and vol_{t-k}. This specification captures the short-run predictable variation in volume. The formulation is motivated by earlier studies which show that lagged volume and volatility have significant power in predicting current volume. The second equation states the volatility–volume relation. The conditional expectation operator E_{t-1} is based on the information available at $t-1$, which contains all lagged variables. We begin our analysis with the two-equation system (3) and then examine systems whereby volume is replaced with either frequency (frq_t) or size (siz_t). We also examine a three-equation system, which relates volatility to trade frequency and trade size simultaneously. For the expanded system, there are two prediction equations, one for frq_t and the other for siz_t, each having lagged vol_t, frq_t, and siz_t as predetermined variables in the equation.

We employ Hansen's (1982) generalized method of moments (GMM) to obtain the estimates in the system of equations simultaneously.[29] The instruments used in the estimation are the predetermined variables specified on the right-hand side of the prediction equations. To illustrate, for the two-equation system, there are 17 predetermined variables, namely eight lagged values of volume and volatility and a vector of ones. The number of orthogonal moment conditions is 34. To ensure a positive definite matrix, we use the Newey and West (1987) robust estimation procedure. To begin the nonlinear GMM estimation, the initial parameter estimates for the prediction equations are obtained using ordinary least squares (OLS). The starting value of d_1 is obtained by substituting the predicated volume, $E_{t-1}(\text{vom}_t)$, into the volatility equation and estimating it by OLS.

Before proceeding with the estimation, we first conduct a series of unit root tests to assess the stationarity of the time series employed. We use the Dickey–Fuller (1979) test and the Phillips and Perron (1988) nonparametric test. Both the t test and the $T(\rho - 1)$ test with and without a trend variable strongly reject the null hypothesis of a unit root for all the time series we examine. We then use the Schwarz (1978) criterion to determine the appropriate lag K in the system of equations. Under the Schwarz criterion, the optimal number of lags should minimize the loss function $SC(k) = T \cdot \log(|\Sigma(k)|) + k \cdot M^2 \cdot \log(T)$, where $\Sigma(k)$ is the estimated covariance matrix of the error term, k is the number of lags in the system, $M = 2$ and 3, respectively, for a two- and three-equation system, and T is the number of

[29] In principle, the loading coefficients in (1) can be estimated jointly with the parameters in the two- or three-equation system. However, this is impractical since convergence proves to be a problem for estimating the vastly increased number of parameters.

TABLE IV
Volatility and Volume

System	1	2	3	4
Constant	−0.957	−0.750	−0.023	−0.543
	(−4.01)	(−3.48)	(−0.03)	(−2.40)
Trade volume	0.193			
	(19.10)			
Trade frequency		1.783		1.661
		(25.83)		(23.29)
Trade size			−17.537	−2.104
			(−9.76)	(−6.32)
Adjusted R^2	0.122	0.132	0.149	0.130

Note. The table reports the results of estimating the volatility–volume relation by GMM. The sample period is January 2, 1998 to December 31, 1998 for a total of 245 trading days. We construct 10-minute trade volume, trade frequency, trade size, return volatility, and bid–ask spread variables for data between 8:00 and 16:00 ET. This results in a total of 48 intraday observations per trading day. Volume is the par value quantity of securities traded within the 10-minute interval. Frequency is the number of trades within the 10-minute interval. Trade size is volume divided by frequency. Volatility is measured by the absolute 10-minute return during the interval. All variables are adjusted for intraday patterns, announcement effects, and time trends. Systems 1, 2, and 3 are two-equation systems and System 4 is a four-equation system. The table only reports the estimated parameters, the t-values in parentheses, and adjusted R^2s for the volatility equation. Estimation results from the prediction equations are not reported.

intraday observations. Our results show that for two- and three-equation systems, the optimal number of lags is eight and six, respectively.

5.3. *Empirical Results*

Table IV reports the estimation results for the volume–volatility relation. The first three systems provide the estimation results of the two-equation system and the fourth system presents the results for the three-equation system. In all cases, only the results of the volatility–volume equation are reported and the parameter estimates of the prediction equations are not shown.

The first system shows that return volatility and trading volume are positively related after accounting for various fixed and predictable regularities and conditional expectations. Thus, the positive volatility–volume relation, documented by numerous studies for the equity markets, is also observed for the Treasury note IDB market.

Systems 2 and 3 examine the individual components of trading volume. The results show that the positive relation observed for the first model holds true only for trade frequency and not for trade size. System 3 exhibits a significant negative relation between volatility and trade size even without controlling for trade frequency. System 4 shows that the asymmetry between the two volume components

TABLE V
Volatility and Volume during Morning and Afternoon Periods

System	1	2	3	4
	Panel A: 8:00–11:00 morning period			
Constant	−1.250	−0.880	−1.359	−1.217
	(−2.44)	(−1.88)	(−1.77)	(−2.84)
Trade volume	0.192			
	(10.29)			
Trade frequency		1.724		1.542
		(13.74)		(11.56)
Trade size			−8.706	−0.890
			(−6.23)	(−1.22)
Adjusted R^2	0.138	0.140	0.118	0.124
	Panel B: 12:00–16:00 afternoon period			
Constant	−1.289	−1.078	0.676	−0.587
	(−4.34)	(−4.21)	(0.74)	(−1.97)
Trade volume	0.203			
	(15.63)			
Trade frequency		1.786		1.767
		(19.64)		(18.14)
Trade size			−15.288	−2.637
			(−8.90)	(−6.56)
Adjusted R^2	0.103	0.119	0.146	0.133

Note. The table reports the results of estimating the volatility–volume relation for high and low volatility periods by GMM. The sample period is January 2, 1998 to December 31, 1998 for a total of 245 trading days. We construct 10-minute trade volume, trade frequency, trade size, return volatility, and bid–ask spread variables for data between 8:00 and 16:00 ET. This results in a total of 48 intraday observations per trading day. Volume is the par value quantity of securities traded within the 10-minute interval. Frequency is the number of trades within the 10-minute interval. Trade size is volume divided by frequency. Volatility is measured by the absolute 10-minute return during the interval. All variables are adjusted for intraday patterns, announcement effects, and time trends. Systems 1, 2, and 3 are two-equation systems and System 4 is a four-equation system. The table only reports the estimated parameters, the t-values in parentheses, and adjusted R^2s for the volatility equation. Estimation results from the prediction equations are not reported.

is preserved when both components are present. The relations in System 4 are also economically meaningful. A coefficient of 1.661 for number of trades means that ten trades are associated with an 87% increase in volatility relative to its mean. A coefficient of −2.104 for trade size implies that a \$1 million increase in trade size is associated with an 11% decline in volatility relative to its mean level.[30]

[30] The increase in volatility for an increase of one trade is calculated as (1.661/100,000)(1/0.000191) = 8.7%. The slope coefficient of 1.661 is deflated by 100,000 because return volatility is scaled up 100,000 times. Similarly, the decrease in volatility due to an increase in \$1 million trade size is computed as (−2.104/100,000)(1/0.000191) = 11.0%.

The evidence suggests that trade frequency reflects the presence of information-based trading. On the other hand, trade size is associated with lower volatility and not higher volatility. Since information-based trading would increase volatility, this indicates that changes in trade size are not induced by information arrival. To gain further insight into the negative relation between trade size and volatility, we split the sample into morning and afternoon trading periods. The morning period is from 8:00 to 11:00 am and covers the release of the vast majority of macroeconomic news.[31] The afternoon period is from noon to 4:00 pm and is the less volatile period. The results are reported in Table V. The estimation of System 4 for these two separate periods shows that the only inference that is different from that in Table IV relates to the trade size coefficient. Specifically, Panel A shows that during the more hectic morning hours, trade size is insignificantly related to return volatility once we control for trade frequency. If trade size contains information its impact on volatility should be most apparent during the morning hours but the result shows no such effect. The insignificant trade size coefficient is similar to that observed by Jones *et al.* (1994) for the Nasdaq market. During the less volatile afternoon trading hours, the coefficient and t-statistic are similar to those reported in Table IV.

The earlier literature on the volatility–volume relation focuses on equity markets and the first stage retail transactions. We have examined the second-stage trading between primary dealers in the IDB market. In a recent paper, Daigler and Wiley (1999) characterized the volume in futures market by data type and find that the volatility–volume relation is positive for public traders but negative for clearing members and floor traders. We focus only on trading by primary dealers and find that even for one set of traders, the components of volume are differentially related to return volatility.

6. CONCLUSIONS

We have examined the interdealer broker-mediated Treasury note market using GovPX data. Our empirical results reveal a surprising dichotomy in the behavior of the two components of volume, namely trade frequency and trade size. Specifically, the results suggest that trade frequency is motivated by information-based trading while trade size has no information content. We support these results by examining intraday patterns, announcement effects, and volatility–volume relations.

Dealers trade more frequently when motivated by the arrival of public and private information. This is supported by several findings:

(1) Return volatility and trade frequency have similar intraday patterns. For example the patterns peak around the time when macroeconomic news are announced.

[31] We are looking for effects beyond the announcement effects since we have already accounted for the macroeconomic effects during the first stage of our estimation.

(2) Trade frequency reacts positively to major macroeconomic news.
(3) Increased trade frequency is associated with increased return volatility.

Dealers' trade size has no information content. This is supported by the results of several analyses:

(1) Trade size has a fairly uniform pattern over the New York trading day.
(2) Trade size is unaffected by major macroeconomic announcements.
(3) Trade size is not positively associated with return volatility.

Despite its pervasive presence in world financial markets, there are few studies of interdealer broker markets. Our analysis of the 5-year Treasury note interdealer broker market reveals volatility–volume relations similar to that observed by Jones *et al.* (1994) for the Nasdaq equity market. In our case, trade size is uninformative in an anonymous market without market makers and the evidence is consistent with the presence of information-based trading.

Our results also reveal intraday patterns and announcement effects that are consistent with the disparate behavior of trade frequency and trade size. Others have examined the effect of announcements on volume, volatility, and spread. However, our approach permits gradual dissipating announcement effects and we incorporate additional factors in examining volatility. Last but not least, we focus on the components of volume in analyzing announcement effects.

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