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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.

JEL-Code: G100, C210, C320.

Keywords: price discovery, liquidity, MTS system.

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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 negotiated in different trading venues trades are fragmented and price discovery is split among markets. Despite the occurrence of 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 similar 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 (thus wiping out possible discrepancies even in quoting obligations). 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., 2010).

Our paper is also related to other empirical studies (Yan and Zivot, 2007; Bui and Sercu, 2009; Kim, 2010, 2011) 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) suggested 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 metrics, the Loss Shares, LS, falls into the category of dynamic price discovery measures and represents a modification of the metrics 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 (Brandt and Kavajecz, 2004; 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 threshold 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 never 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 peripherical 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 indeed 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:

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

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, the Granger Representation Theorem (Engle and Granger, 1987) states that 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.[1]

2.1. Reduced-form price discovery measures

Reduced-form price discovery measures can be obtained using the VEC model (3) expressed in its RMA formulation. The starting point of the two approaches focuses 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 of 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):

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

[1] This is standard practice in the analysis of stock market prices (see, among others, Eun and Sabherwal, 2003, and Chakravarty et al., 2004). As pointed out by Albanesi and Rindi (2000), in the case of bond prices, such a representation is correct as long as the series used do not include the whole life of the asset.

where F is a lower triangular matrix such that $FF' = \Sigma$. As shown in Ballie et al. (2002) and Lehman (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 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.[2] In terms of $\alpha_{\perp}$ the CS can be written as:

$$CS_i = \alpha_{\perp i} / \iota'\alpha_{\perp}\ ,\ i = 1,2 \qquad (6)$$

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

[2] 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. Notice that the latter is not necessarily a random walk, unless $k = 1$ in (3) or in general when $\alpha_{\perp}\Gamma_i = 0$, $i = 1,...,k-1$. Based 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 in the Gonzalo- Granger decomposition can be forecastable and the $\alpha_{\perp}$'s can be interpreted as portfolio weights.

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:

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

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

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

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 Levtchenkova et al. (1999) and 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 identifying 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:

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

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

In order to obtain a bounded metrics 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:

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

The LS is bounded between 0 and 1. Note, however, that the interpretation of the price discovery measure is the opposite with respect to reduced-form price discovery measures: in the LS case, higher values indicate a greater efficiency loss in market i and thus a lower contribution to the price discovery process, and viceversa.

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. According to Dunne et al. (2008), with an outstanding aggregate value of around 4,396 billion Euros in 2006, the European sovereign bond market is the world's largest market for debt securities and it exceeds the size of the US one by roughly 3 billion euros. Galati and Tsatsaronis (2003) estimate that the MTS system accounts for 40 percent of government bond transactions in Europe 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 in 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.[3] Market participants can be classified as either market makers (primary dealers) or market takers (dealers). Primary dealers possess 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.

One of the most striking features of the MTS platform concerns the parallel listing of benchmark government securities (i.e. on-the-run bonds with an outstanding value of at least 5 billion euro that satisfy listing requirements such as number of dealers acting as market makers) on a domestic and on a European (EuroMTS) marketplace. 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. All government marketable securities issued by euro area Member States are listed on their respective domestic MTS platforms. Only benchmark securities are admitted, instead, to trading on EuroMTS. Thus, for benchmark securities dealers are allowed to post their quotes on both market simultaneously (parallel quoting).

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3 This is to avoid the free-riding generated by the existence of less sophisticated traders and allowing for liquidity providers to reduce their exposure when trading (Albanesi and Rindi, 2000). 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. For a detailed discussion of the MTS system, see Scalia and Vacca (1999).

Bond price transaction data are extracted from the MTS (Mercato Telematico dei Titoli di Stato) time series database. 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 in several financial segments.[4] 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).[5] 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.[6] 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 ISIN code for the 107 selected bonds.

[Table 2]

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[4] 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.

[5] 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).

[6] 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.

4. Empirical results

4.1. Unit root, stationarity and cointegration tests

As a preliminary step, we check for the presence of a unit root in each of the 214 individual transaction price series expressed in logarithms. ADF tests (Dickey and Fuller, 1979) are performed on the series, both in levels and first differences.[7] In each case, we are unable to reject the null hypothesis of a unit root at conventional significance levels. On the other hand, differencing the series appears to induce stationarity. The KPSS stationarity tests (Kwiatkowski et al., 1992) corroborate these results.[8]

Given the evidence of $I(1)$-ness for all individual series, testing for cointegration between each of the 107 pairs ($p_{1,t}$, $p_{2,t}$) is the next logical step. The order of autoregression k of the bivariate models (4), formulated in their isomorphic Vector AutoRegression (VAR) representation, is selected on the basis of the Schwarz Information Criterion. The cointegration test developed by Horvath and Watson (1995), which tests the null of no cointegration against the known alternative of rank one with $\beta = (1\ -1)'$, strongly supports the existence of a $(1\quad -1)'$ cointegration vector in all cases, as Table 3 shows.[9]

[Table 3]

4.2. Measuring price discovery in the MTS system

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

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[7] 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 ("fill-in" method).

[8] Complete results are not reported for sake of brevity, but are available on request.

[9] The testing procedure by Horvath and Watson applies to the case of a known cointegration vector. Its computation is straightforward, being based on a Wald test of the error correction term in a VEC model. It produces substantial gains in power compared to standard procedures that do not impose a cointegration vector such as Johansen's maximum eigenvalue and trace tests (Johansen, 1991, 1995).

are reported in Tables 4 and 5, respectively. 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 larger 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.[10] Second, the bootstrap confidence intervals show that the shares are statistically significant less than 0.5 in 83 cases (reported in bold), confirming that the domestic MTS markets are relatively more efficients trading environments. Third, the two LS measures are closely related to each other, with an estimated correlation coefficient equal to 0.90.

[Table 4]

[Table 5]

The contribution of each market to price discovery computed according to the IS and CS methods are reported in Tables 6 to 9. 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 6 and Table 7 report upper and lower bounds for each bond included in the analysis along with 95 percent bootstrapped confidence intervals.

[Table 6]

[Table 7]

As can be seen, while there are 102 statistically significant cases of upper bounds larger than 0.5 (Table 6), there are only 42 of them when lower bounds are taken into account (Table 7). The gap between lower and upper bounds is therefore too wide to draw strong conclusions: one can safely conclude that the domestic MTS market dominates in term of price leadership for only 42 out

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

of 107 bonds in the sample.[11] Non-uniqueness represents a problem, since understanding the cross-sectional determinants of price discovery (discussed later on in the paper) 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 8 give an overall picture quite similar to the one in Table 4 and Table 5: 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 8]

Concerning the results from the CS method, the estimated $\alpha_{\perp}$ in 8 cases contain negative elements which lead to difficulties in the interpretation of the CS (Hasbrouck, (2002; Korenok et al., 2008, among others). 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 9]

Finally, Table 10 and Table 11 present the results for the absolute and square YZ measure respectively. The results are fully consistent with their LS counterparts: in both cases, a greater contribution for the EuroMTS market emerges (as suggested by the positive estimated statistics) and 83 statistically significant negative values of the price discovery measures are estimated. As previously noted, however, the YZ metrics are not bounded, so that a comparison across bonds is not straightforward.

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[11] These very wide bounds are due to non-zero correlations in Σ_e. Shortening the interval of observation could help to reduce these correlations and obtain tighter bounds (Hasbrouck, 1995). However, a number of studies (Booth 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.

[Table 10]

[Table 11]

4.3. Dynamic vs traditional price discovery maesures: a comparison

Further evidence on price discovery in the MTS system is provided in Table 12 where summary statistics (upper panel) and correlation coefficients (lower panel) for LS and the other metrics (namely, IS, CS and YZ) are reported.[12] 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 efficiency loss recorded in the domestic MTS markets ranges between 7 (for the square LS) and 16 percent (for the absolute 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.[13] 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 contribution of the leading market to price discovery. Note also that a direct comparison between a LS and the YZ cannot be performed: as the YZ metrics have a negative value, we can only conclude that they corroborate the previous findings, with a lower degree of adjustment to the news (permanent) shock about the fundamental value taking place on the EuroMTS (especially in the case of the square YZ).

The pair-wise correlations within (between) structural and reduced-form classes of price discovery measures turn out to be positive (negative), as expected. Although all co-movements are strongly statistically significant, we find that correlations are higher (in absolute terms) when

[12] 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.

[13] 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.

comparing pairs of structural price discovery with respect to the comovements between structual and reduced form metrics. Finally, we observe a relatively lower degree of correlation for the square version of LS with respect to the its absoltute counterpart, owing to its higher degree of non-linearity.

[Table 12]

5. Trading segmentation and markets' contribution to price discovery

It is widely recognised that the speed at which information arrivals are processed by market participants in a certain trading venue may be influenced by market-specific characteristics, such as trading activity, prevailing bid/ask spreads and market volatility (Eun and Sabherwal, 2003; Chakravarty et al., 2004, among others). In this Section we seek to assess to what extent market activity influences the process of price formation in the MTS system.

For this purpose, we perform a cross-sectional regression of LS as a function of the share of trading volumes (x_1) recorded in the domestic MTS markets.[14] As Table 3 and 4 show, the 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, $E(LS \mid x) = \gamma_0 + \gamma_1 x_1 = x\gamma$, since the predicted values from the OLS regression cannot be guaranteed to lie in the unit interval.[15] An alternative to the standard OLS specification is $E(LS \mid x) = G(x\gamma)$ where $G(.)$ satisfies $0 < G(z) < 1$, for all $z \in \mathbb{R}$, ensuring that the predicted LS lie in [0,1] interval. The most common functional forms for $G(.)$ are the standard cumulative normal distribution (i.e.

[14] Similar results are obtained by regressing both LS metrics on the share of contracts. The inclusion of additional regressors (namely, quoted spreads and market volatility - measured as the absolute value of price changes) does not alter the main findings of the cross-sectional analysis. Complete results are available on request.

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

the probit model case) and the logistic function (i.e. the logit model case).[16] Given the non-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 13 presents the estimated coefficients for our two structural price discovery measures. In all regressions, the role of trade shares is strongly significant. The negative signs of the estimated coefficients for trade shares indicate that relatively higher trading volumes lead to a decrease in the relative information inefficiency. Moreover, the square LS specification explains a higher percentage of the deviance than the absolute LS. Finally, the logit and probit functional forms outperform their OLS countepart, especially in the case of the square LS measure.

[Table 13]

Because the regressions in Table 13 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 the predicted LS are expected to vary when the regressor 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).[17] The results from this exercise are reported in Figure 1.

[Figure 1]

The graphs on the left-hand side of Panel A and Panel B show the partial effects of changes in the regressor on the absolute and square LS, respectively. As expected, while the partial effects in

[16] 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).

[17] In the regressions where relative spreads and market volatility appear as additional regressors (not reported for the sake of brevity), their values have been kept fixed at the sample averages when computing partial effects of trade (and contract) shares on LS.

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 graphs on the right-hand side in both panels are based on our preferred specification (the logit function), where the bold line with circles represents the partial effects, the dashed lines the 95 percent confidence intervals and the thin solid line the (inverted) main diagonal.

A type of optimal treshold emerges at the point where the diagonal crosses the partial effects line: when the partial effects are below the diagonal, there exists a less than one-to-one relationship between the degree of information inefficiency and degree of trade concentration in the dominant market; by constrast, when the partial effects lie above the diagonal, further concentration of trades in the dominant market translates into negligible gains in terms of efficiency for the dominant market. According to the evidence from the absolute LS, such a threshold corresponds to around 92 percent (with an estimated confidence interval of 87-95 percent) of trades occurring in the domestic MTS markets. This may explain why trades occurring in the EuroMTS have a non-negligible informational content, even though this resembles a prototype of a "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).

Since we are using the domestic MTS market's contribution to price discovery, the interpretation of the regression functions is straightforward. To assess the impact of the main variables of interest (the trade share) 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, the predicted value for the dependent variable is 0.16. By increasing trade shares to 0.80, the inefficiency loss in the domestic MTS market decreases to roughly 0.13, with a reduction 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 relative information inefficiency (which falls from 0.07 to 0.06).

Being affected neither by non-uniqueness nor 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 results based on traditional price discovery measures. When considering them the following should be taken into account: for IS, we use the average between upper and lower bounds; for CS we replace wrongly signed α_2's with zero in order to make that price discovery measure bounded in the [0,1] interval.

The interpretation of the graphs is similar: on the left-hand side the partial effects of changes in the regressor on the IS and CS price discovery measures are reported, whereas on the right-hand side those in the case of the logit function are shown. In these graphs, when the partial effects lie above the diagonal line, the increase in the degree of price discovery in the dominant market is more than proportional to the increaase in the degree of trade concentration; by constrast, when the partial effects are above the diagonal, greater trade shares in the domestic MTS markets lead to relatively small increases in terms of price discovery.

[Figure 2]

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 the costs of trade segmentation might outweigh its benefits if measured by traditional price discovery measures.

6. Conclusions

Over the past few years, the growing availability of high-quality transaction data has led to a number of empirical studies on the European government bond markets. The present paper contributes to this area of the literature by investigating 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 a market's contribution to price discovery is crucially affected by the level of trading activity.

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 relation 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. Government debt managing and the sale of government securities in primary markets are influenced considerably by the features of the secondary market. A pre-requisite for an 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. This means that establishing mandatory trading platforms is not a useful option for debt managers to enhance price discovery. The empirical evidence from the duplicated market setting characterising the MTS system suggests that even in the case of an extremely polarised environment there is a role in price formation for the satellite market. Our findings 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] $^{\Diamond}$	*A*,*B* $^{\Diamond}$
YZ	*S*	$(-\infty,+\infty)$	*B*

<u>*Legenda*</u>

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

Table 2 – Bond 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. 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 – Horvath and Watson test

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	70.83	71.34	71.53	75.13	41.26	108.73	96.82	34.03	129.55	83.99	108.25
2	22.14	54.87	66.23	110.80	44.45	46.91	91.06	56.73	129.04	19.16	109.80
3	66.88	85.41	52.62	79.28	61.00	41.66	120.39	69.80	120.52	69.05	65.88
4	37.34	47.12	29.03	137.60	44.28	25.75	147.80	45.55	171.07	51.65	68.77
5	56.09	70.52	45.90	45.82	55.66	98.40	121.22	.	159.30	69.81	52.92
6	86.28	136.97	110.10	86.40	52.64	48.97	138.49	.	141.64	89.18	98.42
7	53.82	106.31	110.76	.	146.74	71.45	67.03	.	70.05	.	.
8	44.14	93.57	91.41	.	86.32	59.26	157.26	.	119.00	.	.
9	61.65	104.94	54.31	.	97.32	99.09	154.51	.	176.05	.	.
10	55.38	.	103.65	.	77.11	65.69	166.11	.	70.10	.	.
11	.	.	.	.	65.85	42.60	123.54	.	51.92	.	.
12	.	.	.	.	88.98	110.33	55.30	.	171.11	.	.
13	.	.	.	.	72.77	89.41	.	.	65.27	.	.
14	.	.	.	.	73.43	.	.	.	178.11	.	.
15	.	.	.	.	.	.	.	.	190.34	.	.
16	.	.	.	.	.	.	.	.	100.88	.	.
17	.	.	.	.	.	.	.	.	182.88	.	.

Note. Entries in the Table refer to the corresponding bond code reported in Table 1. Wald test statistics for the null of no cointegration against the alternative of a $(1-1)'$ cointegration vector. The 1%, 5% and 10% significance levels are 13.73, 10.18, and 8.30, respectively (see Table 1 of Horvath and Watson, 1995, pp. 996–998).

Table 4 – Absolute LS: *LS* (abs)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.0197** [0.0149 , 0.2509]	**0.0857** [0.0169 , 0.3302]	**0.0310** [0.0151 , 0.2753]	**0.0973** [0.0271 , 0.3920]	**0.1209** [0.0147 , 0.3752]	0.3727 [0.0934 , 0.7485]	**0.1199** [0.0385 , 0.4601]	0.5933 [0.2023 , 0.8664]	**0.2015** [0.0310 , 0.4146]	**0.0902** [0.0211 , 0.3607]	**0.2235** [0.0545 , 0.4065]
2	**0.0824** [0.0097 , 0.4194]	0.3393 [0.1388 , 0.6607]	0.3527 [0.1610 , 0.6845]	**0.1241** [0.0242 , 0.4082]	**0.1115** [0.0287 , 0.3698]	**0.1767** [0.0156 , 0.4610]	0.3570 [0.1023 , 0.7359]	0.3787 [0.1542 , 0.6232]	**0.0914** [0.0160 , 0.2790]	0.2139 [0.0228 , 0.5151]	**0.1552** [0.0179 , 0.3605]
3	**0.0500** [0.0089 , 0.2872]	**0.1626** [0.0292 , 0.3617]	0.2590 [0.0361 , 0.6790]	**0.1513** [0.0650 , 0.4839]	**0.1476** [0.0181 , 0.3460]	**0.1847** [0.0146 , 0.4564]	**0.0410** [0.0240 , 0.2864]	0.6986 [0.3132 , 0.8491]	**0.1246** [0.0408 , 0.3438]	**0.1759** [0.0270 , 0.3832]	**0.0333** [0.0124 , 0.2857]
4	**0.0898** [0.0102 , 0.3930]	**0.1792** [0.0245 , 0.4004]	0.1134 [0.0430 , 0.5802]	**0.1797** [0.0359 , 0.3830]	**0.0432** [0.0096 , 0.3194]	**0.1270** [0.0107 , 0.2940]	**0.0293** [0.0204 , 0.2400]	0.3733 [0.1424 , 0.7610]	**0.1178** [0.0276 , 0.3528]	**0.1728** [0.0202 , 0.3827]	**0.0252** [0.0088 , 0.2522]
5	**0.1157** [0.0104 , 0.3259]	**0.2400** [0.0505 , 0.4591]	**0.0871** [0.0142 , 0.3659]	**0.1672** [0.0663 , 0.4863]	**0.0687** [0.0136 , 0.3022]	**0.0942** [0.0407 , 0.3184]	0.2722 [0.0531 , 0.5273]	.	**0.0361** [0.0190 , 0.2421]	**0.1779** [0.0234 , 0.4159]	**0.0200** [0.0100 , 0.2573]
6	**0.0226** [0.0163 , 0.2273]	**0.0858** [0.0140 , 0.2899]	**0.0355** [0.0151 , 0.2444]	0.4003 [0.1667 , 0.6058]	**0.1779** [0.0177 , 0.4030]	0.3976 [0.1966 , 0.6622]	**0.0497** [0.0190 , 0.2413]	.	**0.0750** [0.0283 , 0.2242]	0.2468 [0.0752 , 0.7007]	**0.0463** [0.0270 , 0.2450]
7	**0.1169** [0.0152 , 0.3566]	**0.2384** [0.0481 , 0.4352]	**0.1147** [0.0304 , 0.3184]	.	**0.1318** [0.0420 , 0.4115]	**0.0426** [0.0130 , 0.2525]	**0.0712** [0.0229 , 0.4109]	.	**0.1829** [0.0515 , 0.3656]	.	.
8	**0.0621** [0.0102 , 0.3275]	**0.1374** [0.0234 , 0.4375]	0.3213 [0.0901 , 0.7955]	.	**0.1853** [0.0382 , 0.4125]	0.2849 [0.0864 , 0.5772]	**0.1387** [0.0341 , 0.3880]	.	**0.0269** [0.0203 , 0.3039]	.	.
9	**0.2002** [0.0530 , 0.4945]	**0.0364** [0.0116 , 0.2371]	**0.0799** [0.0132 , 0.3672]	.	**0.0380** [0.0212 , 0.3013]	**0.0494** [0.0166 , 0.3312]	**0.0180** [0.0118 , 0.2982]	.	**0.2181** [0.0594 , 0.4129]	.	.
10	**0.0735** [0.0096 , 0.3165]	.	**0.1484** [0.0319 , 0.3784]	.	**0.0905** [0.0370 , 0.2343]	0.2083 [0.0468 , 0.5042]	**0.1837** [0.0450 , 0.4199]	.	**0.0902** [0.0320 , 0.3192]	.	.
11	.	.	.	.	**0.0356** [0.0105 , 0.2705]	0.4735 [0.2440 , 0.7225]	**0.0433** [0.0219 , 0.2558]	.	**0.2396** [0.0813 , 0.4552]	.	.
12	.	.	.	.	0.3960 [0.1006 , 0.7389]	0.3479 [0.1462 , 0.6874]	0.5424 [0.2805 , 0.5782]	.	**0.0689** [0.0233 , 0.2293]	.	.
13	.	.	.	.	0.2650 [0.0575 , 0.5373]	0.2468 [0.0794 , 0.6731]	.	.	**0.2176** [0.1094 , 0.3990]	.	.
14	.	.	.	.	**0.0786** [0.0222 , 0.3594]	.	.	.	**0.0896** [0.0311 , 0.2729]	.	.
15	.	.	.	.	.	.	.	.	**0.1058** [0.0398 , 0.2586]	.	.
16	.	.	.	.	.	.	.	.	**0.0854** [0.0377 , 0.2491]	.	.
17	.	.	.	.	.	.	.	.	**0.1837** [0.0450 , 0.4376]	.	.

Note. See Table 2. Price discovery estimates for the domestic MTS markets with a truncation lag m^* set equal to 100. 95% confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares less than 0.5 are reported in bold.

Table 5 – Square LS: *LS* (sq)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**0.0005** [0.0004 , 0.1022]	**0.0072** [0.0004 , 0.1514]	**0.0008** [0.0004 , 0.1164]	**0.0102** [0.0013 , 0.3034]	**0.0174** [0.0004 , 0.2481]	0.2609 [0.0075 , 0.8694]	**0.0099** [0.0015 , 0.4436]	0.6956 [0.0326 , 0.9788]	**0.0499** [0.0012 , 0.2743]	**0.0097** [0.0008 , 0.2501]	**0.0699** [0.0044 , 0.2918]
2	**0.0078** [0.0002 , 0.3611]	0.1432 [0.0141 , 0.8077]	0.2224 [0.0354 , 0.8587]	**0.0273** [0.0013 , 0.3793]	**0.0143** [0.0031 , 0.2180]	**0.0396** [0.0006 , 0.4254]	0.1776 [0.0179 , 0.8890]	0.2335 [0.0290 , 0.7381]	**0.0078** [0.0004 , 0.1055]	0.0635 [0.0007 , 0.5569]	**0.0276** [0.0004 , 0.2015]
3	**0.0028** [0.0002 , 0.1405]	**0.0273** [0.0011 , 0.1807]	0.1037 [0.0031 , 0.9038]	**0.0371** [0.0050 , 0.4597]	**0.0317** [0.0007 , 0.2343]	**0.0444** [0.0004 , 0.3783]	**0.0011** [0.0006 , 0.1374]	0.8216 [0.1141 , 0.9797]	**0.0160** [0.0022 , 0.1402]	**0.0499** [0.0018 , 0.3111]	**0.0010** [0.0003 , 0.1206]
4	**0.0088** [0.0003 , 0.2788]	**0.0384** [0.0009 , 0.2378]	0.0398 [0.0044 , 0.7594]	**0.0356** [0.0018 , 0.2199]	**0.0019** [0.0003 , 0.1689]	**0.0203** [0.0003 , 0.1476]	**0.0010** [0.0005 , 0.1081]	0.1735 [0.0221 , 0.9462]	**0.0120** [0.0009 , 0.1518]	**0.0378** [0.0009 , 0.2518]	**0.0007** [0.0002 , 0.0999]
5	**0.0178** [0.0003 , 0.1954]	**0.0801** [0.0036 , 0.3766]	**0.0080** [0.0005 , 0.2201]	**0.0340** [0.0027 , 0.3755]	**0.0043** [0.0005 , 0.1227]	**0.0142** [0.0020 , 0.2082]	0.1233 [0.0028 , 0.5861]	.	**0.0032** [0.0004 , 0.0675]	**0.0417** [0.0009 , 0.3333]	**0.0004** [0.0002 , 0.0868]
6	**0.0002** [0.0001 , 0.0912]	**0.0086** [0.0003 , 0.1463]	**0.0012** [0.0004 , 0.1150]	0.2176 [0.0266 , 0.6190]	**0.0419** [0.0007 , 0.3178]	0.2590 [0.0348 , 0.8239]	**0.0025** [0.0005 , 0.1155]	.	**0.0134** [0.0011 , 0.0804]	0.0648 [0.0078 , 0.8972]	**0.0024** [0.0008 , 0.0715]
7	**0.0151** [0.0004 , 0.2182]	**0.0662** [0.0025 , 0.3192]	**0.0118** [0.0013 , 0.1710]	.	**0.0151** [0.0016 , 0.2759]	**0.0018** [0.0003 , 0.1005]	**0.0069** [0.0010 , 0.3745]	.	**0.0321** [0.0029 , 0.1684]	.	.
8	**0.0042** [0.0002 , 0.1823]	**0.0211** [0.0010 , 0.3851]	0.2083 [0.0140 , 0.9705]	.	**0.0412** [0.0021 , 0.2908]	0.0961 [0.0072 , 0.6506]	**0.0176** [0.0010 , 0.2455]	.	**0.0006** [0.0004 , 0.1348]	.	.
9	0.0446 [0.0043 , 0.6168]	**0.0014** [0.0002 , 0.0782]	**0.0077** [0.0004 , 0.2334]	.	**0.0013** [0.0005 , 0.1404]	**0.0027** [0.0005 , 0.2015]	**0.0008** [0.0005 , 0.1422]	.	**0.0550** [0.0037 , 0.2819]	.	.
10	**0.0059** [0.0002 , 0.1690]	.	**0.0184** [0.0007 , 0.2198]	.	**0.0104** [0.0020 , 0.0856]	**0.0466** [0.0029 , 0.4306]	**0.0298** [0.0021 , 0.2776]	.	**0.0066** [0.0012 , 0.1247]	.	.
11	.	.	.	.	**0.0013** [0.0002 , 0.1319]	0.4131 [0.0791 , 0.8912]	**0.0029** [0.0005 , 0.1069]	.	**0.0473** [0.0068 , 0.2716]	.	.
12	.	.	.	.	0.4060 [0.0110 , 0.9558]	0.1601 [0.0168 , 0.8609]	0.6223 [0.1567 , 0.6763]	.	**0.0060** [0.0005 , 0.0737]	.	.
13	.	.	.	.	0.0922 [0.0042 , 0.5629]	0.0664 [0.0066 , 0.8701]	.	.	**0.0484** [0.0118 , 0.1978]	.	.
14	.	.	.	.	**0.0056** [0.0007 , 0.2557]	.	.	.	**0.0063** [0.0010 , 0.0712]	.	.
15	.	.	.	.	.	.	.	.	**0.0132** [0.0014 , 0.0931]	.	.
16	.	.	.	.	.	.	.	.	**0.0090** [0.0014 , 0.0713]	.	.
17	.	.	.	.	.	.	.	.	**0.0276** [0.0018 , 0.2501]	.	.

Note. See Table 2 and Table 4.

Table 6 – 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. Price discovery estimates for the domestic MTS markets. 95% confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant shares larger than 0.5 are reported in bold.

Table 7 – 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 and Table 6.

Table 8 – 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 and Table 6.

Table 9 – 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 and Table 6.

Table 10 – Absolute YZ: *YZ* (abs)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**-4.6287** [-4.7883 , -1.0939]	**-2.3678** [-4.0606 , -0.7072]	**-3.4418** [-4.1786 , -0.9678]	**-2.2281** [-3.5802 , -0.4389]	**-1.9839** [-4.2018 , -0.5101]	-0.5206 [-2.2722 , 1.0904]	**-1.9934** [-3.218 , -0.1599]	0.3778 [-1.3717 , 1.8695]	**-1.3768** [-3.4415 , -0.3449]	**-2.3111** [-3.8366 , -0.5722]	**-1.2452** [-2.8537 , -0.3784]
2	**-2.4107** [-4.6232 , -0.3254]	-0.6662 [-1.8251 , 0.6664]	-0.6073 [-1.6507 , 0.7746]	**-1.9542** [-3.6978 , -0.3712]	**-2.0752** [-3.5224 , -0.5332]	**-1.5389** [-4.1417 , -0.1563]	-0.5886 [-2.1722 , 1.025]	-0.4950 [-1.702 , 0.5033]	**-2.2965** [-4.1187 , -0.9493]	-1.3018 [-3.7591 , 0.0603]	**-1.6946** [-4.0046 , -0.5732]
3	**-2.9438** [-4.7124 , -0.9092]	**-1.6387** [-3.5035 , -0.5679]	-1.0512 [-3.2834 , 0.7494]	**-1.7241** [-2.6665 , -0.0645]	**-1.7539** [-3.9932 , -0.6366]	**-1.4847** [-4.2116 , -0.1749]	**-3.1526** [-3.7073 , -0.9130]	0.8407 [-0.785 , 1.7278]	**-1.9500** [-3.1562 , -0.6464]	**-1.5446** [-3.5849 , -0.4759]	**-3.3671** [-4.3802 , -0.9164]
4	**-2.3160** [-4.5757 , -0.4348]	**-1.5218** [-3.6837 , -0.4039]	-2.0566 [-3.1028 , 0.3236]	**-1.5181** [-3.2909 , -0.4770]	**-3.0982** [-4.6347 , -0.7564]	**-1.9276** [-4.5224 , -0.8762]	**-3.5019** [-3.8717 , -1.1529]	-0.5181 [-1.7956 , 1.1581]	**-2.0133** [-3.5622 , -0.6069]	**-1.5660** [-3.8802 , -0.4781]	**-3.6570** [-4.7203 , -1.0869]
5	**-2.0340** [-4.5595 , -0.727]	**-1.1527** [-2.9331 , -0.1642]	**-2.3497** [-4.2385 , -0.5500]	**-1.6056** [-2.6456 , -0.0548]	**-2.6076** [-4.2862 , -0.8367]	**-2.2631** [-3.1588 , -0.7612]	-0.9833 [-2.8818 , 0.1093]	.	**-3.2849** [-3.9463 , -1.1411]	**-1.5307** [-3.7294 , -0.3397]	**-3.8925** [-3.9901 , -1.0598]
6	**-4.3621** [-4.4019 , -1.2236]	**-2.3662** [-4.2522 , -0.8959]	**-3.3026** [-4.178 , -1.1286]	-0.4044 [-1.6095 , 0.4296]	**-1.5307** [-4.0137 , -0.3930]	-0.4153 [-1.4079 , 0.6731]	**-2.9498** [-3.945 , -1.1454]	.	**-2.5117** [-3.5366 , -1.2414]	-1.1157 [-2.5089 , 0.8508]	**-3.0260** [-3.5839 , -1.1255]
7	**-2.0216** [-4.1707 , -0.5902]	**-1.1614** [-2.9843 , -0.2607]	**-2.0432** [-3.4628 , -0.7613]	.	**-1.8855** [-3.1276 , -0.3576]	**-3.1122** [-4.3304 , -1.0855]	**-2.5677** [-3.752 , -0.3601]	.	**-1.4968** [-2.9141 , -0.5511]	.	.
8	**-2.7156** [-4.5778 , -0.7197]	**-1.8368** [-3.7314 , -0.2513]	-0.7479 [-2.313 , 1.3581]	.	**-1.4810** [-3.2272 , -0.3536]	-0.9202 [-2.3584 , 0.3114]	**-1.8260** [-3.3432 , -0.4557]	.	**-3.5885** [-3.8765 , -0.8289]	.	.
9	**-1.3853** [-2.8836 , -0.0221]	**-3.2764** [-4.4472 , -1.1688]	**-2.4434** [-4.3144 , -0.5443]	.	**-3.2324** [-3.8325 , -0.8413]	**-2.9576** [-4.0804 , -0.7029]	**-4.8146** [-5.8043 , -0.8559]	.	**-1.2768** [-2.7628 , -0.3522]	.	.
10	**-2.5348** [-4.6313 , -0.7699]	.	**-1.7475** [-3.414 , -0.4964]	.	**-2.3077** [-3.259 , -1.184]	-1.3354 [-3.0138 , 0.0168]	**-1.4915** [-3.0554 , -0.3232]	.	**-2.3107** [-3.4107 , -0.7572]	.	.
11	.	.	.	.	**-3.3001** [-4.5475 , -0.9920]	-0.1060 [-1.1306 , 0.9569]	**-3.0960** [-3.7989 , -1.0680]	.	**-1.1548** [-2.4247 , -0.1796]	.	.
12	.	.	.	.	-0.4220 [-2.1903 , 1.0402]	-0.6284 [-1.7651 , 0.788]	0.1699 [-0.942 , 0.3152]	.	**-2.6031** [-3.7355 , -1.212]	.	.
13	.	.	.	.	-1.0201 [-2.7976 , 0.1494]	-1.1158 [-2.451 , 0.7223]	.	.	**-1.2798** [-2.0966 , -0.4098]	.	.
14	.	.	.	.	**-2.4611** [-3.7856 , -0.5778]	.	.	.	**-2.3191** [-3.4389 , -0.9798]	.	.
15	.	.	.	.	.	.	.	.	**-2.1344** [-3.1823 , -1.0534]	.	.
16	.	.	.	.	.	.	.	.	**-2.3716** [-3.239 , -1.1032]	.	.
17	.	.	.	.	.	.	.	.	**-1.4912** [-3.0555 , -0.2511]	.	.

Note. See Table 2. Price discovery estimates for the domestic MTS markets with a truncation lag m^* set equal to 100. 95% confidence bounds obtained from 1000 bootstrap replications are in square brackets. Statistically significant negative values are reported in bold.

Table 11 – Square YZ: *YZ* (sq)

	ATS	BEL	ESP	FIN	FRF	GEM	GGB	IRL	MTS	NLD	PTM
1	**-7.6477** [-7.8925 , -2.1729]	**-4.9287** [-7.7506 , -1.7236]	**-7.1243** [-7.7068 , -2.0274]	**-4.5745** [-6.6582 , -0.8312]	**-4.0353** [-7.7999 , -1.109]	-1.0414 [-4.8822 , 1.8953]	**-4.6064** [-6.4839 , -0.2267]	0.8263 [-3.3894 , 3.8327]	**-2.9459** [-6.6858 , -0.9727]	**-4.6281** [-7.0737 , -1.0981]	**-2.5880** [-5.4129 , -0.8869]
2	**-4.8462** [-8.6025 , -0.5705]	-1.7888 [-4.2443 , 1.435]	-1.2515 [-3.3046 , 1.805]	**-3.5734** [-6.6571 , -0.4927]	**-4.2351** [-5.7661 , -1.2776]	**-3.1894** [-7.4461 , -0.3008]	-1.5327 [-4.0071 , 2.0804]	-1.1886 [-3.5105 , 1.036]	**-4.8455** [-7.8542 , -2.1373]	-2.6919 [-7.3073 , 0.2286]	**-3.5616** [-7.7135 , -1.3768]
3	**-5.8673** [-8.7861 , -1.8113]	**-3.5740** [-6.7922 , -1.5118]	-2.1564 [-5.7575 , 2.2402]	**-3.2569** [-5.2984 , -0.1615]	**-3.4205** [-7.318 , -1.1843]	**-3.0697** [-7.7187 , -0.4966]	**-6.8535** [-7.3492 , -1.8373]	1.5273 [-2.0496 , 3.8769]	**-4.1219** [-6.0996 , -1.814]	**-2.9458** [-6.3224 , -0.795]	**-6.9353** [-8.2867 , -1.9864]
4	**-4.7187** [-8.1205 , -0.9504]	**-3.2212** [-7.0001 , -1.1649]	-3.1845 [-5.4199 , 1.1492]	**-3.2981** [-6.2964 , -1.2665]	**-6.2647** [-8.1331 , -1.5935]	**-3.8756** [-8.2315 , -1.7534]	**-6.9346** [-7.6436 , -2.1098]	-1.5608 [-3.7916 , 2.8679]	**-4.4067** [-6.982 , -1.7204]	**-3.2369** [-7.049 , -1.0891]	**-7.2719** [-8.6879 , -2.1989]
5	**-4.0123** [-8.125 , -1.4154]	**-2.4415** [-5.6175 , -0.5039]	**-4.8144** [-7.5784 , -1.2653]	**-3.3456** [-5.9059 , -0.5088]	**-5.4370** [-7.6522 , -1.9672]	**-4.2415** [-6.2208 , -1.3357]	-1.9614 [-5.8669 , 0.3481]	.	**-5.7537** [-7.7789 , -2.6259]	**-3.1357** [-7.023 , -0.6935]	**-7.9132** [-7.9996 , -2.3531]
6	**-8.7735** [-8.8784 , -2.2992]	**-4.7455** [-8.2139 , -1.7642]	**-6.7270** [-7.7682 , -2.0406]	-1.2798 [-3.599 , 0.4851]	**-3.1300** [-7.3324 , -0.7641]	-1.0512 [-3.3233 , 1.5432]	**-5.9760** [-7.6348 , -2.0354]	.	**-4.2976** [-6.8521 , -2.4365]	-2.6696 [-4.8404 , 2.1662]	**-6.0114** [-7.1853 , -2.5646]
7	**-4.1784** [-7.8422 , -1.2759]	**-2.6468** [-6.0073 , -0.7575]	**-4.4313** [-6.6708 , -1.5785]	.	**-4.1810** [-6.4201 , -0.9651]	**-6.3253** [-8.0957 , -2.1912]	**-4.9752** [-6.8601 , -0.5128]	.	**-3.4050** [-5.8444 , -1.5969]	.	.
8	**-5.4692** [-8.3371 , -1.5012]	**-3.8387** [-6.9067 , -0.4678]	-1.3353 [-4.2556 , 3.4943]	.	**-3.1469** [-6.1858 , -0.8916]	-2.2416 [-4.9301 , 0.6216]	**-4.0248** [-6.8775 , -1.123]	.	**-7.4412** [-7.4654 , -1.8591]	.	.
9	**-3.0640** [-5.4397 , 0.4759]	**-6.5981** [-8.348 , -2.4667]	**-4.8528** [-7.8117 , -1.189]	.	**-6.6154** [-7.5822 , -1.8122]	**-5.8973** [-7.5533 , -1.3767]	**-9.9478** [-9.972 , -1.7974]	.	**-2.8431** [-5.5881 , -0.9353]	.	.
10	**-5.1344** [-8.697 , -1.5925]	.	**-3.9746** [-7.2827 , -1.2671]	.	**-4.5591** [-6.2213 , -2.3688]	-3.0192 [-5.8412 , 0.2794]	**-3.4837** [-6.1535 , -0.9566]	.	**-5.0080** [-6.7558 , -1.9487]	.	.
11	.	.	.	.	**-6.6386** [-8.3212 , -1.8847]	-0.3511 [-2.4542 , 2.1028]	**-5.8379** [-7.6383 , -2.1229]	.	**-3.0028** [-4.9877 , -0.9864]	.	.
12	.	.	.	.	-0.3807 [-4.4978 , 3.0743]	-1.6573 [-4.067 , 1.8227]	0.4992 [-1.6832 , 0.7370]	.	**-5.1170** [-7.5094 , -2.5313]	.	.
13	.	.	.	.	-2.2877 [-5.4756 , 0.2528]	-2.6432 [-5.0098 , 1.9017]	.	.	**-2.9779** [-4.4258 , -1.4003]	.	.
14	.	.	.	.	**-5.1733** [-7.2236 , -1.0684]	.	.	.	**-5.0530** [-6.9072 , -2.5677]	.	.
15	.	.	.	.	.	.	.	.	**-4.3162** [-6.5898 , -2.2768]	.	.
16	.	.	.	.	.	.	.	.	**-4.6977** [-6.5653 , -2.5675]	.	.
17	.	.	.	.	.	.	.	.	**-3.5637** [-6.3285 , -1.0982]	.	.

Note. See Table 2 and Table 10.

Table 12 – Comparison across price discovery measures

	Summary statistics					
	LS (abs)	*LS* (sq)	*IS*	*CS*	*YZ* (abs)	*YZ* (sq)
median	0.1246	0.0178	0.8294	0.8294	-1.9500	-4.0123
mean	0.1640	0.0676	0.8075	0.8006	-1.9472	-4.0019
s.e. mean	0.0126	0.0131	0.0147	0.0134	0.1011	0.1958
	Correlations					
LS (abs)	1	0.9	-0.74	-0.73	0.92	0.92
LS (sq)	.	1	-0.67	-0.59	0.70	0.73
IS	.	.	1	0.81	-0.63	-0.62
CS	.	.	.	1	-0.68	-0.68
YZ (abs)	.	.	.	.	1	0.99
YZ (sq)	.	.	.	.	.	1

Note. Average bounds for IS are used. Values for CS larger than 1 are replaced with unity.

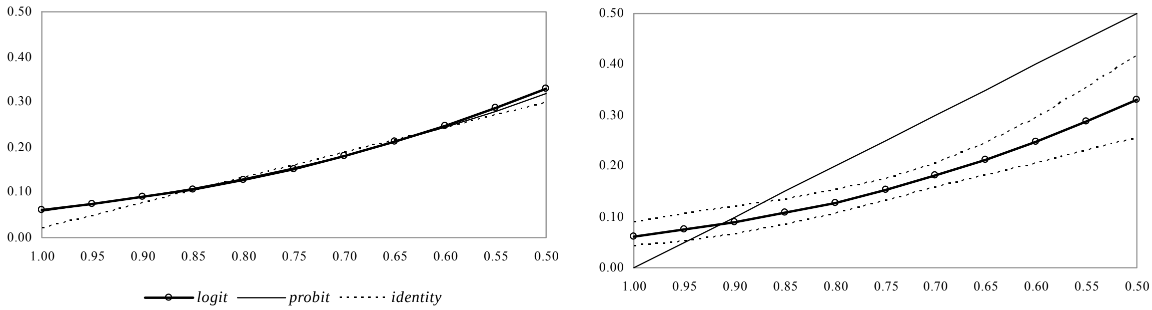
Table 13 – Fraction regression results

	LS (abs)			*LS* (sq)		
logit	-4.0361 (0.9046)	.	.	-10.597 (1.8837)	.	.
probit	.	-2.1735 (0.4967)	.	.	-4.9301 (0.9522)	.
identity	.	.	-0.5551 (0.1424)	.	.	-0.6359 (0.1841)
Deviance explained	0.20	0.20	0.19	0.37	0.39	0.23

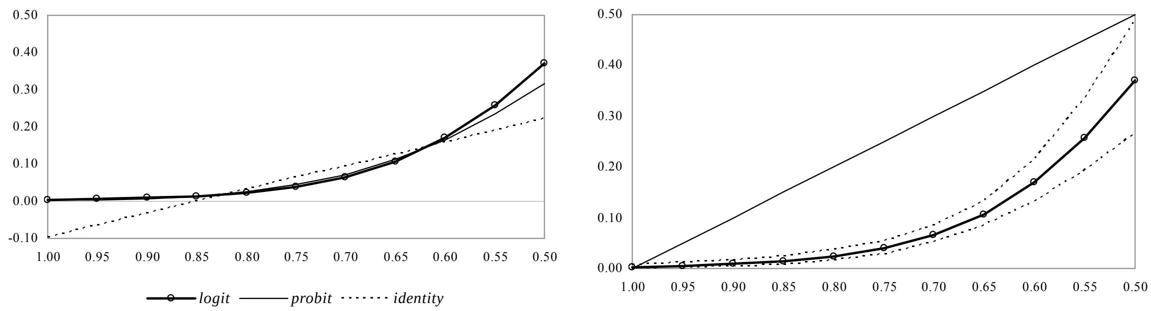
Note. See Table 12. Robust standard errors in parentheses.

Figure 1– Regression functions: dynamic price discovery measures

A. Absolute LS



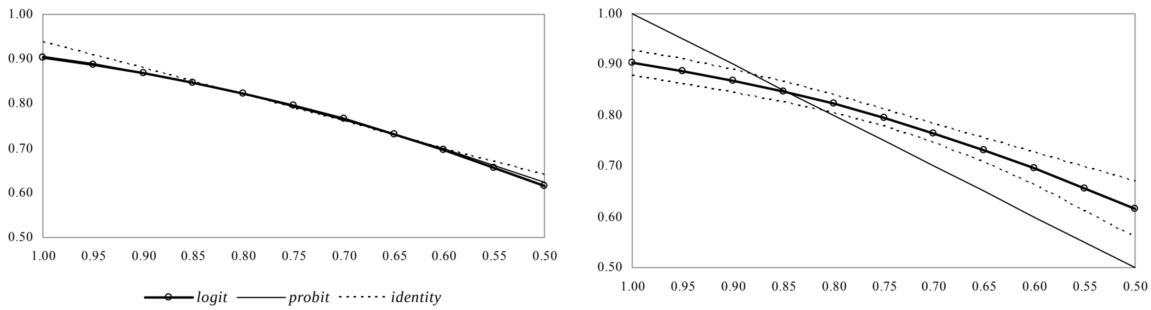
B. Square LS



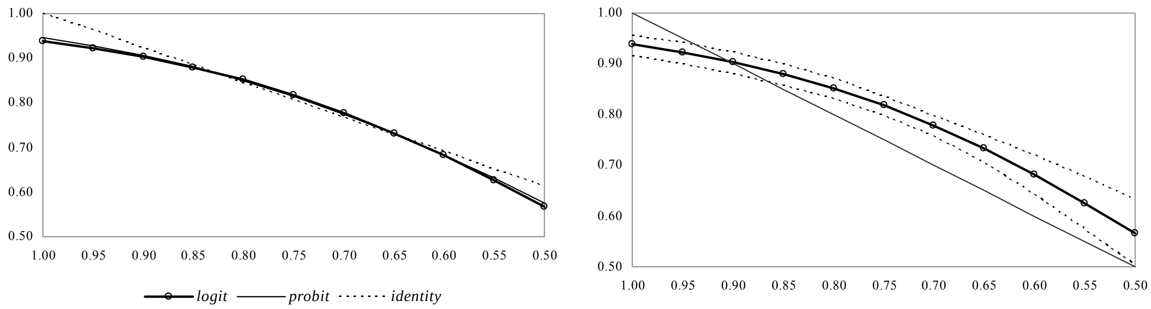
Note. The graphs on the left-hand side show the partial effects of changes in the regressor. The graphs on the right-hand side are based on the logit function, where the bold line with circles represents the partial effects, the dashed lines the 95 percent confidence intervals and the thin solid line the (inverted) main diagonal.

Figure 2 – Regression functions: traditional price discovery measures

A. IS



B. CS



Note. See Table 1 and Figure 1.