Economic News and the Impact of Trading on Bond Prices

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Abstract

This paper studies the impact of trading on government bond prices surrounding the release of macroeconomic news. The results show a significant increase in the informational role of trading following economic announcements, which suggests the release of public information increases the level of information asymmetry in the government bond market. The informational role of trading is greater after announcements with a larger initial price impact and the relation is associated with the surprise component of the announcement and the precision of the public information. The results provide evidence that government bond order flow reveals fundamental information about riskless rates.

When some market participants have private information about the value of an asset, their trades reveal information to the market. In equilibrium, the sensitivity of prices to order flow will depend on the prevailing level of information asymmetry. This concept was first formalized by Glosten and Milgrom (1985) and Kyle (1985), and since that time many researchers have sought to characterize the link between information asymmetry and the impact of trading on prices. This paper studies transaction data from the U. S. Treasury market in order to clarify the informational role of trading in financial markets.

In equity markets, private information is traditionally considered to be advanced knowledge of a firm's cash flows. For example, Koski and Michaely (2000) find that trades preceding dividend announcements have a larger than usual impact on prices. On the other hand, Kim and Verrecchia (1994, 1997) suggest that public information releases may actually increase information asymmetry if market participants differ in their ability to interpret the news. Krinsky and Lee (1996) offer empirical support for this type of private information, finding that the informational role of trading increases after earnings announcements.

Research in currency markets supports a broader view of information asymmetry. Peiers (1997) shows that Deutsche Bank is a price leader prior to German central bank interventions, and Ito, Lyons, and Melvin (1998) provide evidence that Japanese banks are perceived as informed traders in yen currency markets. Lyons (1995) and Cao, Evans, and Lyons (2002) suggest that information asymmetry in FX markets arises from dealers' private access to customer order flow, which could help predict short-term exchange rate movements. Evans and Lyons (2002) and Evans (2002) argue that order flow may perform a more important function, informing market participants about economic fundamentals.

Government bond markets provide an opportunity to clarify the relation between information asymmetry and the informational role of trading. U.S. Treasury securities have fixed and virtually riskless cash flows. Does order flow reveal information in a market with no private information about cash flows? If so, what is the source of the information asymmetry? This paper addresses these issues by studying the impact of trading on government bond prices surrounding the release of macroeconomic news. The informational role of trading is measured using a structural model to infer the asymmetric information component of the effective bid-ask spread. The approach, a generalized version of Madhavan, Richardson, and Roomans (1997), allows the informational role of trading to vary with characteristics of the announcement.

Although microstructure models have been used extensively in equity and foreign exchange markets, this paper is among the first to fit a structural model to government bond transaction data.[1] Since little is known about the efficacy of this type of methodology on bond markets, I also rely on a simple nonparametric approach similar to Koski and Michaely (2000). The robustness checks confirm the effectiveness of the model at capturing variation in the informational role of trading.

I find that the sensitivity of prices to order flow is lower than usual before economic announcements, which is consistent with no information leakage. The informational role of trading increases following announcements, indicating that the release of public information raises the level of information asymmetry in the government bond market. The enhanced informational role of trading is consistent with the interpretation that some market participants have an advantage at determining how macro news influences riskless rates. On the other hand, the information asymmetry may be of a more pedestrian variety, related to inventory oriented information that is security specific. To help characterize the nature of information asymmetry in government bond markets, I examine how the informational role of trading evolves after economic news, as well as how it varies with characteristics of the announcement.

Theoretical models offer predictions of how announcement characteristics will influence the informational role of trading. In the skilled information processor models of Kim and Verrecchia (1994, 1997), the accuracy of private interpretations is unrelated to the precision of the public signal. Thus, information asymmetry is lower following more precise information releases. Alternatively, if the information asymmetry is related to inventory imbalances, an opposite relation could develop. In Cao, Evans, and Lyons' (2002) model, for example, compensation for bearing inventory risk introduces a link between order flow and prices even if customer order flow is uninformed. In the current setting, order flow may provide information as to whether a particular bond should be priced above or below the yield curve even if trading provides no fundamental information about the yield curve.[2] If announcements with greater price impacts generate more hedging demands, then dealers with sizable customer order flows will hold a greater informational advantage following more precise information releases. Thus, information asymmetry would be higher following more precise information releases.

The results indicate that announcements with greater price impacts result in a larger increase in the informational role of trading. The positive relation is associated with both the precision of the public information signal and the surprise component of the announcement. This result is more consistent with the inventory model of Cao, Evans, and Lyons (2002). Although the evidence presents a challenge to existing information processor models, these can be adapted to reflect this result. For example, in the context of the Kim and Verrecchia (1994, 1997) models, the results imply that information processors' skills improve with the surprise and precision of the public information release. Extending the models in this way seems reasonable given that economists are likely to devote more effort to interpreting economic news deemed important by the market.

The increased information asymmetry following announcements dissipates quickly, which provides more direct support for the superior information processor interpretation. Although Fleming and Remolona (1999) document that trading volume remains high for several hours after announcements, I find that the informational role of trading returns to near normal levels within fifteen minutes. The trading environment remains highly liquid during the subsequent fifteen minutes, yet prices are much less volatile and trading has a smaller impact on prices. Consequently, we might expect uninformed traders to be patient with their orders. The extended period of active trading following announcements is consistent with this hypothesis, but it makes it less likely that uncertainty regarding customers' hedging trades would be resolved quickly. Thus, the rapid reduction in the level of information asymmetry suggests that the trading immediately after announcements reveals information that extends beyond security specific information.

Taken together, the results highlight the importance of information asymmetry in the U.S. Treasury market and support the hypothesis that order flow reveals fundamental information about riskless rates. The evidence that prices are more sensitive to order flow during a period of enhanced liquidity is in contrast to the findings of Fleming (2001) and Brandt and Kavajecz (2003), who find more generally a negative relation between trade impact and liquidity. While these authors argue that low liquidity indicates periods with uncertain valuations, I find that the release of public information also generates a brief period of uncertainty regarding bond prices. The results suggest that market participants actively watch trading to help determine the effect of new economic information on riskless rates.

The remainder of the paper is organized as follows: Section I describes the transaction data from the interdealer market for U.S. Treasury securities and the macroeconomic announcement data. Section II follows with a description of the methodology for measuring the impact of trading on transaction prices. Section III presents the empirical results, and Section IV summarizes the conclusions of this study.

I. Data

A. Transaction Data for U.S. Treasuries

Secondary trading of U.S. Treasury securities takes place in an over-the-counter market. Although more than a thousand banks and securities firms operate as Treasury dealers, the majority of trading volume is facilitated by the small number of primary dealers (there were less than forty primary dealers during the sample period). In addition to participating in Treasury auctions, primary dealers provide the Federal Reserve Bank of New York with information on market conditions and facilitate the central bank's open market operations.

Interdealer trading is an integral part of the Treasury market. According to the *Federal Reserve Bulletin* (1993), approximately half of primary dealers' transactions involve other primary dealers. Unlike foreign exchange markets which also have highly active interdealer markets, virtually all trading of U.S. Treasury securities between dealers is conducted anonymously through interdealer brokers.[3] Brokers gather dealers' quote and depth information for bills, notes, bonds, and agency debt securities and post the data on proprietary computer screens that are provided to the dealers.

The transaction data is obtained from GovPX Inc. GovPX consolidates quote and trade information from the interdealer market for U.S. Treasury securities and disseminates it through information providers such as Bloomberg.[4] The dataset contains historical intraday bid and offer quotes along with transaction prices and trade sizes for all Treasury bills, notes, and bonds. One of the advantages of GovPX transaction data is that each trade is accompanied by an indication as to which side initiated the trade. Although trade size is negotiable, all brokered transactions occur at posted bid or ask quotes, which makes determining trade direction straightforward.

As in Fleming and Remolona (1997, 1999) and Boni and Leach (2002), I examine the most recently issued, or “on-the-run,” 5-year Treasury note, which is the most frequently traded bond in the GovPX sample. I focus on trading around the 8:30 a.m. ET release of macroeconomic data and restrict the sample to trades that take place between 8:00 and 9:00 a.m. The sample period spans July 1, 1991 through September 29, 1995 and includes over 75,000 trade observations.

Time stamps occur in the database every minute and each transaction is timed to the minute of the most recent time stamp. However, the time stamps often occur within in the minute (8:13:21, 8:14:21, etc.), so it is often not possible to determine which trades take place immediately before and after an announcement release. In addition, announcements may not be released at precisely 8:30 according to the GovPX clock. I account for these issues by omitting trades around announcements to ensure the price change spans the release. In particular, I omit two trades prior to 8:30 unless the trades occur before 8:28, and five trades after 8:30 unless they occur after 8:32.[5] Admittedly, this method is ad hoc but the results are not sensitive to changes in the procedure.

B. Survey and Announcement Data

The data on economic announcements is obtained from MMS International (now a subsidiary of Standard and Poor's), a widely used source of forecast data for studies of economic announcements. MMS surveys approximately forty money market economists each Friday regarding the upcoming week’s announcements and records information on the median forecast, the 25th and 75th percentile forecasts, the standard deviation of the forecasts, and the announcement realization.

Table I lists the twelve economic announcements released at 8:30 a.m. ET. I focus on a single release time in order to examine differences across announcements while controlling for time-of-day effects, and more macro announcements are released at 8:30 a.m. than any other time. Announcements are released monthly with the exception of the weekly Initial Jobless Claims figures. Table I also reports the units for each macro series. Levels are reported as units, dollars, or as percentages. Changes are reported as either absolute in units or dollars, or as a percentage change from the previous observation.

Announcement surprise is measured as the realized value minus the median survey value. As in Flannery and Protopapadakis (2002) and Balduzzi, Elton, and Green (2001), I standardize surprises to facilitate comparisons across announcements. In particular, for announcement type k on day τ the surprise is defined as:

$$S_{k\tau} = \frac{A_{k\tau} - F_{k\tau}}{\sigma_k} \tag{1}$$

where $A_{k\tau}$ and $F_{k\tau}$ are the actual value and median forecast, and σ_k is the standard deviation of $(A_{k\tau} - F_{k\tau})$. Thus, an announcement surprise equal to 1.0 implies a surprise that is one standard deviation greater than zero for that announcement type. Forecast dispersion measures are standardized in a similar manner. For each measure of dispersion I subtract the mean and divide by the standard deviation for that measure of dispersion. A dispersion measure equal to –1.0 implies that the forecast dispersion is one standard deviation smaller than the average dispersion for that announcement type.

C. Descriptive Statistics

Table II provides descriptive statistics for the transaction data. The table reports information on the variance of transaction prices (in basis points), the average number of transactions and volume per hour, the average size of each transaction, and the average quoted bid-ask spread (in basis points)[6]. The active 5-year note is heavily traded with average hourly volume measured in hundreds of millions of dollars. In the half-hour before announcements, trading intensity is lower than usual, bid-ask spreads are wider than usual, and price volatility is lower than usual. In the 15 minutes immediately following the release of the news, price volatility increases along with trading intensity and trade size. In the next 15 minutes, trading activity continues to increase while quoted bid-ask spreads narrow.

The pattern in trading, volatility, and spreads is consistent with the findings of Balduzzi, Elton and Green (2001) and Fleming and Remolona (1999). Rather than focus on the levels of volume and volatility as in previous work, in this paper I investigate how they interrelate by studying the sensitivity of prices to signed order flow. Figure 1 offers a preliminary look. The chart plots the sequence of transaction prices, designated as buyer- or seller-initiated, from 8:00–9:00 a.m. on November 4, 1994, a day on which the monthly employment number was announced at 8:30.

Although quoted bid-ask spreads are wider than usual before the announcement, the figure shows that transaction prices stay within a narrow range, suggesting a general consensus about the value of the bond. The sentiment of the news is clear in that prices fall immediately after the announcement of higher than expected employment, but the initial price response is followed by increased volatility and trading intensity. Moreover, transaction prices appear much more sensitive to a sequence of buys or sells, which suggests that market participants may be watching order flow to help interpret the news. The next section describes the methodology used to quantify the sensitivity of transaction prices to order flow.

II. Methodology

I measure the informational role of trading by isolating the component of effective bid-ask spreads that is related to information asymmetry. The approach is based on the price formation model of Madhavan, Richardson, and Roomans (1997) (MMR).[7] The MMR model is a generalized version of earlier microstructure models such as Glosten and Milgrom (1985) and Stoll (1989), and it allows the order flow to be autocorrelated, which is a feature of the bond transaction data. The MRR model attributes transaction price changes to unanticipated public information and microstructure effects, and decomposes effective spreads into absolute components rather than relative spread shares.

The model isolates the spread components by examining the relation between transaction price changes and signed order flow. For example, transaction price changes measured from a purchase followed by another purchase reflect the extent to which dealers adjust their quotes upwards in response to the information revealed by the first purchase. Transaction price changes measured from a purchase followed by a sale will reflect both information asymmetry and dealers' compensation for providing liquidity. This idea is formalized in Equation (4) of MMR, which posits the following evolution of transaction price changes:

$$p_t - p_{t-1} = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + e_t \,. \tag{2}$$

The independent variable x_t measures order flow: $x_t = 1$ if the transaction is buyer-initiated and $x_t = -1$ if the trade is seller-initiated. The parameter θ represents the adverse selection component of the bid-ask spread and measures the information revealed by order flow. When order flow is autocorrelated (i.e. buyer-initiated trades are more likely to be followed by buyer-initiated trades, etc.), only the surprise portion of order flow reveals information. The parameter ρ is the first-order autocorrelation coefficient of order flow, and it is used to determine expected order flow (ρx_{t-1}), from which the surprise component is measured.

The parameter ϕ represents compensation for providing liquidity and includes any order processing costs. This component of the spread also captures the effects of dealer inventories to the extent that dealers set wider spreads when they are more concerned about inventory imbalances. Isolating the effects of inventories on the spread is not possible due to the anonymous trading environment of the interdealer market, which prevents tracking dealer inventories. Vitale (1998) indicates this may not be a serious concern. He finds no evidence of inventory effects in the U.K. Treasury market and suggests that this may be due to the availability of many hedging instruments. Nevertheless, dealers' inventory positions could be an important source of information asymmetry. Since dealer inventories are not observable, I study the implications of inventory oriented private information on the evolution of trade impact following announcements as well as how trade impact varies with announcement characteristics.

The MRR model assumes that order size is fixed. Fleming (2001) studies U.S. Treasury market liquidity using a different methodology and finds that signed volume is less effective at explaining price movements than the net number of trades. However, as a robustness check, I investigate the appropriateness of the trade size restriction using a nonparametric approach.

The error term, e_t, includes unanticipated public information released between transactions as well as rounding error due to price discreteness. As in MRR, standard errors of the coefficients are calculated using the Newey-West procedure to obtain a heteroskedasticity consistent estimate of the covariance matrix.[8] Statistical significance is measured using likelihood ratio tests that compare the restricted and unrestricted GMM criterion functions (see Chapter 17 of Davidson and MacKinnon (1993)).

I examine how economic announcements influence the informational role of trading through several modifications to Equation (2). First, to capture the direct effect of economic news on prices, I include additional independent variables. Adjusting Equation (1) to reflect transaction time, let S_{kt} be the standardized surprise component of announcement type k that occurs between time t–1 and t, where k = 1, 2, …, K. If a release of announcement type k takes place between time t–1 and t, then S_{kt} is equal to the standardized surprise, otherwise $S_{kt} = 0$. Equation (2) becomes:

$$p_t - p_{t-1} = (\phi + \theta) x_t - (\phi + \rho\theta) x_{t-1} + \sum_{k=1}^{K} \gamma_k S_{kt} + e_t \tag{3}$$

where the coefficient γ_k measures the sensitivities of prices to announcement type k.[9]

I further generalize Equation (3) by allowing the microstructure parameters to change around announcements and with characteristics of the announcement. Specifically, I include dummy variables to distinguish when trades occur relative to the time of the announcement release. Additional dummy variables permit the microstructure parameters to vary with γ_k, $S_{k\tau}$, and the dispersion among survey forecasts. The specifications are discussed along with the empirical results in the next section.

Since little is known about effectiveness of microstructure models at measuring the determinants of transaction costs in the bond market, I conduct robustness checks using a simple nonparametric approach similar to Koski and Michaely (2000). This methodology differs from the structural model by focusing on sequences of transaction price changes in order to infer the informational role of trading. The objective is to separate the permanent impact of a trade from its temporary impact. The lasting influence of a trade on the price level reveals the information contained in the trade, whereas the temporary impact reflects dealers' order processing costs and compensation for providing liquidity.

Koski and Michaely (2000) measure variation in the information content of equity trading by calculating excess returns for trades of different sizes around dividend announcements. They control for cross sectional differences in expected returns by calculating excess returns relative to a stock-specific benchmark return for each information period. Since I focus on the most recently issued 5-year Treasury note, it is unlikely that the bond will have an expected intraday return different from zero. Thus, I forgo calculating benchmark returns and examine unadjusted transaction returns.[10] In order to confirm the effectiveness of the microstructure model at capturing the impact of trading on prices, I calculate mean transaction price returns for purchases and sales of different trade sizes around announcements and with characteristics of the announcement.

III. Empirical Results

A. Trade Impact Surrounding Economic Announcements

If some dealers are better at determining the precise impact of economic news on prices, either through superior information processing skills or access to customer order flow, theory suggests that the informational role of trading will increase following economic announcements. I examine this hypothesis by allowing the microstructure parameters in Equation (3) to vary before and after announcements as follows:

$$\begin{aligned} p_t - p_{t-1} = {} & (\phi_N + \theta_N) I_{N,t} x_t + (\phi_B + \theta_B) I_{B,t} x_t + (\phi_A + \theta_A) I_{A,t} x_t \\ & -(\phi_N + \rho_N \theta_N) I_{N,t-1} x_{t-1} - (\phi_B + \rho_B \theta_B) I_{B,t-1} x_{t-1} - (\phi_A + \rho_A \theta_A) I_{A,t-1} x_{t-1} \\ & + \sum_{k=1}^{K} \gamma_k S_{kt} + e_t \end{aligned} \tag{4}$$

where $I_{Nt} = 1$ if the transaction at time t takes place on a day without an economic announcement, 0 otherwise. Similarly, the dummy variables $I_{B,t}$ and $I_{A,t}$ designate trades in the half-hour before and after announcements.

Letting α represent a constant and using the expressions

$$v_t = x_t - \rho_N I_{N,t-1} x_{t-1} - \rho_B I_{B,t-1} x_{t-1} - \rho_A I_{A,t-1} x_{t-1} \tag{5}$$

and

$$
\begin{aligned}
u_t = p_t - p_{t-1} &- (\phi_N + \theta_N) I_{N,t} x_t - (\phi_B + \theta_B) I_{B,t} x_t - (\phi_A + \theta_A) I_{A,t} x_t \\
&+ (\phi_N + \rho_N \theta_N) I_{N,t-1} x_{t-1} + (\phi_B + \rho_B \theta_B) I_{B,t-1} x_{t-1} + (\phi_A + \rho_A \theta_A) I_{A,t-1} x_{t-1}\ , \\
&- \sum_{k=1}^{K} \gamma_k S_{kt}
\end{aligned} \tag{6}
$$

then the following population moments implied by Equation (4) exactly identifies the parameter vector $\beta = (\alpha, \theta_N, \theta_B, \theta_A, \phi_N, \phi_B, \phi_A, \rho_N, \rho_B, \rho_A, \gamma_1, \ldots, \gamma_K)$:

$$
E \begin{bmatrix} v_t I_{N,t-1} x_{t-1} \\ v_t I_{B,t-1} x_{t-1} \\ v_t I_{A,t-1} x_{t-1} \\ u_t - \alpha \\ (u_t - \alpha) I_{N,t} x_t \\ (u_t - \alpha) I_{B,t} x_t \\ (u_t - \alpha) I_{A,t} x_t \\ (u_t - \alpha) I_{N,t-1} x_{t-1} \\ (u_t - \alpha) I_{B,t-1} x_{t-1} \\ (u_t - \alpha) I_{A,t-1} x_{t-1} \\ (u_t - \alpha) S_{1t} \\ \vdots \\ (u_t - \alpha) S_{Kt} \end{bmatrix} = 0 \tag{7}
$$

The first three moments determine the autocorrelation in order flow during the different trading intervals, and the remaining equations represent the OLS normal equations.[11] The results are shown in Table III. Panel A reports the estimates and standard errors for the microstructure parameters. Standard t-tests show that all of the microstructure parameters are significantly different from zero with p-values less than 0.001.

The adverse selection parameter θ, which measures the informational role of trading, changes from 0.65 basis points before announcements to 0.94 basis points after announcements. The Chi-squared statistic for the likelihood ratio test of the restriction $\theta_N = \theta_B$ and $\theta_N = \theta_A$ is equal to 96.4, which has a p-value less than 0.001. The pattern in

θ around announcements confirms the anecdotal evidence in Figure 1. Order flow contains relatively little information before the release of economic news and more information than usual afterwards. The reduced information content of trading prior to the announcement suggests that the information is not leaked in the half-hour before the release. The increased information content of trading following the announcement suggests that public information releases raise the level of information asymmetry in the government bond market.

Also of interest is order processing cost parameter ϕ, which measures compensation for providing liquidity. Notably, the parameter is consistently negative and significant at the 0.001 level. This suggests that, on average, dealers consume liquidity in the interdealer market, and their desire to trade mitigates the effects of information asymmetry on transaction costs. Although theory would suggest that $\phi \geq 0$ in a single dealer environment (the dealer would expect to be compensated for providing liquidity), this restriction may not necessarily hold in a quote driven market.[12] For example, Sandas (2001) finds negative order processing costs in the Stockholm Stock Exchange's limit-order market and argues that these costs could reflect rational behavior in an environment with heterogeneous valuations. In the current context, the ability to sell to the most optimistic dealer and buy from the most pessimistic dealer effectively lowers transaction costs.

Unobserved customer trading also makes negative order processing costs more plausible. If dealers are able to trade at more favorable prices with their customers, then they may be willing to submit quotes in the interdealer market that appear suboptimal in the sense that they do not fully reflect the information in order flow. In other words, dealers may consume liquidity in the interdealer market if they are sufficiently compensated for providing liquidity in the retail market.

The idea that dealers use the interdealer market as a source of liquidity is supported by the observation that dealers are not required to submit quotes. Even for the actively traded 5-year note, roughly 3 percent of the time there are no posted quotes on at least one side of the market. Interdealer brokers encourage quote submission by requiring only transaction initiators to pay brokerage fees, which also serves to reduce spreads. A dealer who would like to purchase a Treasury security can avoid the brokerage fee (usually 1/256th or roughly 0.4 basis points) by posting an attractive bid and waiting for a counterparty rather than initiating a transaction at the ask price. This feature of the interdealer market can result in zero or even small negative bid-ask spreads, which are occasionally observed in the data. For example, sampling quotes when transactions are reported, I find roughly 15 percent of observed spreads are zero, and one percent are less than zero.

The variation in ϕ around announcements is intuitive. The order processing cost parameter ϕ is greater than usual (−0.25) before announcements and smaller than usual (−0.41) afterwards. The Chi-squared statistic for the likelihood ratio test of the restriction $\phi_N = \phi_B$ and $\phi_N = \phi_A$ is equal to 36.4, which rejects the null at the 0.001 level. The increased price uncertainty before announcements makes dealers more reluctant to trade. After the information release, increased trading activity and the reduction in price uncertainty increases dealers' willingness to provide liquidity.

Order flow is subject to a considerable amount of autocorrelation, suggesting that orders are typically broken up into smaller trades. The autocorrelation coefficient ρ varies from 0.49 before announcements to 0.54 after. The Chi-squared statistic for the likelihood ratio test of the restriction $\rho_N = \rho_B$ and $\rho_N = \rho_A$ is equal to 23.4, which is significant at the 0.001 level. The estimates indicate that orders are slightly more likely to be separated into different trades following economic news releases.

Panel B of Table III reports the coefficients γ_k and standard errors for the sensitivity of prices to the surprise component of anticipated economic announcements. In general, procyclical indicators such as Housing Starts negatively impact prices, whereas counter-cyclical variables such as Initial Jobless Claims have a positive impact on prices. Eight of the twelve surprise coefficients are statistically different from zero at the 0.01 level, the exceptions being the Index of Leading Indicators, Trade Balances, Exports, and Imports. The price impact varies considerably across announcements with Nonfarm Payrolls having the largest effect on prices. A one standard deviation positive surprise in Nonfarm Payrolls results in a 28 basis point drop in price. The coefficients for the other announcements are smaller, ranging from 12 basis points for the Producer Price Index to 3 basis points for Initial Jobless Claims.

B. Robustness Checks

The model estimates suggest that transaction costs in the interdealer market for Treasury securities are primarily driven by information asymmetry. Moreover, the results indicate that the compensation for providing liquidity in the interdealer market is negative, which implies that quotes are not fully incorporating the information contained in order flow. This result may be related to heterogeneous valuations, as suggested by Sandas (2001), or influenced by unobserved customer trading and the one-sided fee structure of the interdealer market. However, it does raise concerns about model misspecification. In this section, I build support for the model estimates through a number of robustness checks.

I begin with an alternate approach to infer the informational role of trading. The methodology is based on Koski and Michaely (2000) and relies on the sequence of transaction returns to measure the impact of trading on prices. Specifically, I calculate mean cumulative transaction returns for purchases and sales of different sizes surrounding economic announcements. I sort trades into three size groups based on the

33rd and 67th percentiles, which are $4 million and $8 million. Figure 2 plots cumulative transaction returns measured from five trades before to five trades after the trade of interest.[13]

The pattern in Figure 2 corroborates the results in Table III. For each trade size, the influence of trading on price changes is higher than usual following announcements and lower than usual before announcements. The variation in price impact around announcements is larger for purchases than for sales, which is an asymmetry not captured by the model. The figure does, however, provide support for the model's negative estimate of the order processing cost. The cumulative transaction returns do not exhibit the reversals commonly observed in equity markets. Price reversals are associated with the temporary impact of trading on prices and are interpreted as reflecting compensation for providing liquidity. Figure 2 shows that cumulative transaction returns continue upwards after purchases and downwards after sales, suggesting that dealers' submitted quotes are not fully incorporating the autocorrelation in order flow.

Trade size appears to have little influence on trade impact. For both purchases and sales, trades between $4 and $8 million have a larger impact on prices than smaller or larger trades, but the difference is relatively small. Moreover, changing the large trade size category to reflect more extreme sizes, using the 95th percentile of $25 million, does not increase the trade impact. The minimal role of size on trade impact may be related to institutional details of the interdealer market. Although trades occur at posted quotes, trade size can be negotiated through the broker. Quote submitters concerned about information asymmetry would be less likely to allow the trade size to be worked up. This is consistent with Boni and Leach (2002) who find evidence that trade work-ups are smaller than usual following economic announcements.

The pattern in cumulative returns around announcements may be partially driven by differences in the autocorrelation of trading. In order to gauge the statistical significance of the differences in price impact around announcements, Table IV reports noncumulative transaction returns from two trades before to two trades after the transaction of interest. The table shows the difference between the mean transaction return in periods with and without announcements. Statistical significance is measured using two-sample t-tests as well as two-sample nonparametric Kolmogorov-Smirnov tests (see Siegel and Castellan, 1988 for details). The average purchase transaction return for medium sized trades is 0.085 basis points lower before announcements and 0.074 basis points higher after announcements. The statistical tests generally support that the differences are significant for purchases of all trade sizes. Large trades prior to announcements are particularly uninformative and may reflect "sunshine" trading as modeled by Admati and Pfleiderer (1991).

Together, the price impact results support the estimates of the model and indicate that the fixed trade size assumption is not overly restrictive.[14] Another useful inference from Table IV and Figure 2 is that for the interdealer market for U.S. Treasury securities, relying on the autocorrelation in order to infer the informational component of the effective spread is more appropriate than assuming that the information content of trading grows linearly with size, which is the approach in Umlauf (1991) and Vitale (1998).

An additional approach for evaluating model performance is to examine how well it measures transaction costs. In the MMR setup, the model parameters imply a bid-ask spread equal to $2(\theta+\phi)$. Panel A of Table V reports average quoted spreads and model-implied spreads for periods around announcements; standard errors are calculated using the covariance matrix of the GMM estimators. The spread component estimates do not rely on bid-ask quotes but are instead inferred from the autocovariance and other moment conditions of transaction price changes. As a result, model-implied spreads are not constrained to be equal to quoted spreads.

Table V shows that the model produces bid-ask spreads that are smaller than observed quoted spreads. Although Madhavan, Richardson, and Roomans (1997) find a similar result in equity markets, the downward bias does raise concerns about model misspecification. On the other hand, given that quotes can change between the trades of a round-trip transaction, it is not clear whether quoted spreads or the model's implied spreads provide a better measure of round-trip transaction costs.

I develop an alternative measure of transaction costs by comparing average price changes for offsetting trades over different time intervals. Switching from transaction time, which is the approach in Tables III and IV, to calendar time helps control for differences in trading intensity across subsamples. I also adjust for broken up orders, as indicated by the high autocorrelation in order flow, by aggregating uninterrupted sequences of buy or sell transactions.[15] Aggregated trades are characterized by cumulative volume and the volume weighted average price. For each aggregated transaction and for each time interval, transaction costs are measured by comparing the purchase (sale) price to the sale (purchase) price of the first available volume-offsetting aggregate transaction within the given time interval. Table V reports average transaction costs for trades unwound within 5 minutes, between 5 and 10 minutes, and between 10 and 15 minutes.

The table shows that transaction costs generally increase with the length of the round-trip transaction. On days without announcements, unwinding within 5 minutes results in average transaction costs of 0.6 basis points, whereas unwinding between 10 and 15 minutes results in transactions costs of 1.6 basis points. This result suggests that aggregating sequences of buys or sells may not completely control for broken up orders.

Transaction costs tend to level off after 15 minutes. Extending the time horizon beyond that reported in the table to 15-20, 20-25, and 25-30 minutes results in average transaction costs of 1.5, 1.6, and 1.4 basis points.

More importantly, the variation in transaction costs around economic announcements more closely matches model implied spreads than quoted spreads. While average quoted spreads are larger than usual prior to economic news releases and decrease afterwards, the model estimates indicate that effective spreads display the opposite pattern. The results in Panel B support the model's interpretation. Regardless of the time interval considered, round-trip transaction costs in the 15 minutes after announcements are roughly twice as large after economic announcements as before. Transaction costs return closer to normal levels in the next 15 minutes. While model implied spreads vary with quoted spreads more generally,[16] the results indicate that the preponderance of broken up orders combined with increased movement of quotes between transactions makes quoted bid-ask spreads a relatively poor measure of transaction costs around announcements.[17]

Taken together, the robustness checks support the effectiveness of the structural model at measuring the informational role of trading. Although caution should be exercised when using the model to infer the precise level of transaction costs, the evidence suggests that model implied spreads are more successful than quoted spreads at capturing the variation in transaction costs around announcements. In addition, the nonparametric price impact results support the sign of the parameter estimates and indicate that the model is successful at measuring changes in the sensitivity of prices to order flow.

In summary, the model estimates and nonparametric results indicate that the release of macroeconomic news increases the level of information asymmetry in the government bond market. The increased informational role of trading is consistent with differences in the ability of market participants to interpret how economic data influences riskless rates. Alternatively, the information asymmetry may also be related to inventory oriented information that is security specific. To help characterize the source of the information asymmetry, I begin by examining the evolution of trade impact following economic announcements.

C. The Evolution of Trade Impact Around Announcements

Table II shows that trading intensity in the half-hour after economic announcements is approximately twice as large as on days without announcements. Moreover, Fleming and Remolona (1999) document the pattern of increased trading activity continues for roughly four hours after 8:30 a.m. announcements.[18] The extended period of active trading suggests that announcements may induce market participants to rebalance or rehedge their portfolios.

While increased trading activity typically lowers transaction costs, it may also generate inventory related information asymmetry. In the model of Cao, Evans, and Lyons (2002), compensation for bearing inventory risk introduces a link between order flow and prices. As a result, dealers' private access to customer order flow provides them with a useful indicator of short-term price movements. In the current setting, the increased trading activity following announcements may potentially increase the value of dealers' access to customer order flow.

Table II shows that price volatility drops considerably within 15 minutes of the announcement, which would encourage patience on the part of uninformed liquidity motivated traders. As a result, we might expect inventory oriented information asymmetry to be gradually reduced as customers submit their orders to dealers. On the other hand, if the information asymmetry is related to variations in skill at interpreting economic news, a rapid decline in the informational role of trading seems more plausible.

A Treasury market participant who has skill at determining how economic data influences riskless rates is unlikely to possess a monopoly on this type of expertise. Holden and Subrahmanyam (1992) show that competition among multiple informed traders leads prices to incorporate private information quickly. In the current setting, this implies that the informational role of trading will decline as time passes after the announcement. I examine this conjecture by estimating the following equation:

$$\begin{aligned} p_t - p_{t-1} = &\left(\phi_{A1} + \theta_{A1}\right) I_{A1,t} x_t + \left(\phi_{A2} + \theta_{A2}\right) I_{A2,t} x_t \\ &- \left(\phi_{A1} + \rho_{A1}\theta_{A1}\right) I_{A1,t-1} x_{t-1} - \left(\phi_{A2} + \rho_{A2}\theta_{A2}\right) I_{A2,t-1} x_{t-1} + e_t \end{aligned} \tag{8}$$

where $I_{A1,t} = 1$ if the transaction at time t takes place within 15 minutes after the announcement and 0 otherwise, and $I_{A2,t} = 1$ if the trade occurs between 15 and 30 minutes after an announcement and 0 otherwise. Letting α represent a constant and using the expressions

$$v_t = x_t - \rho_{A1} I_{A1,t-1} x_{t-1} - \rho_{A2} I_{A2,t-1} x_{t-1} \tag{9}$$

and

$$\begin{aligned} u_t = p_t - p_{t-1} &- \left(\phi_{A1} + \theta_{A1}\right) I_{A1,t} x_t - \left(\phi_{A2} + \theta_{A2}\right) I_{A2,t} x_t \\ &+ \left(\phi_{A1} + \rho_{A1}\theta_{A1}\right) I_{A1,t-1} x_{t-1} + \left(\phi_{A2} + \rho_{A2}\theta_{A2}\right) I_{A2,t-1} x_{t-1} \end{aligned}, \tag{10}$$

then the moment conditions imposed by this version of the model are:

$$E\begin{bmatrix} v_t I_{A1,t-1} x_{t-1} \\ v_t I_{A2,t-1} x_{t-1} \\ u_t - \alpha \\ \left(u_t - \alpha\right) I_{A1,t} x_t \\ \left(u_t - \alpha\right) I_{A2,t} x_t \\ \left(u_t - \alpha\right) I_{A1,t-1} x_{t-1} \\ \left(u_t - \alpha\right) I_{A2,t-1} x_{t-1} \end{bmatrix} = 0. \tag{11}$$

The results are presented in Table VI. The adverse selection parameter θ is highest in the first fifteen minutes after the announcement (1.01) and then returns to near normal levels in the next fifteen minutes (0.88) even as trading intensity increases (as shown in Table II). The Chi-squared statistic for the likelihood ratio test that $\theta_{A1} = \theta_{A2}$ is equal to 41.2, which rejects the null with a p-value less than 0.001. The quick decline in the informational role of trading is consistent with the multiple informed trader model of Holden and Subrahmanyam (1992) and supports the interpretation that market participants vary in skill at determining how economic news influences riskless rates.

A similar approach can be used to examine whether there is evidence of informed trading prior to the release. I estimate an equation analogous to Equation (8) for the before-announcement period. The results are also reported in Table VI. Although there is an increase in the informational role of trading between the two fifteen minute intervals leading up to the announcement, both estimates are lower than the estimate during the period without announcements shown in Table III. The results do not indicate that traders trade speculatively in the half-hour before announcements.[19]

D. Trade Impact and Announcement Characteristics

Theory offers predictions on how the informational role of trading will vary with characteristics of the announcement, which provides another opportunity for clarifying the nature of information asymmetry in government bond markets. In this section I study how trade impact varies with the surprise and precision of the announcement as well as the divergence in analyst forecasts.

In the skilled information processor models of Kim and Verrecchia (1994, 1997), information processors' skill at interpreting public information is independent of the precision of the public information. Thus, following more precise public information releases the level of information asymmetry is lower, market participants are relatively less concerned about trading with skilled information processors, and the informational role of trading is smaller.

The opposite relation could hold if the information asymmetry is related to dealer inventories. Given that announcements with greater price impacts would likely generate larger shocks to investors' hedging demands, dealers with access to sizable customer order flows would possess a greater informational advantage following more precise information releases. In this setting, we would expect informational role of trading to be higher following more precise public information releases.

Karpoff's (1986) model of trading volume offers additional insights. In an environment with market participants heterogeneous in either their personal valuations or liquidity needs, he demonstrates that trading volume can increase following a public information event even if market participants interpret the information identically, provided they had divergent prior expectations. If the information asymmetry following economic announcements is driven by the heterogeneous liquidity needs of retail customers, Karpoff's (1986) model would predict greater levels of information asymmetry about customer demands following announcements with more divergent prior expectations.

Although these modeling approaches have different implications, their interpretations are not mutually exclusive. For example, a better understanding of how economic news influences hedging demands could be considered superior information processing ability in the Kim and Verrecchia (1994, 1997) setup. Similarly, retail customers could be skilled information processors, which would make inventories informative in the Cao, Evans, and Lyons (2002) model. Moreover, even if retail customers are uninformed, their order flow could reveal fundamental information about the yield curve if it reflects a shift in investor preferences. Although cross sectional results are not able to provide a mutually exclusive interpretation, they do provide additional evidence to help characterize the nature of information asymmetry.

I begin by using a two-step procedure to allow the microstructure parameters to vary with the estimated price impact of that day's announcements. Equation (3), repeated here for expositional purposes, specifies the following relation between transaction price changes and announcement surprises:

$$p_t - p_{t-1} = (\phi + \theta) x_t - (\phi + \rho\theta) x_{t-1} + \sum_{k=1}^{K} \gamma_k S_{kt} + e_t \tag{3}$$

If an announcement of type k takes place between trades t–1 and t, S_{kt} is equal to the standardized surprise, otherwise S_{kt} = 0. As detailed in Equation (1), surprises are defined as the difference between the announced value and the survey forecast, scaled by the standard deviation of all surprises for that macro series. Thus, S_{kt} = 1.0 implies a surprise that is one standard deviation greater than zero for that announcement type.

I first estimate Equation (3) and obtain γ_k, which measures the sensitivity of prices to announcement type k. For each day τ on which an announcement occurs, I then calculate the estimated cumulative price impact, $\left|\sum \gamma_k S_{k\tau}\right|$ for day τ's announcements. I then sort trades into three categories using the 33rd and 67th percentiles of $\left|\sum \gamma_k S_{k\tau}\right|$. Next, for transactions in the half-hour following announcements, I estimate:

$$\begin{aligned} p_t - p_{t-1} = {} & (\phi_1 + \theta_1) I_{1,t} x_t + (\phi_2 + \theta_2) I_{2,t} x_t + (\phi_3 + \theta_3) I_{3,t} x_t \\ & - (\phi_1 + \rho_1\theta_1) I_{1,t-1} x_{t-1} - (\phi_2 + \rho_2\theta_2) I_{A,t-1} x_{t-1} - (\phi_3 + \rho_3\theta_3) I_{3,t-1} x_{t-1} + e_t, \end{aligned} \tag{12}$$

where the subscripts 1, 2, and 3 denote the lowest, middle, and highest tritiles of $\left|\sum \gamma_k S_{k\tau}\right|$. The moment conditions implied by this version of the model are analogous to those shown in Equation (11).

The results are reported in Panel A of Table VII. The table shows that the informational role of trading following economic announcements increases with the estimated price impact of the announcement. The variation in θ shows a monotonic increase across announcement impact groups: 0.81, 0.90, and 1.07. The Chi-squared statistic for the likelihood ratio test that the parameters are equal is 49.75, which has a p-value less than 0.001.

I more explicitly characterize the relation between announcement price impact and the subsequent informational role of trading by partitioning announcement impact into components related to the precision of the information and the magnitude of the surprise. To the extent that economic news releases provide a public signal about the value of government bonds, $|\gamma_k|$, which measures the average sensitivity of prices to surprises in macro series *k*, proxies for the precision of the public signal. For each announcement day τ, I calculate $\sum|\gamma_k I_{k\tau}|$, where γ_k is estimated from Equation (3) and $I_{k\tau}=1$ if announcement type *k* occurred on that day, 0 otherwise. The sum of the precisions is analogous to the price impact constraining the surprise component for each announcement to equal one. A cumulative surprise component is created in a similar manner. For each announcement day τ, I calculate $\sum|S_{k\tau}|$, which is analogous to constraining all announcements to have the same level of precision.

I then reestimate Equation (12), this time double sorting trades into 9 groups based on 33rd and 67th percentiles of $\sum|\gamma_k I_{k\tau}|$ and $\sum|S_{k\tau}|$. The results are reported in panel B of Table VII. The model estimates indicate that the informational role of trading increases monotonically with both the precision of the public information and the magnitude of the announcement surprise. The informational component of the spread θ varies across the announcement precision groups from 0.79 to 1.07 basis points and across the surprise groups from 0.82 to 1.04 basis points. Chi-squared tests reject that the parameters are equal across the subsamples with a p-value less than 0.001.

As a robustness check for the model estimates in Table VII, Figure 3 shows cumulative transaction returns for trades sorted into the three groups based on the announcement surprise $\left|\sum S_{k\tau}\right|$, precision $\sum\left|\gamma_k I_{k\tau}\right|$, and combined price impact $\left|\sum \gamma_k S_{k\tau}\right|$. The pattern for purchase transactions supports the model estimates in that a clear monotonic relation holds between the price impact and the magnitude of the announcement surprise and estimated precision. Although for the sake of brevity I do not report a full table of mean transaction returns (as in Table IV), two sample t-tests and Kolmogorov Smirnov tests reject with a p-value less than 0.001 that the transaction returns for the trade of interest are equal for the highest and lowest tritiles of announcement surprise, announcement precision, and the estimated price impact of the announcement. Although the results for sale transactions are less robust in that the pattern is monotonic and significant only for announcement precision, Figure 3 generally confirms the effectiveness of the model at measuring the influence of announcement characteristics on the informational role of trading.

If the increased information asymmetry among Treasury dealers following economic announcements is influenced by the heterogeneous rebalancing demands of retail customers, Karpoff's (1986) theory of trading volume predicts greater information asymmetry following announcements with more divergent prior expectations. To examine this hypothesis, I use two proxies for dispersion of expectations: the difference between the 25th and 75th percentile forecasts $D_{k\tau}^{per}$ and the standard deviation of the forecasts $D_{k\tau}^{std}$. The measures of dispersion are standardized by subtracting the mean and scaling by the standard deviation. Thus, $D_{k\tau}^{per}=1$ implies that the difference between the 75th and 25th percentile forecast is one standard deviation greater than the average difference for that announcement type. For each announcement day τ, I sum the dispersion measures across announcements and sort trades into three categories using the 33rd and 67th percentiles of $\sum D_{k\tau}^{per}$ and $\sum D_{k\tau}^{std}$. The estimated equation is analogous to Equation (11). The results are shown in Table VIII.

The table documents a modest relation between the informational role of trading and dispersion among analysts' forecasts. While the informational component of the spread θ is not sensitive to changes in forecast dispersion when measured by the interquartile range, it does increase significantly with the standard deviation of forecasts. The apparent difference between the two cumulative dispersion measures is somewhat surprising given the high correlation between the two proxies (0.7). [20] One possible interpretation is that the presence of outlying forecasts, which could influence standard deviation without affecting the interquartile range, more accurately indicates diverse expectations.

Although data on individual forecasts is unavailable, additional evidence for the summary dispersion measures is provided in Figure 4, which shows the price impact results after sorting into groups by $\sum D_{k\tau}^{per}$ and $\sum D_{k\tau}^{std}$. The results indicate that the relation between forecast standard deviation and the informational role of trading is less robust. Neither purchases nor sales display a clear monotonic pattern for either measure of dispersion. Together, the results provide weak support to the conjecture that announcements with greater forecast dispersion generate more rehedging demands and lead to greater levels of information asymmetry.

Overall, the results in this section indicate a positive relation between the influence of economic news on prices and the subsequent informational role of trading. The relation is associated with both the surprise component of the announcement as well as the importance of the macroeconomic series as measured by the average price response. While the evidence presents a challenge to existing information processor models, these could be adapted to reflect this result. In the context of the Kim and Verrecchia (1994, 1997) models, the results suggest that information processors' skills are not independent of the public signal, but instead improve with the surprise and precision of the public information. Incorporating this feature would not alter the fundamental implications of their theory. Moreover, extending the models in this way seems plausible given that skilled economists are likely to devote greater efforts to interpreting economic news considered to be important by the market.

IV. Conclusion

This paper studies the influence of macroeconomic news releases on the informational role of trading in the U.S. government bond market. I rely on a structural model to infer the component of effective spreads related to information asymmetry, and study how the informational role of trading varies around news releases and with characteristics of the announcement. Nonparametric robustness checks confirm the effectiveness of the model at capturing variation in the information content of trading.

I find that prices show an increased sensitivity to order flow in the half-hour following economic announcements, which suggests the release of public information increases the level of information asymmetry in the government bond market. Although trading activity remains high for several hours after announcements, the level of information asymmetry returns to near normal levels within 15 minutes. The evidence suggests that market participants actively watch trading to help determine the influence of new economic information on riskless rates. The informational role of trading increases with the initial impact of the announcement, and the relation is associated with both the surprise component of the announcement and the precision of the public information. The results are consistent with the presence of superior information processors whose comparative advantage improves with the importance of the public information release.

The hypothesis that government bond order flow reveals fundamental information about the yield curve is confirmed by the work of Fleming (2001) and Brandt and Kavajecz (2003), who show that order flow maintains its informational role at the daily and weekly level as well as across securities of different maturities. However, an important contrast emerges when characterizing the conditions under which trading is especially informative. Fleming (2001) and Brandt and Kavajecz (2003) document that trade impact increases during periods of low liquidity, which they argue reflects uncertainty regarding valuation. I find that macroeconomic announcements lead to high liquidity as well as increased trade impact, suggesting that the release of economic information generates uncertainty about the appropriate level of riskless rates. The results indicate that information asymmetry in the government bond market arises not from the absence of relevant public information, but rather from differences in the ability of market participants to interpret the information.

References

Admati, Anat, R., and Paul C. Pfleiderer, 1991, Sunshine Trading and Financial Market Equilibrium, *Review of Financial Studies*, 4, 443-481.

Balduzzi, Pierluigi, Edwin J. Elton, and T. Clifton Green, 2001, Economic News and Bond Prices: Evidence from the U.S. Treasury Market, *Journal of Financial and Quantitative Analysis*, 36, 523-543.

Boni, Leslie, and J. Chris Leach, 2002, "Expandable Limit Order Markets," Working Paper, University of New Mexico.

Brandt, Michael W., and Kenneth A. Kavajecz, 2003, Price Discovery in the U.S. Treasury Market: The Impact of Order Flow and Liquidity on the Yield Curve, Working Paper, University of Pennsylvania.

Cao, H. Henry, Martin D. D. Evans, and Richard K. Lyons, 2002, Inventory Information, Working Paper, University of California, Berkeley.

Cohen, Benjamin H., and Hyun S. Shin, 2002, Positive Feedback Trading Under Stress: Evidence from the U.S. Treasury Securities Market, Working Paper, International Monetary Fund.

Davidson, Russell, and James G. MacKinnon, 1993, Estimation and Inference in Econometrics (Oxford University Press, New York, NY).

Evans, Martin D. D., and Richard K. Lyons, 2002, Order Flow and Exchange Rate Dynamics, *Journal of Political Economy*, 110, 170-180.

Evans, Martin D. D., 2002, FX Trading and Exchange Rate Dynamics, *Journal of Finance*, 57, 2405-2447.

Flannery, Mark J., and Aris A. Protopapadakis, 2002, Macroeconomic Factors *Do* Influence Aggregate Stock Returns, *Review of Financial Studies*, 15, 751-782.

Fleming, Michael J., 2001, Measuring Treasury Market Liquidity, Staff Report, Federal Reserve Bank of New York.

Fleming, Michael J., and Eli M. Remolona, 1997, What Moves the Bond Market? *Federal Reserve Bank of New York Economic Policy Review*, December, 31-50.

Fleming, Michael J., and Eli M. Remolona, 1999, Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information, *Journal of Finance*, 54, 1901-1915.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, *Journal of Financial Economics*, 14, 71-100.

Greene, Jason T., and Scott B. Smart, 1999, Liquidity Provision and Noise Trading: Evidence from the 'Investment Dartboard' Column, *Journal of Finance*, 54, 1885-1899.

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

Holden, Craig W., and Avanidhar Subrahmanyam, 1992, Long-Lived Private Information and Imperfect Competition, *Journal of Finance*, 47, 247-270.

Huang, Roger D., and Hans R. Stoll, 1997, The Components of the Bid-Ask Spread: A General Approach, *Review of Financial Studies*, 10, 995-1034.

Ito, Takatoshi, Richard K. Lyons, and Michael T. Melvin, 1998, Is There Private Information in the FX Market? The Tokyo Experiment, *Journal of Finance*, 53, 1111-1130.

Karpoff, Jonathan M., 1986, A Theory of Trading Volume, *Journal of Finance*, 41, 1069-1087.

Kim, Oliver, and Robert E. Verrecchia, 1994, Market Liquidity and Volume Around Earnings Announcements, *Journal of Accounting and Economics*, 17, 41-67.

Kim, Oliver, and Robert E. Verrecchia, 1997, Pre-announcement and Event-Period Information, *Journal of Accounting and Economics*, 24, 395-419.

Koski, Jennifer Lynch, and Roni Michaely, 2000, Prices, Liquidity, and the Information Content of Trades, *Review of Financial Studies*, 13, 659-696.

Krinsky, Itzhak, and Jason Lee, 1996, Earnings Announcements and the Components of the Bid-Ask Spread, *Journal of Finance*, 51, 1523-1535.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335.

Lyons, Richard K., 1995, Tests of Microstructural Hypotheses in the Foreign Exchange Market, *Journal of Financial Economics*, 39, 321-351.

Massa, Massimo, and Andrei Simonov, 2001, Reputation and Interdealer Trading: A Microstructure Analysis of the Treasury Bond Market, *Journal of Financial Markets*, forthcoming.

Madhavan, Ananth, Mathew Richardson, and Mark Roomans, 1997, Why do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks, *Review of Financial Studies*, 10, 1035-1064.

Madhavan, Ananth, and Seymour Smidt, 1991, A Bayesian Model of Intraday Price Formation, *Journal of Financial Economics*, 30, 99-134.

Peiers, Bettina, 1997, Informed Traders, Intervention, and Price Leadership: A Deeper View of the Microstructure of the Foreign Exchange Market, *Journal of Finance*, 52, 1589-1614.

Sandas, Patrik, 2001, Adverse Selection and Competitive Market Making: Empirical Evidence from a Limit Order Market, *Review of Financial Studies*, 14, 705-734.

Siegel, Sidney, and N. John Castellan, 1988, Nonparametric Statistics for the Behavioral Sciences (McGraw Hill, New York, NY).

Stoll, Hans R., 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance*, 44, 115-134.

Umlauf, Steven R., 1991, Information Asymmetries and Security Market Design: An Empirical Study of the Secondary Market for U.S. Government Securities, *Journal of Finance*, 46, 929-953.

Vitale, Paolo, 1998, Two Months in the Life of Several Gilt-Edged Market Makers on the London Stock Exchange, *Journal of International Financial Markets, Institutions and Money*, 8, 299-324.

Table I

Economic Announcements

Announcements take place on a monthly basis with the exception of Initial Jobless claims, which is announced weekly. Each announcement is released at 8:30 a.m. Eastern Time.

Title	Reporting Agency	Number Reported
Unemployment	Bureau of Labor Statistics	Percentage Level
Consumer Price Index	Bureau of Labor Statistics	Percentage Change
Durable Goods Orders	Bureau of the Census	Percentage Change
Housing Starts	Bureau of the Census	Millions of Units
Index of Leading Indicators	The Conference Board	Percentage Change
Initial Jobless Claims – weekly	Bureau of Labor Statistics	Thousands
Trade Balances	Bureau of the Census, Bureau of Economic Analysis	$ Billions
Nonfarm Payrolls	Bureau of Labor Statistics	Change in Thousands
Producer Price Index	Bureau of Labor Statistics	Percentage Change
Retail Sales	Bureau of the Census	Percentage Change
U.S. Exports	Bureau of the Census, Bureau of Economic Analysis	$ Billions
U.S. Imports	Bureau of the Census, Bureau of Economic Analysis	$ Billions

Table II
Descriptive Statistics for the Active 5-year Treasury Note

This table provides descriptive statistics on the variance of transaction price changes (in basis points), the average number of transactions, volume per hour and per transaction (in $millions), and the average bid-ask spread (in basis points) for the active 5-year Treasury note. The data is grouped into intervals on days with and without announcements. The announcement sample is grouped into intervals before and after the announcement time (8:30 a.m. ET). The sample covers July 1, 1991 to September 29, 1995.

		Announcements Days		
	No Announcements	Before the Release	After the Release	
	8:00 – 9:00	8:00 – 8:30	8:30 – 8:45	8:45 – 9:00
Observations	36563	10182	14739	16120
Std. Dev. of ΔP	1.128	0.957	1.398	1.126
Transactions/hour	65	41	120	131
Volume/transaction	8.0	7.5	9.4	8.9
Volume/hour	515.6	312.0	1126.3	1164.0
Quoted spread	1.690	1.904	1.710	1.552

Table III

The Effect of Economic Announcements on Prices and Components of the Effective Spread

This table reports GMM estimates from the model fit to transaction price changes for the active 5-year Treasury note between 8:00 a.m. and 9:00 a.m. ET during the period July 1, 1991 to September 29, 1995. Indicator variables are used to allow the model parameters to vary around economic announcement release times, which occur at 8:30. Panels A reports the estimated components of the effective spread, with standard errors reported below each estimate. The parameter subscript "N" refers to estimates on days with no announcements. Subscript "B" refers to estimates from trades in the half-hour before announcements (8:00–8:30), and subscript "A" refers to estimates from trades in the half-hour after announcements (8:30–9:00). Also shown are the restrictions and Chi-square p-values for Likelihood Ratio tests that compare the restricted and unrestricted GMM criterion functions. Panel B reports the coefficients γ_k on the standardized surprise component of the announcements.

Panel A: Spread Components

			LR p-value
Adverse Selection Component			
θ_N	θ_B	θ_A	$\theta_N = \theta_B, \theta_N = \theta_A$
0.830	0.654	0.943	0.000
0.014	0.022	0.019	
Order Processing Cost			
ϕ_N	ϕ_B	ϕ_A	$\phi_N = \phi_B, \phi_N = \phi_A$
-0.348	-0.246	-0.410	0.000
0.014	0.020	0.018	
Autocorrelation of Trading			
ρ_N	ρ_B	ρ_A	$\rho_N = \rho_B, \rho_N = \rho_A$
0.523	0.492	0.541	0.000
0.005	0.009	0.005	

Panel B: Announcement Surprise Coefficients

	γ_k	Std. Error
Unemployment	5.19	2.04
Consumer Price Index	-8.02	1.58
Durable Goods Orders	-8.51	0.88
Housing Starts	-5.85	0.72
Index of Leading Indicators	-1.73	1.31
Initial Jobless Claims	3.45	0.53
Trade Balances	4.17	2.98
Nonfarm Payrolls	-27.93	3.86
Producer Price Index	-11.78	1.65
Retail Sales	-6.12	1.29
U.S. Imports	-4.71	2.63
U.S. Exports	3.10	2.47

Table IV

Difference in Mean Transaction Return Between Announcement and Non Announcement Periods

The table reports the difference between the mean transaction price return during announcement and nonannouncement periods, relative to the trade of interest. Trades are grouped into three size categories based on the 33rd and 67th percentiles. The sample covers 8:00 a.m. to 9:00 a.m. ET from July 1, 1991 to September 29, 1995. The Non Announcement period consists of days without announcements, the Before period contains trades in the half-hour before announcements (8:00–8:30), and the After period contains trades in the half-hour after announcements (8:30–9:00). Statistical significance is measured using two sample t-tests and one-sided two sample Kolmogorov-Smirnov tests; p-values are reported below each mean return difference.

	Return Differences Relative to the Trade of Interest									
	Purchases					Sales				
	-2	-1	0	1	2	-2	-1	0	1	2
Panel A: Small Trades										
Before Announcements										
Difference in Mean Return	-0.060	-0.057	-0.053	-0.109	-0.107	0.003	0.012	0.039	0.018	0.072
t-statistic p-value	0.031	0.042	0.035	0.002	0.002	0.928	0.697	0.203	0.590	0.031
KS-statistic p-value	0.066	0.015	0.014	0.003	0.033	0.634	0.112	0.315	0.435	0.006
After Announcements										
Difference in Mean Return	0.064	0.053	0.031	0.051	0.057	0.005	-0.031	-0.040	-0.038	-0.077
t-statistic p-value	0.002	0.009	0.099	0.035	0.016	0.829	0.159	0.078	0.108	0.001
KS-statistic p-value	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.000	0.000	0.000
Panel B: Medium Trades										
Before Announcements										
Difference in Mean Return	-0.025	-0.113	-0.085	-0.076	-0.094	-0.062	0.009	0.040	0.068	0.070
t-statistic p-value	0.452	0.000	0.004	0.012	0.004	0.063	0.780	0.207	0.040	0.032
KS-statistic p-value	0.503	0.000	0.046	0.082	0.004	0.049	0.358	0.127	0.069	0.059
After Announcements										
Difference in Mean Return	0.090	0.070	0.074	-0.001	0.050	-0.104	-0.035	-0.048	-0.016	-0.030
t-statistic p-value	0.000	0.001	0.000	0.971	0.025	0.000	0.132	0.030	0.512	0.206
KS-statistic p-value	0.000	0.000	0.000	0.020	0.000	0.000	0.001	0.000	0.044	0.000
Panel C: Large Trades										
Before Announcements										
Difference in Mean Return	-0.118	-0.116	-0.171	-0.040	0.005	0.088	0.065	0.070	0.025	-0.037
t-statistic p-value	0.008	0.007	0.000	0.200	0.865	0.011	0.063	0.026	0.478	0.301
KS-statistic p-value	0.010	0.032	0.000	0.055	0.886	0.003	0.043	0.101	0.043	0.072
After Announcements										
Difference in Mean Return	0.050	0.057	0.030	0.029	0.042	-0.033	-0.069	-0.014	-0.039	-0.072
t-statistic p-value	0.068	0.030	0.224	0.185	0.042	0.131	0.002	0.493	0.083	0.002
KS-statistic p-value	0.000	0.000	0.000	0.000	0.004	0.002	0.000	0.002	0.000	0.000

Table V
Bid-Ask Spreads and Execution Costs Around Economic Announcements

The table reports transaction cost measures for the active 5-year Treasury note. Panel A shows the mean and standard deviation of quoted bid-ask spreads. Also reported is the bid-ask spread implied by the structural model, which is defined as $2(\theta+\phi)$. Standard errors for the spread estimates are calculated using the covariance matrix of the GMM estimators. Panel B reports round-trip costs for transactions of different durations. For each transaction and for each time interval, transaction costs are measured by comparing the purchase (sale) price to the sale (purchase) price of the first available offsetting transaction within the listed time interval. For example, 10 Minutes refers to transactions that were unwound at the first available offsetting trade between 5 and 10 minutes after the initial transaction. The sample covers the period July 1, 1991 to September 29, 1995.

		Announcement Days		
	No Announcements	Before the Release	After the Release	
	8:00 – 9:00	8:00 – 8:30	8:30 – 8:45	8:45 – 9:00
Panel A: Bid-Ask Spreads				
Quoted Spread	1.690	1.904	1.710	1.552
Standard Deviation	1.308	1.340	1.602	1.145
Model Implied Spread	0.964	0.817	1.120	1.013
Standard Error	0.015	0.024	0.031	0.023
Panel B: Round-Trip Execution Costs				
5 Minutes				
Number of Transactions	3245	1014	1833	1600
Average Transaction Cost	0.604	0.434	0.914	0.824
Standard Deviation	1.215	1.080	1.943	1.372
10 Minutes				
Number of Transactions	2451	665	952	853
Average Transaction Cost	1.372	0.886	1.716	1.340
Standard Deviation	3.216	2.144	7.150	4.549
15 Minutes				
Number of Transactions	1913	375	271	413
Average Transaction Cost	1.568	1.139	2.473	1.000
Standard Deviation	4.770	3.021	8.974	5.884

Table VI
Proximity to the News Release and Components of the Effective Spread

The table reports GMM estimates from the model fit to transaction price changes for the active 5-year Treasury note during the half-hour following economic announcements from the period July 1, 1991 to September 29, 1995. Indicator variables are used to allow the model parameters to vary in 15-minute intervals surrounding the announcement release times, which occur at 8:30 a.m. ET. The table reports the estimated components of the effective spread. The parameter subscript "B1" refers to estimates from trades from 30 to 15 minutes before the announcement (8:00–8:15), and "B2" refers to the 15 minutes before announcements (8:15–8:30). Subscript "A1" refers to estimates from trades in the 15 minutes after the announcement (8:30–8:45), and "A2" refers to the second 15-minute interval (8:45-9:00). Also shown are the restrictions and Chi-square p-values for tests that compare the restricted and unrestricted GMM criterion functions.

		LR p-value			LR p-value
Adverse Selection Component					
θ_{B1}	θ_{B2}	$\theta_{B1} = \theta_{B2}$	θ_{A1}	θ_{A2}	$\theta_{A1} = \theta_{A2}$
0.575	0.708	0.001	1.010	0.877	0.000
0.024	0.035		0.029	0.023	
Order Processing Costs					
ϕ_{B1}	ϕ_{B2}	$\phi_{B1} = \phi_{B2}$	ϕ_{A1}	ϕ_{A2}	$\phi_{A1} = \phi_{A2}$
-0.157	-0.320	0.000	-0.451	-0.370	0.025
0.023	0.032		0.029	0.022	
Autocorrelation of Trading					
ρ_{B1}	ρ_{B2}	$\rho_{B1} = \rho_{B2}$	ρ_{A1}	ρ_{A2}	$\rho_{A1} = \rho_{A2}$
0.462	0.473	0.567	0.535	0.547	0.223
0.012	0.014		0.008	0.007	

Table VII
Estimated Price Impact and Components of the Effective Spread

The table reports GMM estimates from the model fit to transaction price changes for the active 5-year Treasury note during the half-hour following economic announcements from the period July 1, 1991 to September 29, 1995. In each panel, the parameters are allowed to vary with announcement characteristics using indicator variables based on the 33rd and 67th percentiles. In panel A, the parameters vary with the total estimated price impact of that day's announcements, $\left|\sum \gamma_k S_{kt}\right|$, where S_{kt} is the announcement surprise and γ_k is the estimated sensitivity of prices to announcement type *k* as estimated in Table III. In Panel B, the announcement price impact is decomposed into components related to the precision of the information and the announcement surprise. Each day's cumulative announcement precision is measured by $\sum\left|\gamma_k I_{kt}\right|$, where I_{kt} is an indicator variable for announcement type *k* on day τ. Cumulative announcement surprise is measured as $\sum\left|S_{kt}\right|$. Trades are double sorted into groups based on the 33rd and 67th percentiles of $\sum\left|S_{kt}\right|$ and $\sum\left|\gamma_k I_{kt}\right|$. Also shown are the restrictions and Chi-square p-values for tests that compare the restricted and unrestricted GMM criterion functions.

Panel A: Total Price Impact

	Small	Medium	Large	LR p-value
Adverse selection	θ_{Sm}	θ_{Med}	θ_{Lg}	$\theta_{Sm}=\theta_{Med},\theta_{Med}=\theta_{Lg}$
	0.813	0.903	1.069	0.000
	0.028	0.030	0.035	
Order processing costs	ϕ_{Sm}	ϕ_{Med}	ϕ_{Lg}	$\phi_{Sm}=\phi_{Med},\phi_{Med}=\phi_{Lg}$
	-0.331	-0.412	-0.464	0.006
	0.026	0.029	0.034	
Autocorrelation of trading	ρ_{Sm}	ρ_{Med}	ρ_{Lg}	$\rho_{Sm}=\rho_{Med},\rho_{Med}=\rho_{Lg}$
	0.545	0.553	0.527	0.098
	0.009	0.009	0.009	

Panel B: Determinants of Announcement Price Impact and the Adverse Selection Component

		Announcement Surprise			
		Small	Medium	Large	All
					θ_{Low}
Announcement Precision	Low	0.733	0.833	0.857	0.790
		0.034	0.047	0.065	0.026
					θ_{Med}
	Med	0.875	0.937	1.059	0.942
		0.049	0.048	0.077	0.032
					θ_{High}
	High	1.013	1.063	1.081	1.069
		0.099	0.064	0.047	0.036
		θ_{Sm}	θ_{Med}	θ_{Lg}	
	All	0.819	0.946	1.038	
		0.028	0.031	0.035	
	LR p-value	$\theta_{Sm}=\theta_{Med},\theta_{Med}=\theta_{Lg}$		0.000	
		$\theta_{Low}=\theta_{Med},\theta_{Med}=\theta_{High}$		0.000	

Table VIII

Dispersion Among Economic Forecasts and Components of the Effective Spread

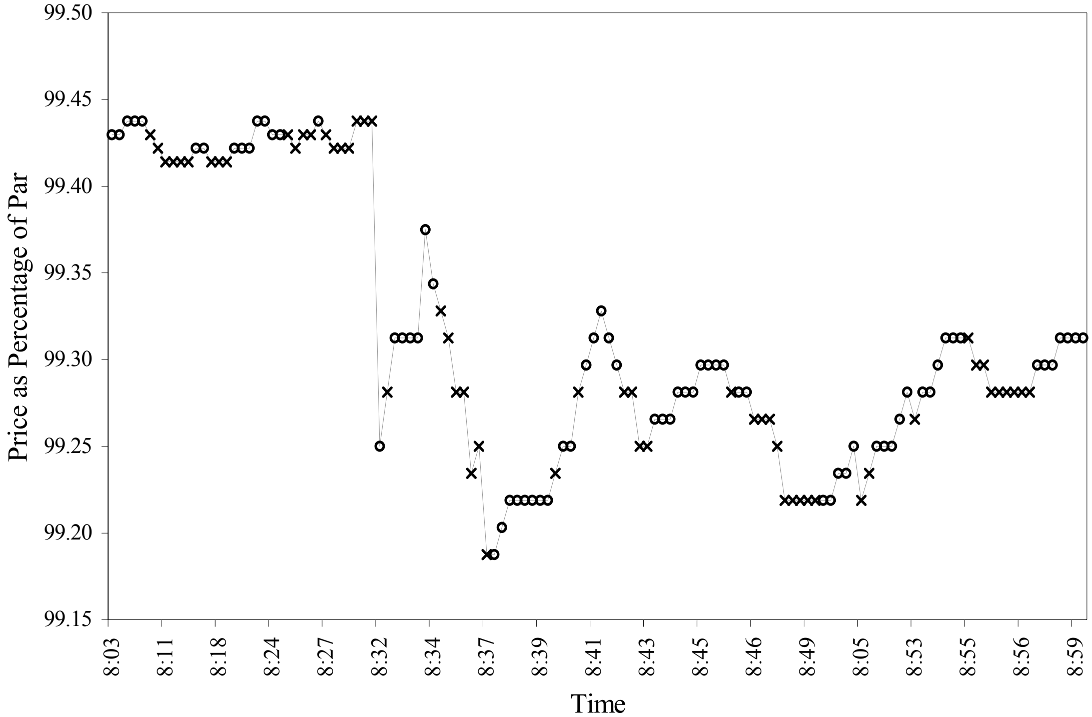
The table reports GMM estimates from the model fit to transactions price changes for the active 5-year Treasury note during the half-hour following economic announcements from the period July 1, 1991 to September 29, 1995. In each panel, the parameters are allowed to vary with measures of forecast dispersion using indicator variables based on the 33rd and 67th percentiles. In panel A, forecast dispersion is proxied by the difference between the 75th percentile forecast and the 25th percentile forecast. In Panel B, forecast dispersion is measured using the standard deviation of the forecasts. Also shown are the restrictions and Chi-square p-values for tests that compare the restricted and unrestricted GMM criterion functions.

Panel A: 75th – 25th Percentile Forecast

	Low	Medium	High	LR p-value
Adverse selection	θ_{Low}	θ_{Med}	θ_{High}	$\theta_{Low} = \theta_{Med}, \theta_{Med} = \theta_{High}$
	0.945	0.927	0.954	0.410
	0.034	0.030	0.032	
Order processing costs	ϕ_{Low}	ϕ_{Med}	ϕ_{High}	$\phi_{Low} = \phi_{Med}, \phi_{Med} = \phi_{High}$
	-0.393	-0.418	-0.417	0.759
	0.032	0.029	0.031	
Autocorrelation of trading	ρ_{Low}	ρ_{Med}	ρ_{High}	$\rho_{Low} = \rho_{Med}, \rho_{Med} = \rho_{High}$
	0.521	0.549	0.552	0.009
	0.009	0.009	0.009	

Panel B: Standard Deviation of Forecasts

	Low	Medium	High	LR p-value
Adverse selection	θ_{Low}	θ_{Med}	θ_{High}	$\theta_{Low} = \theta_{Med}, \theta_{Med} = \theta_{High}$
	0.845	0.962	1.029	0.000
	0.028	0.033	0.035	
Order processing costs	ϕ_{Low}	ϕ_{Med}	ϕ_{High}	$\phi_{Low} = \phi_{Med}, \phi_{Med} = \phi_{High}$
	-0.324	-0.424	-0.490	0.000
	0.028	0.032	0.030	
Autocorrelation of trading	ρ_{Low}	ρ_{Med}	ρ_{High}	$\rho_{Low} = \rho_{Med}, \rho_{Med} = \rho_{High}$
	0.506	0.558	0.559	0.000
	0.009	0.009	0.009	


99.50
99.45
99.40
99.35
99.30
99.25
99.20
99.15
Price as Percentage of Par
8:03
8:11
8:18
8:24
8:27
8:32
8:34
8:37
8:39
8:41
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8:45
8:46
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8:05
8:53
8:55
8:56
8:59
Time

Figure 1

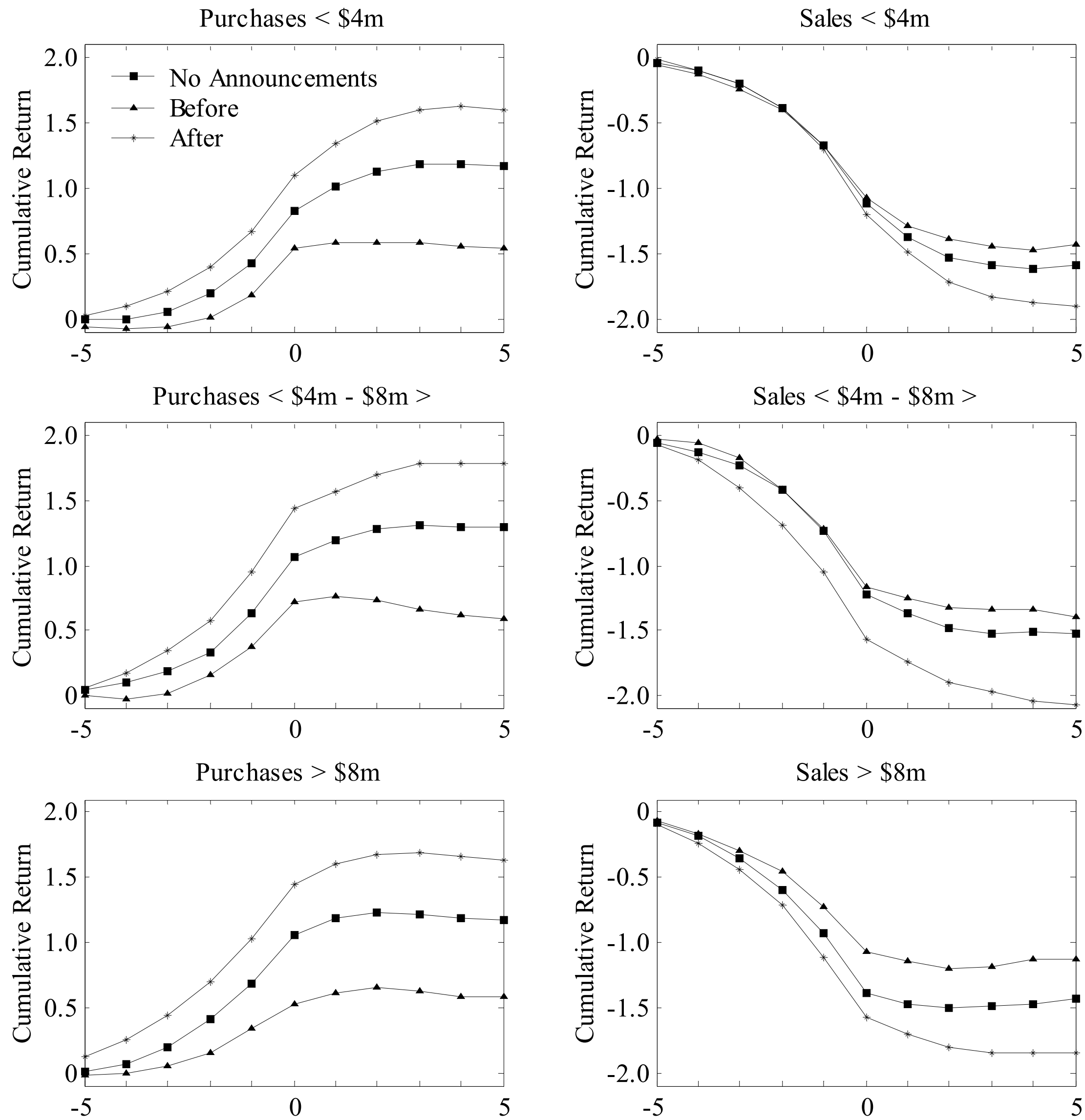
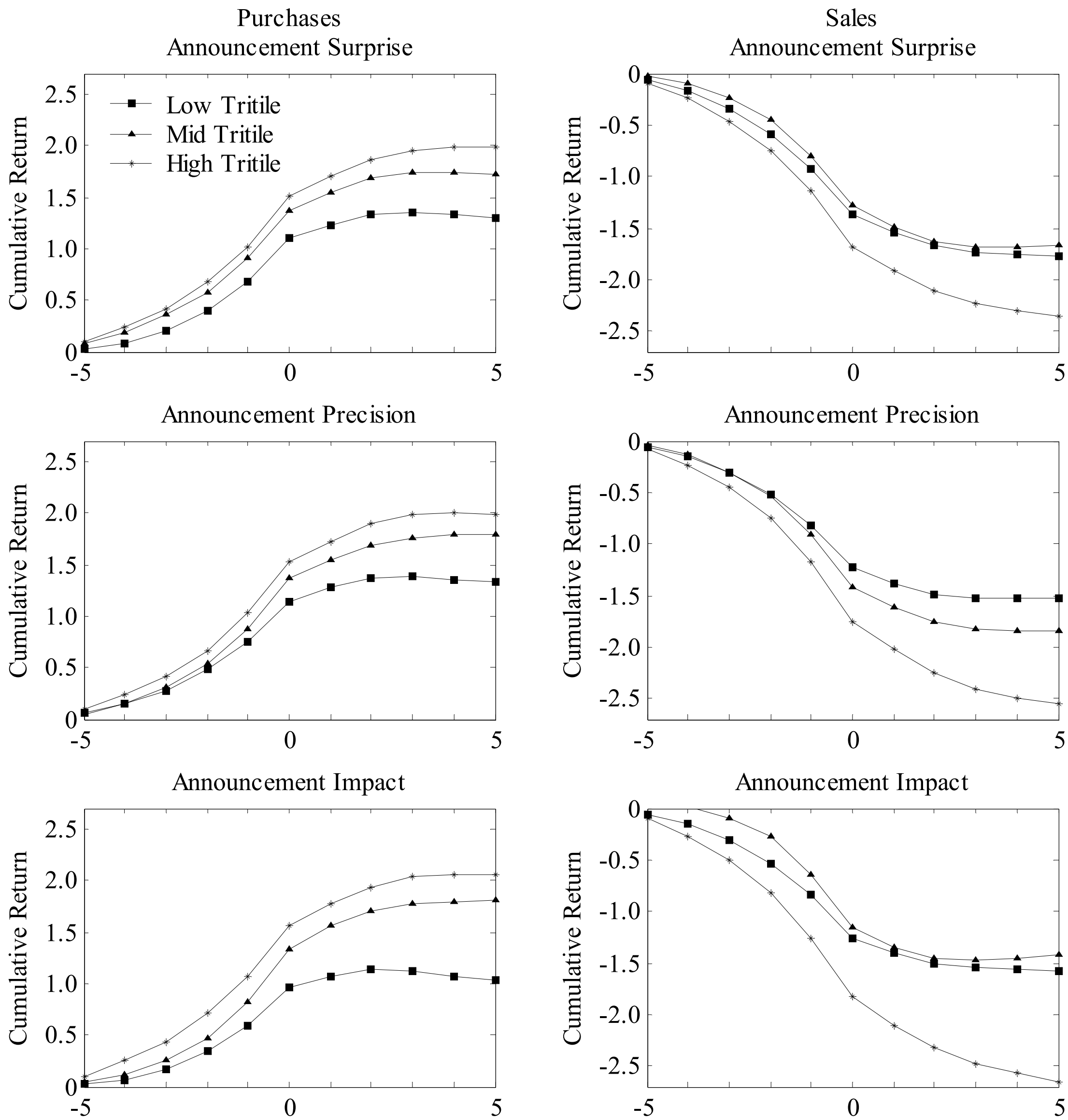

Purchases < $4m
Sales < $4m
Purchases < $4m - $8m >
Sales < $4m - $8m >
Purchases > $8m
Sales > $8m
No Announcements
Before
After
Cumulative Return

Figure 2



Purchases
Announcement Surprise
Sales
Announcement Surprise
Announcement Precision
Announcement Precision
Announcement Impact
Announcement Impact
Cumulative Return
Low Tritile
Mid Tritile
High Tritile

Figure 3

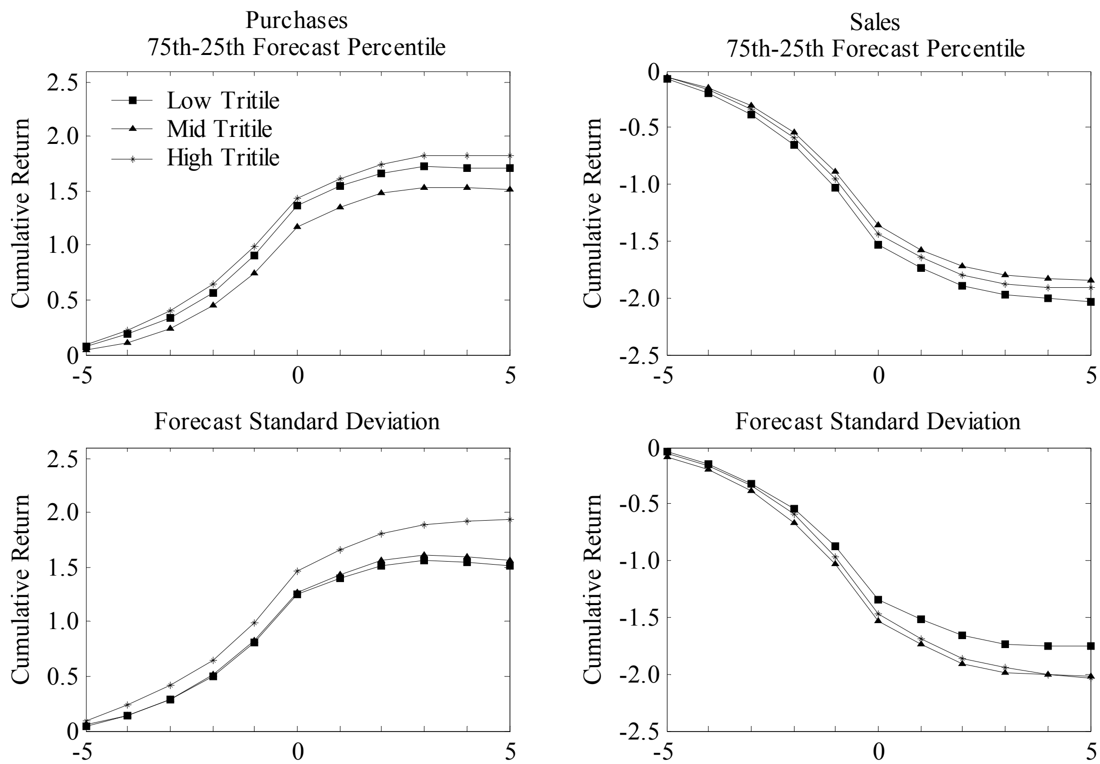

Purchases
75th-25th Forecast Percentile
Sales
75th-25th Forecast Percentile
Forecast Standard Deviation
Forecast Standard Deviation
Cumulative Return
Low Tritile
Mid Tritile
High Tritile

Figure 4

Figure 1. Employment announcement response. The chart shows the series of transaction prices for the active 5-year Treasury note on November 4, 1994 from 8:00–9:00 a.m. ET, and consists of 128 trades. Buyer-initiated trades are indicated with an "o," and seller-initiated transactions are indicated with an "x."

Figure 2. Economic announcements and trade impact. The chart shows cumulative returns based on transaction prices relative to the purchase or sale of interest. Trades are grouped into three size categories based on the 33rd and 67th percentiles. Small trades are less than \$4 million, medium trades are between \$4 and \$8 million, and large trades are greater than \$8 million. The sample covers from 8:00 a.m. to 9:00 a.m. ET during the period July 1, 1991 to September 29, 1995. The No Announcements period consists of days without announcements. The Before period contains trades in the half hour before announcements (8:00–8:30), and the After period contains trades in the half-hour after announcements (8:30–9:00).

Figure 3. Economic announcement characteristics and trade impact. The chart shows cumulative returns based on transaction prices relative to the purchase or sale of interest. In the top row, trades are sorted into three groups using the 33rd and 67th percentiles of that day's cumulative announcement surprise $\Sigma|S_{kt}|$. In the second row, trades are sorted into groups based on the level of that day's cumulative announcement precision $\Sigma|\gamma_k I_{kt}|$, where γ_k is the sensitivity of prices to announcement type *k* as estimated in Table III, and I_{kt} is an indicator variable that is equal to 1 if announcement type *k* is released on day τ, and 0 otherwise. In the last row, returns are shown for the trades sorted into groups based on the combined impact of that day's announcements $|\Sigma \gamma_k S_{kt}|$. The sample contains trades of the active 5-year Treasury note from 8:30 a.m. to 9:00 a.m. ET on days with economic announcements during the period July 1, 1991 to September 29, 1995.

Figure 4. Dispersion among economic forecasts and trade impact. The chart shows returns based on transaction prices relative to the purchase or sale of interest. Trades are sorted into three groups using the 33rd and 67th percentiles of two measures of forecast dispersion. In the first row, dispersion among

analysts' forecasts of macroeconomic data is measured as the difference between the 75th and 25th percentile forecasts. In the second row, forecast dispersion is measured as the standard deviation of analysts' forecasts. The sample contains trades for the active 5-year Treasury note from 8:30 a.m. to 9:00 am ET on days with economic announcements during the period July 1, 1991 to September 29, 1995.

[*]Goizueta Business School, Emory University, 1300 Clifton Rd., Atlanta, GA 30322, clifton_green@bus.emory.edu. This article is based on a chapter of my dissertation at New York University, and an earlier version is titled "News Releases, Private Information, and Intraday Price Movements in the U.S. Treasury Market." I appreciate the comments of Edwin Elton (my dissertation chairman), Hank Bessembinder, Stephen Figlewski, Michael Fleming, Kenneth Garbade, Martin Gruber, Joel Hasbrouck, Anthony Lynch, Matthew Richardson, and seminar participants at the 1999 Western Finance Association meetings, Arizona State, Boston College, Columbia, Cornell, Dartmouth, Emory, Indiana University, University of Georgia, Lehman Brothers, University of Maryland, New York University, Notre Dame, Penn State, University of Pittsburgh, and University of Virginia. I also wish to acknowledge Nasdaq for providing financial assistance and GovPX Inc. for providing the data.

[1] Umlauf (1991) fits a Kyle (1985) type model to study the lead-lag relation between interdealer and retail prices before interdealer prices were publicly available. Vitale (1998) uses a Madhavan and Smith (1991) type model to measure the effects of dealer inventories on U. K. Treasury prices. Cohen and Shin (2002) fit a Hasbrouck (1991) type model and emphasize the relation between price changes and future order flow.

[2] For example, knowing a retail customer plans to sell a considerable amount of a particular bond to rehedge their interest rate exposure could be useful in predicting short-term price movements.

[3] The reliance on interdealer brokers also contrasts with the Italian treasury market. For example, Massa and Simonov (2001) study reputation effects in the direct interdealer trading of Italian Treasury securities.

[4] During the time period of the study, four of the five inter-dealer brokers (Garban, Hilliard Farber, Liberty and RMJ) report their quotes to GovPX. These brokers cover approximately 75 percent of the trades in the interdealer market.

[5] I determine the width of the event window by ensuring that the window includes the first relatively large price change around 8:30, where large refers to two standard deviations greater than the average price change in the five minutes leading up to the event. Omitting two trades before versus five trades after is a result of the increased trading intensity following announcements.

[6] The term basis point (one hundredth of one percent) is more commonly used to describe bond yields. Here and throughout, I use basis point to describe changes in price as a percentage of par.

[7] Greene and Smart (1999) use the MMR approach to examine equity spread components around analyst recommendations.

[8] Five lags are used to construct the Newey-West estimate of the covariance matrix. Including more lags does not alter the significance of the results.

[9] As discussed in Section II.A, I aggregate trades around the event time to ensure that the price change spans the announcement release. Since trade direction is not well defined for these trades, I set x_t and x_{t-1} equal to zero for trades immediately following announcements.

[10] Data limitations also prompt the reliance on unadjusted transaction returns. I examine relatively narrow time intervals around announcements. Requiring each trade to have 20 previous trades in the same interval on the same day from which to construct a benchmark return, as in Koski and Michaely (2000), greatly reduces the number of observations.

[11] As in MRR, the moment conditions used to determine the autocorrelation in order flow implicitly force the constant term in the partial autocorrelation regression to be zero. Relaxing this assumption by including an additional moment condition for the constant term does not appreciably change the results.

[12] In practice, the model yields positive spreads as long as $\theta > -\phi$.

[13] The results are not sensitive to adjusting the number of leads or lags. The response patterns are similar when using 10 or 20 trades.

[14] I also reestimated Equation (3), allowing θ and ϕ to vary around announcements and with the trade size categories defined in Figure 2. The estimates show that medium sized trades have a slightly larger impact on prices than small or large trades, but the pattern around announcements is apparent for each size category. The table is not reported for brevity.

[15]Comparing an individual purchase transaction to the first available sale transaction often results in a negative measure of transaction costs, which reflects the fact that, on average, purchases are likely to be followed by additional purchases.

[16] I estimate the model on nonannouncement days sorted into quartiles based on average quoted spreads and find model implied spreads increase monotonically with quoted spreads.

[17] Additional evidence for the inability of quoted spreads to capture variation in transaction costs around announcements is obtained by examining transaction price changes for trades where quoted spreads are zero at both time t and t-1. Individual (non-aggregated) trades at time t-1 that are unwound at time t result in average transaction costs of 0.05 basis points before announcements and 0.17 basis points after announcements, and the means are statistically different at the 0.01 level according to two sample t-tests.

[18] For example, in the current sample there are an average of 57 trades each day from 11:00 a.m. to 12:00 a.m. on days without announcements, and 69 trades on days with announcements. The means are statistically different at the 0.01 level according to a two sample t-test.

[19] It is possible that informed dealers trade prior to the half-hour before announcements, in which case the level of information asymmetry may be larger in earlier periods. The frequency of information releases makes it difficult to define a longer pre-event period, in that the pre-event period for one announcement may coincide with the post-event period for an earlier release.

[20] The correlation between the tritile-based dummy variables is smaller (roughly 0.4).