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2015

Online at <https://mpra.ub.uni-muenchen.de/61440/>

MPRA Paper No. 61440, posted 6 February 2015 22:38 UTC

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Abstract

Inter-dealer trading in US Treasury securities is almost equally divided between two electronic trading platforms that have only slight differences in terms of their relative liquidity and transparency. BrokerTec is more active in the trading of 2-, 5-, and 10-year T-notes while eSpeed has more active trading in the 30-year bond. Over the period studied, eSpeed provides a more pre-trade transparent platform than BrokerTec. We examine the contribution to ‘price discovery’ of activity in the two platforms using high frequency data. We find that price discovery does not derive equally from the two platforms and that the shares vary across term to maturity. This can be traced to differential trading activities and transparency of the two platforms.

Keywords: Microstructure; Treasury market; Bid-ask spread; Price discovery

JEL classification: G10; G12; G14; D4; C32

¹ We thank BG Cantor and ICAP for providing generous access to their data. We thank KX-Systems, Palo Alto, and their European partner, First Derivatives, for providing their database software Kdb+. We thank the UK Economic and Social Science Research Council for support under grant number RES-000-22-2177. Financial support for Li from the Australian Research Council (ARC) under Discovery Grant (DP130103210) is also gratefully acknowledged.

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Abstract

Inter-dealer trading in US Treasury securities is almost equally divided between two electronic trading platforms that have only slight differences in terms of their relative liquidity and transparency. BrokerTec is more active in the trading of 2-, 5-, and 10-year T-notes while eSpeed has more active trading in the 30-year bond. Over the period studied, eSpeed provides a more pre-trade transparent platform than BrokerTec. We examine the contribution to ‘price discovery’ of activity in the two platforms using high frequency data. We find that price discovery does not derive equally from the two platforms and that the shares vary across term to maturity. This can be traced to differential trading activities and transparency of the two platforms.

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1. Introduction

Many financial markets are fragmented. At a basic level many markets are fragmented according to the characteristics of the traders involved. Thus, we commonly observe markets with wholesale (broker to broker, B2B) and retail segments (broker to customer, B2C) that have well defined rules separating activity in each space. Fragmentation within the wholesale segment usually occurs for different reasons to those relevant to the wholesale-retail split. Information asymmetry and transparency play important roles in the segmentation of wholesale financial markets. In the case of high sensitivity to the presence of large incipient trades it is well known that fragmentation can often become extreme, resulting in completely opaque transactions between pairs of agents. But do minor differences in trader characteristics and information asymmetry matter for the location of price discovery where trading remains post-trade transparent? We find significant differences in the location and speed of price discovery in the case of the inter-dealer market in US Treasury Securities. This is probably the largest and most liquid wholesale financial market in the world (excluding foreign exchange markets) and yet it is almost equally divided between two electronic trading platforms that are very similar in terms of their liquidity and transparency. It is, at present unknown as to which of the two segments is the most important source of ‘price discovery’. It is also not clear what additional costs are incurred by trading in the less efficient segment.

The present study attempts to uncover the effects of mild differences in pre-trade transparency and liquidity to answer these questions. We examine the location of ‘price discovery’ and the differential trading costs across this important, almost homogeneous, market. Specifically, we use very high frequency synchronized microstructure data from the eSpeed and BrokerTec markets. BrokerTec is more active in the trading of 2-, 5-, and 10-year T-notes than eSpeed, which has more active trading for 30-year bonds. The two main electronic trading platforms also have slight differences in their ‘pre-trade’ transparency. The eSpeed platform is more pre-trade transparent than the BrokerTec platform. We find that BrokerTec produces a lower bid-ask spread on average than eSpeed. Our findings are also in line with the experimental results of Bloomfield and O’Hara (1999, 2000) about the location of price discovery in the less transparent platform. More price discovery takes place in the less transparent market (BrokerTec).

This platform more frequently possesses a more efficient price. Both of the markets share the same long-run driving dynamic and price adjustment away from disequilibrium between the two markets is mostly located in the movement of prices on the more transparent eSpeed platform. Overall, the size of the price adjustment (‘error correction’) on eSpeed is larger than on BrokerTec. However, the adjustment coefficient on the more transparent platform is only accurately estimated if the empirical analysis is general enough to control for adjustment to bid-ask spread disequilibrium as well as cross-platform disequilibrium.

We find that the evidence in support of price discovery on BrokerTec has been changing over time and it does not apply equally across all maturities. Where eSpeed has a liquidity advantage in the longer maturities it also accounts for more of the price discovery and less of the adjustment to disequilibrium. Overall the differences in the cost of trading in the alternative trading platforms are not large. In the absence of a significant cost differential between the two platforms we suggest that the main benefit to larger participants of maintaining a presence on both markets is as a protection against the risks of market outages due to technical catastrophes. The small risk of such a costly event seems to be just enough to keep the market fragmented. Another possible reason is the presence of large costs of changing allegiance from one platform to another for the smaller participants.

Most of the extant literature examines only one or other of the two main trading platforms. As far as we know, there are no papers that employ synchronized event-by-event data from these two major platforms. Fragmentation and price discovery is examined by Biais (1993), and the case of dual platforms with differential transparency has been analyzed theoretically and experimentally in Bloomfield and O’Hara (1999 and 2000). Our analysis is an important step in the process of evidencing the findings of the theoretical assertions already made in this theoretical and experimental literature.

The rest of the paper is organized as follows: Section 2 reviews the literature. Section 3 introduces the development of US Treasury market electronic trading platforms and the sample data set. The methodology is developed in Section 4. Section 5 reports the empirical results. Section 6 provides conclusions and implications of the paper.

2. Literature Review

The extant theoretical literature on market transparency finds that the level of transparency and the relative transparency of market segments has significant effects on market quality (including liquidity, trading costs, and price discovery). A wide variety of studies considers the merits of different trading mechanisms² and relates these to liquidity and transparency characteristics - and in particular to those studied by Bloomfield and O'Hara (2000). More literature can be found in O'Hara (1995), Hasbrouck (2007) and De Jong and Rindi (2009). Here we present a selective review focusing on market transparency, price discovery and the literature of relevance to the US treasury market.

Biais (1993) shows that quotation transparency is likely to increase market efficiency and improve liquidity. Pagano and Roell (1996) argue that greater transparency enhances market liquidity by reducing the opportunities for dealers to take advantage of relatively uninformed participants. Moreover, they suggest that increasing transparency will mainly reduce the average trading costs of uninformed traders.

Bloomfield and O'Hara (1999) use a laboratory experiment to investigate effects on market equilibrium under different degrees of market transparency. They suggest that transparency significantly increases the informational efficiency of market price but widens the bid-ask spreads. In a transparent market, the mid-point of bid and ask converges to intrinsic value more quickly. These results are consistent with the finding of Pagano and Roell (1996). They also show that spreads increase in more transparent conditions. Moreover, they find that the degree of market transparency has important effects on market equilibrium.

Of most relevance to the current study, Bloomfield and O'Hara (2000) examine whether a transparent market segment would survive when faced with direct competition from a less transparent one for the same asset. They focus on the growing regulatory and market concern with market fragmentation. Their concern is that the ability to hide trades in less transparent parallel segments undermines the attractiveness of established markets, and

² For example, Seppi (1997) finds that small and large investors prefer a hybrid specialist/limit order market, while mid-sized investors prefer pure limit order markets.

thereby reduces their crucial role in price discovery. They design two laboratory experiments which involve multiple dealers operating in two market segments with different degrees of transparency. They use a game theoretic approach to model dealer behavior in this context. They find that differential transparency has significant effects on market behaviour. Low-transparency dealers have better performance than transparent participants; they offer lower spreads and capture more of the order flow. Low-transparency dealers set prices more efficiently and they have more opportunities to set and trade at inside spreads. They make a profit from using their information advantage, while dealers in the more transparent segment make a loss. They also suggest that dealers would endogenously choose to trade in the less transparent market and eventually give rise to the demise of the transparent segment. These findings support the fears of dealers regarding the increasing fragmentation of some markets including the rise of dark pool crossing networks.³ Other experimental studies include Flood, Huisman, Koedijk and Mahieu (1999) and Flood, Koedijk, Dijk and Leeuwen (2002).

There are many related studies on effects of transparency. Baruch's (2005) theoretical model shows that an increase in transparency reduces liquidity providers' market power and greater transparency leads to more informative prices. Bessembinder, Maxwell and Venkataraman (2005) find that trading costs were reduced for large institutional traders following the introduction of TRACE. The above literature appears to favor increased transparency from a market efficiency and investor protection point of view. However, there are contributions to the literature that questions this conclusion. Madhavan (1996) found trade disclosure increased the costs of trading for large traders. Madhavan, Porter and Weaver (2005) find that greater transparency reduced market liquidity and led to a reduction of market depth. Other studies in this vein that focus on equity markets include, Simaan, Weaver and Whitcomb (2003), Boehmer (2004) and Aitken *et al.* (2006). Drudi and Massa (2002) investigate how dealers behave in parallel markets with differential transparency for the same Italian sovereign bonds and they find that informed dealers may refrain from trading in the more transparent market in order to benefit from their informational advantage in the less transparent market. Alternatively, informed

³ Anecdotal evidence of this effect is often brought into discussions with market regulators. An example is concerns the effects of the cross-listing of French shares on the London Stock Exchange (LSE). Dealers on the Paris Bourse invariably report a loss of trading volume and liquidity provision in Paris reflecting the greater relative opacity of the LSE.

traders may use the more transparent market to influence price. They also suggest that the less transparent market improves the liquidity of the more transparent market. In this respect, their results are consistent with the findings of Bloomfield and O'Hara (2000). Other event studies include Bortoli, Jarnecic and Johnstone (2006), Boehmer, Saar and Yu (2005) and Scalia and Vacca (1999).

As far as the US Treasury market is concerned. Brandt and Kavajecz (2002) find that in the absence of material public information events, order flow imbalances account for a substantial portion of the day-to-day fluctuations of the yield curve and the role of the order flow depends crucially on the liquidity of the Treasury market. Dunne, Moore and Portes (2006) examine a transparency change which occurred in June 2003 on the US Treasury market. They find that effective spreads increase as a result of a small increase in transparency of the eSpeed platform. They conclude that differential market transparency adversely affects the risks borne by dealers. As a result this can adversely affect market liquidity. Mizrach and Neely (2008) highlight the role of the futures markets in price discovery of US Treasury market. Fleming and Mizrach (2009) assess the microstructure of US treasury market using data from the BrokerTec trading platform. They find that market liquidity is greater than that found in earlier studies that use data only from voice-assisted brokers. They also found that the price effect of trade on BrokerTec is quite small and is even smaller once orderbook information is considered. Also using the intraday data from the BrokerTec electronic trading platform, Jiang, Lo and Verdelhan (2011) identify jumps in U.S. T-bond prices and investigate what causes such unexpected large price changes. They examine the relative importance of macroeconomic news announcements versus liquidity shocks in explaining the observed jumps. In addition, they examine the informativeness of order flow immediately after bond price jumps.

In the literature of price discovery in market microstructure models, there are two competing approaches to estimating the parameters of price discovery in cointegrated time series: the information shares as defined in Hasbrouck (1995) and the permanent-transitory decomposition of Gonzalo and Granger (1995), applied in the market microstructure literature by e.g. Booth, So and Tse (1999), Baillie et al. (2002), Harris et al. (2002). These two models complement each other and provide different views of the price discovery process between markets. The Hasbrouck model considers each market's

contribution to the variance of the innovations to the common factor, while the Gonzalo and Granger model focuses on the components of the common factor and the error correction process and they attribute a greater share of price discovery to the market that adjusts least to the price movement in the other markets. De Jong (2002) derives the relationship between the two approaches. Putniņš (2013) concisely reviews the latest development in this area, and clarifies what the ‘information share’ and the ‘component share’ exactly measure. Our study is focusing on the same US Treasury securities that traded on two very similar and competitive platforms, BrokerTec and eSpeed. We aim to identify which platform is more informative in the sense that prices of the platform adjust least to the true efficient price. So, we adopt the Gonzalo and Granger model in this paper.

3. The US Treasury Market Electronic Trading Platforms and Data

In the US Treasury Market the assets being traded are very simple in terms of possible asymmetric information about cash flows and default characteristics. The only source of asymmetric information in the inter-dealer segment of this market is ‘position information’ and perhaps information about differential trading strategies. This market is inherently very liquid and so it is unlikely that prices depart from fundamentals for long or that trading costs differ significantly regardless of where trading takes place. Also, since the market is very transparent, fragmentation is easy to facilitate in the sense that a reference price is available from which to benchmark bilateral transactions. While the market is very homogeneous it is not perfectly so. The two main electronic trading platforms have slight differences in their ‘pre-trade’ transparency and their share of activity. In this section, we give a brief introduction on the development of the US Treasury market detailing the important differences between the main platforms.

The US Treasury market plays an important role in the international financial system because of its size, liquidity and low transaction cost. There were more than \$5 trillion US Treasury securities outstanding at the end of the sample period chosen for this study (i.e., as of August 31, 2008). Foreign and international investors held around \$2.7 trillion of the market supply. The first tier of the secondary US Treasury market is a dealer-based market. Primary dealers are the most important and key private sector players in the Treasury market and account for most of the overall trading volume (primary dealer daily average trading volume in US Treasury securities was approximately \$570 billion

during 2007). There were 16 primary dealers active in the Treasury market as at October 2008.⁴

Before 1999, all trading in the B2B market took place OTC (over the counter) by phone via bilateral voice-assisted inter-dealer negotiations. Since then most of the trading has migrated to fully electronic platforms (Mizrach and Neely, 2006). The ground work for executable platforms began when the GovPX system for recording and disseminating voice-brokered trades was introduced in the mid-1990s. GovPX was the first real attempt to centralize prices and this vastly improved the post-trade transparency of the Treasury market. The first large platform where limit-order placement and electronic trade execution was possible was on the eSpeed platform introduced by Cantor Fitzgerald in 1999. In June 2000, BrokerTec Global LLC, a rival electronic trading platform, began operations. BrokerTec had been formed the previous year as a joint venture of seven large fixed income dealers. BrokerTec was acquired in May 2003 by ICAP plc which was itself the outcome of a merger in 1999 between Garban plc and Intercapital plc.

As the transition to electronic trading continued the eSpeed and BrokerTec platforms have competed for market share particularly in the ‘on-the-run’ treasuries. While eSpeed captures some of the ‘off-the-run’ market this part of the market remains mostly voice brokered. Mizarch and Neely (2006) estimated that BrokerTec accounted for about 61% of trading activity in the on-the-run treasuries and eSpeed 39%. We can confirm that, for the sample period covered here, the market share of BrokerTec increased slightly in most maturities since 2005. We do not have access to information about who the subscribers are to each of the two platforms but it is well known that the larger dealers maintain a presence on both markets while smaller dealers often choose one or the other.

Both eSpeed and BrokerTec platforms are fully automated electronic trading platforms where buyers are matched to sellers without human intervention. They both provide pre-trade transparency in the form of electronic screens which display various levels of the orderbook. There is wide use of the transaction prices (post-trade transparency) in the wider market through services such as Bloomberg. However, important subtle

⁴ This represents a low point. There were 20 Primary Dealers in Oct 2007, 40 in 1998 and 46 in 1988. In July 2009 the Federal Reserve Bank of New York announced interest from 4 new applicants and there were signs of increased appetite among other dealers due to the increased volatility in yields and the increased size of the Treasury market due to the financial turmoil.

differences remain regarding pre-trade transparency. Pre-trade views of the orderbooks are disseminated differently. There is a terser (and less transparent) presentation of the BrokerTec orderbook.

The main differences in pre-trade transparency can be traced to developments in September 2002, when Cantor Fitzgerald launched a product called “Cantor Market Data” and soon afterwards launched a real-time data product (Cantor G3) that featured views of limit orders, trading stacks and last traded price for each of the five on-the-run UST Benchmarks. An example of the G3 view is given in Figure 1⁵. This view is very easy to interpret and reveals whether bids and asks are made up from multiple buyers and sellers, single or multiple substantial orders or multiple small orders. Market participants can instantly see the five best prices and total size for each price on each side of the book and the individual order sizes for the best bid and ask. There is no hidden quantity at the various levels of the book. Cantor G3 also shows the recent trend for the 10 most recent trades. For the period studied, BrokerTec has hidden and displayed order volume at each of the limit-order prices. The choice of what amount to display is not mandated. When a transaction exceeds the limit-order quantity there is a chance that hidden quantity will be available to fill the order at the same price.

[Insert Figure 1 here]

Thus, while the two platforms are broadly similar they differ in terms of hidden orders, how widely the orderbook is viewed and the ease with which the order-book information can be understood at a glance. Both platforms allow for the possibility of ‘work-ups’. In terms of clientele it is widely known in the industry that eSpeed has more of the share of the dealers who represent buy-side participants from the life assurance and pensions industry. This has led to a slight dominance by eSpeed in the trading of treasuries at the longer maturity. BrokerTec has a larger share of activity in all other maturity categories and this has been growing slightly over time, see Figure 2.

[Insert Figure 2 here]

Data:

⁵ See <http://www.cantorg3.com/g3vision/launch/index.html>.

Our data contains records of limit orderbook events from BrokerTec and eSpeed. The sample periods involve non-contiguous months (April, June and August) in 2002, 2004 and 2005. We also have all of 2003. The daily coverage runs from 8:00am to 5:30pm EST. We examine the 2, 5, 10 and 30 year “on-the-run” Treasuries. Each record includes best ask and best bid prices at event frequency and we also have the orderbook quantities which allows us to ascertain the relative liquidity of the two platforms over time and by maturity. Our empirical analysis concentrates on the price data. We match records at all events with the prevailing prices from the two platforms at the following frequencies (5, 10, 15 and 30 second intervals). Tables 1 show that the average depth on BrokerTec is nearly twice that on eSpeed at the shorter maturities. BrokerTec also provides the narrower bid-ask spreads in short and medium term maturities (2-, 5-, 10-Year) while eSpeed provides tighter bid-ask spreads on average at the very long-term maturity (30-year). Note the use of A , B and a , b to denote the best ask and best bid price of BrokerTec and eSpeed respectively. Similarly, S and s denotes the bid-ask spread of BrokerTec and eSpeed. We adopt this notation for the remainder of the paper.

[Insert Table 1 here]

4. Methodology

To investigate the mechanics of price discovery, we use Gonzalo-Granger’s (1995) permanent-transitory decomposition approach. The Gonzalo-Granger approach focuses on the components of the common factor and the error correction process; it measures each market’s contribution to the common factor, where the contribution is defined to be a function of the markets’ error correction coefficients. The Gonzalo-Granger model starts from the estimation of vector error correction model which in this case will be:

$$\begin{pmatrix} \Delta A_t \\ \Delta B_t \\ \Delta a_t \\ \Delta b_t \end{pmatrix} = \Pi \begin{pmatrix} A_{t-1} \\ B_{t-1} \\ a_{t-1} \\ b_{t-1} \end{pmatrix} + \sum_{i=1}^p \Gamma_i \begin{pmatrix} \Delta A_{t-i} \\ \Delta B_{t-i} \\ \Delta a_{t-i} \\ \Delta b_{t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{pmatrix}, \quad (1)$$

where A_t , B_t are the ask and bid prices of BrokerTec, and where a_t , b_t are the ask and bid prices of eSpeed and we write $\Pi = \alpha_{4 \times r} \beta'_{r \times 4}$. Following the notation of De Jong (2002), the Gonzalo-Granger decomposition, implies that the permanent component is $\beta_{\perp} f_t$

$$f_t = \theta'(A_t, B_t, a_t, b_t)' = (\alpha'_\perp \beta'_\perp)^{-1} \alpha'_\perp (A_t, B_t, a_t, b_t)',$$

and θ is a 4×1 vector (with elements adding up to one) that measures the contribution of market i to price discovery (see also Booth, So and Tse, 1999, and Harris et al., 2002).

We note that if all elements in $(A_t, B_t, a_t, b_t)'$ are integrated of order one and no cointegrating relationships exist, then $\Pi = 0$; if elements in $(A_t, B_t, a_t, b_t)'$ are stationary $I(0)$ variables, then the matrix Π must be of full rank; if Π is of rank r ($0 < r < 4$) the elements in $\Pi(A_{t-1}, B_{t-1}, a_{t-1}, b_{t-1})'$ are linear combinations that are stationary. If the variables in $(A_t, B_t, a_t, b_t)'$ are $I(1)$, these linear combinations must correspond to cointegrating vectors. If Π has a reduced rank $r \leq 3$, this means that there are r independent linear combinations of the 4 elements in $(A_t, B_t, a_t, b_t)'$ that are stationary, that is: there exist r cointegrating relationships. In the case of reduced rank, we can write $\Pi = \alpha_{4 \times r} \beta'_{r \times 4}$. The linear combinations $\beta'(A_{t-1}, B_{t-1}, a_{t-1}, b_{t-1})'$ present the r cointegrating relationships. The coefficients in α measures how the elements in $(\Delta A_t, \Delta B_t, \Delta a_t, \Delta b_t)'$ adjust to the r “equilibrium errors” $\beta'(A_{t-1}, B_{t-1}, a_{t-1}, b_{t-1})'$.

The maximum likelihood based procedure proposed by Johansen (1988) is most commonly used in the literature to test for the number of cointegrating relations. Assuming $(A_t, B_t, a_t, b_t)'$ is a vector of $I(1)$ variables, the approach of Johansen is based on the estimation of the above equations by maximum likelihood, while imposing the restrictions $\Pi = \alpha\beta'$ for a given value of r . The Johansen approach involves testing hypothesis about the rank of the long-run matrix Π , or – equivalently – the number of columns in β . For a given r , it can be shown (see, e.g. Hamilton, 1994) that the ML estimate of β equals the matrix containing the r eigenvectors corresponding to the r largest eigenvalues of a 4×4 matrix. We can use the estimated eigenvalues to test hypotheses about the rank of Π , for example, the so-called trace test and the maximum eigenvalue test. The two tests are actually likelihood ratio tests, but don't have the usual Chi-squared distributions. Instead, the appropriate distributions are multivariate

extensions of the Dikey-Fuller distributions. More details can be found in Johansen (2002).

It is worth noting that in $\Pi = \alpha\beta'$, the parameters α and β are not uniquely identified. The cointegrating vectors in β have to be normalized in some way to obtain unique cointegrating relationships. One interesting case is when the rank of Π is three. This leads intuitively to a set of restriction implying that each price changes is affected by its own lagged spread and the price gap between the two platforms. The restrictions required to achieve this are as follows:

$$\beta' = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 1 & 1 & -1 & -1 \end{bmatrix}. \quad (2)$$

We test that the rank of Π is three and then test the above set of restrictions. We examine the size and significance of the adjustment parameters under this set of restrictions and this reveals the response by each price attributable to cross-platform disequilibrium and to own-platform bid-ask spread disequilibrium. We also note that if β' is specified as (2), we have $\beta_{\perp} = \iota$, a 4×1 vector of ones and this simplifies the calculation of the price discovery parameter θ .

5. Results

In this section, we first implement some exploratory testing regarding the long-run equilibrium between the two trading platforms. For instance, we investigate the long-run relationships between bid or ask prices on the two platforms separately. We then analyze the bid and ask prices on both platforms jointly using the Johansen procedure and we then examine where price discovery takes place. We get very different estimated magnitudes of adjustment to cross-platform disequilibrium when we apply the more general approach and this highlights a large source of error when the bid-ask spread disequilibria are dropped from the analysis. Nevertheless, we still find substantial support for the main hypothesis that eSpeed is the market that adjusts to true valuation errors and this implies that BrokerTec is where price discovery mainly occurs.

5.1 Exploratory Tests

We first show the Augmented Dickey-Fuller tests of whether the bid and ask price levels and their first differences on each platform are stationary. The results for the bid price (and the first difference of bid price) from the BrokerTec platform is shown in Table 2 Panel A (and Panel B for 1st difference series). The stationarity and cointegration testing gives the expected results. It is clear that non-stationarity of the bid price level cannot be rejected.⁶ We can also reject non-stationarity for the case of the first difference of the bid price series. The results for the other 3 series are not shown but give similar conclusions. Also, we find that the bid and ask prices on each platform are cointegrated with each other which implies that the bid-ask spread itself is stationary in each platform.

[Insert Table 2 here]

We can then make use of the Engle and Granger (1987) two-step procedure to estimate the long-run relationship between the two platforms using either the ask or bid prices to represent underlying value on each platform. This involves testing for non-stationarity of the two series believed to be cointegrated followed by estimation of a cointegrating relation and an Error Correction Model (ECM). If the prices of the two platforms are integrated of order 1 and cointegrated, the variables have the following error-correction form (here we only show the case of bid prices):

$$\begin{bmatrix} \Delta B_t \\ \Delta b_t \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \hat{e}_{t-1} + \begin{bmatrix} \sum_{i=1} a_{11}(i) & \sum_{i=1} a_{12}(i) \\ \sum_{i=1} a_{21}(i) & \sum_{i=1} a_{22}(i) \end{bmatrix} \begin{bmatrix} \Delta B_{t-i} \\ \Delta b_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \quad (3)$$

The ECM representation allows for testing of weak exogeneity and causality. This allows us to test whether disequilibrium between the two prices explains future movements in prices to restore equilibrium. If the burden of adjustment is unevenly shared we obtain insights about which platform is a better representation of underlying value at any instant and which platform produces prices that are, most likely, still responding to recent information shocks. To examine whether there is evidence of cointegration between the bid price on BrokerTec and the bid price on eSpeed, we estimate; $B_t = \beta_0 + \beta_1 b_t + e_t$, where e_t should be found to be stationary.

The regression result is shown in table 3. The relationship is:

⁶ The other results of the testing of price levels and their first difference are available from the authors on request. Both of the bid and ask price level of two platform are non-stationary, and their first difference are stationary.

$$B_t = 0.0287 + 0.9997b_t + e_t$$

A joint test is performed to examine whether the constant is significantly different from 0 and the slope coefficient is different from 1. The resulting F-test is 4.6347 with significance level 0.0097. Similarly, although the slope parameter is close to 1 it is statistically different from it.

[Insert Table 3 here]

Testing for the stationarity of the residual $\{e_t\}$ is done with a standard augmented Dickey-Fuller test with the appropriate number of lags.⁷ The regression results (available from the authors on request) show clearly that the residual $\{e_t\}$ is stationary and the cointegration relation is valid. This also implies that an ECM representation is valid. We therefore proceed to the ECM regression, Eq. (3), using the residuals from the equilibrium regression.

From table 4, we see that the estimated coefficient α_2 is 0.8899 with a standard error of 0.0179 and the coefficient of α_1 is -0.1019 with a standard error of 0.0133. This reveals that both of the bid price series from BrokerTec and eSpeed share a long-run equilibrium. Moreover, the signs of the adjustment coefficients are in accord with convergence toward the long-run equilibrium. Thus, in response to a positive discrepancy, $\hat{e}_{t-1} > 0$, the bid price of eSpeed tends to increase while the bid price of BrokerTec tends to decrease. Nevertheless, the bid price of BrokerTec moves, on average, a little while the bid price of eSpeed moves a lot to correct for disequilibrium. The bid price adjustment of eSpeed is significantly larger than BrokerTec. This implies BrokerTec is the long-run anchor for price. Reversing the Engle-Granger cointegrating relation does not change this result.

⁷ We use estimates of 1%, 5% and 10% critical values for ADF, from MacKinnon 1996, with $N=1$, assuming no trend in the cointegrating relation. For any sample size T , the estimated critical value is $\beta_{\infty} + \beta_1/T + \beta_2/T^2$ where the following table provides the required parameters. Our sample size is so large that we were able to use the β_{∞} values;

Level	β_{∞}	β_1	β_2
1%	-3.434	-5.999	-29.25
5%	-2.862	-2.738	-8.36
10%	-2.567	-1.438	-4.48

The conclusion also remains the same if we test for evidence of cointegration between the ask prices on the two platforms.

[Insert Table 4 here]

5.2 Price Discovery

So far, we have examined the long-run equilibrium and adjustment to disequilibrium for the bid or ask prices on the two platforms separately. The main weakness associated with this analysis is the fact that price adjustments could be reflecting temporary bid-ask spread movements rather than market (mid-price) or true value movements. To control for these different sources of price adjustment we need to conduct the analysis jointly. Thus, to test whether the equilibrating behavior within each platform is about “price discovery” rather than just bid-ask spread adjustments we must analyze the internal cointegrating relationships simultaneously. To achieve this we now turn to the maximum likelihood methods proposed by Johansen (1988) (one that allows the response to bid-ask disequilibrium to be accounted for as part of general price adjustment). We show that this gives much more plausible differences in the speed of adjustment on the two platforms found using the simpler analysis.

We already tested for non-stationarity of the various price levels and for stationarity of their first differences so we proceed to application of the Johansen cointegration analysis directly. We use the maximum orders of lags from these test regressions in our application of the multivariate Johansen procedure. We implement the rank test described in Section 5 and after testing for the restriction of three cointegrating vectors (which is accepted) we test for the normalizations on the cointegrating vectors in β that give rise to the within-platform adjustment and cross-platform adjustment as described earlier (these restrictions are also accepted).

We take the 5-year/5-second intervals in April 2005 for example. The maximum number of lags used in the Johansen representation of the four equation system of equations is picked as 5 (see table 5).

[Insert Table 5 here]

The rank test result is reported in table 6. This reveals that the rank of Π is three.

[Insert Table 6 here]

That is, there are three cointegration relationships. Recall that we need to normalize the cointegrating vectors in β to obtain unique cointegrating relationships. As described earlier, the restriction is specified in Eq. (2). The test of this set of restrictions is accepted. This has a Chi-square statistic of 7.285 with a p-value 0.063. The estimated equation (excluding details of the short-run parameter estimates) is reproduced below as follows:

$$\begin{bmatrix} \Delta A_t \\ \Delta B_t \\ \Delta a_t \\ \Delta b_t \end{bmatrix} = \begin{bmatrix} -0.169 & 0.014 & -0.092 \\ (-36.298) & (3.119) & (-36.169) \\ 0.166 & -0.021 & -0.096 \\ (35.529) & (-4.596) & (-37.746) \\ 0.036 & -0.173 & 0.145 \\ (8.416) & (-41.324) & (61.246) \\ -0.013 & 0.146 & 0.147 \\ (-3.065) & (34.551) & (61.302) \end{bmatrix} \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 1 & 1 & -1 & -1 \end{bmatrix} \begin{bmatrix} A_{t-1} \\ B_{t-1} \\ a_{t-1} \\ b_{t-1} \end{bmatrix} + \sum_{i=1}^5 \Gamma_i \begin{bmatrix} \Delta A_{t-i} \\ \Delta B_{t-i} \\ \Delta a_{t-i} \\ \Delta b_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

This reveals that bid and ask price changes on BrokerTec are mainly affected by the lagged BrokerTec spread disequilibria and the lagged disequilibrium between the two platforms but there is also a significant small effect emanating from the lagged spread in the other platform. Likewise, the bid and ask price changes on eSpeed are affected by the lagged eSpeed spread and the lagged price gap between the two platforms. There is only a small effect running from the lagged spread of the other platform. Overall it is interesting to see that more of the price adjustment is related to bid-ask spread disequilibrium than to cross-platform disequilibrium and this highlight the need to control for such effects.

We can conclude from the differences in the magnitude of the response to cross-platform disequilibrium that more price discovery takes place on the BrokerTec platform. This confirms the findings using transaction data but now we find that the difference between the two platforms is not as stark as before. Both BrokerTec and eSpeed share the long-run driving dynamics. The signs of the adjustment coefficients are as expected, with prices on the BrokerTec platform tending to decrease in response to cross-platform disequilibrium and price on the eSpeed platform tending to increase in response to disequilibrium. The magnitude of the eSpeed adjustment to cross-platform disequilibrium is roughly one-third greater than that on BrokerTec. The calculated parameter of price discovery is $\theta' = (0.3117, 0.2969, 0.1733, 0.2181)'$, and the share for BrokerTec is 60.9%

while the share for eSpeed is 39.1%. So we can conclude with more confidence than before that eSpeed does more of the price adjustment to bring about long-run equilibrium. But the difference in the magnitude of the adjustment coefficients is not as stark as before.

The 2-, 5- and 10-year Treasury instruments have similar results to those above (available from the authors on request). However, the 30-year Treasury provides a different story. We analyze the 30-year bond data at 30-second intervals in August 2005. Tables 7 and 8 report the Ljung-Box statistics and rank tests results respectively, the maximum order of lags is 5 and the rank is 3.

[Insert Table 7 and 8 here]

The result is reproduced here for convenience.

$$\begin{bmatrix} \Delta A_t \\ \Delta B_t \\ \Delta a_t \\ \Delta b_t \end{bmatrix} = \begin{bmatrix} -0.021 & -0.043 & -0.226 \\ (-1.365) & (-3.297) & (-15.564) \\ 0.275 & -0.014 & -0.238 \\ (19.437) & (-1.180) & (-17.335) \\ 0.071 & -0.189 & 0.172 \\ (5.021) & (-15.393) & (12.478) \\ -0.137 & 0.398 & 0.123 \\ (-8.282) & (27.821) & (7.693) \end{bmatrix} \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 1 & 1 & -1 & -1 \end{bmatrix} \begin{bmatrix} A_{t-1} \\ B_{t-1} \\ a_{t-1} \\ b_{t-1} \end{bmatrix} + \sum_{i=1}^5 \Gamma_i \begin{bmatrix} \Delta A_{t-i} \\ \Delta B_{t-i} \\ \Delta a_{t-i} \\ \Delta b_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

The result gives us an opposite story to that at the other maturities. Thus, in the case of the 30-year maturity, more price discovery takes place on the eSpeed platform. As before, both the BrokerTec and eSpeed platforms share the long-run driving dynamics. As expected, price on BrokerTec tends to decrease in response to disequilibrium and the price of eSpeed tends to increase in response to the disequilibrium. The speed of the adjustment on BrokerTec is almost twice the magnitude of that on eSpeed. This implies that price discovery for the long maturity Treasuries resides in the eSpeed platform and that adjustment to price changes occurs in the BrokerTec platform. This is further confirmed by the calculated parameter of price discovery $\theta' = (0.2352, 0.1458, 0.2387, 0.3803)'$, and the share for BrokerTec is 38.1% and the share for eSpeed is 61.9%. eSpeed is more attractive for the 30-year maturity in terms of transaction cost because it provides tighter bid-ask spreads on average (See Table 1). This implies a transaction cost effect on price discovery rather than a transparency effect.

6. Conclusion

This paper focuses on the effect of differential trading activities and pre-trade transparency of competing inter-dealer electronic platforms in the US Treasury Market. The analysis of simultaneously observed high-frequency data from these two very similar markets provides a unique opportunity to examine where price discovery is most concentrated under only mild differences in conditions. The two similarly transparent trading platforms differ mainly in terms of hidden limit orders and their shares of trading activity.

The findings only become reliable when bid and ask prices from both platforms are estimated in a joint cointegration relation where three cointegrating relations are imposed and a particular set of cointegrating relations imposed. The three equilibrium relations reflect long-run levels of the bid-ask spreads (one for each platform) and an equilibrium value of the Treasury instrument being traded - around which prices on the two platforms fluctuate. Overall the analysis suggests that more price discovery takes place in the more active but less transparent market (BrokerTec for the shorter maturities). The price dynamics on the less transparent market represent most of the long-run driving forces of the entire market. Most of the adjustment to disequilibrium occurs in the more transparent market. The magnitude of adjustment to fundamental value is almost twice as large on the less transparent market. However, the findings are reversed in the case of the longer-term maturity where eSpeed has a clientele-list advantage (where the clients are from the insurance industry and are more likely to trade longer dated Treasuries). This implies that transparency alone does not provide the full explanation about the location of price discovery.

The fact that the more active and less transparent market seems to be winning more market share over time is partly consistent with the propositions of Bloomfield and O'Hara (2000) which asks whether more transparent markets can survive in such a context. However, the two platforms have continued to co-exist despite the differences in transparency. This probably reflects the sheer depth of this particular market and the legacy of their respective histories (particularly the fixed costs that have been incurred by some smaller participants who are only active on one or other of the two platforms and not both and for whom a change would be expensive and the benefits only marginal).

Despite the movements in market shares it seems that the two platforms will continue to co-exist into the foreseeable future. Some of the largest participants seem to be willing to stay engaged in both markets for reasons that go beyond the small cost advantages they could generate by concentrating their activities on just one. The advantages for these large players seem to be enough to warrant continuation of the current equilibrium in market structure. The most likely benefit is the insurance that all participants obtain from having a back-up venue to facilitate execution of transactions if there is a market ‘outage’ in one platform (such as during the 9/11 atrocity). This benefit might be part of the explanation as to why the severe outcome forwarded by Bloomfield and O’Hara has not materialized.

Clearly, it is interesting that neither platform has chosen to differentiate itself in a major way in terms of transparency which suggests that they are aware of the damage that such a unilateral change can bring to their market share. This also serves as a reminder for market regulators that dual platforms are likely to remain opposed to transparency changes unless all platforms are forced to move by a similar amount in this direction simultaneously.

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Figure 1. The Cantor G3 view of the US Treasury Market

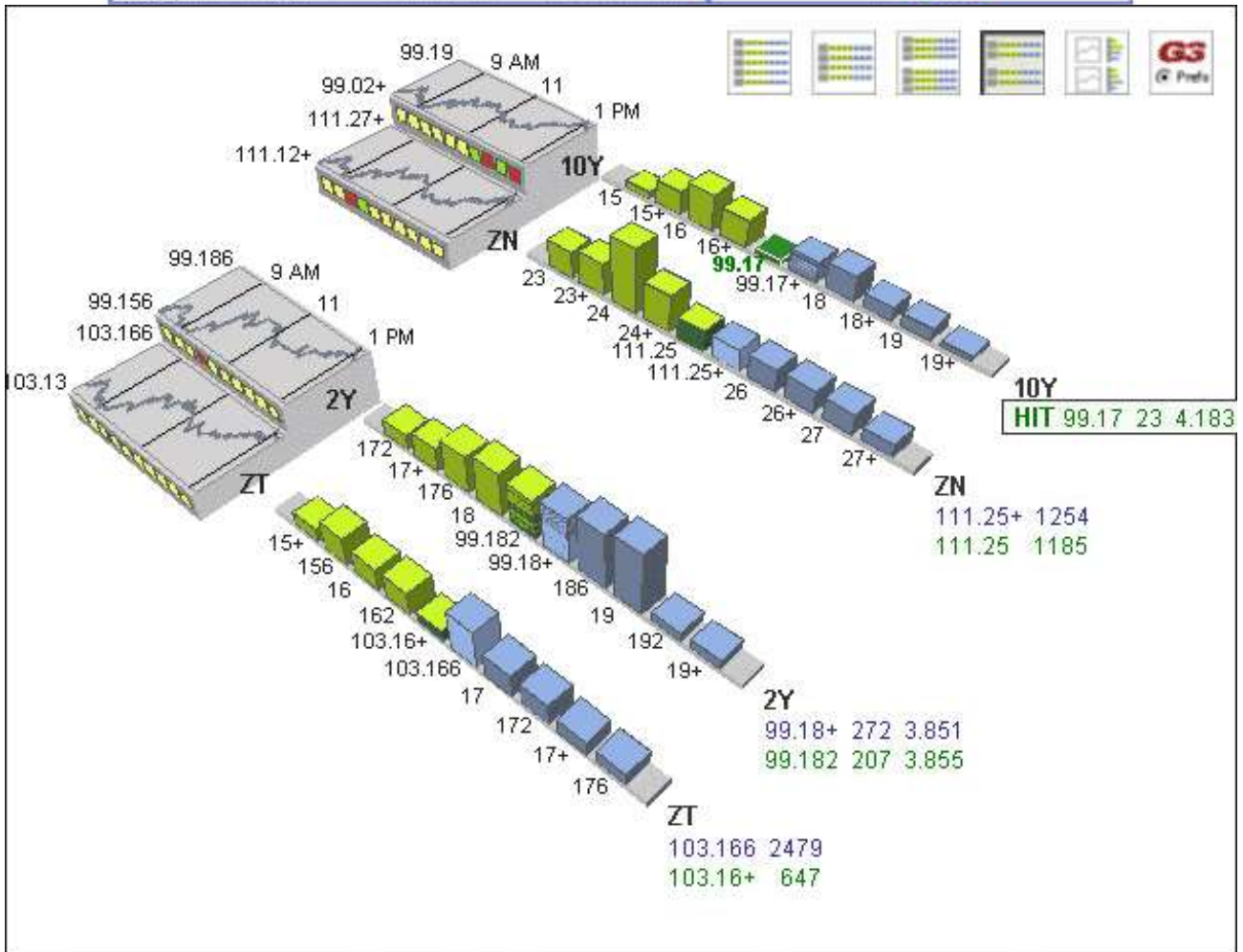


Figure 2

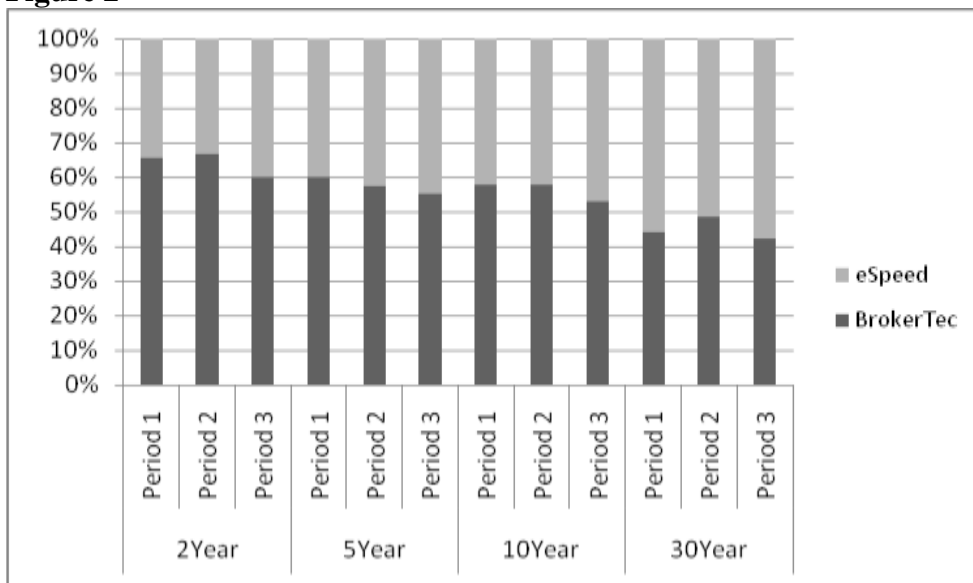


Figure 2 shows that participants prefer to trade 2-, 5- and 10-year Treasury instruments on BrokerTec and to trade the 30-year treasury on eSpeed. Over the three periods in 2005 there is some slight evidence that eSpeed was increasing its share of activity somewhat.

Table 1. Summary statistics for the US treasuries

Panel A	2_Year			5_Year		
	April	June	August	April	June	August
AQ	134.27 (0.341)	156.021 (0.981)	240.72 (0.760)	39.35 (0.000)	39.196 (0.174)	56.870 (0.398)
BQ	152.87 (0.102)	173.781 (0.583)	237.17 (0.209)	38.614 (0.199)	38.537 (0.889)	57.013 (0.729)
aQ	89.267 (0.983)	99.246 (0.610)	189.99 (0.464)	31.597 (0.222)	32.851 (0.890)	50.983 (0.851)
bQ	91.604 (0.656)	101.341 (0.111)	181.96 (0.462)	29.901 (0.719)	31.448 (0.851)	49.305 (0.287)
S	0.008 (0.003)	0.008 (0.004)	0.008 (0.003)	0.009 (0.009)	0.009 (0.006)	0.008 (0.004)
s	0.009 (0.003)	0.009 (0.003)	0.008 (0.003)	0.009 (0.006)	0.009 (0.004)	0.009 (0.004)

Panel B	10_Year			30_Year		
	April	June	August	April	June	August
AQ	39.316 (0.402)	37.300 (0.512)	51.968 (0.460)	5.815 (0.035)	5.166 (0.012)	6.233 (0.207)
BQ	40.464 (0.103)	37.306 (0.053)	50.748 (0.114)	5.830 (0.275)	5.156 (0.366)	6.182 (0.386)
aQ	29.501 (0.226)	30.973 (0.639)	45.268 (0.698)	5.114 (0.070)	4.417 (0.236)	5.458 (0.178)
bQ	30.673 (0.284)	30.229 (0.991)	44.4 (0.574)	5.215 (0.337)	4.336 (0.054)	5.442 (0.717)
S	0.017 (0.009)	0.017 (0.008)	0.016 (0.008)	0.038 (0.153)	0.033 (0.032)	0.033 (0.024)
s	0.018 (0.008)	0.017 (0.071)	0.017 (0.007)	0.034 (0.033)	0.031 (0.038)	0.030 (0.025)

Note: We use AQ (aQ) to denote the quantity at the best ask price of BrokerTec (eSpeed). BQ (bQ) is the quantity at the best bid price of BrokerTec (eSpeed). S (s) is bid-ask spread of BrokerTec (eSpeed). The number in each entry is the average over 2002 to 2005, and the numbers in brackets are standard deviations.

Table 2. ADF test results for bid price and 1st difference of bid price on BrokerTec

Panel A: Regression Results, ADF Test for Stationarity of Bid Price (B)				
Variable	Coefficient	t- Statistics		
Constant	0.0312 (0.0165)	1.8915		
ΔB (Lag1)	-0.0348 (0.0068)	-5.1492		
...		
ΔB (Lag6)	0.0153 (0.0064)	2.3761		
B (Lag1)	-0.0003 (0.0002)	-1.9396		
Ljung-Box Q-Statistics				
		Lags	LB-Stat	Signif
Usable Observations	21459	Q(1-0)	0.0085	0.9267
Degrees of Freedom	21451	Q(2-0)	0.0159	0.9920
R^2	0.0031	Q(3-0)	0.1352	0.9873
\overline{R}^2	0.0025	Q(4-0)	0.2135	0.9947
Mean of Dependent Variable	-0.0007	Q(5-0)	0.2458	0.9985
Std Error of Depend Variable	0.0489	Q(6-0)	0.2460	0.9997
Durbin-Watson Statistic	2.0013	Q(7-0)	0.3533	0.9998
Panel B: Regression Results, ADF Test for Stationarity of Change in Bid Price (ΔB)				
Variable	Coefficient	t- Statistics		
Constant	-0.0010 (0.0003)	-2.9809		
$\Delta \Delta B$ (Lag1)	0.03215 (0.0136)	2.3622		
...		
$\Delta \Delta B$ (Lag5)	-0.01102 (0.00494)	-2.2322		
ΔB (Lag1)	-1.0641 (0.0152)	-69.857		
Ljung-Box Q-Statistics				
		Lags	LB-Stat	Signif
Usable Observations	21458	Q(1-0)	0.414	0.5201
Degrees of Freedom	21450	Q(2-0)	0.581	0.7479
R^2	0.5214	Q(3-0)	0.642	0.8868
\overline{R}^2	0.5213	Q(4-0)	0.644	0.9580
Mean of Dependent Variable	-0.0001	Q(5-0)	1.925	0.8594
Std Error of Depend Variable	0.0701	Q(6-0)	2.854	0.8269
Durbin-Watson Statistic	2.0060	Q(7-0)	2.896	0.8945

This table contains ADF test regression results. In Panel A the dependent variable is ΔB , the first difference of the bid price of the BrokerTec platform while in Panel B it is the first difference of the same bid price series. The test parameter and t-statistic is highlighted in bold typeface. The appropriate critical values of the t-statistic for testing the null hypothesis that the coefficient on the lagged level (or lagged first difference in the case of Panel B) is not equal to zero is provided in footnote 6. For the case of an extremely large sample, these are -2.567, -2.862 and -3.4336 at the 1%, 5% and 10% levels of significance respectively. It is therefore not possible to reject the null hypothesis that the bid price of BrokerTec has a unit root while we can easily reject the presence of a unit root in the case of the first difference of the bid price. The Ljung-Box Q-statistic does not reveal any significant autocorrelations among the residuals.

Table 3

Variable	Coefficient	t- Statistics	Significant
Constant	0.0287 (0.0110)	2.6227	0.0087
B	0.9997 (0.0001)	9108.3092	0.0000
Usable Observations		37644	
Degrees of Freedom		37642	
R^2		1.0000	
\bar{R}^2		0.9995	
Mean of Dependent Variable		99.778	
Std Error of Dependent Variable		1.9259	
Durbin-Watson Statistic		2.0007	

Note that B is independent variable.

Table 4.1 VAR/System - Estimation by Least Squares (Dependent Variable ΔB)

Variable	Coefficient	t- Statistics	p-value
ΔB (Lag1)	-0.0082 (0.0129)	-0.6393	0.5226
ΔB (Lag2)	-0.0059 (0.0110)	-0.5445	0.5860
ΔB (Lag3)	-0.0259 (0.0087)	-2.9533	0.0031
Δb (Lag1)	-0.0206 (0.0115)	-1.7856	0.0741
Δb (Lag2)	-0.0050 (0.0094)	-0.5314	0.5951
Δb (Lag3)	-0.0003 (0.0067)	-0.0514	0.9589
Constant	-0.0012 (0.0003)	-3.8825	0.0001
RES(Lag1)	-0.1019 (0.0133)	-7.6385	0.0000

		F-Tests -- Dependent Variable DB		
		Variable	F-Statistic	Significant
Usable Observations	23545	ΔB	3.1880	0.0226
Degrees of Freedom	23537	Δb	1.998	0.1116
Standard Error of Estimate	0.0477			
Sum of Squared Residuals	53.7049			
Mean of Dependent Variable	-0.0011			
Std Error of Dependent Variable	0.0479			
Durbin-Watson Statistic	2.0009			

Table 4.2 VAR/System - Estimation by Least Squares (Dependent Variable Δb)

Variable	Coefficient	t- Statistics	p-value
ΔB (Lag1)	-0.0162 (0.0173)	-0.9343	0.3501
ΔB (Lag2)	-0.0036 (0.0148)	-0.2493	0.8030
ΔB (Lag3)	-0.0207 (0.0118)	-1.7600	0.0784
Δb (Lag1)	-0.0283 (0.0155)	-1.8194	0.0688
Δb (Lag2)	-0.0158 (0.0126)	-1.2475	0.2121
Δb (Lag3)	-0.0002 (0.0090)	-0.0237	0.9810
Constant	-0.0009 (0.0004)	-2.3172	0.0205
RES(Lag1)	0.8899 (0.0179)	49.5420	0.0000

		F-Tests -- Dependent Variable Db		
		Variable	F-Statistic	Significant
Usable Observations	23545	ΔB	1.3238	0.2646
Degrees of Freedom	23537	Δb	1.6702	0.1710
Standard Error of Estimate	0.0642			
Sum of Squared Residuals	97.19			
Mean of Dependent Variable	-0.0011			
Std Error of Dependent Variable	0.0772			
Durbin-Watson Statistic	2.0004			

Table 5. Ljung-Box Q-Statistics of cross correlations.

Lags	Ljung-Box-Stat	Significance Level	Ljung-Box-Stat	Significance Level
Q(1 to 1)	0.0309	0.8603	6.9876e-04	0.9789
Q(1 to 2)	0.0461	0.9772	1.3853e-03	0.9993
Q(1 to 3)	0.0565	0.9964	0.1074	0.9909
Q(1 to 4)	0.4164	0.9811	1.3022	0.8610
Q(1 to 5)	0.8295	0.9751	1.3783	0.9266

Note: We provide here the L-B test results pertaining to the bid price series from the two platforms. The results for the ask series are qualitatively similar.

Table 6. Rank test results.

r	$\hat{\lambda}_i$	λ_{trace}	Frac95	P-Value
0	0.117	36511.6	63.659	0.000
1	0.093	21431.7	42.770	0.000
2	0.076	9580.0	25.731	0.000
3	0.000	6.981	12.448	0.357

Note: Frac95 is the 5% critical value of the test.

Table 7. Ljung-Box Q-Statistics of cross correlations.

Lags	Ljung-Box-Stat	Significance Level	Ljung-Box-Stat	Significance Level
Q(1 to 1)	4.8280e-03	0.9446	2.5419e-04	0.9872
Q(1 to 2)	0.0158	0.9921	4.6766e-04	0.9997
Q(1 to 3)	0.0214	0.9991	5.2999e-04	0.9999
Q(1 to 4)	0.0214	0.9999	6.4329e-03	0.9999
Q(1 to 5)	0.1437	0.9996	0.0367	0.9999

Note: We provide here the L-B test results pertaining to the bid price series from the two platforms. The results for the ask series are qualitatively similar.

Table 8. Rank test results.

r	$\hat{\lambda}_i$	λ_{trace}	Frac95	p-value
0	0.138	8068.9	63.659	0.000
1	0.125	4786.5	42.770	0.000
2	0.080	1843.9	25.731	0.000
3	0.000	9.028	12.448	0.183

Note: Frac95 is the 5% critical value of the test.