Price discovery and trade fragmentation in a multi-market environment: Evidence from the MTS system

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Abstract

This paper proposes new metrics for the process of price discovery on the main electronic trading platform for euro-denominated government securities. Analysing price data on daily transactions for 107 bonds over a period of twenty-seven months, we find a greater degree of price leadership of the dominant market when our measures (as opposed to the traditional price discovery metrics) are used. We also present unambiguous evidence that a market's contribution to price discovery is crucially affected by the level of trading activity. The implications of these empirical findings are discussed in the light of the debate about the possible restructuring of the regulatory framework for the Treasury bond market in Europe.

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1. Introduction

According to the efficient market hypothesis asset prices should fully reflect the available information set. The timely incorporation of information into market prices, the so-called process of "price discovery", can be facilitated if agents recognise a certain trading venue as a polar market where informative prices are provided to market participants. Instead, when the same financial instrument is traded in different venues, trades are fragmented and price discovery is split among markets. Despite trade fragmentation, competition across trading platforms can be beneficial since it can drive down the cost of capital for market participants by lowering costs and risks for investors. The balance between benefits and costs arising from a multi-platform environment cannot be established ex-ante: it is mainly an empirical question.

The issue of how trade fragmentation affects price discovery and in which market price leadeship occurs, that is where more timely and informative prices are provided, is extremely relevant not only for investors' pricing and hedging purposes but also for the supervisory activity of public authorities. In the empirical literature on multi-market price discovery, two popular measures are the Component Shares (Harris et al., 1995), CS, and the Information Shares (Hasbrouck, 1995), IS. While these approaches have been applied to stocks (Huang, 2002), credit derivatives (Blanco et al., 2005), foreign exchange (Tse et al., 2006) and commodity (Figuerola-Ferretti and Gonzalo, 2010) markets, there is scant empirical evidence (and generally focused on the relationship between spot and future prices) for the government fixed income securities market (Upper and Werner, 2002; Brandt et al., 2007; Chung et al., 2007). Understanding how information is incorporated into prices in the case of this specific financial segment is even more crucial since it also has policy implications for public debt management. An efficient secondary Treasury bond market is indeed the most important channel for the domestic funding of budget deficits and increases the effectiveness of monetary policy as well as the degree of overall financial stability.

This paper aims at quantifying the degree of price discovery in the MTS (Mercato Telematico dei Titoli di Stato) system, the main electronic platform for euro-denominated government bonds, where parallel quoting for benchmark bonds can take place on a centralised European trading venue (EuroMTS) competing with a number of (relatively large) domestic markets. As in Caporale and Girardi (2011), we focus on these two cash markets for euro-denominated government securities. However, whilst that study tested if the duplicated market setting of the MTS system allows some degree of information disclosure even in the "satellite market" (Hasbrouck, 1995), here we examine how trade fragmentation affects the degree of price discovery across competitive trading venues.

As the speed at which information arrivals are processed by market participants in a certain trading venue can be influenced by market-specific characteristics as well as by institutional arrangements (Huang, 2002), a proper modelling approach to assessing the role of trade fragmentation in the process of price discovery must be able to discriminate between these two possible types of driving factors. The duplicated market setting of the MTS system is well-suited for this purpose owing to the similarity of market-making obligations across trading venues and the possibility for market-makers to post for the same bond parallel quotes in the domestic and the European platforms. These features enable us to focus on market characteristics alone, and in particular on how trading concentration impacts on price leadership.

Our analysis brings together different, though connected, strands of research. It is naturally related to the expanding literature investigating how the secondary market for euro-denominated securities functions. Previous studies have focused on the dynamic relationship between trading activity and price movements (Cheung et al., 2005) or between yield dynamics and order flow (Menkveld et al., 2004), on the determination of the benchmark status among securities of similar maturity (Dunne et al., 2007), on the analysis of yield differentials between sovereign bonds (Beber et al., 2009), and on whether endogenously determined liquidity and trading activity conditions are driven by common factors for the European market as a whole (Caporale et al., 2012).

Our paper is also related to other empirical studies (Yan and Zivot, 2007; Bui and Sercu, 2009; Kim, 2010) emphasising the intrinsic dynamic nature of the process of price discovery. Even though widely used and easy to compute, both CS and IS only measure the contemporaneous response of asset prices to the arrival of new information. Further limitations arise from non-uniqueness (for the IS) and possibly non-boundedness (for the CS) problems. Yan and Zivot (2007) suggest instead a framework, based on the accumulation of impulse responses to shocks to the efficient price, which takes into account the dynamics of the process of price formation. Our proposed metric, the Loss Shares, LS, falls into the category of dynamic price discovery measures and represents a modification of the metric by Yan and Zivot (2007) which makes them bounded in the [0,1] interval.

Price discovery and trading activity (and more generally, liquidity conditions) are intimately related (Eun and Sabherwal, 2003; Chakravarty et al., 2004). Their interaction is very important for regulators, as market infrastructures may be improved in order to encourage competition among dealers and across trading platforms. Further policy relevance comes from the Directive 2004/39/EC disciplining the functioning of Markets in Financial Instruments in Europe (MiFID), which has generated a heated debate among academics and practitioners on whether and how to extend the MiFID regime to the Treasury bond market. Consequently, our analysis should be of interest to supervisory authorities and debt managers dealing with multi-platform environments for trading government securities.

The contribution of the present study is twofold. First, it develops new price discovery measures; second, it applies them to investigate whether there exist optimal thresholds in the trade-off between trade concentration and information efficiency for incorporating information into prices in a multi-market environment in the case of euro-denominated government securities, an investigation not carried out before. Analysing daily transaction price data for 107 European Treasury bonds over a period of twenty-seven months, and applying our measures, we find a greater role for the trading of government securities on the domestic platforms in the disclosure of information about their (unobservable) efficient price than traditional measures would indicate. Also, the polarisation between central and peripheral markets appears to be stronger when the dynamics are taken into account, and a market's contribution to price discovery appears to be crucially affected by the level of trading activity. Moreover, moving from a polarised environment where a market dominates in terms of trades and price discovery to a situation where trades are equally split between two trading venues (perfect market segmentation) does not affect the dominant role of the polar market in terms of price leadership.

The paper is structured as follows. Section 2 describes the empirical framework used to construct the price discovery measures. Section 3 outlines the key institutional features of the MTS system and provides details of the dataset. Sections 4 and 5 discuss the estimation results. Section 6 offers some concluding remarks.

2. The empirical framework

Consider a security traded on platform $i = 1, 2$. Let $p_t = (p_{1,t}, p_{2,t})'$ denote a 2×1 vector of (log) prices observed in the two markets. We assume that the efficient price of the bond follows a random walk process shared by the two market prices. Since the prices in p_t have a common efficient price they should not drift far from each other and therefore should be cointegrated as follows:

$$\beta' p_t = p_{1,t} - p_{2,t} \sim I(0) \tag{1}$$

Whether the two log-price series, albeit individually non-stationary, are linked to one another by a stationary long-run equilibrium condition can be tested in the context of a dynamic system for a pair ($p_{1,t}$, $p_{2,t}$). To do this, we start from the reduced-form Moving Average (RMA) model in its Wold representation form:

$$\Delta p_t = \Psi(L)e_t \;,\; \Psi(L) = \sum\nolimits_{k=0}^{\infty} \Psi_k L^k \;,\; \Psi_0 = I_2 \tag{2}$$

where the matrix polynomial $\Psi(L) = \Psi(1) + (1-L)\Psi^*(L)$ is such that the elements of $\{ \Psi_k \}_{k=0}^{\infty}$ are 1-summable, $E[e_t] = 0$, $E[e_t, e_s'] = \Sigma_e$ if $s = t$ and $E[e_t, e_s'] = 0$ otherwise.

If condition (1) holds, then Δp_t has a Vector Error Correction (VEC) model representation of infinite order (approximated by the VEC model of finite order $k-1$), which is the empirical reduced-form model:

$$\Delta p_t = \alpha(\beta' p_{t-1} - \mu) + \sum_{j=1}^{k-1} \Gamma_j \Delta p_{t-j} + e_t \tag{3}$$

where the vector β takes the form $(1 \; -1)'$, the vector α (with elements $\alpha_1 < 0$ and $\alpha_2 > 0$) contains the feedback coefficients which measure the average adjustment speed for each price to eliminate the price differential and the term μ captures systematic differences in the two prices.

2.1. Reduced-form price discovery measures

Reduced-form price discovery measures focus on the long-run impact of the reduced-form shocks on the levels of p_t, which is given by $\Psi(1) = I_2 + \Psi_1 + \Psi_2 + \ldots$, where $\Psi(1)$ has rank one if condition (1) holds.

Following Johansen (1991), the long-run impact matrix $\Psi(1)$ can be decomposed as:

$$\Psi(1) = \beta_\perp (\alpha_\perp' \Gamma(1) \beta_\perp)^{-1} \alpha_\perp' = \xi \alpha_\perp' \tag{4}$$

where $\Gamma(1) = I_2 - \sum_{j=1}^{k-1}\Gamma_j$, $\alpha_\perp$ and $\beta_\perp$ are 2×1 matrices such that $\alpha'\alpha_\perp = 0$ and $\beta'\beta_\perp = 0$. Let also $\psi = (\psi_1 \;\; \psi_2)$ denote the common row of $\Psi(1)$. As shown in Hasbrouck (1995), since $\beta'\Psi(1) = 0$ and $\beta = (1 \;\; -1)'$, the rows of $\Psi(1)$ are identical. This is because the long-run impact of any innovation on the price of the same asset in multiple markets is expected to be identical.

Hasbrouck (1995) measures price discovery in the i-th market as the contribution of market i to the variance of the permanent shock (market i's Information Share, IS):

$$IS_i = \frac{([\psi F]_i)^2}{\psi\Sigma_e\psi'} \;,\; i = 1,2 \tag{5}$$

where F is a lower triangular matrix such that $FF' = \Sigma_e$. As shown in Ballie et al. (2002), for the bivariate case with $\beta = (1 \;\; -1)'$ we have $\psi = \alpha'_\perp$. Since price innovations are generally correlated across markets, the matrix Σ_e is likely to be non-diagonal. In such a case, Hasbrouck's approach can only provide upper and lower bounds on the information shares of each trading venue.

Based on the Gonzalo and Granger (1995)'s permanent-transitory decomposition, the Component Share, CS, metric proposed by Harris et al. (1995) measures each market's contribution to the common efficient price.[1] In terms of $\alpha_\perp$ the CS can be written as:

$$CS_i = \frac{\alpha_{\perp i}}{\iota'\alpha_\perp} \;,\; i = 1,2 \tag{6}$$

[1] Such a decomposition assumes that: 1) the permanent component is a linear combination of the series contained in vector p_t; 2) the transitory components do not Granger-cause the permanent one in the long run. Note that the latter is not necessarily a random walk, unless $k = 1$ in (3) or in general when $\alpha_\perp\Gamma_i = 0$, $i = 1,...,k-1$. On the basis on the efficient markets hypothesis, Hasbrouck (1995) argues that this must be the case for a sensible interpretation. Possible violations of the random walk hypothesis may imply that the permanent component can be forecastable and the $\alpha_\perp$'s can be interpreted as portfolio weights.

where $\alpha_{\perp i}$ is the i-th element of $\alpha_{\perp}$ and ι is a vector of 1's. Also note that for the bivariate case with $\beta = (1\ -1)'$ we have that $\alpha_{\perp 1} = \alpha_2$ and $\alpha_{\perp 2} = -\alpha_1$, so that CS_i can be computed directly from the reduced-form VEC model (4). CS_i lies in the interval [0,1] (provided that the elements in $\alpha_{\perp}$ are positive which ensures that both α's in (3) are correctly signed). Note finally that high (low) values of the statistics indicate a large (small) contribution of the i-th market to price discovery.

2.2. Dynamic price discovery measures

Building on a structural cointegration model with one permanent and one transitory shock, Yan and Zivot (2007) propose a dynamic price discovery measure calculated from the impulse response functions (IRFs) of a market's price to the permanent innovation of common trend. Following Yan and Zivot (2007), we assume that $\Delta p_t \equiv [\Delta p_{1,t}, \Delta p_{2,t}]'$ admits the following Structural Moving Average (SMA) representation:

$$\Delta p_t = D(L)\eta_t \ , \ D(L) = \sum\nolimits_{k=0}^{\infty} D_k L^k \ , \ D_0 \neq I_2 \qquad (7)$$

where the elements of $\{D_k\}_{k=0}^{\infty}$ are 1-summable and the matrix D_0 defines the contemporaneous correlation structure of Δp_t. Yan and Zivot (2007) identify the structural parameters in (7) derived from the RMA (2) formulation as:

$$\Delta p_t = \Psi(L)e_t = \Psi(L)G^{-1}Ge_t = \Theta(L)\theta_t = \Theta(L)HH^{-1}\theta_t = D(L)\eta_t = \begin{bmatrix} d_1^P(L) & d_1^T(L) \\ d_2^P(L) & d_2^P(L) \end{bmatrix} \begin{bmatrix} \eta_t^P \\ \eta_t^T \end{bmatrix} \qquad (8)$$

where $\Theta(L) = \Psi(L)G^{-1}$, $\theta_t = Ge_t$, $E[\theta_t] = 0$ and $E[\theta_t, \theta_s'] = \Sigma_\theta$ if $s = t$ and $E[\theta_t, \theta_s'] = 0$ otherwise, H is a unique lower triangular matrix with 1's along the principal diagonal such that $\Sigma_\theta = HCH'$, C is a unique diagonal matrix with positive entries along the principal diagonal, $D(L) = \Theta(L)H$, with $D_0 = G^{-1}H$, $\eta_t = H^{-1}\theta_t$, where η_t (θ_t) contains the (un-) orthogonalised permanent and transitory disturbances.

In order to retrieve the elements of η_t, a three-step procedure is followed. First, the elements of the matrix G are obtained by applying the procedure outlined in Gonzalo and Ng (2001), which makes it possible to define the (un-orthogonalised) permanent and transitory innovations from the reduced-form disturbances e_t's as $\theta_t = [\theta_t^P \;\; \theta_t^T]' = Ge_t = [\,\alpha'_\perp \,\vdots\, \beta\,]\,e_t$ such that:

$$\lim_{m\to\infty} \frac{\partial E_t[p_{t+m}]}{\partial \theta_t^P} = \lim_{m\to\infty} \sum_{l=0}^{m} \frac{\partial E_t[\Delta p_{t+l}]}{\partial \theta_t^P} \neq 0 \;,\; \lim_{m\to\infty} \frac{\partial E_t[p_{t+m}]}{\partial \theta_t^T} = \lim_{m\to\infty} \sum_{l=0}^{m} \frac{\partial E_t[\Delta p_{t+l}]}{\partial \theta_t^T} = 0 \tag{9}$$

The second step consists in calibrating the long-run impacts of the (un-orthogonalised) permanent shock on the price variable such that they are the same. From condition (4) and if $\theta_t^P = \alpha'_\perp e_t$, the long-run impact of a unit change in θ_t^P will be equal to ξ. As pointed out by Yan and Zivot (2007), a natural identification restriction is that a unit change in θ_t^P will have a unit impact on all price variables. This has two implications: first, ξ will be equal to a 2×1 vector of 1's; second, $\alpha_\perp$ will be the common row vector of the long-run matrix $\Psi(1)$.

The third step concerns the rotation of the un-orthogonalised permanent and transitory disturbances to achieve uncorrelated shocks. Accordingly, the variance-covariance matrix for the elements in θ_t, Σ_θ, is factored as $\Sigma_\theta = HCH'$, so that the variance-covariance matrix of the orthogonalised shocks, $\eta_t = H^{-1}\theta_t$, turns out to be diagonal:

$$E[\eta_t, \eta'_t] = H^{-1}\Sigma_\theta (H^{-1})' = C = diag(\sigma_P^2, \sigma_T^2) \tag{10}$$

Under these conditions the long-run impact matrix for the SMA representation is:

$$D(1) = \Theta(1)H = \Psi(L)G^{-1}H = \Psi(1)D_0 = \begin{bmatrix} d_1^P(1) & d_1^T(1) \\ d_2^P(1) & d_2^T(1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} \tag{11}$$

so that conditions (9) translate into the following ones:

$$\lim_{m\to\infty} \frac{\partial E_t[p_{t+m}]}{\partial \eta_t^P} = \lim_{m\to\infty} \sum_{l=0}^{m} \frac{\partial E_t[\Delta p_{t+l}]}{\partial \eta_t^P} = 1 \;,\; \lim_{m\to\infty} \frac{\partial E_t[p_{t+m}]}{\partial \eta_t^T} = \lim_{m\to\infty} \sum_{l=0}^{m} \frac{\partial E_t[\Delta p_{t+l}]}{\partial \eta_t^T} = 0 \tag{12}$$

Conditions (13) are the basis to construct the price discovery measure IRFs, $f_{i,m}$, $i = 1, 2$:

$$f_{i,m} = \frac{\partial E_t[p_{i,t+m}]}{\partial \eta_t^P} = \sum_{l=0}^{m} \frac{\partial E_t[\Delta p_{i,t+l}]}{\partial \eta_t^P} = \sum_{l=0}^{m} d_{i,l}^P \tag{13}$$

where $d_{i,l}^P$ represents the coefficient on the l-th lag of $d_i^P(L)$. A numerical summary of $f_{i,m}$'s is given by the price discovery efficiency loss for market i at a given horizon m in response to a unit permanent trend shock and is defined as the difference between $f_{i,m}$ and its asymptotic value $d_i^P(1) = 1$:

$$\varpi_i(m^*) = \sum_{m=0}^{m^*} \ell(f_{i,m} - 1) \tag{14}$$

where m^* is a truncation lag sufficiently large to ensure that $f_{i,m^*} \approx 1$ and $\ell(.)$ is a symmetric loss function, such as the absolute loss ($\ell(.) = |.|$) or the square loss ($\ell(.) = (.)^2$). Yan and Zivot (2007) measure the degree to which the market is informative in terms of price discovery as:

$$YZ_i = \ln\left[\frac{\varpi_i(m^*)}{\varpi_j(m^*)}\right] \qquad i, j = 1, 2 \text{ with } i \neq j \tag{15}$$

where positive (unbounded) values indicate lower efficiency for market i, and viceversa.

In order to obtain a bounded metric with a straightforward intepretation, we propose a new price discovery measure, the loss share, LS, based on condition (15), which is defined as the ratio of the efficiency loss in a market and the total absolute loss:

$$LS_i^* = \varpi_i(m^*) / \sum_{j=1}^{2} \varpi_j(m^*) \;, \qquad i = 1, 2$$

Note, however, that the interpretation of such a measure is the opposite with respect to reduced-form price discovery measures: higher values of LS_i^* indicate a greater efficiency loss in market i and thus a lower contribution to the price discovery process, and viceversa. A direct comparison between the ratio of the efficiency loss and traditional price discovery measures can be made conveniently by expressing markets' contribution to price discovery as:

$$LS_i = (1 - LS_i^*) = \frac{\varpi_j(m^*)}{\sum_{j=1}^{2} \varpi_j(m^*)} , \qquad i = 1, 2 \tag{16}$$

so that, according to our metric (always bounded between the [0,1] interval), the contribution to price discovery of a given market is directly related to the degree of information inefficiency observed in the remaining market(s).

Table 1 summarises the main features of the different price discovery measures discussed above in terms of identification structure, boundedness properties and statistical inference methods.

[Table 1]

3. Exchanges and data

Trading on the secondary Treasury market can occur via four channels: inter-dealer (B2B) platforms and dealer-to-customer (B2C) electronic trading platforms, either multi-dealer or single-dealer, OTC inter-dealer via voice brokers and OTC dealer-to-customer trading. B2B platforms are essentially for the trading of Treasury bonds and generally operate via cross-matching methods.

In the European case, MTS, Icap/BrokerTec Eurex Bonds and eSpeed are the main ones. In particular, the MTS system accounts for 40 percent of government bond transactions in Europe (Galati and Tsatsaronis, 2003) and for around 72 percent of the volume of electronic trading of European cash government bonds (Persaud, 2006). Similar figures are provided by BearingPoint (2005), according to which around 75 percent of trades within the B2B segment takes place on the MTS platform.

The MTS system is an example of quote-driven electronic order book markets for government securities. Proposals are firm, immediately executable and aggregated in a limit order book. Trades are anonymous and the identity of the counterpart is only revealed after an order is executed for clearing and settlement purposes.[2] Market participants can be classified as either market makers (primary dealers) or market takers (dealers). Primary dealers have exclusive rights to participate in auctions and, at the same time, are obliged to quote prices for government securities issued in the secondary markets under specific terms (in general, maximum bid-ask spread and minimum quantity). In contrast, dealers cannot enter quotes into the system and are obliged to trade bonds on the basis of bid/ask quotes placed by the market makers.

All government marketable securities issued by euro area Member States are listed on their respective domestic MTS platforms. Only benchmark securities (i.e. on-the-run bonds with an outstanding value of at least 5 billion euro that satisfy listing requirements such as the number of dealers acting as market makers) are admitted, instead, to trading on the European (EuroMTS) marketplace. Thus, for benchmark securities dealers are allowed to post their quotes on both markets simultaneously (parallel quoting). Despite their similar architecture, the domestic MTS and the EuroMTS markets differ in that the former aims at satisfying the issuer's liquidity needs within a regulated setting whilst the latter is an inter-dealer market.

Bond price transaction data are extracted from the MTS (Mercato Telematico dei Titoli di Stato) time series database, whose structure is discussed in Dufour and Skinner (2004). As in Caporale and Girardi (2011), daily observations cover the period from January 2, 2004 to March 31, 2006. This sample period corresponds to a relatively quiet period in financial markets since it ends a few weeks before the sudden appearance of severe liquidity problems

[2] Full anonymity has been recently reached through the introduction of the central counterparty (CCP) system, which aims at eliminating any risk faced by participants in trading with other dealers.

in several financial segments.[3] Although there is plenty of evidence that cross-market price adjustments tend to occur at a higher frequency than a daily one, the use of daily observations for bond prices appears to be reasonable since government bonds are traded less frequently and in larger blocks than other financial assets (such as currency or stocks).[4] Furthermore, Green and Joujon (2000) argue that daily resettlements create a strong argument for using daily closing prices, since they determine the cash flows of traders.

For each trading day, the dataset reports a time stamp, the nominal value of trading volume, the average size of trades, the last transaction price recorded before the 17.30 Central European Time close, and the average best bid/ask spread throughout the trading day. We consider government bonds issued by all euro area Member States, except for Luxembourg.[5] For each country, we select all benchmark government bonds traded in January 2004 maturing after the end of our estimation horizon. Table 2 reports the International Securities Identification Number (ISIN) code for the 107 selected bonds.

[Table 2]

4. Price discovery estimates

The estimated values of LS with absolute and square loss functions in the domestic

[3] Mizrach (2008) finds that the ABX index, aggregator of the performance of a variety of credit default swaps on asset backed securities, exhibits significant jumps as early as mid-2006, well before any problem in the mortgage market were discussed in the press or policy circles. Moreover, using the same dataset as in Caporale and Girardi (2011) allows us to make a direct comparison with their findings.

[4] Previous studies on intra-day price discovery (mainly focused on stock or currency markets) have used data at various frequency, ranging from a few minutes (see, among others, Booth et al., 2002; Huang, 2002; Kim, 2010) to a few seconds (Hasbrouck, 1995; Yan and Zivot, 2007).

[5] Namely, Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. Luxembourg is not included in the analysis since there are no Luxembourgian bonds quoted in MTS markets in the sample period considered.

MTS markets are reported in Tables 3 and 4, respectively.[6] In all cases, the truncation lag m^* is set equal to 100. In each table, 95 percent confidence bounds obtained from 1000 bootstrap replications are reported in square brackets.

The results are interesting in a number of respects. First, the absolute (square) LS implies that the estimated loss shares are lower than 0.5 in only three cases, suggesting that prices in the domestic MTS markets are the most informative for the purpose of price discovery.[7] Second, the bootstrap confidence intervals show that the shares are statistically significant and higher than 0.5 in 83 cases (reported in bold), confirming that the domestic MTS markets are relatively more efficient trading environments. Third, the two LS measures are closely related to each other, with an estimated correlation coefficient equal to 0.90.

[Table 3]

[Table 4]

Tables 5 to 8 report the contribution of each market to price discovery computed according to the IS and CS methods. Since the IS approach involves a Choleski factorisation of the covariance matrix of the innovations in prices on the two exchanges, a particular ordering of prices needs to be chosen. As the information shares are not unique, Table 5 and Table 6 report upper and lower bounds for each bond included in the analysis along with 95 percent bootstrapped confidence intervals.

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[6] The metrics introduced in Section 2 above require equally spaced data without missing values. Following Upper and Werner (2002), in the presence of missing observations we use the last available transaction price (the "fill-in" method). According to standard unit root and stationarity tests, the 214 individual transaction price series expressed in logarithms are integrated processes of order one. Moreover, the Horvath and Watson (1995) cointegration test for the null of no cointegration against the known alternative of rank one with $\beta = (1\ -1)'$ strongly supports the existence of a $(1\ \ -1)'$ cointegration vector in all 107 pairs ($p_{1,t}$, $p_{2,t}$). The complete results are not reported for reasons of space, but are available on request.

[7] Namely, the bonds with code GR0133002155, IE0006857530 and IE0031256328.

[Table 5]

[Table 6]

As can be seen, while there are 102 statistically significant cases of upper bounds larger than 0.5 (Table 5), there are only 42 of them when the lower bounds are taken into account (Table 6). The gap between lower and upper bounds is therefore too wide to draw strong conclusions; however, one can safely state that the domestic MTS market dominates in term of price leadership for only 42 out of 107 bonds in the sample.[8] Non-uniqueness represents a problem, since understanding the cross-sectional determinants of price discovery (discussed later on) requires a unique value instead of upper and lower bounds. A practical though not fully theoretically justifiable way to overcome such a problem is to compute the average of those bounds (see Ballie et al., 2002). The results in Table 7 give an overall picture quite similar to the one emerging in Table 3 and Table 4: there are only two cases with a contribution lower than 0.5 and the domestic MTS market shares turn out to be larger than 0.5 in 87 cases.

[Table 7]

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[8] These very wide bounds are due to non-zero correlations in Σ_e. The contemporaneous correlation coefficient of the residuals of the estimated bivariate VEC models ranges from 0.05 to 0.86, with a mean value of 0.42. Furthermore, in 54 out of 107 models the correlation coefficient turns out to be statistically significant at the 5 percent level. Shortening the interval of observation could help to reduce these correlations and obtain tighter bounds (Hasbrouck, 1995). However, a number of studies (Baillie et al., 2002; Huang, 2002; Eun and Sabherwal, 2003) have found a wide divergence between upper and lower bounds even when using prices sampled at a few minute intervals (a very high frequency for the case of euro-denominated government securities). Therefore, wide bounds are inevitable for our IS measure. A simple regression analysis of the difference between upper and lower IS bounds on the correlation coefficient reveals that error correlation enters positively and significantly and explains about 79 percent of the cross-sectional variation of the upper and lower IS spread.

Concerning the results from the CS method (Table 8), the estimated $\alpha_{\perp}$ in 8 cases contain negative elements, which leads to difficulties in the interpretation of the CS (Hasbrouck, 2002). The domestic MTS markets' contribution to price discovery indeed turn out to be larger than unity. Focusing now on the remaining 99 meaningful estimates of price discovery, the CS method indicates for the domestic MTS markets a statistically significant share larger than 0.5 in 77 cases.

[Table 8]

Further evidence on price discovery in the MTS system is provided in Table 9 where we report summary statistics (upper panel) and correlation coefficients (lower panel) for LS and the other metrics (namely, IS and CS).[9] Based on the standard error of the means, all average values are significantly different from zero at the 1 percent level. According to the LS, the domestic MTS markets' contribution to price discovery ranges between 84 (for the absolute LS) and 93 percent (for the square LS). The evidence from the traditional price discovery measures is similar, even though the contribution of the domestic MTS markets to the discovery of the efficient price seems to be lower.[10] The comparison of the median values of our price discovery measures with those from IS and CS further corroborates this conclusion. Our findings reveal that measures taking into accont only the contemporaneous response of asset prices to new fundamental information about asset values tend to underestimate the

[9] For the computation of summary statistics and correlations for IS we use the average bounds, whilst for CS we follow Blanco et al. (2005) and replace values larger than 1 with unity.

[10] The small differences between the present results and those in Caporale and Girardi (2011) can be explained by the different information criterion chosen to estimate the VEC models. While in Caporale and Girardi (2011) the optimal lag of the bivariate VEC models was chosen according to the Akaike Information Criterion, the price discovery measures used in the present study are based on VEC models whose optimal lag structure is determined using the Schwarz Information Criterion.

contribution of the leading market to price discovery.[11]

The pair-wise correlations between the various metrics turn out to be positive, as expected. Although all co-movements are highly statistically significant, the pair correlations for structural price discovery are higher than those between structural and reduced form metrics. Finally, we observe a relatively lower degree of correlation for the square version of LS with respect to the its absolute counterpart, owing to its higher degree of non-linearity.

[Table 9]

5. Trading segmentation and markets' contribution to price discovery

It is widely recognised that market-specific characteristics, such as trading activity, prevailing bid/ask spreads and market volatility may influence the speed at which information arrivals are processed by market participants in a certain trading venue (Eun and Sabherwal, 2003; Chakravarty et al., 2004, among others).

A well-functioning market is indeed characterised not only by high trading volumes but also by low price volatility and tiny bid/ask spreads. More liquid markets, with a continuous trade flow, tend to record small price variations; in contrast, less liquid markets, with extensive non-trading intervals, are likely to exhibit a higher return volatility: this suggests an inverse link between (relative) standard deviations of price changes and the degree of contribution to price discovery. Likewise, it is reasonable to expect an inverse relationship between price discovery measures and bid/ask spreads, since these constitute the largest part of trading costs.

In order to assess to what extent observable market characteristics influence the process

[11] It would be interesting in future work to compute the LS metrics with high-frequency data in order to test whether the dominant market's contribution to the price discovery process is higher than implied by traditional price discovery measures.

of price formation in the MTS system, we perform a cross-sectional regression of LS as a function of: a) the share of trading volumes (x_{tra}), defined as the ratio of the nominal trading volumes on the domestic MTS market to the aggregate nominal trades on both domestic MTS and EuroMTS markets (over the sample period); b) the relative volatility (x_{vol}), given by the difference (domestic MTS minus EuroMTS) between the absolute price changes (from equally-weighted daily averages over the sample period); c) the relative transaction costs (x_{spr}), obtained as the difference (domestic MTS minus EuroMTS) between the best bid/ask spreads throughout the day (from equally-weighted daily averages over the sample period).[12]

Table 10 presents summary statistics of the observable market characteristics in our cross-sectional analysis.

[Table 10]

As Table 3 and 4 show, LS is constrained within the interval between 0 and 1. Because of the bounded nature of the dependent variable, we cannot implement an Ordinary Least Squares (OLS) regression, $E(LS \mid x) = \gamma_0 + \gamma_1 x_{tra} + \gamma_2 x_{vol} + \gamma_3 x_{spr} = x\gamma$, since the predicted values from the OLS regression cannot be guaranteed to lie in the unit interval.[13] An alternative to the standard OLS specification is $E(LS \mid x) = G(x\gamma)$ where $G(.)$ satisfies $0 < G(z) < 1$, for all $z \in \Re$, ensuring that the predicted LS lies in [0,1] interval. The most common functional forms for $G(.)$ are the standard cumulative normal distribution (i.e. the probit model case) and the logistic function (i.e. the logit model case).[14] Given the non-

[12] Data for the explanatory variables used in the cross-section analysis are taken from the MTS database (Dufour and Skinner, 2004).

[13] See, among others, Bastos (2010) for a similar application of fraction regression models.

[14] Note that with the identity function the fraction regression model collapses to the standard OLS regression. The quasi-maximum likelihood estimator of γ is consistent and asymptotically normal regardless of the distribution of the LS conditional on the x's (Papke and Wooldridge, 1996).

linearity of the functions $G(x\gamma)$, the partial effects of the explanatory variables on LS are not constant, in contrast to the standard OLS case. Table 11 reports the estimated coefficients for each of the three different functional forms when the dependent variable is the absolute (Panel A) and the square loss (Panel B).

[Table 11]

In all regressions, the role of trade shares is highly significant. The positive signs of the estimated coefficients for trade shares indicate that relatively higher trading volumes lead to an increase in the relative contribution to price discovery. The opposite holds for volatility and transaction costs: LS metrics turn out to be inversely related to those two market characteristics, in a way consistent with standard market microstructure arguments and with the evidence from other financial segments, such as equity markets (Eun and Sabherwal, 2003; Chakravarty et al., 2004). Note also that relative spreads have a minor role in explaining price discovery: trading cost differentials between the domestic MTS and EuroMTS appear not to be a major factor for choosing a trading platform rather than another, corroborating the conclusions of Cheung et al. (2005). Moreover, the square LS specification accounts for a higher percentage of the deviance than the absolute LS, with the logit and probit functional forms outperforming their OLS countepart (especially in the case of the square LS measure). Finally, in all specifications relative trading activity is by far the most relevant factor in explaining cross-section variability in price discovery measures, as the decomposition of the explained deviance shows.

Because the regressions in Table 11 involve different functional forms, the meaning of the regression coefficients are not the same. By contrast, the regression functions, $E(LS \mid x)$, have a direct probabilistic interpretation. Accordingly, we compute the response predictions $E(LS \mid x)$ from the estimated models in order to assess how the predicted LS are expected to vary when the share of trading volumes is assumed to change from its maximum (corresponding to the case of total trading dominance) to 0.5 (that is, the case of perfect trade segmentation).[15] The results from this exercise are reported in Figure 1.

[Figure 1]

The upper graphs of Panel A and Panel B show the partial effects of changes in the trade share on the absolute and square LS, respectively. As expected, while the partial effects in the OLS case are constant, those from logit and probit specifications are non-linear (especially for the square LS case). Note also that the linear OLS framework produces unsatisfactory results for the square LS case, with negative predicted values when trade shares are assumed to take values greater than 0.85. The lower graphs in both panels are based on our preferred specification (the logit function), with the dotted bold line representing the partial effects, the dashed lines the 95 percent confidence intervals and the thin solid line the main diagonal.

A type of optimal treshold emerges at the point where the diagonal crosses the partial effects line: when the partial effects are above the diagonal, there is a higher than one-to-one response of the contribution to price discovery to degree of trade concentration in the corresponding market; by constrast, when the partial effects lie below the diagonal, further concentration of trades translates into small gains in terms of price discovery. According to the evidence from the absolute LS, such a threshold corresponds to around 92 percent (with an estimated confidence interval of 89-95 percent) of trades occurring in the domestic MTS markets. This may explain why trades occurring in the EuroMTS have a non-negligible

[15] When computing partial effects of trade shares on LS, relative spreads and market volatility have been set equal to the sample averages. Similar results to those presented in Table 11 are obtained by regressing both LS metrics and traditional price discovery measures on the share of contracts (i.e. the ratio between the total number of contracts to the domestic MTS market and the aggregate number of contracts to both domestic MTS and EuroMTS markets, over the sample period) instead of the trade shares. The complete set of results is available on request.

informational content, even though this resembles a prototype of “satellite market” (in the sense of Hasbrouck, 1995), as previuosly documented in Caporale and Girardi (2011). In the case of the square LS, full concentration of trades in the dominant market removes inefficiency losses in that trading venue (suggesting perfect concentration and thus zero segmentation).

To assess the impact of the main variables of interest (the trade shares) on the relative contribution of the dominant market, we focus on the logit specification for the absolute LS, in order to provide more conservative evidence. As the sample mean for the trade share is 0.74 (see Table 10), the predicted value for the dependent variable is 0.84. By increasing trade shares to 0.80, the relative contribution to price discovery associated with the domestic MTS market increases to roughly 0.87, with an increase of around 3 percentage points. By contrast, an increase of the dependent variable from 0.95 to 1 (perfect market concentration) yields only marginal gains in terms of a reduction in the relative information inefficiency and thus a greater contribution to revealing the efficient price (which rises from 0.93 to 0.94).

Since they are not affected either by non-uniqueness or by unboundedeness problems, as discussed in Section 4.2 above, the LS metrics are more appropriate for our purposes. For the sake of completeness, Figure 2 reports the same simulation exercise for the LS metrics when the two traditional price discovery measures are used as the response variable.[16] The results strongly support the previous findings, although the evidence from traditional price discovery measures suggests a greater role for trades in the satellite market (with a treshold value ranging between 85 and 90 percent). This leads to overestimating the role of the satellite market and consequently underestimating the contribution of the polar market, suggesting that

[16] When considering traditional price discovery measures, the following should be taken into account: for IS, we use the average of upper and lower bounds; for CS we replace wrongly signed α_2 ’s with zero in order to make the price discovery measure bounded in the [0,1] interval.

the benefit from a multi-platform environment might be overvalued if measured by traditional price discovery measures.

[Figure 2]

6. Conclusions

This paper investigates the role of trade segmentation in the process of price discovery in the market for euro-denominated government securities. We propose new metrics (the efficiency loss shares) to assess the degree of price discovery occurring in the MTS (Mercato Telematico dei Titoli di Stato) system, a duplicated market setting where parallel quoting for benchmark bonds can take place on a centralised European trading venue competing with a number of domestic markets.

Analysing price data on daily transactions for 107 bonds over a period of twenty-seven months, we find a greater degree of price leadership of the dominant market when our measures (as opposed to the traditional price discovery metrics) are used. Our results suggest that neglecting the dynamic nature of the process may lead to understimating the price leadeship of the dominant market. We also present unambiguous evidence that the level of trading activity crucially affects a market's contribution to price discovery. The proposed econometric approach is of more general interest, since it does not include any variables which are highly market-specific and thus can also be applied to investigate the relationship between trade segmentation and price leadership in other financial segments. The distinguishing features of the markets examined here are the close institutional linkage between the two trading venues and the policy relevance of a multi-platform environment in the context of euro-denominated government bond trading.

In the light of the debate on whether and how to extend the MiFID regime to the Treasury bond market, our findings are of extreme importance for supervisory authorities. It is well known that the features of the secondary market influence considerably government debt managing and the sale of government securities in primary markets. In this respect, a pre-requisite for efficient secondary markets is the abolition of unnecessary barriers to the establishment of a fully integrated multi-platform environment in order to allow competition across platforms to drive down the cost of capital.

Our findings suggest, however, that policy interventions aimed at fostering competition across market venues by setting an “optimal” number of alternative trading platforms are likely to be ineffective (or even distorting) since the choice of where investors trade should be ultimately determined by individual preferences. On the one hand, the simulation results from fraction regressions suggest that even in the case of an extremely polarised environment there is a role in price formation for the satellite market. This means that establishing mandatory trading platforms is not a useful option for debt managers to enhance price discovery. On the other hand, the empirical evidence from the duplicated market setting characterising the MTS system suggests that a move toward the case of perfect market segmentation should not affect the dominance (in term of its contribution to price discovery) of the polar market, since investors’ habits make it difficult to migrate from a trading platform to another.

Our results also have implications for how debt managers should ascertain the fulfilment of market-making obligations. Since informative prices are the key ingredient in ensuring the sale of government securities in the primary market at the best achievable price, the market activity of primary dealers should be evaluated (and to some extent rewarded) on the basis of the platform on which, on average, information is more quickly incorporated into prices.

Admittedly, no attempt has been made in this paper to investigate how information asymmetries among market participants affect the price formation mechanism in the European market of Treasury securities or to what extent the ongoing financial turmoil has affected the process of price discovery in the MTS system. These issues are beyond the scope of the present study, and will be the subject of future research.

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Table 1 – Properties of price discovery measures

Metrics	*Identification*	*Boundedness*	*Inference*
LS	*S*	[0,1] $^{+}$	*B*
IS	*R*	[0,1] $^{\bullet}$	*B*
CS	*R*	[0,1] $^{\lozenge}$	*A*,*B* $^{\lozenge}$
YZ	*S*	(-∞,+∞)	*B*

S:	structural identification structure
R:	reduced-form identification structure
$^{+}$:	always
$^{\bullet}$:	when upper and lower bounds are averaged (Ballie et al., 2002)
$^{\lozenge}$:	*iff* both feedback coefficients in model (3) are correctly signed
B:	bootstrap-based confidence intervals
A:	asymptotic intervals

Note. LS, IS, CS and YZ stand for the price discovery measure based on loss share, information share, component share and Yan and Zivot (2007) methods, respectively. See conditions (5), (6), (15) and (16) of the main text.

Table 2 – ISIN codes

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	AT0000383518	BE0000286923	ES0000012239	FI0001004822	FR0000187361	DE0001135176	GR0110014165	IE0006857530	IT0001448619	NL0000102101	PTOTECOE0011
2	AT0000383864	BE0000291972	ES0000012387	FI0001005167	FR0000187635	DE0001135192	GR0114012371	IE0031256211	IT0003080402	NL0000102317	PTOTEGOE0009
3	AT0000384227	BE0000296054	ES0000012411	FI0001005332	FR0000187874	DE0001135200	GR0114015408	IE0031256328	IT0003171946	NL0000102606	PTOTEJOE0006
4	AT0000384821	BE0000297060	ES0000012445	FI0001005407	FR0000188328	DE0001135218	GR0124006405	IE0032584868	IT0003190912	NL0000102671	PTOTEKOE0003
5	AT0000384938	BE0000298076	ES0000012452	FI0001005514	FR0000188690	DE0001135226	GR0124011454	.	IT0003242747	NL0000102689	PTOTEWOE0009
6	AT0000384953	BE0000300096	ES0000012783	FI0001005522	FR0000188989	DE0001135234	GR0124015497	.	IT0003256820	NL0000102697	PTOTEXOE0016
7	AT0000385067	BE0000301102	ES0000012791	.	FR0000189151	DE0001135242	GR0124018525	.	IT0003271019	.	.
8	AT0000385356	BE0000302118	ES0000012825	.	FR0010011130	DE0001141380	GR0124021552	.	IT0003357982	.	.
9	AT0000385745	BE0000303124	ES0000012866	.	FR0103230423	DE0001141398	GR0124024580	.	IT0003413892	.	.
10	AT0000385992	.	ES0000012882	.	FR0103840098	DE0001141406	GR0128002590	.	IT0003472336	.	.
11	.	.	.	.	FR0104446556	DE0001141414	GR0133001140	.	IT0003477111	.	.
12	.	.	.	.	FR0105427795	DE0001141422	GR0133002155	.	IT0003493258	.	.
13	.	.	.	.	FR0105760112	DE0001141430	.	.	IT0003522254	.	.
14	.	.	.	.	FR0106589437	.	.	.	IT0003532097	.	.
15	.	.	.	.	.	.	.	.	IT0003535157	.	.
16	.	.	.	.	.	.	.	.	IT0003611156	.	.
17	.	.	.	.	.	.	.	.	IT0003618383	.	.

Note. The bond markets are those of Austria (ATS), Belgium (BEL), Spain (ESP), Finland (FIN), France (FRF), Germany (GEM), Greece (GGB), Ireland (IRL), Italy (MTS), the Netherlands (NLD) and Portugal (PTE).

Table 3 – Domestic MTS markets' contribution to price discovery: Absolute LS - LS (abs)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.9803** [0.7491 , 0.9851]	**0.9143** [0.6698 , 0.9831]	**0.9690** [0.7247 , 0.9849]	**0.9027** [0.6080 , 0.9729]	**0.8791** [0.6248 , 0.9853]	0.6273 [0.2515 , 0.9066]	**0.8801** [0.5399 , 0.9615]	0.4067 [0.1336 , 0.7977]	**0.7985** [0.5854 , 0.9690]	**0.9098** [0.6393 , 0.9789]	**0.7765** [0.5935 , 0.9455]
2	**0.9176** [0.5806 , 0.9903]	0.6607 [0.3393 , 0.8612]	0.6473 [0.3155 , 0.8390]	**0.8759** [0.5918 , 0.9758]	**0.8885** [0.6302 , 0.9713]	**0.8233** [0.5390 , 0.9844]	0.6430 [0.2641 , 0.8977]	0.6213 [0.3768 , 0.8458]	**0.9086** [0.7210 , 0.9840]	0.7861 [0.4849 , 0.9772]	**0.8448** [0.6395 , 0.9821]
3	**0.9500** [0.7128 , 0.9911]	**0.8374** [0.6383 , 0.9708]	0.7410 [0.3210 , 0.9639]	**0.8487** [0.5161 , 0.9350]	**0.8524** [0.6540 , 0.9819]	**0.8153** [0.5436 , 0.9854]	**0.9590** [0.7136 , 0.9760]	0.3014 [0.1509 , 0.6868]	**0.8754** [0.6562 , 0.9592]	**0.8241** [0.6168 , 0.9730]	**0.9667** [0.7143 , 0.9876]
4	**0.9102** [0.6070 , 0.9898]	**0.8208** [0.5996 , 0.9755]	0.8866 [0.4198 , 0.9570]	**0.8203** [0.6170 , 0.9641]	**0.9568** [0.6806 , 0.9904]	**0.8730** [0.7060 , 0.9893]	**0.9707** [0.7600 , 0.9796]	0.6267 [0.2390 , 0.8576]	**0.8822** [0.6472 , 0.9724]	**0.8272** [0.6173 , 0.9798]	**0.9748** [0.7478 , 0.9912]
5	**0.8843** [0.6741 , 0.9896]	**0.7600** [0.5409 , 0.9495]	**0.9129** [0.6341 , 0.9858]	**0.8328** [0.5137 , 0.9337]	**0.9313** [0.6978 , 0.9864]	**0.9058** [0.6816 , 0.9593]	0.7278 [0.4727 , 0.9469]	.	**0.9639** [0.7579 , 0.9810]	**0.8221** [0.5841 , 0.9766]	**0.9800** [0.7427 , 0.9900]
6	**0.9774** [0.7727 , 0.9837]	**0.9142** [0.7101 , 0.9860]	**0.9645** [0.7556 , 0.9849]	0.5997 [0.3942 , 0.8333]	**0.8221** [0.5970 , 0.9823]	0.6024 [0.3378 , 0.8034]	**0.9503** [0.7587 , 0.9810]	.	**0.9250** [0.7758 , 0.9717]	0.7532 [0.2993 , 0.9248]	**0.9537** [0.7550 , 0.9730]
7	**0.8831** [0.6434 , 0.9848]	**0.7616** [0.5648 , 0.9519]	**0.8853** [0.6816 , 0.9696]	.	**0.8682** [0.5885 , 0.9580]	**0.9574** [0.7475 , 0.9870]	**0.9288** [0.5891 , 0.9771]	.	**0.8171** [0.6344 , 0.9485]	.	.
8	**0.9379** [0.6725 , 0.9898]	**0.8626** [0.5625 , 0.9766]	**0.6787** [0.2045 , 0.9099]	.	**0.8147** [0.5875 , 0.9618]	0.7151 [0.4228 , 0.9136]	**0.8613** [0.6120 , 0.9659]	.	**0.9731** [0.6961 , 0.9797]	.	.
9	**0.7998** [0.5055 , 0.9470]	**0.9636** [0.7629 , 0.9884]	**0.9201** [0.6328 , 0.9868]	.	**0.9620** [0.6987 , 0.9788]	**0.9506** [0.6688 , 0.9834]	**0.9820** [0.7018 , 0.9882]	.	**0.7819** [0.5871 , 0.9406]	.	.
10	**0.9265** [0.6835 , 0.9904]	.	**0.8516** [0.6216 , 0.9681]	.	**0.9095** [0.7657 , 0.9630]	0.7917 [0.4958 , 0.9532]	**0.8163** [0.5801 , 0.9550]	.	**0.9098** [0.6808 , 0.9680]	.	.
11	.	.	.	.	**0.9644** [0.7295 , 0.9895]	0.5265 [0.2775 , 0.7560]	**0.9567** [0.7442 , 0.9781]	.	**0.7604** [0.5448 , 0.9187]	.	.
12	.	.	.	.	0.604 [0.2611 , 0.8994]	0.6521 [0.3126 , 0.8538]	0.4576 [0.4218 , 0.7195]	.	**0.9311** [0.7707 , 0.9767]	.	.
13	.	.	.	.	0.7350 [0.4627 , 0.9425]	0.7532 [0.3269 , 0.9206]	.	.	**0.7824** [0.6010 , 0.8906]	.	.
14	.	.	.	.	**0.9214** [0.6406 , 0.9778]	.	.	.	**0.9104** [0.7271 , 0.9689]	.	.
15	.	.	.	.	.	.	.	.	**0.8942** [0.7414 , 0.9602]	.	.
16	.	.	.	.	.	.	.	.	**0.9146** [0.7509 , 0.9623]	.	.
17	.	.	.	.	.	.	.	.	**0.8163** [0.5624 , 0.9550]	.	.

Note. See Table 2. The price discovery estimates are obtained from conditions (14) and (16) of the main text, with the loss function $\ell(.) = |.|$ and a truncation lag m^* set equal to 100. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 4 – Domestic MTS markets' contribution to price discovery: Square LS - LS (sq)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.9995** [0.8978 , 0.9996]	**0.9928** [0.8486 , 0.9996]	**0.9992** [0.8836 , 0.9996]	**0.9898** [0.6966 , 0.9987]	**0.9826** [0.7519 , 0.9996]	0.7391 [0.1306 , 0.9925]	**0.9901** [0.5564 , 0.9985]	0.3044 [0.0212 , 0.9674]	**0.9501** [0.7257 , 0.9988]	**0.9903** [0.7499 , 0.9992]	**0.9301** [0.7082 , 0.9956]
2	**0.9922** [0.6389 , 0.9998]	0.8568 [0.1923 , 0.9859]	0.7776 [0.1413 , 0.9646]	**0.9727** [0.6207 , 0.9987]	**0.9857** [0.7820 , 0.9969]	**0.9604** [0.5746 , 0.9994]	0.8224 [0.1110 , 0.9821]	0.7665 [0.2619 , 0.9710]	**0.9922** [0.8945 , 0.9996]	0.9365 [0.4431 , 0.9993]	**0.9724** [0.7985 , 0.9996]
3	**0.9972** [0.8595 , 0.9998]	**0.9727** [0.8193 , 0.9989]	0.8963 [0.0962 , 0.9969]	**0.9629** [0.5403 , 0.9950]	**0.9683** [0.7657 , 0.9993]	**0.9556** [0.6217 , 0.9996]	**0.9989** [0.8626 , 0.9994]	0.1784 [0.0203 , 0.8859]	**0.9840** [0.8598 , 0.9978]	**0.9501** [0.6889 , 0.9982]	**0.9990** [0.8794 , 0.9997]
4	**0.9912** [0.7212 , 0.9997]	**0.9616** [0.7622 , 0.9991]	0.9602 [0.2406 , 0.9956]	**0.9644** [0.7801 , 0.9982]	**0.9981** [0.8311 , 0.9997]	**0.9797** [0.8524 , 0.9997]	**0.9990** [0.8919 , 0.9995]	0.8265 [0.0538 , 0.9779]	**0.9880** [0.8482 , 0.9991]	**0.9622** [0.7482 , 0.9991]	**0.9993** [0.9001 , 0.9998]
5	**0.9822** [0.8046 , 0.9997]	**0.9199** [0.6234 , 0.9964]	**0.9920** [0.7799 , 0.9995]	**0.9660** [0.6245 , 0.9973]	**0.9957** [0.8773 , 0.9995]	**0.9858** [0.7918 , 0.9980]	0.8767 [0.4139 , 0.9972]	.	**0.9968** [0.9325 , 0.9996]	**0.9583** [0.6667 , 0.9991]	**0.9996** [0.9132 , 0.9996]
6	**0.9998** [0.9088 , 0.9999]	**0.9914** [0.8537 , 0.9997]	**0.9988** [0.8850 , 0.9996]	0.7824 [0.3810 , 0.9734]	**0.9581** [0.6822 , 0.9993]	0.7410 [0.1761 , 0.9652]	**0.9975** [0.8845 , 0.9995]	.	**0.9866** [0.9196 , 0.9989]	0.9352 [0.1028 , 0.9922]	**0.9976** [0.9285 , 0.9992]
7	**0.9849** [0.7818 , 0.9996]	**0.9338** [0.6808 , 0.9975]	**0.9882** [0.8290 , 0.9987]	.	**0.9849** [0.7241 , 0.9984]	**0.9982** [0.8995 , 0.9997]	**0.9931** [0.6255 , 0.9990]	.	**0.9679** [0.8316 , 0.9971]	.	.
8	**0.9958** [0.8177 , 0.9998]	**0.9789** [0.6149 , 0.9990]	0.7917 [0.0295 , 0.9860]	.	**0.9588** [0.7092 , 0.9979]	0.9039 [0.3494 , 0.9928]	**0.9824** [0.7545 , 0.9990]	.	**0.9994** [0.8652 , 0.9994]	.	.
9	**0.9554** [0.3832 , 0.9957]	**0.9986** [0.9218 , 0.9998]	**0.9923** [0.7666 , 0.9996]	.	**0.9987** [0.8596 , 0.9995]	**0.9973** [0.7985 , 0.9995]	**0.9992** [0.8578 , 0.9995]	.	**0.9450** [0.7181 , 0.9963]	.	.
10	**0.9941** [0.8310 , 0.9998]	.	**0.9816** [0.7802 , 0.9993]	.	**0.9896** [0.9144 , 0.9980]	**0.9534** [0.5694 , 0.9971]	**0.9702** [0.7224 , 0.9979]	.	**0.9934** [0.8753 , 0.9988]	.	.
11	.	.	.	.	**0.9987** [0.8681 , 0.9998]	0.5869 [0.1088 , 0.9209]	**0.9971** [0.8931 , 0.9995]	.	**0.9527** [0.7284 , 0.9932]	.	.
12	.	.	.	.	0.5940 [0.0442 , 0.9890]	0.8399 [0.1391 , 0.9832]	0.3777 [0.3237 , 0.8433]	.	**0.9940** [0.9263 , 0.9995]	.	.
13	.	.	.	.	0.9078 [0.4371 , 0.9958]	0.9336 [0.1299 , 0.9934]	.	.	**0.9516** [0.8022 , 0.9882]	.	.
14	.	.	.	.	**0.9944** [0.7443 , 0.9993]	.	.	.	**0.9937** [0.9288 , 0.9990]	.	.
15	.	.	.	.	.	.	.	.	**0.9868** [0.9069 , 0.9986]	.	.
16	.	.	.	.	.	.	.	.	**0.9910** [0.9287 , 0.9986]	.	.
17									**0.9724** [0.7499 , 0.9982]		

Note. See Table 2. The price discovery estimates are obtained from conditions (14) and (16) of the main text, with the loss function $\ell(.) = (.)^2$ and a truncation lag m^* set equal to 100. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 5 – Domestic MTS markets' contribution to price discovery: IS - upper bounds

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.9847** [0.8701 , 0.9999]	**0.9903** [0.8919 , 0.9999]	**0.9596** [0.8264 , 0.9995]	**0.9174** [0.7636 , 0.9891]	**0.9808** [0.8119 , 0.9999]	**0.8434** [0.6993 , 0.952]	**0.9609** [0.8536 , 0.999]	0.5830 [0.2888 , 0.8839]	**0.9944** [0.9400 , 0.9999]	**0.9375** [0.7986 , 0.9966]	**0.9385** [0.8221 , 0.9918]
2	**0.9874** [0.6578 , 0.9999]	**0.8557** [0.6321 , 0.9727]	**0.7390** [0.5154 , 0.9020]	**0.9856** [0.9052 , 0.9999]	**0.9820** [0.8019 , 0.9999]	**0.9741** [0.8021 , 0.9999]	**0.8690** [0.7367 , 0.9669]	**0.8287** [0.6137 , 0.9625]	**0.9990** [0.9681 , 0.9999]	**0.9020** [0.5175 , 0.9995]	**0.9982** [0.9465 , 0.9999]
3	**0.9994** [0.9096 , 0.9999]	**0.9433** [0.7956 , 0.9976]	**0.8693** [0.6409 , 0.9855]	**0.9466** [0.8309 , 0.9981]	**0.9625** [0.8091 , 0.9997]	**0.9383** [0.6940 , 0.9993]	**0.9756** [0.8916 , 0.9998]	0.5225 [0.3315 , 0.7446]	**0.9929** [0.9419 , 0.9999]	**0.9572** [0.8116 , 0.9995]	**0.9844** [0.8784 , 0.9999]
4	**0.9690** [0.7648 , 0.9999]	**0.9831** [0.8662 , 0.9999]	**0.9358** [0.7192 , 0.9997]	**0.9505** [0.8513 , 0.9934]	**0.9884** [0.8242 , 0.9999]	**0.9644** [0.7894 , 0.9999]	**0.9842** [0.9199 , 0.9999]	0.6548 [0.3813 , 0.8838]	**0.9948** [0.9466 , 0.9999]	**0.9522** [0.7664 , 0.9993]	**0.9997** [0.9226 , 0.9999]
5	**0.9788** [0.8392 , 0.9999]	**0.9653** [0.8219 , 0.9996]	**0.9735** [0.8008 , 0.9999]	**0.8980** [0.7998 , 0.9645]	**0.9684** [0.8186 , 0.9996]	**0.9735** [0.8974 , 0.9998]	**0.9616** [0.8657 , 0.9986]	.	**0.9972** [0.9563 , 0.9999]	**0.9136** [0.7416 , 0.9883]	**0.9971** [0.9514 , 0.9999]
6	**0.9836** [0.8998 , 0.9999]	**0.9950** [0.9521 , 0.9999]	**0.9999** [0.9565 , 0.9999]	**0.8839** [0.7577 , 0.9686]	**0.9571** [0.8142 , 0.9996]	0.7050 [0.4312 , 0.9012]	**0.9996** [0.9667 , 0.9999]	.	**0.9972** [0.9497 , 0.9999]	**0.8623** [0.6905 , 0.9746]	**0.9783** [0.8972 , 0.9998]
7	**0.9549** [0.7736 , 0.9996]	**0.9320** [0.8125 , 0.9902]	**0.9010** [0.7677 , 0.9755]	.	**0.9339** [0.8387 , 0.9869]	**0.9972** [0.8960 , 0.9999]	**0.9724** [0.8610 , 0.9999]	.	**0.9920** [0.9382 , 0.9999]	.	.
8	**0.9740** [0.7821 , 0.9999]	**0.9542** [0.8353 , 0.9988]	**0.8246** [0.6811 , 0.9203]	.	**0.9508** [0.8130 , 0.9982]	**0.8551** [0.6676 , 0.966]	**0.9667** [0.8978 , 0.9979]	.	**0.9996** [0.9606 , 0.9999]	.	.
9	**0.8313** [0.6124 , 0.9564]	**0.9986** [0.9509 , 0.9999]	**0.9720** [0.8085 , 0.9999]	.	**0.9884** [0.9032 , 0.9999]	**0.9923** [0.9224 , 0.9999]	**0.9938** [0.9425 , 0.9999]	.	**0.9868** [0.9375 , 0.9999]	.	.
10	**0.9900** [0.8823 , 0.9999]	.	**0.9597** [0.8702 , 0.9975]	.	**0.9952** [0.9235 , 0.9999]	**0.9384** [0.7678 , 0.9979]	**0.9681** [0.9035 , 0.9984]	.	**0.9917** [0.9442 , 0.9999]	.	.
11	.	.	.	.	**0.9855** [0.8724 , 0.9999]	0.7584 [0.4798 , 0.9422]	**0.9751** [0.8983 , 0.9998]	.	**0.9962** [0.9601 , 0.9999]	.	.
12	.	.	.	.	**0.7447** [0.5645 , 0.8913]	**0.8398** [0.6796 , 0.9393]	**0.9852** [0.8896 , 0.9999]	.	**0.9969** [0.9639 , 0.9999]	.	.
13	.	.	.	.	**0.8599** [0.6633 , 0.9679]	**0.8078** [0.6327 , 0.9295]	.	.	**0.9991** [0.9757 , 0.9999]	.	.
14	.	.	.	.	**0.9798** [0.8546 , 0.9999]	.	.	.	**0.9999** [0.9750 , 0.9999]	.	.
15	.	.	.	.	.	.	.	.	**0.9997** [0.9741 , 0.9999]	.	.
16	.	.	.	.	.	.	.	.	**0.9954** [0.9558 , 0.9999]	.	.
17	.	.	.	.	.	.	.	.	**0.9922** [0.9530 , 0.9999]	.	.

Note. See Table 2. The price discovery estimates are obtained from condition (5) of the main text, the MTS prices being the first variable in the Choleski factorisation of the Σ_e matrix. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 6 – Domestic MTS markets' contribution to price discovery: IS - lower bounds

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.8364** [0.6228 , 0.9538]	0.6652 [0.4320 , 0.8527]	0.7069 [0.4859 , 0.8648]	0.5528 [0.3396 , 0.7306]	**0.8419** [0.5667 , 0.977]	0.2797 [0.1401 , 0.4578]	0.3445 [0.1765 , 0.5177]	0.3099 [0.0812 , 0.6567]	**0.7922** [0.6374 , 0.8998]	0.5701 [0.3594 , 0.7521]	**0.7661** [0.5952 , 0.8856]
2	**0.9464** [0.5393 , 0.9998]	0.4910 [0.2420 , 0.7082]	0.4594 [0.2391 , 0.6735]	0.5557 [0.3650 , 0.7187]	**0.8668** [0.5849 , 0.9894]	0.6853 [0.3913 , 0.8741]	0.2178 [0.0972 , 0.3886]	0.5366 [0.2985 , 0.7557]	**0.7655** [0.6327 , 0.8668]	0.8727 [0.4710 , 0.9986]	**0.8882** [0.7477 , 0.9680]
3	**0.9536** [0.7760 , 0.9995]	**0.7520** [0.5355 , 0.8955]	0.4303 [0.1836 , 0.6753]	0.4097 [0.2332 , 0.6030]	**0.8946** [0.6925 , 0.9868]	**0.8216** [0.5142 , 0.9634]	0.5655 [0.3880 , 0.7236]	0.2858 [0.1306 , 0.5118]	**0.7134** [0.5612 , 0.8295]	**0.8432** [0.6360 , 0.9616]	**0.8140** [0.6076 , 0.9466]
4	**0.8299** [0.5310 , 0.9665]	**0.8242** [0.6078 , 0.9483]	0.5245 [0.2362 , 0.7794]	**0.6751** [0.5075 , 0.8000]	**0.8548** [0.5696 , 0.9791]	**0.8999** [0.7816 , 0.9999]	**0.6770** [0.5199 , 0.7958]	0.3795 [0.1421 , 0.6557]	0.6286 [0.4692 , 0.7481]	**0.8012** [0.5394 , 0.9495]	**0.9328** [0.7522 , 0.9975]
5	**0.9079** [0.7043 , 0.9915]	0.7375 [0.4991 , 0.8907]	**0.8111** [0.5364 , 0.9593]	0.3738 [0.2459 , 0.5079]	**0.8961** [0.6909 , 0.9932]	0.3381 [0.1955 , 0.5014]	0.4999 [0.3257 , 0.6590]	.	**0.6853** [0.5322 , 0.8034]	0.5520 [0.3212 , 0.7327]	0.6375 [0.4711 , 0.7757]
6	0.6471 [0.4555 , 0.7974]	**0.6877** [0.5425 , 0.8253]	**0.7326** [0.5493 , 0.8648]	0.4112 [0.2550 , 0.5801]	0.7174 [0.4879 , 0.9056]	0.5058 [0.2391 , 0.7486]	**0.7087** [0.5556 , 0.8228]	.	0.6441 [0.4730 , 0.7747]	0.3899 [0.2007 , 0.6084]	**0.7025** [0.5298 , 0.8393]
7	0.7512 [0.4813 , 0.9117]	0.5767 [0.3938 , 0.7325]	0.6187 [0.4372 , 0.7678]	.	0.4588 [0.3103 , 0.6033]	**0.8385** [0.5955 , 0.957]	0.4875 [0.2801 , 0.6779]	.	**0.6747** [0.5169 , 0.7924]	.	.
8	**0.9139** [0.6609 , 0.9951]	0.4793 [0.2844 , 0.6605]	0.2635 [0.1315 , 0.4003]	.	.0.6560 [0.4352 , 0.8154]	0.4721 [0.2586 , 0.6734]	0.4607 [0.3228 , 0.5977]	.	0.6490 [0.4797 , 0.7994]	.	.
9	0.6671 [0.4219 , 0.8467]	**0.8344** [0.6563 , 0.945]	0.7492 [0.4760 , 0.913]	.	0.6554 [0.4495 , 0.8078]	0.5814 [0.3884 , 0.753]	0.4585 [0.3008 , 0.6012]	.	**0.6571** [0.5224 , 0.7752]	.	.
10	**0.8901** [0.6924 , 0.9834]	.	0.5530 [0.3878 , 0.7005]	.	**0.7293** [0.5273 , 0.8846]	0.6452 [0.3962 , 0.8413]	0.4599 [0.3274 , 0.6000]	.	0.5028 [0.3576 , 0.6291]	.	.
11	.	.	.	.	**0.8347** [0.6209 , 0.9537]	0.4335 [0.1715 , 0.6987]	0.5904 [0.4249 , 0.7366]	.	0.4204 [0.2874 , 0.5558]	.	.
12	.	.	.	.	0.4287 [0.2493 , 0.6209]	0.4535 [0.2722 , 0.6151]	0.3702 [0.1780 , 0.5848]	.	**0.6513** [0.5196 , 0.7731]	.	.
13	.	.	.	.	0.5299 [0.3003 , 0.7250]	0.4405 [0.2542 , 0.6242]	.	.	0.6238 [0.4860 , 0.7398]	.	.
14	.	.	.	.	0.6711 [0.4261 , 0.8452]	.	.	.	**0.7277** [0.5792 , 0.8339]	.	.
15	.	.	.	.	.	.	.	.	0.5175 [0.3767 , 0.6423]	.	.
16	.	.	.	.	.	.	.	.	**0.6493** [0.5006 , 0.7789]	.	.
17	.	.	.	.	.	.	.	.	0.4390 [0.3132 , 0.5665]	.	.

Note. See Table 2. The price discovery estimates are obtained from condition (5) of the main text, with MTS prices being the last variable in the Choleski factorisation of the Σ_e matrix. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 7 – Domestic MTS markets' contribution to price discovery: IS - average of upper and lower bounds

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.9105** [0.7464 , 0.9737]	**0.8278** [0.6619 , 0.9186]	**0.8333** [0.6561 , 0.9324]	**0.7351** [0.5516 , 0.8598]	**0.9114** [0.6893 , 0.9800]	0.5616 [0.4197 , 0.7049]	**0.6527** [0.5151 , 0.7586]	0.4465 [0.1850 , 0.7703]	**0.8933** [0.7887 , 0.947]	**0.7538** [0.5790 , 0.8743]	**0.8523** [0.7086 , 0.9387]
2	**0.9669** [0.5986 , 0.9963]	0.6734 [0.4370 , 0.8405]	0.5992 [0.3772 , 0.7877]	**0.7707** [0.6351 , 0.8581]	**0.9244** [0.6934 , 0.9855]	**0.8297** [0.5967 , 0.9345]	0.5434 [0.4169 , 0.6778]	0.6826 [0.4561 , 0.8591]	**0.8823** [0.8008 , 0.9284]	0.8874 [0.4943 , 0.9984]	**0.9432** [0.8485 , 0.9767]
3	**0.9765** [0.8444 , 0.9906]	**0.8476** [0.6656 , 0.9466]	0.6498 [0.4122 , 0.8304]	**0.6781** [0.5321 , 0.8007]	**0.9285** [0.7508 , 0.9929]	**0.8799** [0.6041 , 0.9815]	**0.7706** [0.6398 , 0.8618]	0.4042 [0.2310 , 0.6282]	**0.8532** [0.7515 , 0.9133]	**0.9002** [0.7238 , 0.9808]	**0.8992** [0.7430 , 0.9691]
4	**0.8994** [0.6479 , 0.9812]	**0.9037** [0.7370 , 0.9715]	0.7302 [0.4777 , 0.8896]	**0.8128** [0.6794 , 0.8967]	**0.9216** [0.6969 , 0.9794]	**0.9321** [0.8143 , 0.9917]	**0.8306** [0.7199 , 0.8979]	0.5172 [0.2617 , 0.7697]	**0.8117** [0.7079 , 0.8724]	**0.8767** [0.6529 , 0.9746]	**0.9662** [0.8386 , 0.9851]
5	**0.9434** [0.7718 , 0.9923]	**0.8514** [0.6605 , 0.9453]	**0.8923** [0.6686 , 0.9748]	**0.6359** [0.5228 , 0.7362]	**0.9322** [0.7547 , 0.9936]	**0.6558** [0.5465 , 0.7507]	**0.7307** [0.5957 , 0.8289]	.	**0.8412** [0.7443 , 0.8983]	**0.7328** [0.5314 , 0.8605]	**0.8173** [0.7113 , 0.8830]
6	**0.8154** [0.6777 , 0.8978]	**0.8413** [0.7473 , 0.9085]	**0.8662** [0.7583 , 0.9168]	**0.6475** [0.5064 , 0.7744]	**0.8373** [0.6511 , 0.9520]	0.6054 [0.3351 , 0.8249]	**0.8541** [0.7620 , 0.9047]	.	**0.8207** [0.7114 , 0.8832]	0.6261 [0.4456 , 0.7915]	**0.8404** [0.7135 , 0.9195]
7	**0.8531** [0.6275 , 0.9558]	**0.7543** [0.6031 , 0.8614]	**0.7599** [0.6024 , 0.8716]	.	**0.6964** [0.5745 , 0.7951]	**0.9179** [0.7457 , 0.9665]	**0.7299** [0.5705 , 0.8386]	.	**0.8333** [0.7276 , 0.8952]	.	.
8	**0.9440** [0.7215 , 0.9948]	**0.7167** [0.5599 , 0.8297]	0.5440 [0.4063 , 0.6603]	.	**0.8034** [0.6241 , 0.9069]	0.6636 [0.4631 , 0.8197]	**0.7137** [0.6103 , 0.7978]	.	**0.8243** [0.7215 , 0.8887]	.	.
9	**0.7492** [0.5171 , 0.9015]	**0.9165** [0.8139 , 0.9482]	**0.8606** [0.6423 , 0.9549]	.	**0.8219** [0.6763 , 0.9017]	**0.7868** [0.6554 , 0.872]	**0.7261** [0.6217 , 0.7985]	.	**0.8219** [0.7300 , 0.8874]	.	.
10	**0.9401** [0.7874 , 0.9851]	.	**0.7563** [0.6299 , 0.8490]	.	**0.8622** [0.7254 , 0.9337]	**0.7918** [0.5820 , 0.9204]	**0.7140** [0.6155 , 0.7992]	.	**0.7473** [0.6509 , 0.8139]	.	.
11	.	.	.	.	**0.9101** [0.7467 , 0.9735]	0.5960 [0.3257 , 0.8204]	**0.7828** [0.6616 , 0.8683]	.	**0.7083** [0.6238 , 0.7751]	.	.
12	.	.	.	.	0.5867 [0.4069 , 0.7561]	0.6467 [0.4759 , 0.7772]	**0.6777** [0.5843 , 0.7372]	.	**0.8241** [0.7568 , 0.8685]	.	.
13	.	.	.	.	0.6949 [0.4818 , 0.8465]	0.6242 [0.4434 , 0.7769]	.	.	**0.8115** [0.7371 , 0.8580]	.	.
14	.	.	.	.	**0.8255** [0.6403 , 0.9205]	.	.	.	**0.8638** [0.7788 , 0.9074]	.	.
15	.	.	.	.	.	.	.	.	**0.7586** [0.6757 , 0.8152]	.	.
16	.	.	.	.	.	.	.	.	**0.8224** [0.7468 , 0.8673]	.	.
17	.	.	.	.	.	.	.	.	**0.7156** [0.6331 , 0.7824]	.	.

Note. See Table 2. The price discovery estimates are obtained from condition (5) of the main text and by computing the average value of upper and lower bounds. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 8 – Domestic MTS markets' contribution to price discovery: CS

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.8875** [0.7002 , 1.0784]	**0.8936** [0.6693 , 1.1533]	**0.7922** [0.6038 , 0.9921]	**0.7035** [0.5237 , 0.8824]	**0.8667** [0.6300 , 1.1378]	0.5704 [0.4040 , 0.7541]	**0.7384** [0.5107 , 0.9673]	0.4540 [0.2457 , 0.6964]	**0.9098** [0.7335 , 1.1058]	**0.7370** [0.5535 , 0.9321]	**0.7353** [0.5900 , 0.8908]
2	**0.9118** [0.5993 , 1.2405]	0.6372 [0.4357 , 0.8291]	0.5481 [0.3910 , 0.7055]	**0.8445** [0.6318 , 1.0725]	**0.8884** [0.6637 , 1.1341]	**0.8352** [0.5807 , 1.0838]	0.5501 [0.3655 , 0.7648]	0.6148 [0.4421 , 0.8019]	**0.9614** [0.8018 , 1.1365]	**0.7716** [0.5279 , 1.0746]	**0.9517** [0.7705 , 1.1599]
3	**0.9773** [0.7581 , 1.2167]	**0.7585** [0.5826 , 0.9441]	0.6519 [0.4246 , 0.8756]	**0.7267** [0.5300 , 0.9508]	**0.8339** [0.6620 , 1.0203]	**0.7574** [0.5259 , 0.9911]	**0.8239** [0.6477 , 1.0113]	0.4115 [0.2854 , 0.5613]	**0.8932** [0.7214 , 1.0782]	**0.8055** [0.6317 , 1.0016]	**0.8684** [0.6712 , 1.109]
4	**0.8336** [0.5926 , 1.0721]	**0.8621** [0.6562 , 1.0911]	0.7480 [0.4878 , 1.0176]	**0.7430** [0.5912 , 0.8958]	**0.8990** [0.6515 , 1.1543]	1.1877 [0.7792 , 1.6477]	**0.8567** [0.6993 , 1.0120]	0.4840 [0.3000 , 0.6800]	**0.9012** [0.7116 , 1.0862]	**0.8096** [0.6122 , 1.0149]	**0.9817** [0.7656 , 1.2300]
5	**0.8645** [0.6710 , 1.0793]	**0.8031** [0.5968 , 1.0167]	**0.8338** [0.5980 , 1.1033]	0.6293 [0.4955 , 0.7703]	**0.8290** [0.6398 , 1.0795]	**0.7704** [0.5647 , 1.0041]	**0.7616** [0.5798 , 0.9531]	.	**0.9291** [0.7458 , 1.1238]	0.6923 [0.4981 , 0.8758]	**0.9269** [0.7279 , 1.1494]
6	**0.8589** [0.6735 , 1.0497]	**0.9136** [0.7524 , 1.1245]	1.0129 [0.7979 , 1.2452]	0.6116 [0.4619 , 0.7826]	**0.7956** [0.6067 , 1.0458]	0.5357 [0.3636 , 0.7081]	**0.9763** [0.7994 , 1.1551]	.	**0.9337** [0.7400 , 1.1265]	0.6358 [0.4552 , 0.8356]	**0.8374** [0.6725 , 1.0205]
7	**0.7965** [0.5829 , 1.0072]	**0.7125** [0.5522 , 0.8805]	**0.6950** [0.5556 , 0.8360]	.	**0.7156** [0.5698 , 0.8663]	**0.9460** [0.7065 , 1.1819]	**0.8058** [0.5836 , 1.0351]	.	**0.8879** [0.7140 , 1.0612]	.	.
8	**0.8499** [0.6245 , 1.0784]	**0.7571** [0.5588 , 0.9612]	**0.5534** [0.3937 , 0.6938]	.	**0.7815** [0.5990 , 0.9558]	0.6193 [0.4429 , 0.8004]	**0.7657** [0.6098 , 0.9368]	.	**0.9711** [0.7605 , 1.2323]	.	.
9	**0.6613** [0.5059 , 0.8121]	1.0484 [0.8118 , 1.3338]	**0.8294** [0.5970 , 1.0678]	.	**0.8796** [0.6765 , 1.0814]	**0.8937** [0.6844 , 1.1280]	**0.8863** [0.6748 , 1.1010]	.	**0.8539** [0.7058 , 1.0228]	.	.
10	**0.8947** [0.6861 , 1.1378]	.	**0.7620** [0.5992 , 0.9366]	.	**0.9285** [0.7347 , 1.1519]	**0.7538** [0.5527 , 0.9747]	**0.7708** [0.6201 , 0.9464]	.	**0.8672** [0.6799 , 1.0582]	.	.
11	.	.	.	.	**0.8805** [0.6817 , 1.0934]	0.5310 [0.3267 , 0.7461]	**0.8237** [0.6621 , 0.9966]	.	**0.9037** [0.7045 , 1.1267]	.	.
12	.	.	.	.	0.5941 [0.4608 , 0.7297]	0.6073 [0.4586 , 0.7452]	1.2477 [0.8154 , 1.7567]	.	1.0875 [0.8878 , 1.3363]	.	.
13	.	.	.	.	0.6420 [0.4655 , 0.8142]	0.5815 [0.4329 , 0.7320]	.	.	1.0449 [0.8493 , 1.2555]	.	.
14	.	.	.	.	**0.8588** [0.6434 , 1.0705]	.	.	.	1.0137 [0.8128 , 1.2209]	.	.
15	.	.	.	.	.	.	.	.	0.9721 [0.7706 , 1.1839]	.	.
16	.	.	.	.	.	.	.	.	1.1013 [0.8859 , 1.3534]	.	.
17	.	.	.	.	.	.	.	.	**0.8606** [0.6794 , 1.0684]	.	.

Note. See Table 2. The price discovery estimates are obtained from condition (6) of the main text. 95 percent confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 9 – Domestic MTS markets' contribution to price discovery: comparison between different measures

	LS (abs)	*LS* (sq)	*IS*	*CS*
		Summary statistics		
median	0.8754	0.9822	0.8173	0.8294
mean	0.8360	0.9323	0.7851	0.8006
s.e. mean	0.0126	0.0131	0.0116	0.0134
		Correlations		
LS (abs)	1	0.90	0.74	0.73
LS (sq)	.	1	0.67	0.59
IS	.	.	1	0.81
CS	.	.	.	1

Note. LS (abs), LS (sq) are obtained from conditions (14) and (16) of the main text, with a truncation lag m^* set equal to 100 and the loss function $\ell(.) = |.|$ and $\ell(.) = (.)^2$, respectively. IS and CS are computed according to conditions (5) and (6) of the main text, respectively. Average bounds for IS are used. Values for CS larger than 1 are replaced with unity.

Table 10 – Observable market characteristics: summary statistics

	x_{tra}	x_{vol}	x_{spr}
mean	0.7428	-0.0017	-0.0053
min	0.4647	-0.0914	-0.0722
max	0.9229	0.0315	0.2085
I quartile	0.6803	-0.0059	-0.0198
median	0.7368	0.0003	-0.0032
III quartile	0.8244	0.0070	0.0046

Note. x_{tra} is defined as the ratio of the nominal trading volumes on the domestic MTS market to the aggregate nominal trades on both domestic MTS and EuroMTS markets (over the sample period); x_{vol} is the difference (domestic MTS minus EuroMTS) between the absolute price changes (from equally-weighted daily averages over the sample period); x_{spr} is obtained as the difference (domestic MTS minus EuroMTS) between the best bid/ask spreads throughout the day (from equally-weighted daily averages over the sample period).

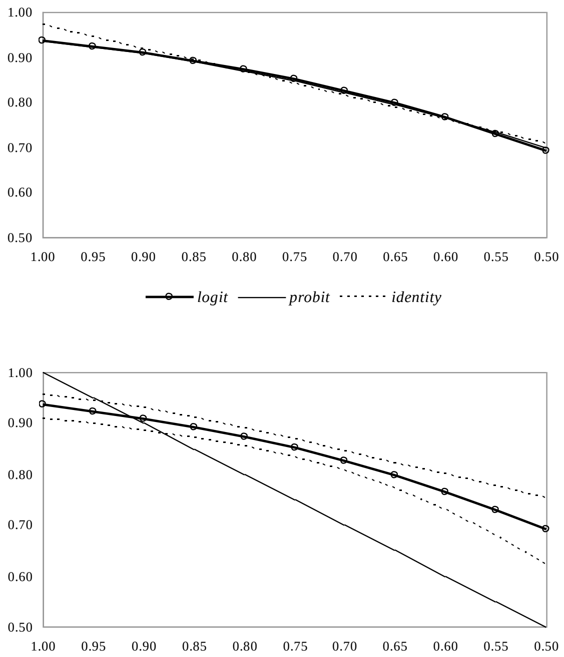
Table 11 – Fraction regression results

		A. - *LS* (abs)			B. - *LS* (sq)		
		logit	probit	ols	logit	probit	ols
Trade share:	x_{tra}	**3.7321**	**2.0243**	**0.5256**	**10.030**	**4.7265**	**0.6207**
		(0.8612)	(0.4883)	(0.1391)	(1.7528)	(0.9319)	(0.1822)
Relative volatility:	x_{vol}	**-16.150**	**-8.1545**	**-1.8083**	*-30.199*	*-14.513*	**-1.4153**
		(5.8029)	(-3.0296)	(-0.6345)	(16.266)	(7.6225)	(-0.7073)
Relative spread:	x_{spr}	-3.6872	-2.0195	-0.4344	-6.2197	-3.1808	-0.2476
		(2.8652)	(-1.4654)	(-0.3587)	(5.1111)	(2.2603)	(-0.2667)
Deviance explained		0.28	0.29	0.26	0.44	0.46	0.27
	x_{tra}	0.20	0.20	0.19	0.37	0.39	0.23
of which due to:	x_{vol}	0.07	0.07	0.06	0.06	0.06	0.04
	x_{spr}	0.01	0.02	0.01	0.01	0.01	0.00

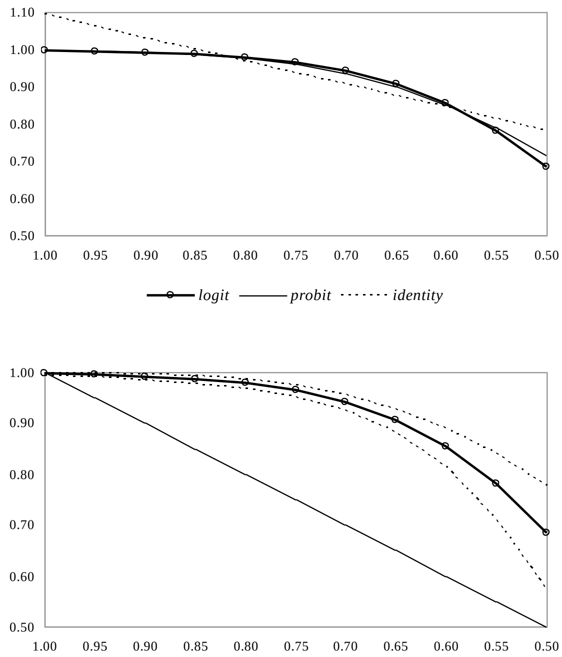
Note. See Table 10. In each panel, the conditional mean of the loss share is computed as $E(LS \mid x) = G(x\gamma)$, where $G(.)$ can be the logistic function (column logit), the standard cumulative normal distribution (column probit) or the identity function (column ols). Robust standard errors are reported in parentheses. Statistically significant coefficients at the 95 (90) percent level are in bold (italics).

Figure 1– Regression functions: dynamic price discovery measures

A. LS (abs)



B. LS (sq)

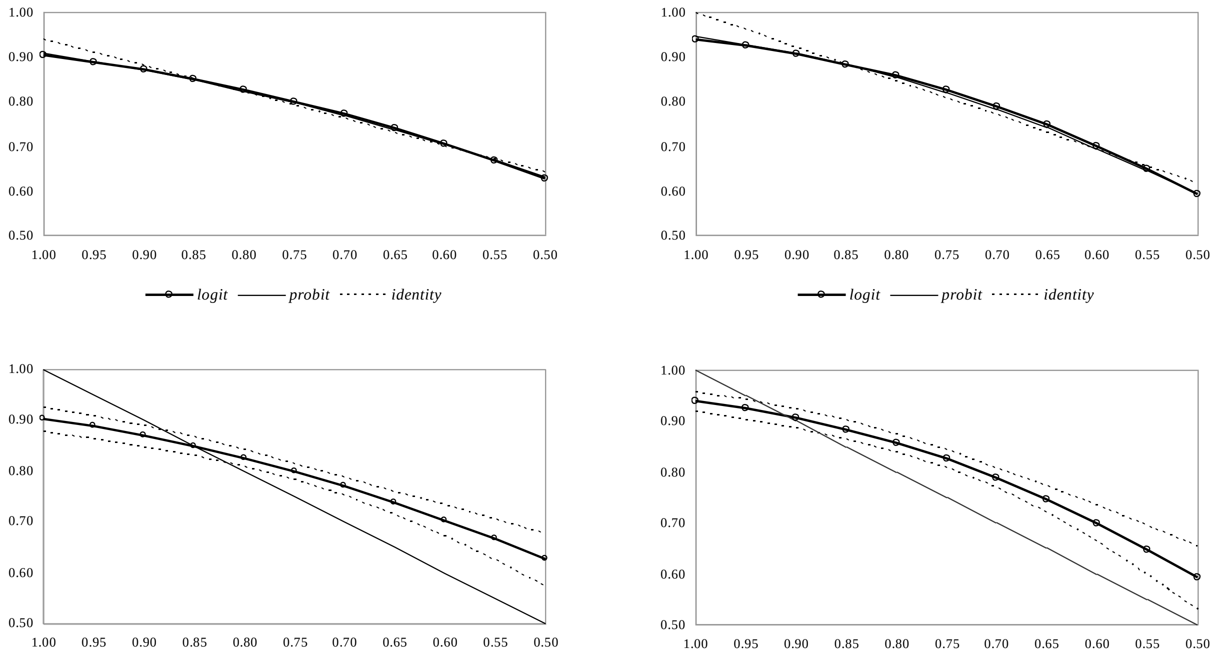


Note. LS (abs), LS (sq) are obtained from conditions (14) and (16) of the main text, with a truncation lag m^* set equal to 100 and the loss function $\ell(.) = |.|$ and $\ell(.) = (.)^2$, respectively. In each panel, the upper graph shows the partial effects of changes in the trade share, whilst the lower graph is based on the logit function, where the dotted bold line represents the partial effects, the dashed lines the 95 percent confidence intervals and the thin solid line the main diagonal.

Figure 2 – Regression functions: traditional price discovery measures

A. IS

B. CS



Note. IS and CS are computed according to conditions (5) and (6) of the main text, respectively. Average bounds for IS are used. In each panel, the upper graph shows the partial effects of changes in the trade share, whilst the lower graph is based on the logit function, where the dotted bold line represents the partial effects, the dashed lines the 95 percent confidence intervals and the thin solid line the main diagonal.