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Price Discovery in the U.S. Treasury Market: Automation vs. Intermediation

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This paper examines the contribution to price discovery by electronic and voice-based trading systems in the U.S. Treasury market. Evidence shows that the electronic trading system has more price discovery and that trading automation increases the speed of incorporating information into prices. However, human trading generates significant price discovery, though its volume is low. The relative contribution of a trading system to price discovery depends on liquidity, volatility, volume, trade size, and order imbalance. The voice-based trading system contributes more to price discovery when trade size is large and liquidity is low. These findings provide important implications for the design of electronic markets for securities with different characteristics and trading environments.

Key words: price discovery; electronic trading; information share; liquidity; error correction
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1. Introduction

Technological innovations have been rapidly transforming the organization and operation of markets. Many markets that have traditionally relied upon collocation of traders and products are transitioning to electronic platforms. Rapid changes and the widespread availability of technology have spurred considerable interest in research on the economic consequences of the development of information systems and information technology (see Banker and Kauffman 2004, Anandalingam and Raghavan 2005). The design of information systems can affect market quality (see Bard and Bejjani 1991, Anandalingam et al. 2005). A central issue in this field of research involves designing electronic market mechanisms and evaluating the impacts of information technology on operations and market quality (see Bard and Bejjani 1991, Bakos 1997, Anandalingam et al. 2005, Campbell et al. 2005, Viswanathan 2005). A number of studies have contributed to understanding how technology affects markets generally[1] and how traders choose different trading channels (Brynjolfsson and Smith 2000, Brynjolfsson et al. 2009, Overby and Jap 2009). There is substantial evidence that the adoption of electronic trading systems can dramatically lower operating and transaction costs and improve liquidity, but it may also generate undesirable effects, such as increasing trading risk, volatility, and adverse selection.

Although information technology has affected almost every sphere of the economy, its impact on financial markets is especially conspicuous.[2] Not surprisingly, a vast literature is devoted to the study of the effects of electronic trading in financial markets (Cardella et al. 2010). Similar to the findings for the products market, information technology has provided benefits, such as increasing the speed of information processing and the efficiency of trading and settlement and lowering operation and trading costs and latency. Although technology improves operational efficiency and liquidity in financial markets, a question remains whether it can improve pricing efficiency and reduce information risk.

[1] See, for example, Clemons and Weber (1997), Dewan and Mendelson (1998, 2001), Easley et al. (2009), and Garvey and Wu (2010). For a comprehensive survey of important studies of electronic trading for nonfinancial and financial markets, see Banker and Kauffman (2004).

[2] The financial industry is highly dependent on information technology and is one of the most information-intensive sectors of the U.S. economy. On average, a financial firm allocates about 20% of its capital outlays to information systems, and half of the revenue of trading desks goes to information technology (Dewan and Mendelson 1998).

Advanced information and communication technology have enabled information propagation and arbitrage at lighting speeds, which has the potential to reduce pricing errors and enhance risk sharing, hedging, and securities allocation in financial markets. This could ultimately reduce firms' cost of capital and increase the efficiency of financial markets. However, technology has complex effects that are not always desirable, and the empirical evidence on the effects of trading automation is mixed. For example, Hendershott and Riordan (2009) find that algorithmic trading (AT) contributes more to discovery of the efficient price than does human trading. Hendershott and Moulton (2011) show that increasing automation and trading speed after the New York Stock Exchange's (NYSE) introduction of its Hybrid Market reduces the noise in prices, making prices more efficient, but raises the adverse selection component of the effective spread. Hendershott et al. (2011) show that AT narrows bid-ask spreads, decreases adverse selection, and reduces trade-related price discovery. Their findings suggest that AT improves liquidity and increases the informativeness of quotes. By contrast, Hasbrouck and Saar (2009) find that "fleeting orders" induced by improved technology can impair market liquidity. A fleeting order occurs when a trader submits and quickly cancels a hidden limit order or uses an immediate-or-cancel order. This type of limited order consumes liquidity rather than provides liquidity. Kirilenko et al. (2011) find that high-frequency trading in an electronic market may amplify price volatility and compete for liquidity, and Jarrow and Protter (2011) show that it can cause mispricing. Levecq and Weber (2002) find that electronic trading can decrease market depth. Moreover, electronic trading could increase market vulnerability as experienced by several "flash crashes" recently, and high-frequency trading facilitated by technology could be used to manipulate the market (Nishimura 2010).

This paper contributes to the current literature by examining the impact of fully automated trading on price discovery in the U.S. Treasury market. In the secondary Treasury market, virtually all trades between dealers are handled by interdealer brokers (IDBs). There are two types of interdealer trading systems: electronic and voice-based. In the former, orders are matched electronically, whereas in the latter, orders are placed and trades are executed over the telephone. By interacting with dealers over the phone, a voice broker is able to collect more information and provide more services to participating dealers. A voice broker can also search and negotiate with a compatible trading partner on behalf of the client to obtain a better price. These services are valuable when an order size is large and volume is thin. Trading through voice brokers takes up more time, but orders may be executed with price improvement. By contrast, electronic brokers offer speedy trading and anonymity, which may encourage informed trading and enhance information efficiency. It remains unclear to what extent each trading system contributes to price discovery in the Treasury market as a whole and in different segments of this market.

The interdealer broker market of Treasuries provides an excellent laboratory for studying the roles of automation versus human intermediaries in the price discovery process. First, Treasury securities traded on the electronic and voice-based systems are virtually identical instruments. Their payoff structure is similar, and there is no complicated firm-specific information involved, as there is in the trading of stocks and equity derivatives. Second, Treasury securities are traded by dealers and interdealer brokers using the same trading and settlement procedures, except that one venue is automated and the other is voice-based. This enables us to better control for the effects associated with differences in security characteristics, trading mechanisms, and market structure, which was not feasible in previous studies on price discovery involving different trading systems, and to provide a more accurate assessment of the effect of electronic trading.[3]

Barclay et al. (2006) are the first to study the choice of trading venues by dealers in the Treasury securities to determine what human services are difficult to replicate in a fully automated trading system. Their study emphasizes the aspects of liquidity provision and the matching function of the two trading systems. They find that human intermediaries can uncover hidden liquidity and facilitate better matching of less liquid off-the-run Treasury securities. In this paper, we extend their study to focus on the price discovery function of electronic and voice-based trading systems. The issue with regard to the voice broker's informational role is important because recent studies have uncovered significant information asymmetry in the Treasury market, contrary to the perception that there is little information asymmetry in Treasury securities (see Brandt and Kavajecz 2004, Green 2004, Li et al. 2009). Our work complements the Barclay et al. (2006) study by exploring the informational roles

[3] For example, past studies on the price discovery contribution of regional exchanges, NASDAQ, and electronic communications networks (ECNs) for the NYSE-listed stocks were unable to isolate the effects of differences in market structure and the quote-setting process (see Benveniste et al. 1992, Heidle and Huang 2002). Similar problems are encountered by studies on information efficiency of spot versus derivatives markets (see Easley et al. 1998). As a consequence, it is unclear whether differences in price discovery contributions between these venues are due to different market structures/trading mechanisms, security characteristics, trading platforms, or something else.

of electronic and voice interdealer brokers in the price discovery process under information asymmetry.

Understanding the price discovery process in the Treasury market is important for academicians, practitioners, policy makers, and designers of information systems. Price discovery—the efficient and timely incorporation of new information into security price—is arguably the most important function of securities markets (see Lehmann 2002). Financial economists are interested in the information efficiency and price discovery efficacy of a trading venue. The Treasury market is a large market, with marketable issues of about \$9.1 trillion.[4] From the investment perspective, it is essential to ascertain how price is formed in this market. Measuring information efficiency and tracking the price discovery process are of particular interest to policy makers who monitor market conditions regularly and have a great deal of concern about market quality. A question of fundamental importance is whether trading automation improves market quality. Understanding whether electronic trading improves the efficiency of price discovery has important implications for designers of trading platforms. Well-designed trading platforms are beneficial to traders and investors. Previous studies show that the success of an electronic trading system depends on a number of factors, which vary by market (see Hendershott 2003, Choudhury and Karahanna 2008). There are very few studies on the factors influencing the adoption of the electronic trading system and its effects in the bond market. Our study of this issue in the Treasury market hence provides valuable information for the design of electronic markets.

Recently, there has been increasing interest in the issue of price discovery in the Treasury market (see, for example, Fleming and Remolona 1999, Balduzzi et al. 2001, Huang et al. 2002, Green 2004, Brandt and Kavajecz 2004, He et al. 2009, Li et al. 2009). Most studies examine issues related to price discovery of the Treasury market using the data from GovPX, a firm that consolidates quote and trade information from several voice interdealer brokers. In contrast, we assess the contribution to price discovery by voice-based and electronic trading systems of the interdealer broker market using both GovPX data and an electronic transaction data set made available by BrokerTec. Boni and Leach (2002) examine depth discovery using only the GovPX data. Mizrach and Neely (2006) use the eSpeed data to examine the effect of trade automation on bid-ask spreads, trading volume, and price impacts. Our paper differs from these studies by comparing price discovery across trading venues using a long-span comprehensive transaction data set and systematic price discovery measures.

By exploring the roles of electronic and human trading systems in the Treasury market, our paper extends the current literature of market microstructure. First, we document the first evidence on price discovery across trading venues in the interdealer brokerage market of Treasuries. We find that the electronic trading system has the most price discovery. The electronic platform appears to assume a more dominating role in price discovery in the Treasury market than in the equity market (see Huang 2002, Theissen 2002). This discrepancy is attributable to large volume, less quality uncertainty, and relative homogeneity in Treasury securities, which make it easier to trade in the electronic market.

Second, although the trading volume is low, human trading generates significant price discovery. Given the low market share of the voice-based trading system, the amount of price discovery on this system is relatively high. The voice-based trading system contributes more to price discovery in the segment of large-size trades. Because large-size trades account for a significant portion of total volume, voice brokers' services are valuable even for active, liquid, on-the-run securities. Third, the contribution to price discovery by each trading venue varies with trading environments. On days when trading is less active and liquidity is low, when trades are larger, when it is more costly to supply liquidity by placing a firm limit order, and when a dealer has a larger imbalance between buying and selling, the contribution of the electronic trading system to price discovery is lower. This finding implies that price discovery will be quite different for off-the-run securities. Because voice brokers provide more liquidity to these securities, they are expected to play a more important role in price discovery of the off-the-run Treasury market. This is consistent with the finding that voice brokers have a much larger market share in off-the-run Treasuries (see Barclay et al. 2006).[5] Our results also suggest that human services will be more important during turbulent periods when liquidity is scarce. Last, the speed of incorporating information into Treasury prices has improved substantially since the adoption of the electronic trading system, and the information share of the electronic trading system has increased significantly surrounding the macroeconomic news announcement. Results strongly suggest that traders prefer the electronic trading venue that offers speedier order execution in anticipating that prices will react quickly to the news announcement.

[4] See *Treasury Bulletin*, Federal Debt, June 2011. Of the total Treasury debt outstanding (\$14.3 trillion), the amount of nonmarketable debt is \$5.2 trillion.

[5] Barclay et al. (2006) report that electronic brokers' market share for off-the-run issues is only 12%.

Our paper also contributes to the literature of information systems and information technology by extending our understanding of how technology affects markets more generally. Although electronic trading has come to play a very important role in the equity market, the adoption of the fully automated trading system has been quite slow in the bond market. The issue of electronic trading in the bond market is an important and underexplored area. Understanding why electronic platforms are less successful in parts of the fixed-income market has important implications for developers of new trading platforms. For example, previous studies have suggested that human intermediation survives primarily because there is quality and information uncertainty in traded products (see Overby and Jap 2009). However, our paper shows that human intermediation remains important in active homogeneous securities, such as Treasuries, that have little quality uncertainty and simple payoff structures. Thus, information uncertainty and product quality risk are not the sole issues in the design and implementation of the electronic trading system. Our findings suggest that when deciding the appropriate mixture of electronic and human-assisted trading channels or adding communication devices to assist trading by participants, designers should also consider specific factors such as trade size, the cost of liquidity provision, nature of information flow, securities characteristics, liquidity externality, and trading environments pertaining to different markets.

Our results show that electronic and human trading systems perform different functions and contribute to price discovery in different segments of the Treasury market. Human intermediaries play a more important role in times of low market liquidity and high order imbalance and volatility. This finding suggests that a combination of electronic and human trading systems can improve the welfare of market participants. Moreover, the structure of markets matters. For a market dominated by large institutions with block trades and illiquid securities, human services remain important. This is true even for markets with standardized instruments of little quality and information uncertainty, like Treasuries. Unless the electronic system can successfully replicate all valuable services of human intermediaries, our results suggest that a role remains for human intermediation.

The remainder of this paper is organized as follows. Section 2 describes empirical methodology and the procedure for estimating the amount of price discovery. Section 3 discusses the data and presents empirical results. Section 4 examines the determinants of information shares. Section 5 reports additional tests for the amount of new information incorporated into prices of transactions with different sizes and macroeconomic news announcement effects. Section 6 concludes the paper.

2. Trading Venues and Price Discovery

When securities are traded in a single centralized market, price discovery is solely produced by that market. Conversely, when trades of a security take place in multiple trading venues, questions naturally arise as to the relative contribution of each venue to price discovery of the whole market. The answer to this question depends to a large extent on the functions that each trading system performs and how valuable these functions are for market participants.

In the interdealer brokerage market of Treasuries, electronic and voice-based systems perform several similar functions. Limit order information is continuously displayed in both trading systems, and dealers can trade aggressively by hitting an existing limit order or trade passively by submitting a limit order through either venue. Trade prices and volume are made publicly available immediately after transactions through the Internet and data vendors. More recently, the electronic trading platform has added a number of features that mimic voice brokers' services to traders with large orders to fill, i.e., auto-refresh to replace a limit order once it is executed, a reserve size feature to indicate likely additional demand, and a negotiation feature to directly negotiate large trades. Despites these efforts, there remain unique human services that cannot be replicated by the electronic trading platform, particularly when there is complex qualitative information that cannot be easily conveyed through the electric trading system.

An important function of voice brokers is bringing together counterparties with substantial size to trade for liquidity reasons or trades with complicated terms that are difficult to match. When the order is large or terms are complicated, a bilateral search for the most favorable quotes by an individual dealer can be cumbersome. Acting as the focal point for buy and sell orders, voice brokers reduce the cost of information search and waiting time for trade execution. Voice brokers play a subtle role in matching larger orders. In negotiating with the other party, the voice broker conceals information about his client and transaction amount. This is particularly desirable for a large trade because revealing the order information will place a trader at a disadvantage when trading requires extensive search for the counterparty. The broker will only reveal the buyer's information to a natural counterparty with similar size and needs to trade. Through repeated interactions with buyers and sellers, the voice broker may uncover hidden liquidity and detect informed trades to protect his or her customers from adverse selection.

Orders matched by voice brokers carry higher cost and so a higher commission is charged, which results in higher marginal cost of liquidity supply. By contrast, because orders are matched without human intervention, the electronic trading platform incurs lower cost per trade and charges a lower commission. Lower cost of trading and speedy order execution attracts traders to participate in the electronic system. These are the main reasons that the market share of the electronic trading system has increased steadily since its inception.

Market microstructure theory suggests that informed traders choose to trade in a venue with higher liquidity and greater depth. Also, informed traders like to trade in a venue where their activity is less likely to be detected, fearing that revealing their presence will drive liquidity traders out of the marketplace. This means that informed traders would prefer a trading venue that offers liquidity, anonymity, and speedy execution. The electronic platform seems to have most of these features that suit informed traders.

On the other hand, the electronic trading platform has no brokers to facilitate trades. Customer orders are directly crossed with one another. Although speedy matching and lower trading costs are quite appealing to liquidity traders, without brokers' assistance their orders may be executed with prices deviated from the full-information or fundamental value. Imperfect information coupled with high speed of trading may generate larger or more frequent temporary price distortions. As such, transaction prices in the electronic trading system may be subject to errors. By contrast, voice brokers provide more information to traders to facilitate trading. Thus, it is not clear whether the electronic trading system would always prevail in price discovery. In this section, we construct empirical measures to determine which trading venue contributes more to price discovery in the interdealer Treasury market.

Price discovery measures are constructed by the methods suggested by Hasbrouck (1995) and Gonzalo and Granger (1995) to gauge the contribution to price discovery by electronic and voice-based IDB trading systems. These are two widely accepted price discovery measures for security trading in multiple markets in microstructure literature (see Huang 2002, Lehmann 2002, Yan and Zivot 2010). We outline the estimation procedure here. Constructing these measures requires a specification of price dynamics. Consider two trading systems with prices represented by two cointegrated I(1) series $P_t = (x_t, y_t)'$, which share a common implicit efficient (equilibrium) price. The error-correction term of the cointegrated I(1) price series is $z_t = \beta' P_t = x_t + \beta_2 y_t$, and the (normalized) cointegration vector is $\beta = (1, \beta_2)'$. The vector error-correction model (VECM) can be expressed as[6]

$$\Delta P_t = \alpha\beta' P_{t-1} + A_1 \Delta P_{t-1} + A_2 \Delta P_{t-2} + \cdots + A_{r-1}\Delta P_{t-r+1} + e_t, \tag{1}$$

where $\alpha = (\alpha_1, \alpha_2)'$ and $\Delta = 1 - B$ is the first difference operator. α_j reveals the speed of price correction when price in one market deviates from that in the other market. A smaller $|\alpha_j|$ means a lower speed of correction to the price in the other market and more price discovery in market j. In the special case of $\alpha_1 = 0$ and $\alpha_2 \neq 0$, the first market does not correct for the price difference and only the second market does. Thus, the first market is credited for the entire amount of price discovery. The error term e_t is a zero-mean vector of serially uncorrelated innovations with a covariance matrix $\Omega = (\sigma_{ij})$, where $\sigma_{11} = \sigma_1^2$ and $\sigma_{22} = \sigma_2^2$ are the innovation variances and $\sigma_{12} = \sigma_{21} = \rho\sigma_1\sigma_2$ is the covariance with ρ being the correlation of innovations in the two markets.

Prices for the same security traded in different markets would tend to converge to a common efficient price in the long run but might deviate from each other in the short run because of imperfect market conditions. The Hasbrouck measure is defined as the proportional contribution of a market's innovation to the innovation in the common efficient price. This price discovery measure essentially captures the extent of the efficient price variation explained by the innovation in each market. By contrast, the Gonzalo–Granger method decomposes the price into the permanent and transitory components and associates the permanent component with the long run price. The weight given to price discovery is defined as the change in the permanent component with respect to the information shock. For convenience, we refer to the common factor weight in the Gonzalo–Granger model as the GG measure and use the term "information share" to represent the contribution of a trading system to price discovery of the Treasury market for both measures in the remaining analysis.

The Gonzalo–Granger measure for x_t and y_t are defined as

$$GG_x = \frac{-\alpha_2}{\alpha_1 - \alpha_2} \quad \text{and} \quad GG_y = \frac{\alpha_1}{\alpha_1 - \alpha_2}. \tag{2}$$

As indicated, the GG measure is primarily based on the speed (the α coefficient) of the error-correction term, or how price in each market changes in response to the preceding price disequilibrium in the two markets. By contrast, the Hasbrouck measure accounts for the innovation e_t in the two markets, in

[6] The VECM setup is consistent with the microstructure model suggested by Glosten (1987).

addition to the speed of adjustment. The Hasbrouck measures for x_t and y_t are given as follows:

$$H_x(U)=\frac{(-\alpha_2\sigma_1+\alpha_1\rho\sigma_2)^2}{(-\alpha_2\sigma_1+\alpha_1\rho\sigma_2)^2+(\alpha_1\sigma_2\sqrt{1-\rho^2})^2},$$
$$H_y(L)=\frac{(\alpha_1\sigma_2\sqrt{1-\rho^2})^2}{(-\alpha_2\sigma_1+\alpha_1\rho\sigma_2)^2+(\alpha_1\sigma_2\sqrt{1-\rho^2})^2}. \quad (3)$$

Given the ordering of $P_t=(x_t, y_t)'$, the above measures generate the maximum value (upper bound) for the first price series x_t and the minimum value (lower bound) for the second price series y_t. Reversing the order and reestimating the VECM for $(y_t, x_t)'$ gives the upper bound $H_y(U)$ for y_t and the lower bound $H_x(L)$ for x_t. When the correlation (ρ) of the innovations across the series is low, the two bounds are tight and their average is an effective summary measure of the information share.

Both Hasbrouck and GG measures have merits and drawbacks, and there is no consensus as to which one is superior. Lehmann (2002) and the references therein give a thorough comparison between these two measures. In our basic estimation, we report both price discovery measures for comparison. However, for brevity we focus on the Hasbrouck measure in the extended empirical analysis because results for the GG measure are qualitatively similar.

For the analysis to be meaningful, it is important to check if the I(1) cointegration assumption is satisfied for the two price series representing the electronic and voice-based trading systems. Our analysis begins with performing the augmented Dickey-Fuller (ADF) unit root test for the price series. After confirming that unit root exists in each price series and that the two series are cointegrated, we set up a VAR model for the bivariate price series and use BIC to determine the AR order in the model. This in turn determines the AR order used in the VECM model. We use Johansen's trace statistic to determine the number of cointegration vectors. As shown later, our empirical evidence points to one cointegration vector and hence the $\alpha\beta'$ specification for the lagged disequilibrium error in (1) is appropriate.

Based on the estimated VECM model, we compute the information share measures. For the Hasbrouck measure, upper and lower bounds are calculated. In addition, we examine the dynamic relations between the two price series and analyze the pattern of impulse response to a unit shock in each trading system. We now turn to empirical estimation.

3. Data and Estimation of Price Discovery Measures

Trades and quotes of Treasury securities are from GovPX and BrokerTec data sets. The GovPX, Inc. was set up under the guidance of the Public Securities Association as a joint venture by primary dealers and several interdealer brokers in 1991 to increase public access to Treasury prices. GovPX consolidates trade and quote information from voice interdealer brokers. Historically, the interdealer brokerage market was operated primarily through a voice-based system. Later, several interdealers developed platforms for electronic trading. Acquired by ICAP in May 2003, BrokerTec provides access to a pool of liquidity that includes major participants in both the U.S. and European fixed-income markets. Publicly accessible trade and quote data for the electronic trading platform are made available by BrokerTec.

The GovPX data set contains detailed individual security information such as CUSIP, coupon, and maturity date and an indicator of whether the security is trading when issued, on-the-run, or off-the-run. The GovPX data date back to 1991 (June 17). The BrokerTec data set also includes individual Treasury security information, price, and quantity but only for on-the-run issues. We have BrokerTec data from October 2001. The BrokerTec data are continuously available on the daily basis only for the 2-, 5-, and 10-year on-the-run Treasuries though the data set covers other maturities. Therefore, we focus on the 2-, 5-, and 10-year on-the-run notes.[7] Because our empirical analysis requires both GovPX and BrokerTec data, our study period starts from October 2001. The sample period ends in 2005.

Both data sets contain quote and trade information and trade side (buy or sell). The quote data include the best bid and ask prices, associated yields, the time of each bid and offer, and the respective bid and ask size (depths). The trade data include the time of trade, trade size, price, and yield. The BrokerTec data set includes a variable for identifying each individual trade, whereas the GovPX reports accumulated trading volume instead. Trades in the GovPX data set can be identified by changes in accumulated volume. However, GovPX stopped reporting accumulated volume after March 2001, so we need to use other information to determine trades.

In this study, we identify trades in the GovPX data set based on the information for changes in trade sign (hit or take), price and size, and workup information. Interdealer brokers provide their customers with real-time screens of quotes, workups, and transactions they are working. When receiving new information, a broker inputs it to the system, causing a new line of observations to be generated in the data system, which updates all variables appropriately to reflect

[7] For example, the data for 3- and 30-year on-the-run Treasuries are not continuous partly because these securities are not auctioned regularly.

Table 1 Summary Statistics of Treasury Data

Maturity	Data	Price	Volume	Number of trades	Number of quotes	Quoted spread	Trade size (millions)	Price volatility	Market depth
2 years	BrokerTec	99.967	14.648	1,147	21,614	1.107	12.771	0.103	23.019
	GovPX	99.974	1.395	53	919	1.588	26.313	0.079	12.822
5 years	BrokerTec	99.781	12.361	1,903	53,487	1.721	6.496	0.279	10.688
	GovPX	99.760	0.629	46	472	2.937	13.660	0.168	3.402
10 years	BrokerTec	100.001	9.349	1,869	54,957	2.932	5.002	0.448	8.048
	GovPX	100.051	0.596	38	373	4.379	15.683	0.242	1.749

Notes. This table reports average daily price, trading volume (in billions), number of trades and quotes, quoted spread (in hundredths of a percent of midquotes), trade size (in millions), volatility, and depth (in millions) for the 2-, 5-, and 10-year on-the-run Treasury notes over the period of October 2001 to December 2005. Data are from GovPX and BrokerTec. The quoted spread is the ask price minus the bid price divided by the midquote. Price volatility (σ) is calculated each day using the range-based method of Alizadeh et al. (2002), where $\sigma_t = \exp[\ln(\max p_t - \min p_t) - 0.43]$. Depth is measured by the average of bid and ask quote size.

the information. Our identification procedure is that whenever a line (record) of observations in the data set has updates on any of three important items—trade sign, price, or size—we treat it as a new trade record. This could be a new trade just occurred or a workup just completed by an IDB. To check the reliability of this trade identification algorithm, we use the GovPX data from 1992 to 1999, a period when accumulated trading volume is reported, such that trades can be identified accurately and a large number of transactions are covered, to evaluate the precision of our procedure. Overall, we find our procedure can identify about 96% of the actual trades. However, the procedure also picks up some trades that are not actual trades. This type 2 error amounts to 2.3% of the actual trades.

Another issue is related to the reporting process of workup trades. Both electronic and voice brokers adopt the expandable limit order protocol, which grants a trader whose order has been executed the right-of-refusal to trade additional volume at the same price. The workup process refers to this quantity negotiation period. Although strict anonymity is enforced throughout the workup process in both trading systems, there is a difference in the reporting procedure of workup trades by electronic and voice brokers.[8] The GovPX posts the completed transaction after all trading interest is exhausted at the initially agreed upon price. By contrast, the BrokerTec reports each individual component (increment) as a separate trade. This reporting discrepancy induces a downward bias in trade size and an upward bias in the number of transactions on the BrokerTec system. To provide a consistent comparison for the transactions of the two trading systems, we cumulate the components of workup trades on BrokerTec into transactions comparable to GovPX trades. BrokerTec provides timestamp and detailed information such as the name and CUSIP of the security, price, workup state, and whether an order is aggressive or passive. These important data allow us to identify the individual components associated with a workup trade precisely and to sum all individual components of a workup trade from BrokerTec into a completed trade to provide a consistent comparison with the GovPX trade.

Table 1 reports the summary statistics of average daily trading price (p), volume ($billion), trading frequency, number of quotes, bid-ask spread, trade size, volatility, and depth based on the data set adjusted for BrokerTec workup trades. The quoted bid-ask spread (in hundredths of a percent of price) is the ask price minus the bid price divided by the midquote. Bond price volatility (σ) is calculated each day using the range-based method suggested by Alizadeh et al. (2002), where $\sigma_t = \exp[\ln(\max p_t - \min p_t) - 0.43]$. Depth is measured by the average of bid and ask quote size. Bid-ask (quoted) spreads are lower and volume, trading frequency, depth, and price volatility are higher for the electronic trading system. Notably, average trade size is much larger for the voice-based trading system.

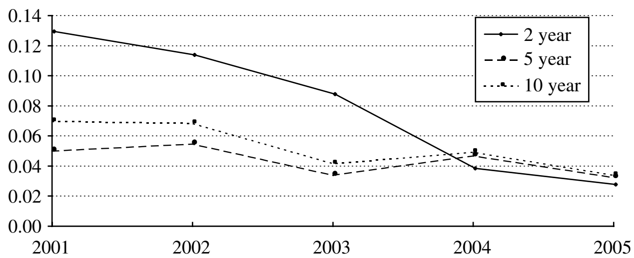
Figure 1 shows the time trend in GovPX's market share in terms of trading volume. The market share of the voice-based trading system has declined since 2001. At the same time, the electronic trading system has gained the market share in all segments of the interdealer broker market of on-the-run Treasuries.

Price series are constructed from GovPX and BrokerTec data sets at five-minute intervals from 7:30–17:00.[9] If a price is not available at the end of an interval, we linearly interpolate the prices right before and after the end of that interval. If there is no price

[8] We thank an anonymous referee for pointing out this reporting discrepancy.

[9] Although the Treasury market is a 24-hour round-the-clock market, the number of transactions drops significantly after 17:00 ET. We hence constrain the trading period to 7:30 to 17:00 ET each day.

Figure 1 GovPX's Market Share (Trading Volume)



Notes. This figure plots the time trend of GovPX's market share in terms of the trading volume of 2-, 5-, and 10-year on-the-run Treasuries over the period from October 2001 to December 2005. The vertical axis indicates the fraction of GovPX volume to the total combined trading volume in the interdealer broker market.

at all within an interval, that interval is regarded as having missing data.

3.1. Unit Root Test, Number of Cointegration Vectors, and VECM Estimation

Either midquotes or transaction prices can be used in empirical estimation. Hasbrouck (1995) indicates that results based on transaction prices are vulnerable to the problem of autocorrelation induced by infrequent trading and stale prices. By contrast, quotes are updated more frequently and therefore are more informative. Also, using quotes avoids trade identification errors for GovPX data. As in Hasbrouck (1995), our estimation of information shares and inferences are mainly based on the quote data.

We first examine temporal properties of each Treasury issue. For both BrokerTec and GovPX prices, the standard t-test fails to reject the null hypothesis that the differenced price series have a zero mean over the entire sample period. We then perform the ADF unit root test for each price series. The ADF test regression takes the following form:

$$\Delta p_t = \pi p_{t-1} + \sum_{j=1}^{q} \psi_j \Delta p_{t-j} + \varepsilon_t \tag{4}$$

where p_t represents the midquote or transaction price for a trading system at time t. The null hypothesis is that there is a unit root, and the test aims at examining if π is zero. For the lag order, we first try $q = 6$ and repeat with 12 lags. We found that these two choices of lag order q reach the same test conclusion, suggesting that results are robust. The ADF tests for each bond group all fail to reject the null hypothesis that there is a unit root. The p-values of the tests are all higher than 0.5.

We apply Johansen's trace test to the VECM to determine the number of cointegrated vectors. For each bond group, the hypothesis of no cointegration vector is rejected at the 1% significance level, and the hypothesis that there is one cointegration vector cannot be rejected. Furthermore, the maximum likelihood estimates of the cointegration vector β_2 in all the VECM models are essentially -1. This implies the error-correction term is $z_t = x_t - y_t$, or simply the price difference between the two trading systems. This is a sensible and intuitive result because in the long-run equilibrium the price difference between the two trading systems should approach zero. In sum, our results show that the price series in each respective market is an I(1) process, whereas the price difference is I(0) or stationary, and there exists a long-term equilibrium relationship between the electronic and voice-based trading systems.

Table 2 reports the results of VECM estimation using midquotes over the whole sample period. The α estimate sheds light on how BrokerTec and GovPX prices adjust to correct the disequilibrium in the preceding period. As shown, α_1 estimates are all negative, which are quite small but significant (in all cases except one). α_2 estimates are all positive, much larger than α_1, and highly significant. This renders the following interpretations. Suppose prices in the two markets are in disequilibrium, say the BrokerTec price is higher (lower) than the GovPX price in the preceding period. The model implies that the GovPX price will increase (decrease) in the next period, thus correcting the positive (negative) disequilibrium error. For the BrokerTec price, it will decrease (increase) to correct the disequilibrium error, but the magnitude of changes is much smaller.

The pattern of α estimates suggests that overall the electronic trading system generates more price discovery than the voice-based trading system for all bond groups. In addition, it is more often that the price in the voice-based trading system adjusts to the price in the electronic trading system. This finding implies that voice brokers incorporate the price information on the electronic platform in their pricing.

Based on the VECM estimates, one can construct the Hasbrouck and Gonzalo–Granger measures to assess the contribution to price discovery by each trading system. Several interesting observations can be made before constructing these measures. First, as shown in Table 2, the innovation variance in the electronic trading system σ_1 is higher than that in the voice-based trading system σ_2, suggesting more information shocks in the former. Second, the correlation ρ of the price innovations across the two markets is low, ranging from 0.2 to 0.3. As such, Hasbrouck's upper and lower bounds are expected to be tight, and the midpoint is an effective summary measure of the information share. Finally, although results suggest that the electronic trading system has more price discovery, it is important to note that price discovery does not entirely come from this venue. The significance of α_1 suggests that the human trading system still plays a role in price discovery.

The dynamic relation between the two trading systems can be inferred from the AR coefficients in the

Table 2 Estimation of VECM and Price Discovery Measures

Maturity	β_2	α_1	α_2	$A_{11}^{(1)}$	$A_{12}^{(1)}$	$A_{21}^{(1)}$	$A_{22}^{(1)}$	σ_1	σ_2	ρ
2 years	−1.000	−0.003	0.018	−0.235	0.109	0.139	−0.134	0.020	0.017	0.305
	(−358.67)	(−3.37)	(25.96)	(−70.62)	(29.28)	(47.25)	(−40.90)			
5 years	−1.000	−0.001	0.035	−0.094	0.023	0.052	−0.028	0.046	0.041	0.219
	(−261.19)	(−1.47)	(44.04)	(−27.01)	(6.03)	(16.82)	(−8.28)			
10 years	−1.000	−0.006	0.023	−0.302	0.090	0.033	−0.013	0.086	0.061	0.227
	(−117.77)	(−6.28)	(31.36)	(−82.58)	(18.02)	(12.53)	(−3.55)			

	2-year notes		5-year notes		10-year notes	
Venue	Hasbrouck (U, L)	GG	Hasbrouck (U, L)	GG	Hasbrouck (U, L)	GG
BrokerTec	(0.986, 0.827)	0.872	(0.999, 0.937)	0.964	(0.966, 0.839)	0.780
GovPX	(0.173, 0.014)	0.128	(0.063, 0.001)	0.036	(0.161, 0.034)	0.220

Notes. The upper panel reports estimation of the vector error-correction model (VECM) for $P_t = (x_t, y_t)'$, where x_t and y_t are the BroketTec and GovPX midquotes, respectively. The model has the form $\Delta P_t = \alpha\beta' P_{t-1} + A_1\Delta P_{t-1} + A_2\Delta P_{t-2} + \cdots + A_{r-1}\Delta P_{t-r+1} + e_t$. $\beta = (1, \beta_2)'$ is the normalized cointegration vector, $\alpha = (\alpha_1, \alpha_2)'$ is the vector of the speed of price correction, and e_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix $\mathrm{Var}(e_t) = \Omega = (\sigma_{ij})$, where $\sigma_{11} = \sigma_1^2$, $\sigma_{22} = \sigma_2^2$, and $\sigma_{12} = \sigma_{21} = \rho\sigma_1\sigma_2$. $\Delta = 1 - B$ is the first difference operator. The sample period is from October 2001 to December 2005, and t-values are in parentheses. The t-values for the cointegration vector are scaled down by 100. Data are arranged at five-minute intervals. The AR order is chosen by BIC. We report the first-order AR coefficient $A_1 = (A_{ij}^{(1)})$, where i and $j = 1, 2$. $A_{11}^{(1)}$ and $A_{21}^{(1)}$ show how the price change in the electronic trading system one period earlier affects price changes for both electronic and voice-based trading systems in the next period. $A_{12}^{(1)}$ and $A_{22}^{(1)}$ are similar but correspond to the price change originated in the voice-based trading system. The lower panel reports the Gonzalo–Granger measure and the upper (U) and lower (L) bounds of the Hasbrouck measure in parentheses.

VECM model. Let $A_s = (A_{ij}^{(s)})$ where $A_{ij}^{(s)}$ is the (i, j)th element of the sth AR coefficient A_s in (1) and $i, j = 1$ (electronic) and 2 (voice) are indicators of the trading systems. The off-diagonal elements capture how the price change in one system is affected by the preceding price changes in the other system. The relationships between two time series can be classified as unidirectional, bidirectional or no feedback relations. For the unidirectional relation, the coefficient matrix A_s is either upper or lower triangular; that is, for $i \neq j$, all $A_{ij}^{(s)} = 0$ and $A_{ji}^{(s)} \neq 0$ such that one trading venue affects the other but not the other way around. For the bidirectional relation, trading venues affect each other, or $A_{ij}^{(s)} \neq 0$ and $A_{ji}^{(s)} \neq 0$. For no feedback relation between two venues, we have $A_{ij}^{(s)} = 0$ and $A_{ji}^{(s)} = 0$ for all s.

The AR coefficients reported in Table 2 are for the first lag. The diagonal elements $A_{11}^{(1)}$ and $A_{22}^{(1)}$ are negative and significant, whereas the off-diagonal elements $A_{12}^{(1)}$ and $A_{21}^{(1)}$ are positive and significant. For the rest of the AR coefficients at higher lags, the estimates are naturally different but their sign and significance remain broadly the same and are omitted for brevity. Results suggest that a bidirectional relation exists between the electronic and voice-based trading systems and that the preceding price change in one system affects the other.

3.2. Estimation of Price Discovery Measures

From the VECM parameter estimates, we can obtain price discovery measures for the two trading systems. The lower part of Table 2 reports the estimates of the Hasbrouck and GG measures for all Treasury issues. Results show that the contribution of the electronic trading system to price discovery is much larger. The upper and lower bounds of the Hasbrouck measure are fairly tight, and the estimates range from 0.83 to about 1. The GG measure varies from 0.78 for the 10-year note to 0.96 for the 5-year note. Although the GG measure is generally smaller than the Hasbrouck measure, the pattern of both measures is similar. We also estimate the VECM model and price discovery measures based on transaction prices and results (omitted for brevity) show a similar pattern.

Overall, the electronic trading system has much more price discovery, but voice brokers continue to play a role. The estimates of the information share of the electronic trading system in the Treasury market are higher than those documented for the equity market (see Huang 2002, Theissen 2002). This can be attributed to the greater share of trading volume in the electronic market for Treasuries, which facilitates price discovery. This discrepancy could also be due to our better control of the institutional factors to identify the effect of electronic trading more precisely or the relative homogeneity of Treasuries that makes it easier to trade these securities in the electronic market.

We also obtain price discovery measures based on 30-minute intervals, and results are qualitatively the same. In addition, we estimate information shares by year and find that these estimates are quite stable over time. These results (omitted for brevity) suggest that our information share estimates are robust to different trading intervals and sample periods.

3.3. Impulse Response Function

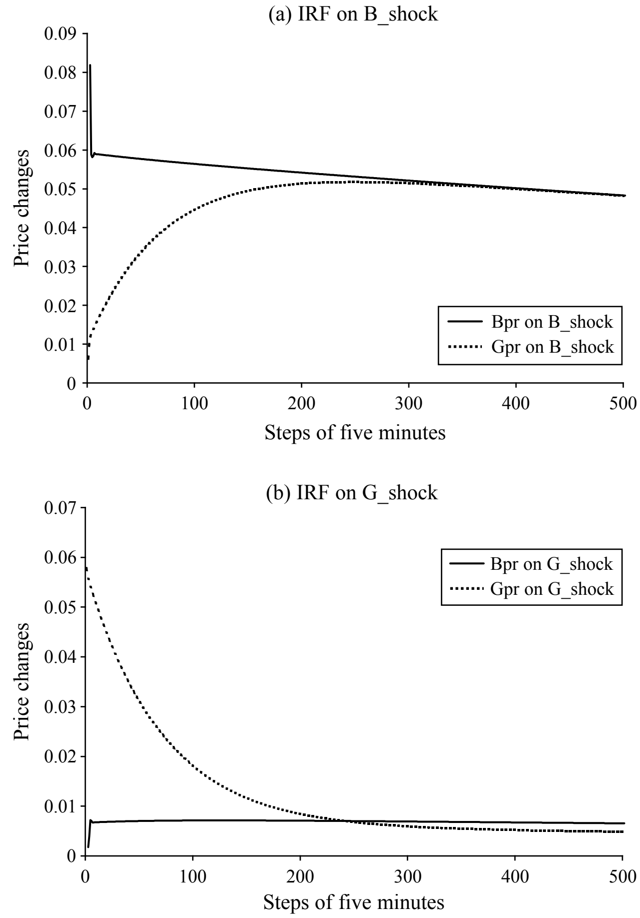
Along with measuring information shares, it is useful to examine the speed and dynamic price responses to an information shock in each trading system. This task can be accomplished by employing the impulse response function (IRF). Again, let $P_t = (x_t, y_t)'$ be a vector of BrokerTec and GovPX prices. Based on the VAR estimates, we can construct the orthogonal impulse response function. This is accomplished by diagonalizing the error covariance matrix before computing the IRF from the transformed VAR model.[10]

For brevity, we report the IRF values only for the 10-year note because results for other Treasuries show a similar pattern. Figure 2 plots the price response up to 500 steps; each step represents a five-minute interval. Figure 2(a) shows the IRFs of BrokerTec (solid line) and GovPX prices (dashed line) for a unit (or a dollar) shock from the electronic trading system, which we refer to as the B_shock. Figure 2(b) plots the IRFs for a unit shock from the voice-based system, or the G_shock.

Figure 2(a) shows that when there is a shock in the electronic trading system (B_shock), the price responds almost instantly, jumping up by about \$0.08 and quickly reducing to \$0.06. Then, the effect gradually dies down, indicating a partial reversal in the price. The price in the voice-based trading system moves up gradually by about \$0.05 in response to the shock from the electronic trading system. The response is not instant as in the electronic trading system. It takes about 250 steps of five minutes to reach the peak and the effect then diminishes gradually.

In contrast, the response to a shock from the voice-based trading system exhibits a different pattern. Figure 2(b) shows that a unit shock from the voice-based system (G_shock) has a relatively mild but nontrivial effect on the price in the electronic system. In contrast, the G_shock moves the GovPX price up sharply by about \$0.06 and the effect diminishes in about 300 steps of five minutes. Compared with Figure 2(a), the reversion is substantial in the voice-based trading system and lasts longer. Relative to that in the electronic system, the lesser of the initial shock is eventually incorporated into the quoted price, suggesting a greater transience of quote movements in the voice-based system. Overall, perturbations from the voice-based trading system (GovPX)

Figure 2 **Impulse Response Function (IRF) for 10-Year Treasury Notes**



Notes. The graphs show how the price responds to a unit (dollar) shock in each trading system for the 10-year note. We plot the orthogonal IRF (vertical axis) up to 500 steps (horizontal axis), and each step represents five minutes. Panel (a) shows the orthogonal IRF of BrokerTec price (labeled as Bpr, solid line) and GovPX price (labeled as Gpr, dashed line) resulting from a unit shock in the electronic trading system (B_shock). Panel (b) is similar but corresponds to a unit shock in the voice-based trading system (G_shock).

have a moderate impact on the electronic trading system (BrokerTec), whereas shocks from the electronic system have a much larger impact on the price in the voice-based trading system. This is consistent with our finding earlier that the electronic trading system is credited for most of price discovery. The prices in both trading systems eventually converge.

4. Determinants of the Price Discovery Mechanism

4.1. Liquidity and Price Discovery

Informed trading and market liquidity tend to reinforce each other. Microstructure theory suggests that a trading venue with high liquidity attracts informed trading and has more price discovery. We next examine whether the information share of a trading venue is conditional on liquidity.

[10] It is well known that the orthogonal impulse response will depend on the imposed ordering (see Zivot and Wang 2006, Chap. 11). In our case, we put BrokerTec prices as the first series because the electronic trading system has a much higher information share than does the voice-based trading system and so is a more appropriate ordering.

Liquidity has many dimensions, and we incorporate various proxies to reflect different interpretations of liquidity (Lin et al. 2011). Common liquidity proxies include bid-ask spreads and depth. Besides these liquidity proxies, we construct a market quality index (MQI), which is defined as average quoted depth divided by the percentage of bid-ask spread to midquote. Beber et al. (2009) find that this variable is a more parsimonious measure for market liquidity. In addition, we consider trading volume. Volume is a coarse measure of liquidity. A potential drawback of volume is that it is positively correlated with volatility, which may impede liquidity.

All variables are expressed as the ratio of the value of a variable for the electronic system to that for the voice-based system. We use the 30th and 70th percentiles of each liquidity variable, in terms of the ratio, as the cutoffs to separate the entire sample into low-, medium-, and high-liquidity days. For each variable except the bid-ask spread, if its value (ratio) on a particular day is below the 30th percentile, that day is classified as a low-liquidity day for the electronic trading system. Conversely, if it is above the 70th percentile, that day is classified as a high-liquidity day. For bid-ask spreads, days with high bid-ask spreads are low-liquidity days and so a high- (low)-liquidity day is set below (above) the 30th (70th) percentile. We then examine whether the information share of the electronic trading system tends to be higher on days with relatively high liquidity.

Table 3 shows the average information share of the electronic trading system on high- and low-liquidity days. On average, the information share of the electronic trading system is significantly larger on days when its liquidity is high relative to the voice-based trading system. That is, when volume, depth, and MQI are higher or bid-ask spreads are lower on the electronic system, its information share is larger.

Results show that liquidity and price discovery go together. This is a reason why the electronic trading system has more price discovery; i.e., because volume is higher on the electronic trading system, it contributes more to price discovery. However, given that the market share of GovPX is about 5%, the amount of price discovery (about 10%) is relatively high for GovPX. Results also imply that the voice-based trading system will contribute more to price discovery in the off-the-run market because it has much higher off-the-run volume than the electronic trading platform (see Barclay et al. 2006).

4.2. Information Share Regressions

The preceding results are based on the univariate analysis. We next conduct multivariate regression analysis on the determinants of the information share. The regression analysis provides the incremental effect of a particular variable by controlling for the effects of other variables. Besides liquidity variables, we incorporate other factors that are potentially important for the information share of a trading system.

Given the above finding that the information share of a trading venue strongly depends on market

Table 3 Liquidity and Price Discovery

		Depth		Volume		MQI		Bid-ask spread	
Maturity	Liquidity	Hasbrouck	GG	Hasbrouck	GG	Hasbrouck	GG	Hasbrouck	GG
2 years	Low	0.704	0.660	0.756	0.715	0.741	0.704	0.707	0.716
	High	0.772	0.747	0.811	0.742	0.772	0.748	0.842	0.747
	Difference	0.068***	0.087***	0.055***	0.027	0.031**	0.044***	0.135***	0.031*
5 years	Low	0.896	0.847	0.910	0.845	0.885	0.833	0.902	0.853
	High	0.925	0.869	0.948	0.899	0.946	0.914	0.932	0.885
	Difference	0.029**	0.022	0.038***	0.054***	0.061***	0.081***	0.030***	0.032***
10 years	Low	0.840	0.804	0.852	0.768	0.851	0.773	0.847	0.740
	High	0.899	0.868	0.896	0.840	0.901	0.849	0.899	0.858
	Difference	0.059***	0.064***	0.044***	0.072***	0.050***	0.076***	0.052***	0.118***

Notes. This table reports information shares of the electronic trading platform in low- and high-liquidity days. The Hasbrouck measure is based on the midpoint. The sample period is from October 2001 to December 2005. Liquidity proxies are depth, volume, the market quality index (MQI), and bid-ask spread. MQI is the average quoted depth divided by the percentage of bid-ask spread to midquote. Each liquidity variable is defined as the ratio of the variable for the electronic trading system to that for the voice-based trading system. The sample is divided into low, medium, and high periods using 30th and 70th percentiles as cutoffs for each liquidity variable. For each variable except the bid-ask spread, if its value (ratio) on a particular day is below the 30th percentile, that day is classified as a low-liquidity day for the electronic trading system. If it is above the 70th percentile, that day is classified as a high-liquidity day. For bid-ask spreads, days with high bid-ask spreads are low-liquidity days and so a high-(low)-liquidity day is set below (above) the 30th (70th) percentile.

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

liquidity, the first explanatory variable we incorporate is liquidity. We employ bid-ask spreads, depth, and MQI as liquidity variables. In addition, we use zero returns as an alternative liquidity measure, which measures the percentage of intraday intervals during the day for which price does not change because of infrequent trading. This liquidity measure has been used by a number of studies and has been shown to capture liquidity information (see Pu et al. 2011). Along with these variables, we include trading volume, trade size, and order imbalance in the regression model. Informed traders prefer a trading venue with high volume. All else equal, the information share of a trading venue should increase as its volume gets higher.

In the interdealer brokerage market, dealers submit limit orders and the cost of placing a limit order is higher in an inactive market with lower frequency of trading. Traders are less willing to place limit orders in an inactive market because these orders will be exposed for longer periods of time. Placing a limit order is like granting a put option to the rest of the market. The cost of granting a put option is higher the longer the time the limit order is exposed and the less active the market is. We measure the time length of limit order exposure by the interval between trades. Another important determinant of the put option value is return volatility. Higher volatility leads to a higher option value and thus a higher cost of placing the limit order. However, the role of volatility is more complicated in that high volatility also implies noisier price signals, which lower the information content of trades. Both put option and noisy price arguments suggest that the information share should be negatively related to volatility.

Moreover, we control for the effects of security characteristics and news announcements. We account for the effect of bond characteristics in information share regressions because previous studies have shown that informed trading tends to cluster in certain maturity segments (e.g., Brandt and Kavajecz 2004). Specifically, we estimate the following regression:

$$\begin{aligned} IS_{1,t} = {} & c + b_i(L_{1i,t}/(L_{1i,t}+L_{2i,t})) + b_5(OI_{1,t}/(OI_{1,t}+OI_{2,t})) \\ & + b_6(RV_{1,t}/(RV_{1,t}+RV_{2,t})) + b_7(T_{1,t}/(T_{1,t}+T_{2,t})) \\ & + b_8(Size_{1,t}/(Size_{1,t}+Size_{2,t})) \\ & + b_9(Volume_{1,t}/(Volume_{1,t}+Volume_{2,t})) \\ & + b_{10}Dummy1_t + b_{11}Dummy2_t + b_{12}News_t + \varepsilon_t, \end{aligned} \quad (5)$$

where the dependent variable IS_1 is the daily information share of the electronic trading system. The subscript of each variable has a value equal to 1 for the electronic trading system and 2 for the voice-based trading system. L_i, $i = 1, 2, 3$, or 4 is a liquidity variable represented by the bid-ask spread, depth, MQI, and percentage zero returns, respectively. *OI* is the order imbalance in percentage of trading volume, *RV* is return volatility, *T* is the average time interval between trades, *Size* is the average trade size for each security, and *Volume* is trading volume. All variables are measured at daily intervals. *Dummy*1 and *Dummy*2 are dummy variables for 5- and 10-year Treasury notes, respectively, to capture the effect of securities with different maturities. *News* is a dummy variable to identify days with macroeconomic announcements. Data of economic announcements are obtained from Bloomberg and Thomson Financial *International Financing Review*. Following Green (2004), we focus on the 12 economic news releases; *News* equals 1 if there is at least one macroeconomic announcement on a given day and 0 otherwise.

Correlated trading shocks in multiple securities may incur contemporaneous correlation in the errors across securities. We employ the generalized least squares regression method to account for both contemporaneous correlation and heteroskedasticity in the variance–covariance of the error term. Parameters are estimated by pooling time series and cross-sectional observations. The correlation among explanatory variables is generally quite modest with only few exceptions for that between liquidity proxies. In empirical estimation, we report two sets of results; one includes only a liquidity variable at a time and the other includes all liquidity variables along with other variables. The regression that includes all liquidity variables gives the incremental effect of each liquidity variable on the information share conditional on other variables.

Table 4 reports results of the regression.[11] All liquidity variables are significant at the 1% level when they are included in the regression separately. Results show that liquidity variables are important determinants of the information share even after controlling the effects of other variables. The information share of the electronic trading system is significantly higher on days when its bid-ask spread and percentage zero returns are lower and depth, MQI, and volume are higher. The information share of the electronic trading system is significantly lower on days when order imbalance and volatility are higher. The coefficient of trade size is negative and significant in most cases, indicating that larger trade size leads to a lower information share of the electronic trading system. The information share of the electronic trading system tends to be higher for 5- and 10-year Treasury notes.

[11] For brevity, we only report the results using the Hasbrouck midpoints. Results using the GG measure are similar.

Table 4 Regression Tests

c	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	R^2
0.811^{***}	-0.330^{***}					-0.229^{***}	-0.158	-0.052	0.505^{***}	0.120^{***}	0.098^{***}	-0.012	0.111
(6.08)	(−8.78)					(−4.46)	(−0.62)	(−1.19)	(2.84)	(8.58)	(5.34)	(−1.08)	
0.737^{***}		0.143^{***}				-0.288^{***}	0.030	-0.100^{**}	0.551^{**}	0.131^{***}	0.107^{***}	-0.017	0.069
(3.74)		(2.82)				(−5.39)	(0.11)	(−1.99)	(2.08)	(8.67)	(5.19)	(−1.48)	
0.764^{***}			0.256^{***}			-0.301^{***}	0.086	-0.120^{***}	0.453^{**}	0.122^{***}	0.098^{***}	-0.018	0.075
(3.88)			(3.12)			(−5.65)	(0.31)	(−2.54)	(2.10)	(7.92)	(4.74)	(−1.58)	
0.898^{***}				-0.254^{***}		-0.321^{***}	0.044	-0.080^{*}	0.420^{*}	0.114^{***}	0.090^{***}	-0.016	0.080
(4.49)				(−4.24)		(−6.05)	(0.16)	(−1.76)	(1.75)	(7.34)	(4.30)	(−1.40)	
0.727^{***}					-0.164^{**}	-0.276^{***}	-0.032	-0.097^{**}	0.454^{**}	0.136^{***}	0.113^{***}	-0.014	0.071
(3.68)					(−2.18)	(−5.05)	(−0.11)	(−2.07)	(2.16)	(8.88)	(5.43)	(−1.24)	
1.019^{***}	-0.381^{***}	0.251^{***}	0.229^{*}	-0.189^{***}	-0.192^{*}	-0.245^{***}	-0.034	-0.091^{*}	0.427^{**}	0.122^{***}	0.104^{***}	-0.017	0.128
(5.05)	(−7.76)	(2.72)	(1.68)	(−3.13)	(−1.88)	(−4.45)	(−0.12)	(−1.91)	(1.97)	(7.69)	(4.94)	(−1.52)	

Notes. This table contains estimation of the following regression model:

$$IS_{1,t} = c + b_i(L_{1i,t}/(L_{1i,t}+L_{2i,t})) + b_5(OI_{1,t}/(OI_{1,t}+OI_{2,t})) + b_6(RV_{1,t}/(RV_{1,t}+RV_{2,t})) + b_7(T_{1,t}/(T_{1,t}+T_{2,t}))$$
$$+ b_8(Size_{1,t}/(Size_{1,t}+Size_{2,t})) + b_9(Volume_{1,t}/(Volume_{1,t}+Volume_{2,t})) + b_{10}Dummy1_t + b_{11}Dummy2_t + b_{12}News_t + \varepsilon_t.$$

All variables are measured at daily intervals. IS_1 is the Hasbrouck (midpoint) information share of the electronic trading system. The sample period is from October 2001 to December 2005. Explanatory variables have subscript equal to 1 for BrokerTec and 2 for GovPX data. L_i, for $i = 1$, 2, 3, or 4, is the liquidity variable represented by the bid-ask spread, depth, MQI, and percentage zero returns, respectively. *OI* is the order imbalance in percentage of daily trading volume. *MQI* equals average quoted depth divided by the percentage of bid-ask spread to midquote. *RV* is daily return volatility. *Volatility* is calculated using the range-based approach of Alizadeh et al. (2002). *T* is the average trading interval, *Size* is the average trade size, and *Volume* is the daily volume for each security. *Dummy*1 is the dummy variable for the 5-year note. If it is a 5-year note, $Dummy1 = 1$; otherwise $Dummy1 = 0$. *Dummy*2 is the dummy variable similarly defined for the 10-year note. *News* is a dummy variable to identify whether there is an economic announcement on that day. Following Green (2004), we incorporate 12 economic announcements released at 8:30 A.M. E.T. $News = 1$ if there is at least one macroeconomic announcement; otherwise, $News = 0$. The t-values are in parentheses.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The coefficient of news announcements is insignificant after controlling the effects of other variables. The bottom row of Table 4 reports the result when all liquidity variables are included. On average, the bid-ask spread and depth are more important in terms of both the size of the coefficient and t-statistics. Return volatility, trade size, and volume remain significant even after including all liquidity variables. Overall, results show that liquidity, volatility, volume, trade size, and order imbalance are important determinants of the information share.

5. Additional Tests

In the previous sections we examine price interactions between the two trading systems and the extent of the contribution of each trading system to price discovery in the Treasury market. These analyses rely on cointegration econometrics to identify the informativeness of quotes and trades and price leadership. In this section, we employ an alternative approach based on price contributions of trades to see which trading venue provides the most informative prices and quotes.

5.1. Price Contributions of Trading Venues

Barclay and Warner (1993) use the weighted price contribution (WPC) measure to identify which trades contain more information. We apply this method to measure the price leadership of different trading systems in the Treasury market. The WPC method relies on the averaging process over time to remove the effects of transitory price movements and retain the permanent (information-related) price component, whereas the cointegration analysis explicitly accounts for these movements. The WPC method has several advantages. First, it is not conditional on a specific specification for the price process, so it is free from the model specification bias. Second, the WPC summarizes price discovery contribution by a single measure that can be used conveniently in cross-sectional analyses. Last, WPCs can be computed easily to measure the amount of price discovery by each trading venue for trades of different sizes.

The weighted price contribution by venue v for security i can be calculated as

$$WPC_{i,v} = \sum_{t=1}^{T} \left(\frac{|\Delta p_t^i|}{\sum_{t=1}^{T} |\Delta p_t^i|} \right) \frac{\Delta p_t^{i,v}}{\Delta p_t^i}, \tag{6}$$

where $\Delta p_t^{i,v}$ is the sum of all price changes for trades emanating from venue v for security i on day t, and T is the total number of trading days over the sample period. The first term of WPC is the weighting factor for each Treasury security and the second term is the relative contribution of venue v to the price change on day t. Furthermore, we can calculate the WPC for trades of different size (s) in venue v for security i.

By partitioning trades into different size groups, we can assess whether there are significant differences in price contributions by the two trading venues for trades of different size.

Although the WPC is a reliable measure of the total price discovery, it does not reveal the information per trade. Because the electronic system has more trades, it is naturally expected to have more price discovery. However, this does not necessarily imply that individual trades in the voice-based trading system are less informative. To gauge the amount of price discovery per trade, we divide the WPC by the weighted fraction of trades occurring in each trading platform:

$$WPCT_{i,v} = WPC_{i,v} \Big/ \sum_{t=1}^{T} \left(\frac{|\Delta p_t^i|}{\sum_{t=1}^{T} |\Delta p_t^i|} \right) \frac{t_t^{i,v}}{t_t^i}, \qquad (7)$$

where $t_t^{i,v}$ is the number of trades in venue v for security i on day t. The WPCT will be close to one if all trades are equally informative.

Table 5 reports trading activity and the weighted price contribution by trading venue. Panel A shows the distribution of trades by size and the trading volume associated with each size group. Trades from BrokerTec and GovPX databases are combined and divided into five size groups. Results show the mix of trades varies noticeably between the electronic and voice-based trading systems. Trades in the electronic system are of smaller size. About 58% of the trades in the electronic trading system have a size less than \$5 million but only 1.85% of the trades are greater than \$50 million. Conversely, a high portion of large-size orders are executed through voice brokers. As

Table 5 Trading Activity and Price Contributions by Trading Venue

Panel A: Distribution of trades and volume by size

	BrokerTec		GovPX	
Trade size	% of total number of trades	% of total volume	% of total number of trades	% of total volume
<5 M	57.98	15.06	31.18	3.68
5–10 M	20.72	17.03	28.67	10.45
10–20 M	12.35	20.88	15.65	12.27
20–50 M	7.10	27.16	16.32	29.48
≥50 M	1.85	19.87	8.18	44.12

Panel B: Weighted price contributions

	2 years		5 years		10 years		Overall		
Trade size	BrokerTec	GovPX	BrokerTec	GovPX	BrokerTec	GovPX	BrokerTec	GovPX	Diff.
<5 M	0.3289	0.0336	0.4442	0.0327	0.6042	0.0432	0.4391	0.0369	0.4022***
5–10 M	0.2080	0.0504	0.2816	0.0240	0.1764	0.0239	0.2253	0.0350	0.1903***
10–20 M	0.1773	0.0319	0.0748	0.0439	0.0628	0.0242	0.1283	0.0293	0.0990***
20–50 M	0.0600	0.0636	0.0256	0.0268	0.0205	0.0231	0.0388	0.0331	0.0057***
≥50 M	0.0179	0.0294	0.0175	0.0289	0.0076	0.0141	0.0110	0.0232	−0.0122***
Overall	0.7921	0.2089	0.8437	0.1563	0.8715	0.1285	0.8425	0.1575	0.6850***

Panel C: Weighted price contributions per trade

	2 years		5 years		10 years	
Trade size	BrokerTec	GovPX	BrokerTec	GovPX	BrokerTec	GovPX
<5 M	1.2823	6.0547	0.7521	22.1963	0.5374	13.6299
5–10 M	0.8433	4.8871	0.9220	12.6084	0.9669	5.6066
10–20 M	0.8873	5.8060	0.9387	17.5527	1.0141	4.3320
20–50 M	0.8010	5.7730	1.0381	2.0672	1.0351	2.2362
≥50 M	1.2089	2.1793	1.0672	1.3847	1.0160	1.2350
Overall	0.9667	5.3040	0.9269	14.3867	0.9736	8.4382

Notes. Panel A reports the distribution of trades and volume for the electronic (BrokerTec) and voice-based (GovPX) trading systems. The sample period is from October 2001 to December 2005. Trades are divided into five groups based on trade size. Panel B reports the weighted price contributions (WPCs) for 2-, 5-, and 10-year on-the-run Treasuries by trade size and venue. The bottom line reports the overall average WPC across size groups by trading venue for each security. The last three columns report the average WPC across securities for each size group and the entire sample for BrokerTec and GovPX and their differences. Panel C reports the weighted price contributions per trade (WPCTs) for 2-, 5-, and 10-year on-the-run Treasuries by trade size and venue. The bottom line reports the overall average WPCT across size groups by trading venue for each security.

***Indicates significance of the difference in average WPCs at the 1% level.

shown, about 25% of the total trades in the voice-based system have a trade size greater than or equal to \$20 million, compared to about 9% for the electronic platform. For the voice-based trading system, trades with a size greater than \$50 million account for 44% of total volume. By contrast, for the electronic platform, they account for only about 20% of total volume.

Panel B of Table 5 reports WPCs for both electronic and voice-based trading systems. Consistent with the findings associated with the information share estimates, the electronic trading system accounts for a large proportion of price discovery. As shown at the bottom of panel B, on average the weighted price contribution of the electronic trading system is 84%, whereas the voice-based trading system has 16%. The proportion of price discovery contributed by the electronic system ranges from 87% for 10-year notes to 79% for 2-year notes.

Results are more revealing when we further divide trades into different size groups. The *t*-test shows that all differences between the WPCs of the two trading system are significant at the 1% level. For trades with a sizes less than \$5 million, on average the electronic trades account for 44% of price discovery across all securities, whereas the voice-based trades have less than 4%. Clearly, electronic trading is more important than voice-based trading is for price discovery in the segment of small-size trades.

Results however show a different picture for large-size trades. For trades with size greater than \$50 million, on average, the weighted price contribution of the electronic trading system is 1.1% across all securities, whereas it is 2.3%, or twice as much, for the voice-based trading system. This difference is significant at the 1% level. Moreover, for trades with sizes greater than or equal to \$20 million and less than \$50 million, the WPCs are all higher for the voice-based trading system when they are measured by each Treasury note individually. Results indicate that the voice-based trading system plays a more important role in the segment of large-size trades. As shown in panel A, small-size trades take up a substantial portion of transactions in the electronic trading system, whereas the large-size trades account for a large portion of volume in the voice-based trading system. Together, results in panels A and B suggest that small trades in the electronic system are more informative than those in the voice-based system, whereas the opposite occurs for large trades.

The weighted price contribution is largest for trades of small size (less than \$5 million). This finding contrasts with Barclay and Warner's (1993) stealth trading hypothesis, which predicts that informed traders concentrate on medium-size trades. However, the results for small trades should be interpreted with caution. The small trades account for about 58% of trades in the electronic trading system (see panel A) but only 44% of the price discovery. Thus, on a per-trade basis, small trades seem not that informative, relative to large trades. On the other hand, small trades only account for 15% of BrokerTec volume, which suggests that smaller trades are more informative on a per-volume basis.

Panel C reports the results for the WPC per trade (or WPCT). Results show that GovPX's WPCT is much greater than one and tends to increase as trade size decreases because of high volume of large-size trades. Results show that although the total price discovery for trades in the voice-based trading system is low, individual trades generate significant price discovery on a per-trade basis. This finding suggests that individual trades in the voice-based trading system contain valuable information despite lower trading frequency and volume on this venue.

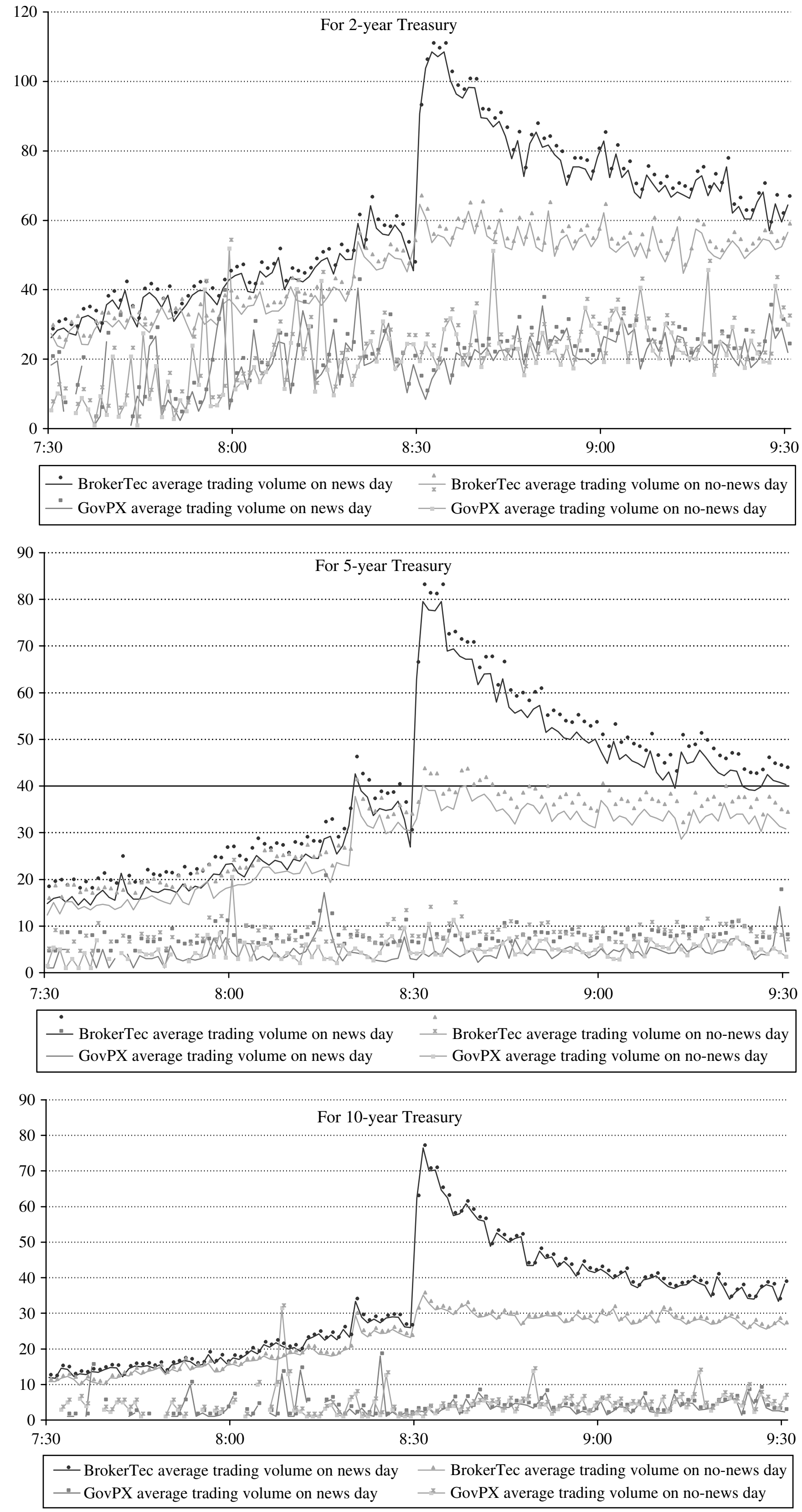
5.2. Macroeconomic News Announcement Effects

Macroeconomic news has a strong impact on the trading activity of Treasuries. Previous studies have documented pronounced effects of macroeconomic announcements on returns and information asymmetry in the Treasury market (see Balduzzi et al. 2001, Huang et al. 2002, Green 2004). Because these macroeconomic announcements are scheduled events, traders may prefer a trading venue that offers speedier order execution in anticipating that prices will react quickly to the news announcement.

Figure 3 plots the intraday pattern of trading volume between 7:30 and 9:30 for the days with and without a news announcement. Results show that BrokerTec's trading volume increases substantially after macroeconomic announcements on news days. Previous studies have shown that information asymmetry increases surrounding the news announcement time. These studies are based on the GovPX data, and it is unclear whether this phenomenon will remain or become even stronger after the electronic trading platform is introduced. In this subsection, we examine changes in the information share surrounding the macroeconomic news release.

Panel A of Table 6 compares trading volumes between news and no-news days for both trading systems at the intervals of 8:00–8:30 and 8:30–9:00. We report both differences and ratios of volumes. For each Treasury issue, rows 1 and 2 report the results for BrokerTec (B) and GovPX (G), respectively, and row 3 reports the difference $(B - G)$ in the volume differences or ratios between BrokerTec and GovPX. Results show that for BrokerTec, trading volume is always higher on news days. The differences are all significant at the 1% level. In addition, the increase in trading volume at the 8:30–9:00 interval (after the

Figure 3 The Effect of Macroeconomic News Announcements on Trading Volume



Notes. This figures plot the average trading volume (in million dollars) of 2-, 5-, and 10-year on-the-run Treasuries at one-minute intervals for BrokerTec and GovPX trading platforms for days with and without macroeconomic news announcements during the intraday period of 7:30 A.M–9:30 A.M. The sample period is from October 2001 to December 2005.

Table 6 Volume and Information Shares Surrounding the Macroeconomic News Announcement

Panel A: Effects of news announcements on volume

		Volume (news) vs. volume (no-news)				Difference (b − a)	
		(a) 8:00–8:30		(b) 8:30–9:00			
Maturity	Market	Difference	Ratio	Difference	Ratio	Difference	Ratio
2 years	BrokerTec (B)	201.52*** (6.58)	1.30	1087.68*** (9.35)	1.88	886.16*** (8.74)	0.58
	GovPX (G)	−3.96 (−0.47)	0.85	18.69 (1.48)	1.23	22.66 (1.50)	0.38
	B − G	205.48*** (6.49)	0.45	1068.98*** (9.14)	0.65	863.50*** (8.43)	0.20
5 years	BrokerTec (B)	88.65*** (4.64)	1.13	801.85*** (12.14)	1.85	713.20*** (12.42)	0.72
	GovPX (G)	−6.96 (−1.47)	0.95	−13.11 (−1.62)	0.99	−6.15 (−1.52)	0.04
	B − G	95.61*** (4.90)	0.18	814.96*** (12.27)	0.85	719.35*** (12.50)	0.68
10 years	BrokerTec (B)	93.45*** (5.39)	1.22	726.39*** (9.54)	1.92	632.94*** (9.32)	0.70
	GovPX (G)	0.20 (0.14)	1.06	0.78 (0.20)	1.03	0.58 (0.15)	-0.03
	B − G	93.25*** (5.37)	0.16	725.60*** (9.52)	0.88	632.35*** (9.31)	0.72
Overall	BrokerTec (B)	127.87*** (9.19)	1.21	871.97*** (16.61)	1.87	744.10*** (16.36)	0.66
	GovPX (G)	−3.94 (−0.83)	1.02	6.82 (0.93)	1.20	10.76 (1.28)	0.18
	B − G	131.82*** (9.09)	0.19	865.15*** (16.36)	0.67	733.33*** (15.93)	0.48

Panel B: Effects of news announcements on information shares

	ΔIS = IS (news) − IS (no-news)			
Maturity	(a) 8:00–8:30	(b) 8:30–8:40	(c) 8:40–8:50	(d) 8:50–9:00
2 years	0.0152 (0.96)	0.0868*** (2.99)	0.0458 (1.63)	0.0158 (0.59)
5 years	0.0083 (0.49)	0.0731** (2.57)	0.0459 (1.49)	−0.0108 (−0.33)
10 years	−0.0061 (−0.26)	0.0841** (2.24)	0.0591 (1.57)	0.0191 (0.51)

Notes. Panel A compares trading volumes on news and no-news days. The difference columns report volume differences (in million dollars) between news and no-news days and differences in volume differences between BrokerTec and GovPX at each time interval and between the time intervals of 8:00–8:30 and 8:30–9:00. The ratio columns report the ratio of volume on news days to no-news days for BrokerTec and GovPX, and the difference in the ratios between the two trading systems at each time interval and between the two time intervals. The sample period is from October 2001 to December 2005. Panel B reports the difference in BrokerTec's information share (IS) between days with news and without news surrounding the macroeconomic news release at 8:30 A.M. The sample period is from October 2001 to December 2005. The BrokerTec information share (IS) is based on the Hasbrouck measure. The two-sample t-test of whether the IS difference, ΔIS = IS (news) − IS (no-news), is equal to 0 or not is reported.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, and t-statistics are in parentheses.

news announcement) is significantly higher than the volume at the 8:00–8:30 interval (before the news announcement) at the 1% level. In contrast, none of the volume differences between news and no-news days is significant for GovPX. When comparing the differences in volume increases on a news day between the two trading systems (row 3 for each security), we find that the increase in the trading volume on a news day is significantly higher for BrokerTec across all securities. The volume ratio shows a similar pattern. The ratio of volume on news days to that on no-news days is always greater than one and is close to two in the post-announcement period for BrokerTec. The volume ratio for BrokerTec is always higher than for GovPX with an overall average difference (B − G) of 0.67 and 0.19 for the 8:30–9:00 and 8:00–8:30 intervals, respectively. In addition, the ratio is substantially higher at the 8:30–9:00 interval than at 8:00–8:30 interval with an average difference of 0.66 across all Treasury issues for BrokerTec and 0.18 for GovPX. The differences between the ratios of BrokerTec and GovPX are economically significant. Results show that BrokerTec captures most of the volume increase after a news announcement. To the extent that information-based trading is positively related to trading volume (see Admati and Pfleiderer 1988), one would expect the information share to be higher for BrokerTec after the news announcement.

The results in panel B of Table 6 support this hypothesis. Panel B reports the difference in the BrokerTec information shares between news and no-news days before and after the macroeconomic news announcement at 8:30. To provide more details for the information assimilation process, we further divide the half-hour interval after the news announcement into three 10-minute intervals. Results show that the information share (IS) for BrokerTec increases on news announcement days. The increase in the information share concentrates on the 10-minute interval right after the news announcement (8:30–8:40). Note that although the trading volume also increases before the announcement, the increase in the BrokerTec information share is not significant at the 5% level at the 8:00–8:30 interval.

The most striking finding is that BrokerTec's information share increases substantially immediately after the news announcement and then tapers off. As shown in panel B, the increase in the information share is sizable at the interval of 8:30–8:40 and significant at least at the 5% level across all Treasury notes. However, the BrokerTec information share increment declines quickly and becomes insignificant at the intervals of 8:40–8:50 and 8:50–9:00. By 9:00, the information share returns to about the same level as it was before the news announcement (8:00–8:30).

The pattern of news announcement effects in panel B contrasts with the finding of Green (2004).[12] Green finds that information asymmetry and the adverse selection component of effective spreads increase after a news announcement and these increases persist 30 minutes after the news release (8:30 to 9:00). By contrast, we find that the information effect has largely materialized in the first 10-minute interval after the news announcement. Results show that information has been incorporated into prices much faster since the inception of the electronic trading platform. This evidence strongly supports the hypothesis that electronic trading increases the efficiency of price discovery in the Treasury market.

6. Conclusion

The effect of electronic trading on market quality is an area of ongoing debate among academicians, practitioners, and regulators. The existing literature focuses on the equity and derivatives markets. This issue is underexplored for the bond market, and our paper attempts to fill this gap. Also, the literature compares the effect of trading automation on market quality across market structures, but it is difficult to control for all differences across markets. This paper contributes to the current literature by examining the effect of electronic trading on the quality of a fixed-income market with relatively homogeneous instruments of simple payoff structures. An advantage of our study is that we compare the functions of electronic and human-assisted venues within the same market that contains standard instruments with low quality uncertainty and identical trading mechanisms. This overcomes the difficulty encountered in previous studies and results in a cleaner measurement of the effect of technology that would otherwise be confounded with the effects of differences in market structures and trading mechanisms.

This paper documents the first empirical evidence for the contribution of the fully automated trading system to price discovery in the Treasury market relative to human intermediaries. We find that the electronic trading system has more price discovery, which is facilitated by higher trading volume. Trading automation in the interdealer brokerage market has significantly increased the speed of incorporating new information and the efficiency of price discovery. Empirical evidence shows that the electronic trading system captures a big chunk of the increase in trading volume surrounding the macroeconomic announcement and its contribution to price discovery increases significantly. This finding supports the hypothesis that informed traders use a trading venue that offers speedier order execution to capitalize their informational advantage in anticipating that prices will react quickly to the news announcement.

Although the trading volume is low, human-assisted trades generate significant price discovery. The VECM estimate of the price discovery parameter associated with the voice-based system is statistically significant. Trades facilitated by voice brokers contain more information on a per-trade basis than do

[12] For example, in Table VI of Green (2004, p. 1224), the adverse selection parameter at the 8:45–9:00 interval is 0.877, which is significant at the 1% level (with a standard error of 0.023) and much higher than those before the news announcement, 0.575 at 8:00–8:15 and 0.708 at 8:15–8:30.

electronic trades. In addition, voice brokers contribute more to price discovery in the segment of large-size trades (greater than or equal to $50 million), with a weighted price contribution twice as large as that of electronic trades. Given that large-size trades account for a large portion of trading volume, voice brokers have a significant role in price discovery. Previous studies argue that voice brokers' services are most valuable in assisting the trading of relatively inactive off-the-run securities. Our analysis shows that a role remains for human intermediaries even for active on-the-run issues, especially in the segment of large trades.

Most previous studies have employed the GovPX data to investigate the price discovery process of the Treasury market. This data set consolidates the trade and quote information from a subset of voice brokers. Our results show that trading automation has dramatically transformed the landscape of the interdealer brokerage market. Therefore, it would be interesting to revisit the issues related to information asymmetry, macroeconomic announcement effects, and order flow information in the Treasury market using the new electronic trading data.

Finally, our findings have important implications for designers of trading platforms. That voice brokers continue to dominate in the segments of large-size trades and off-the-run securities suggests that the fully automated trading system has not yet been able to replicate all of the valuable human services successfully. For developers of electronic trading platforms, the challenge is how to add features to the electronic trading system to emulate valuable human services in the IDB market. A possible direction to gain the market share for the segment of large-size trades is to design a system that will allow traders with large orders to electronically search for natural counterparties without revealing their identity and trading interest. Such a system should permit more flexibility and less time constraint for these counterparties to electronically negotiate for trades with complicated terms. There has been some success in the equity market with regard to this aspect (e.g., LiquidNet and Pipepine), suggesting that there is room to improve the electronic trading system in the IDB market. On the other hand, it would seem to be more challenging to expand the role of electronic trading in the off-the-run Treasury market. Here the main issue is that trading is infrequent and volume is relatively low. History has revealed that the fully automated trading system has not fared well for markets with a thin trading volume. One such example is the corporate bond market, which remains heavily human dependent. Low frequency of trading imposes a high cost on placing a limit order for illiquid securities. Until the electronic trading system can attract a critical mass of trading volume for traders to benefit from network and liquidity externalities, it will remain difficult to gain the market share in the segment of off-the-run securities. To overcome this problem, the developer of electronic platforms may need to consider nontechnological factors, such as incentives and membership interests, to attract large dealers and order providers to establish an initial network and liquidity base that will encourage other dealers to participate in the electronic market. An establishment of this type of structure, coupled with effective devices to monitor and adjust limit orders promptly to changing market conditions to reduce cost of the embedded option, could boost the chance for the electronic trading system to attract more trading activity and volume in the off-the-run market.

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