

Cross-listing, price discovery and the informativeness of the trading process[☆]

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Abstract

This paper analyzes the price discovery process of securities that trade on multiple markets with trading sessions that totally or partially overlap. Building on Hasbrouck's (1995) information share approach, we introduce a methodology that distinguishes two sources of information asymmetries between markets: trade-related and trade-unrelated informative shocks. This approach determines how much of each market's relative contribution to the price discovery process (during the overlapping period) is attributable to its own trading activity. We provide empirical evidence on the contribution of the NYSE to the price discovery process of Spanish cross-listed stocks during the daily (two-hour) overlapping interval.

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I. Introduction

When an asset is traded on multiple markets a crucial question naturally arises: which market contributes most to the discovery of the efficient price? In the last few years, alternative methodological approaches have been proposed to measure relative contributions when the trading sessions of the different markets overlap. Harris et al. (1995) infer each market's weight in price discovery from the error correction terms of a vector error correction (VEC) model. Hasbrouck (1995) proposes a common trend representation to model all the markets' quotes. The fraction of the variance of the common stochastic trend that is explained by each market's innovations defines its information share. Finally, Harris et al. (2002) use the common factor estimation method proposed by Gonzalo and Granger (1995). In this last methodology, the long memory component of stock prices is characterized as a weighted average of the contemporaneous trade prices. The weights signify the incidence of trades that permanently move prices on each market. A special issue of the *Journal of Financial Markets* (2002, vol. 5, (3)) provides some discussion on these econometric methodologies.

Tse (2000) argues that different data sets (quotes versus trades), rather than models or periods, matter when measuring relative contributions to price discovery. Thus, market "A" trades may provide information to market "B" traders even if the economic meaning of market "A" quotes is negligible. Therefore, a methodology intended to study the price discovery process of a dually listed stock should take into account at least both quotes and trades. Current methodologies do not openly model the trading process and so cannot differentiate between trade-related and trade-unrelated sources of information. As a result, they provide an incomplete characterization of the dominant-satellite relationships (Garbade and Silber, 1979).

In this paper, we propose a theoretical framework in which two markets simultaneously trade the same stock. Each market forms its sequence of conditional expectations about the security's ultimate value drawing on the revisions of its available information set. There are two possible sources of information asymmetries between markets: agents endowed with superior information, and public announcements characterized as noisy signals (e.g., Harris and Raviv, 1993). First, we assume that informed traders reveal their privileged information through trading. Because these agents must decide where to exploit their information advantage (Chowdhry and Nanda, 1991), trade-related information may cause transitory differences in the markets' expectations. Second, trade-unrelated information is simultaneously exposed to all markets, but markets differ in their ability to process it (e.g., Kim and Verrecchia, 1994). A noisy public signal provides the market that has superior processing capacity with a temporary advantage over the other markets. In this context, a pure satellite market has an uninformative trading process that cannot shed light on the interpretation of public information.

We show that the natural empirical counterpart of our theoretical framework is a VEC model that explicitly identifies the informative (unexpected) component of trading. Following Hasbrouck (1995), we use the common trend representation of this VEC model to measure each market's trading activity contribution to the long-term volatility of the stock. As an application, we study the case of the Spanish ADRs listed in the NYSE during the year 2000. We focus on the daily, two-hour, overlapping interval between the NYSE and the Spanish Stock Exchange (SSE). We strongly accept the null hypothesis that the NYSE trading activity does not contribute to the price discovery of the Spanish ADRs.

Indeed, for almost all stocks, we can assert that the global contribution of the NYSE is negligible; that is, the NYSE is close to being a pure satellite market of the SSE.

The paper is organized as follows. In Section 2, we present the theoretical framework. In Section 3, we introduce and discuss the empirical model. In Section 4, we define the information share measures. In Section 5, we describe the data set. In Section 6, we summarize the results for the NYSE and the SSE. Finally, we conclude in Section 7.

2. Motivation

Consider a stock that trades on two different markets, a home or domestic market (D) and a secondary or foreign market (F), whose trading sessions overlap during a given time interval. The following structural model describes the price discovery process of the cross-listed stock during that overlapping interval,

$$m_t = m_{t-1} + z_t = m_{t-1} + \lambda_D w_t^D + \lambda_F w_t^F + w_t, \quad (1)$$

$$m_t^i = m_{t-1} + \lambda_i w_t^i + (\tilde{w}_t - J_t^i), \quad (2)$$

$$x_t^i = \gamma_1^i \tilde{m}_t^i + w_t^i, \quad (3)$$

$$q_t^i = m_t^i + S_t^i, \quad (4)$$

with $i = \{D, F\}$.

The efficient price m_t in (1) is the expected “true” value of the stock at some terminal time given all the information available in period t , say ϕ_t . Innovation z_t represents all the valuable information revealed in t . Each market expectation in (2), m_t^D and m_t^F , may differ from m_t and from each other in the short run because of information asymmetries. Next, we describe the components of z_t and the two sources of information asymmetries considered.

First, public disclosures are characterized as noisy signals, that is, valuable information is communicated with some distortion. Hence, public disclosures constitute imperfect information. In this context, markets may differ in the quality of their judgments when they are not equally competent in isolating the useful information. In [Kim and Verrecchia's \(1994\)](#) model, profits announcements are noisy signals that may lead to different interpretations. We adapt their framework here. For simplicity, we characterize the stochastic processes w_t , δ_t , ζ_t^D , and ζ_t^F as zero-mean, homoskedastic, uncorrelated at all leads and lags, and mutually uncorrelated innovations, with $E[\delta_t^2] = \sigma_\delta^2$, and $E[(\zeta_t^i)^2] = \sigma_{\zeta,i}^2 \forall i$. The public signal is $\tilde{w}_t = w_t + \delta_t$, where w_t represents the informative component and δ_t is the distorting component. Simultaneously to the dissemination of $\tilde{w}_t$ each market observes $J_t^i = \delta_t + \zeta_t^i$, with ζ_t^i being the information a market gleans about the random error.

In Eq. (2), each market reviews its expectation by $(\tilde{w}_t - J_t^i)$ right after the announcement. The quality of each market judgment depends on the precision of J_t^i . The higher (lower) the ratio $\sigma_{\zeta,D}^2/\sigma_{\zeta,F}^2$, the worse (better) the processing ability of market D relative to market F. Let ρ be the correlation coefficient between $(\tilde{w}_t - J_t^D)$ and $(\tilde{w}_t - J_t^F)$, such that $1 \geq \rho \geq 0$. When $\rho = 1$, both markets observe the same information and have the same posterior beliefs about the announcement; $\rho = 0$, on the contrary, means fully heterogeneous posterior beliefs. Since w_t in [1,2] becomes public knowledge in the period

after the announcement, the market with superior processing capacity has only a temporary advantage over the other market.

Second, informed traders cause short-term divergences in expectations between markets when they exploit their information advantage through selectively trading either on D or on F . The zero-mean and uncorrelated stochastic process w_t^i in [2], with $E[(w_t^i)^2] = \sigma_i^2$, represents a trade-related innovation updating the market i 's information set. The parameter λ_i measures how much of w_t^i is brand new information, in a similar fashion to the λ parameter in Kyle (1985). Eq. (2) implies that each market knows about the contemporaneous trade-related information of the other market with one lag.¹ This asymmetry disappears quickly since any specific information given away in t becomes common information in the next period. This imposes short-term convergence in expectations between markets. We allow $E[w_t^D w_t^F] \neq 0$; this is the case in which the same informed investor or different traders endowed with the same privileged information simultaneously trade on D and F .

In Eq. (3), the trading process x_t^i is a linear function of both public and private information. Specifically, x_t^i is a measure of the accumulated signed traded volume up to t , with $x_0^i = 0$. A $\Delta x_t^i = x_t^i - x_{t-1}^i > 0$ implies more buyer-initiated trading than seller-initiated trading in t . It is easy to check that x_t^i is a non-stationary $I(1)$ process since Δx_t^i is covariance-stationary. The first term on the RHS of (3) shapes the predictable component of x_t^i given ϕ_{t-1} and $(\tilde{w}_t - J_t^i)$. The parameter γ_1^i determines the impact of all the common information revealed up to time $t-1$ (ϕ_{t-1}) and the contemporaneous shock $(\tilde{w}_t - J_t^i)$; that is, $\tilde{m}_t^i = m_{t-1} + (\tilde{w}_t - J_t^i)$. The trade-related innovations, w_t^D and w_t^F , are unpredictable given the available information set of each particular market.

Eq. (3) supposes that $E[w_t^i w_{t-j}^j] = 0 \forall j$ since our model presumes a predetermined sequence of events in t : public signals are revealed before the contemporaneous trade-related shocks, and quote updates follow contemporaneous trade-related and public disclosures. Therefore, public disclosures are characterized as trade-unrelated shocks.

We average quotes in (4) using the quote midpoint (q_t^i). The quote q_t^i incorporates all the information revealed up to t on market i (m_t^i), but also a zero-mean covariance-stationary transitory component (S_t^i) that impounds microstructure effects. The size of $|S_t^F - S_t^D|$ depends on disparities in market-making costs (like inventory control), market frictions (like the tick size), and other microstructure issues.

In this framework, market D contributes at least as much as market F to price discovery whenever $\lambda_D \geq \lambda_F$ and $\sigma_{\xi,D}^2 \leq \sigma_{\xi,F}^2$, with $\sigma_\delta^2 \neq 0$. To understand the dynamics of the model, let us discuss a few particular cases. To start with, consider that public disclosures are not noisy signals ($\sigma_\delta^2 = 0$ or $\sigma_\delta^2 \neq 0$ and $\sigma_{\xi,i}^2 = 0 \forall i$). In this case, w_t is communicated simultaneously to both markets without distortion. The unique source of information asymmetry is the trade-related information. The revisions in the expectations about the true value of the stock have a common component (w_t) and a market-specific component ($\lambda_i w_t^i$). In this scenario, F is a pure satellite market when all the trade-related information is revealed at market D ($\lambda_F = 0$). Namely, if $\lambda_F = 0$ then $q_t^F = m_{t-1} + w_t + S_t^F$ and $q_t^D = m_t + S_t^D$; that is, D has a more precise expectation in t than F . Similarly, consider

¹This assumption may be interpreted in different ways. Market D (F) may have access to the trade-related information of market F (D) with some lag. Alternatively, a given market may have access to the contemporaneous trade-related information of the other market in real-time, but may be unable to evaluate it immediately or as fast as the market in which the shock takes place.

the case where $\sigma_\delta^2 \neq 0$, $\sigma_{\delta,D}^2 \cong 0$, and $\sigma_{\delta,F}^2$ is very large. The judgments of the F agents are so imprecise that the updating of their expectations due to any public announcement is unreliable, and hence transitory. Specifically, when $\lambda_F = 0$, then $q_t^F \cong m_{t-1} + S_t^F$ and $q_t^D = m_t + S_t^D$; that is, $q_t^F \cong q_{t-1}^D$ when $S_t^F - S_{t-1}^F$ is close to zero.

The characterization of a satellite-dominant relationship in the two previous cases is not the same. Assume that $\lambda_D = \lambda_F = 0$. In the second example, F is still a satellite market because of its limited capacity to interpret public signals. In the first example, however, F would be as contributive as market D . Similarly, if $\rho = 1$ both markets would have the same posterior beliefs about the announcement, and so would be equally informative.

Finally, q_t^i in [4] is a non-stationary process. The non-stationary component m_{t-1} is common to all quotes. Therefore, quotes are co-integrated with a theoretical co-integration vector $(1, -1)$; that is $q_t^D - q_t^F$ defines a stationary process. In addition, x_t^D and x_t^F depend on $\tilde{m}_t^D$ and $\tilde{m}_t^F$, respectively, having a non-stationary component m_{t-1} in common. Consequently, the linear combination $(\gamma_1^{D-1}, -\gamma_1^{F-1})$ defines a theoretical co-integration vector between the trading processes. Indeed, the quote and trade processes are also co-integrated since the vector $(1, 1, -\gamma_1^{D-1}, -\gamma_1^{F-1})$ defines another co-integration relationship. Consequently, the appropriate empirical counterpart to our framework is an error-correction model with four equations. The next section develops this empirical specification.

3. The empirical model

The most common efficient parameterization of a vector of co-integrated variables is, from Granger's Representation Theorem in Engle and Granger (1987), a VEC model. The standard error correction representation of the market quotes for a cross-listed stock is

$$\begin{aligned}\Delta q_t^D &= \tilde{\alpha}^D(q_{t-1}^D - \beta q_{t-1}^F) + \tilde{\Phi}_D^D(L)\Delta q_{t-1}^D + \tilde{\Phi}_F^D(L)\Delta q_{t-1}^F + u_t^D, \\ \Delta q_t^F &= \tilde{\alpha}^F(q_{t-1}^D - \beta q_{t-1}^F) + \tilde{\Phi}_D^F(L)\Delta q_{t-1}^D + \tilde{\Phi}_F^F(L)\Delta q_{t-1}^F + u_t^F,\end{aligned}\quad (5)$$

with $\Delta q_t^i = (q_t^i - q_{t-1}^i)$. The terms $\tilde{\Phi}_k^i(L)$, for k and $i = \{D, F\}$, are stationary autoregressive polynomials in the lag operator L ($L^z y_t = y_{t-z}$). The component $(q_{t-1}^D - \beta q_{t-1}^F)$ is the normalized error correction term. Presumably, β is equal to 1. The α^i term is the response of the market i to a divergence from the other market's quotes. If both α^D and α^F were statistically significant, we would be facing a two-way price discovery process (see Harris et al., 1995).

From the discussion in the previous section, the innovations $u' = (u_t^D, u_t^F)$ in (5) include both trade-related and trade-unrelated shocks. Explicitly, let u_t^D be

$$u_t^D = \tilde{\theta}_D^D(L)w_t^D + \tilde{\theta}_F^D(L)w_t^F + \varepsilon_t^D, \quad (6)$$

where $\tilde{\theta}_k^i(L)$ are stationary lag polynomials. Eq. (6) captures usual features of intra-daily data due to market frictions and specific trading rules. Because of market frictions, q_t^i may not instantaneously reproduce all the information trades released in t .² Thus, the

²NYSE rules state that the specialist should maintain a fair and orderly market. This includes the responsibility for stabilizing prices in their assigned stocks. The specialist ensures that trading in the stocks moves smoothly throughout the day. In the SSE there is no specialist or similar figure. However, the existence of hidden orders and stopped orders may also delay the full revelation of the information behind trades. Alternatively, traders with

unexpected component of trades may have lagged effects on the quote midpoint (e.g., Hasbrouck, 1991a). The vector of trade-unrelated shocks $\varepsilon' = (\varepsilon_t^D, \varepsilon_t^F)$ incorporates the information inferred from noisy public signals, $(\tilde{w}_t - J_t^D)$ and $(\tilde{w}_t - J_t^F)$ in our structural model, but also idiosyncratic features of each market that we do not model explicitly. We expect $E(\varepsilon_t^D \varepsilon_t^F) \neq 0$ due to a common factor. When market participants in D and F have similar posterior beliefs about public signals, ε_t^D and ε_t^F may be correlated.

So as to identify the components in [6], let us modify [5] by allowing the quote process to be

$$\begin{aligned}\Delta q_t^D &= \alpha^D(q_{t-1}^D - \beta q_{t-1}^F) + \Phi_D^D(L)\Delta q_{t-1}^D + \Phi_F^D(L)\Delta q_{t-1}^F + \theta_D^D(L)\Delta x_t^D + \theta_F^D(L)\Delta x_t^F + \varepsilon_t^D, \\ \Delta q_t^F &= \alpha^F(q_{t-1}^D - \beta q_{t-1}^F) + \Phi_D^F(L)\Delta q_{t-1}^D + \Phi_F^F(L)\Delta q_{t-1}^F + \theta_D^F(L)\Delta x_t^D + \theta_F^F(L)\Delta x_t^F + \varepsilon_t^F,\end{aligned}\quad (7)$$

where Δx_t^i is market i 's net trading activity in t . The generating process of Δx_t^D (Δx_t^F would be alike) is given by

$$\Delta x_t^D = \Pi_{x,D}^D(L)\Delta x_{t-1}^D + \Pi_{x,F}^D(L)\Delta x_{t-1}^F + \Pi_{q,D}^D(L)\Delta q_{t-1}^D + \Pi_{q,F}^D(L)\Delta q_{t-1}^F + w_t^D, \quad (8)$$

with $\Pi_{h,k}^i(L)$, for $h = \{x, q\}$ and $k = \{D, F\}$. All lag polynomials are stationary. By substituting recursively (8) into (7), it is straightforward to see that (7,8) is equivalent to (5,6). In Eq. (8), the trading process does not depend on the contemporaneous change in market quotes. This is because quotes and trades are not determined simultaneously: the quote revisions follow the net trading activity. The model allows causality running from lagged quote revisions to trades but not contemporaneously. This causality structure is very common among theoretical adverse selection cost models (e.g., Huang and Stoll, 1997).

At this point, the model (7,8) is incomplete. The theoretical framework in the previous section allowed for multiple co-integration relationships. Indeed, in our four variable VEC model, we could find up to three linearly independent combinations of $y_t' = (q_t^D, q_t^F, x_t^D, x_t^F)$ which ensure that these variables converge to their long-run steady-state. Some of these linear combinations were discussed in Section 2. Therefore, we end up with an empirical model with 4 equations, and with $r \leq 3$ co-integrating vectors,

$$A\Delta y_t = \alpha\beta'y_{t-1} + B(L)\Delta y_{t-1} + \xi_t, \quad (9)$$

where $\xi_t' = (\varepsilon_t^D, \varepsilon_t^F, w_t^D, w_t^F)$, α is a $4 \times r$ matrix representing the speed of adjustment to disequilibrium, β is the $4 \times r$ matrix of long-run coefficients,

$$A = \begin{bmatrix} 1 & 0 & -\theta_{D,0}^D & -\theta_{F,0}^D \\ 0 & 1 & -\theta_{D,0}^F & -\theta_{F,0}^F \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B(L) = \begin{bmatrix} \Phi_D^D(L) & \Phi_F^D(L) & \theta_D^{*D}(L) & \theta_F^{*D}(L) \\ \Phi_D^F(L) & \Phi_F^F(L) & \theta_D^{*F}(L) & \theta_F^{*F}(L) \\ \Pi_{q,D}^D(L) & \Pi_{q,F}^D(L) & \Pi_{x,D}^D(L) & \Pi_{x,F}^D(L) \\ \Pi_{q,D}^F(L) & \Pi_{q,F}^F(L) & \Pi_{x,D}^F(L) & \Pi_{x,F}^F(L) \end{bmatrix},$$

with $\theta_k^{*i}(L) = (\theta_k^i(L) - \theta_{k,0}^i)L^{-1}$, k and $i = \{D, F\}$.

(footnote continued)

heterogeneous priors and private information may take some intervals of trading to have their expectational differences resolved (e.g., Kyle, 1985).

Notice that the empirical model (9) shares the main features of the structural model in Section 2, including the contemporaneous causality running from trades to quotes; lagged causality from quotes to trades; uncorrelated (by definition) trade-related and trade-unrelated shocks; multiple co-integration relationships involving trades and quotes, and all the relevant information being inferred from the history of trades and quotes.³

In Section 2, trade-unrelated shocks were made equal to public disclosures and trade-related shocks were made equal to private information. In model (9), we identify the trade-related innovations under the assumption that the expected component of the trading process only (linearly) depends on the past quote and trade history – as in the theoretical framework. The trade-unrelated shocks are then characterized as the trade-unrelated part of the quote revision innovation, as in Hasbrouck (1991a, 2002). These shocks are trade-unrelated because of the causality assumption. As in the theoretical framework, we might be tempted to equate all private information with (w_t^D, w_t^F) and all public information with $(\varepsilon_t^D, \varepsilon_t^F)$. In practice, however, this dichotomy is not so clear.

On the one hand, in order driven markets quote revision innovations may reflect private information if informed traders submit limit orders instead of market orders. The usual claim is that informed traders prefer to submit market orders since their information is short lived (e.g., Angel, 1992; Glosten, 1994). Nonetheless, Kaniel and Liu (2001) show that a patient informed trader may be reluctant to submit large market orders since by doing so s/he signals that the stock is mispriced. Moreover, if s/he intends to submit a large market order when his/her valuation is close to the current quotes, s/he would bear price risk. In a hybrid market, the quote revision innovations may reflect private information if either the market makers or the limit order traders possess superior information. Thus, Harris and Panchapagesan (2003) show that the main information advantage of the NYSE specialist is his/her privileged knowledge of the limit order book.

On the other hand, the assumption that trade innovations do not contain public information may be formalized as the requirement that public information is not useful in predicting the trade innovation. Under the conjecture that the relevant public information set is the history of quotes and trades, (w_t^D, w_t^F) in (9) should be unpredictable given ϕ_{t-1} . In practice, however, there are several reasons why this assumption may be violated. First, the relevant public information set might include other decision variables not explicitly modeled in (9). Indeed, $(\varepsilon_t^D, \varepsilon_t^F)$ and (w_t^D, w_t^F) may proxy for decision variables in the price discovery process or deterministic components that we have omitted. Second, Hasbrouck (1991a) claims that public information may affect posterior trading decisions when market imperfections or constraints, like price smoothing rules, verbal quotes in the crowd, stale limit orders, etc., impede quote revisions from fully reflecting the public information. Indeed, limit orders in the crowd that are never disseminated off the floor could be considered as private rather than public information.

These remarks indicate that the line that separates public and private information is thinner in empirical treatments than in theoretical ones. Therefore, some information effects could be erroneously attributed to public or private sources. Additionally, since D and F may have different microstructures, relative transparency also plays a role. For the

³A similar VECM was originally proposed in an unpublished paper by Escribano and Pascual (2000) to study possible asymmetries in the responses of ask and bid quotes to trade related shocks.

less transparent market, the thin line between public and private information will be even more imprecise. As a result, model (9) should be more precise in separating trade-inferred information and information gathered from other sources than in separating public and private information. Since our main concern is to determine how much any change in the efficient price is related to the trading activity of each market, model (9) is a correct tool. Nonetheless, we must keep in mind that the estimated innovations will always be contingent on the linear autoregressive structure imposed in model (9).⁴

4. The information content of trades

Hasbrouck (2002) confronts the information share approach in Hasbrouck (1995) with the permanent-transitory approach in Harris et al. (2002). He shows that in the case of a two-market model with private and public information, similar to the one presented in this paper, the information share approach is more reliable. The bound generated by the information share approach contains (up to the estimation error) the true value. This cannot be said for the permanent-transitory approach. In this paper, we slightly modify the information share approach.

Hasbrouck (1991b) defines the information content of the trading process as the variance of the expected impact of a trade innovation on the efficient price. In our case,

$$Var(E[\Delta m_t | \Delta x_t^i - E(\Delta x_t^i | \phi_{t-1}^i)]). \quad (10)$$

From (8), Eq. (10) is equivalent to

$$I^i = Var(E[\Delta m_t | w_t^i]). \quad (11)$$

Under the assumption that w_t , w_t^F and w_t^D are mutually uncorrelated, Eq. (11) is a proper absolute measure of the portion of the price discovery attributable to the trading activity of market i . The relative information content of market i 's trading process is

$$SIS^i = \frac{Var(E[\Delta m_t | w_t^i])}{Var(\Delta m_t)}. \quad (12)$$

Similar measures can be defined for the trade-unrelated shocks.

Every VEC model has an associated common trend model representation implied by the co-integration relationships. The vector moving average (VMA) representation of (9) is

$$\Delta y_t = \Psi(L)\xi_t, \quad (13)$$

where $\Psi(L)$ is a lag polynomial. Consider the first two equations in [13], $\Delta q_t = \psi(L)\xi_t$, where $\Delta q_t' = (\Delta q_t^D \Delta q_t^F)$ and $\psi(L)$ represents the first two rows in $\Psi(L)$. By recursive

⁴There are other issues to mention. First, Section 2 predicts $E(e_t^D e_t^F) \neq 0$ due to noisy public disclosures. Thus, the empirical model is a system of seemingly unrelated equations that could be efficiently estimated by SURE (Zellner, 1962). In empirical applications, the correlation between the e_t^i terms is expected to increase with the length of the time intervals used to construct the time series in model (9). Consequently, short time intervals mitigate the benefits of using SURE. We are indebted to Bruce N. Lehmann for this observation. Second, Chiang and Lin (1999) show that the existence of a minimum price variation and the bid-ask bounce may induce a bias in the estimation of a VEC model using high-frequency transaction price data. However, the authors also show that by using quote midpoints this bias is considerably reduced.

substitution and using $\psi(L) = \psi(1) + (1 - L)\psi^*(L)$, with $\psi^*(L) = (\psi(L) - \psi(1))(1 - L)^{-1}$,

$$q_t = \psi(1) \sum_{\tau=1}^t \xi_\tau + \psi^*(L) \xi_t. \quad (14)$$

The first term on the RHS of (14) is the common long-run (permanent) component. The second term is a zero-mean weakly stationary (transitory) component. Co-integration entails $\delta'\Psi(1) = 0$, where δ is any co-integration vector. Under the theoretical assumption that the difference between the market quotes is stationary, $\delta' = (1 \ -1 \ 0 \ 0)$, we have that $\psi_1(1) = \psi_2(1) = \psi_{(1 \times 4)}$, with $\psi_k(1)$ representing the k th row in $\Psi(1)$. Intuitively, the common long-run component implies that the long-run impact of a new shock on either D or F should have the same permanent impact on all quotes. It follows that $\psi \xi_t$ measures the impact of a shock on the information efficient price.

Let $Var(\xi_t) = \Omega_{(4 \times 4)}$. Then, the long-run variance would be given by $Var(\Delta m_t) = \psi \Omega \psi'$. Our aim is to identify the part of this long-run variance that is explained by each market's information. Under the assumption of no correlation between (w_t^D, w_t^F) and $(\varepsilon_t^D, \varepsilon_t^F)$, a correct measure of (12) would be

$$SIS^i = \frac{\psi_i^2 \sigma_{w^i}^2}{\psi \Omega \psi'}, \quad (15)$$

where $Var(E[\Delta m_t | w_t^i]) = \psi_i^2 \sigma_{w^i}^2$ and ψ_i is the i th component of the row vector ψ .

If the innovations in $\xi_t' = (\varepsilon_t^D \ \varepsilon_t^F \ w_t^D \ w_t^F)$ are correlated, the covariance terms in Ω could be attributed to any shock. In this paper, we follow Hasbrouck's suggestion of constructing upper and lower bounds for the information shares. We orthogonalize the residual variance-covariance matrix using the Cholesky factorization and rotate the ordering of the variables to maximize and minimize the explanatory power of each particular shock. The Hasbrouck modeling framework is problematic wherever the contemporaneous correlation of shocks across markets is substantive. In that case, [Huang \(2002\)](#) and [Booth et al. \(2002\)](#) show wide gaps between the upper and lower bounds on the information shares. In our implementation, a high frequency sampling may be required to reduce a substantive contemporaneous correlation of trade-related and/or trade-unrelated shocks across markets.

5. Data and model specification

We apply our methodology to the case of the Spanish firms listed in the NYSE as ADRs in 2000. Discarding foreign subsidiaries and participated firms, there were 5 Spanish cross-listed stocks, with ticker symbols BBV, ELE, REP, SCH and TEF. These stocks are permanently among the 35 most liquid stocks in the SSE. They embody 66% of the euro value of the 2000 SSE trading, and 5% of the dollar value of the NYSE trading of European stocks.

NYSE data is taken from the TAQ-2000 database. We drop quote and trade registers prior to the opening quote of the NYSE and all trades that are not codified as "regular". Trades performed at the same price and with the same time stamp are treated as just one trade. Quotes with bid-ask spreads lower than or equal to zero or depth equal to zero have been eliminated. Trades are classified as buyer or seller initiated using the [Lee](#)

and Ready (1991) algorithm. Price and quote files are coupled using the so-called “five second rule”.⁵

Spanish data is supplied by the SSE Interconnection System, called SIBE. The SIBE is an electronic order-driven market where the most liquid stocks trade. SIBE operates continuously between 3:00 a.m. to 11:30 a.m. (New York Time). The NYSE and the SSE sessions overlap from 9:30 a.m. to 11:30 a.m.⁶ The database consists of trade and quote files. The quote files contain all the updates of the five best ask and bid quotes on the limit order book, time stamped at the nearest hundredth of a second. The trade files provide detailed information about trades, including size and marginal (last share) price. There is no lag between the reporting time of an updated quote and the time stamp of the transaction that triggers it. Thus, it is straightforward to classify trades as buyer or seller initiated depending on the side of the book they hit. We express the SSE quotes in US\$ applying the corresponding intra-daily exchange rate, provided by Reuters. This series has a 1-minute resolution and contains the last exchange rate quoted each minute.

We construct the time series in model (9) with five different clock-time periodicities (from 1 to 5 min). First, Δq_t^i is computed as the difference between the log quote midpoint at the end and at the beginning of each interval. Second, the trading process is summarized either by the net share volume (NV_t) or by the net number of trades (NT_t). The NV_t is defined as the difference between the buyer-initiated and the seller-initiated volume in the interval t . The NT_t is defined as the difference between the number of buyer-initiated and seller-initiated trades. We assume that indicators of net (signed) trading activity are more informative about the signed changes in market quotes than indicators of total volume traded. The trade indicator Δx_t^i in (9) is computed as

$$\Delta x_t^i = \text{sign}_t \left(\ln \left| \sum_{k=1}^z v_k \right| \right), \quad (16)$$

where $\sum_{k=1}^z v_k$ is either NV_t or NT_t , and sign_t equals 1 if $\sum_{k=1}^z v_k > 0$ and -1 if $\sum_{k=1}^z v_k < 0$. Therefore, x_t^i is computed as $\sum_{j=0}^{t-1} \Delta x_{t-j}^i$, starting with $x_0^i = 0$. Trading measures are rescaled dividing x_t^i by 10,000.

Using the augmented Dickey and Fuller (1979), Phillips and Perron (1988) and the Kwiatkowski et al. (1992) tests for all stocks and for all clock-time intervals, we accept the unit root for $y_t' = (q_t^D \ q_t^F \ x_t^D \ x_t^F)$. The optimal lag-length of the VEC model is determined

⁵Ellis et al. (2000) and Odders-White (2000) have compared alternative classification rules. Both papers find that the Lee and Ready's algorithm outperforms other classification routines like the quote rule and the tick rule. However, both papers found that the algorithm misclassifies transactions executed inside the quotes. Ellis et al. propose to apply the tick-rule not only to the midpoint trades, as in Lee and Ready's algorithm, but also to all the trades inside the quotes. The authors show that, for Nasdaq-listed stocks, this procedure improves over extant classification rules. However, there is no test evidencing that this alternative method improves the classification for NYSE-listed stocks. We applied both algorithms and did not find remarkable differences. In any case, Odders-White observes that the biases introduced by the classification rules are more relevant for large and frequently traded stocks. Finally, Blume and Goldstein (1997) showed that the “five-second rule” could not be generalized to all sample periods and markets. However, Odders and White (2000) also show that the “five-second rule” does not seem to explain much of the bias induced by the Lee and Ready's algorithm.

⁶Before 1-17-2000 continuous trading in Spain was from 3:30 to 11:00 (New York Time); the overlapping trading period was just one hour and a half. Moreover, the end of daylight saving time is the first Sunday of April in the US and the last Sunday of March in Spain. Hence, during the last week of March, the stock exchanges overlap only during one hour.

using the Akaike Information Criteria (AIC) on a VAR model for y_t . We use Johansen's (1988, 1991, 1992) methodology to test how many co-integration vectors span the co-integration space. Tests for model specification are undertaken jointly with tests for co-integration rank.

Regarding the model specification tests, we follow the so-called Pantula (1989) principle (see also Harris, 1995).⁷ In all cases, the selected model has an intercept in the co-integration space that accounts for differences in the measurement units of Δx_t^i and Δq_t^i . It includes neither drifts nor linear trends in the short run part of the model. Using NV_t , the trace statistic indicates $r = 3$ co-integration vectors, for all stocks and for all time periodicities. Hence, there is only one common trend determining the long-run steady state of all the variables. Using NT_t , the co-integration rank is $r = 3$ for two stocks (TEF and BBV) and $r = 2$ for the others. Therefore, some stocks need a second common trend, apparently associated with the trading process, to guarantee convergence to the steady state.

We carry out tests on α and β in (9), using the Johansen methodology implemented in *Cats* for *Rats*. First, we check whether the last two rows of α are zeros, meaning that there is no loss of information from not modeling the determinants of Δx_t^D and Δx_t^F , and it is therefore valid to proceed with a two-equation system. We strongly reject this weak exogeneity hypothesis for all stocks except Δx_t^F for REP and STD in the NT_t model and only for some time-periodicities. Second, we test whether the $(1 - 1 \ 0 \ 0)$ vector defines one of the structural economic relationships underlying the long-run model. We accept this as a non-binding restriction for all stocks except STD, but generally with a non-zero intercept, that is $(1 - 1 \ 0 \ 0 *)$. Possible explanations for this intercept are divergences between the market quotes due to market frictions (e.g., the tick size), inventory control by the NYSE specialist, or a less than accurate exchange rate time series. We also considered other theoretical co-integration vectors but we ended with mixed findings.⁸ In the following section, we estimate model (9) with only the $(1 - 1 \ 0 \ 0 *)$ restriction in the long-run matrix (β). Results with unrestricted and fully identified betas, available upon request, are identical.⁹

6. Empirical analysis

In Table 1A, we report the trading shares of both markets during the overlapping interval. If the SSE and the NYSE trades were equally informative, we would expect the trade-related information shares to be close to these trading shares. This panel reports remarkable differences between TEF and the other Spanish stocks.

In Table 1B the overlapping period is divided into equally spaced time intervals of 1, 3 and 5 min. Panel B.1 (B.2) shows the percentage of intervals with at least one new quote

⁷The "Pantula principle" consists of choosing the models with lowest rank and then the model with less deterministic components. We consider two alternative specifications: (a) Intercept in the co-integration space and no deterministic components in the short-run part. (b) Intercept in the short-run part and intercept in the co-integration space. Other specifications are discarded by the properties of our time series.

⁸The theoretical co-integration vector $(0 \ 0 \ * \ *)$, co-integration between the trading processes, is a non-binding constraint for 4 stocks in the NV_t model and 2 stocks in the NT_t model. Moreover, $(1 \ 0 \ * \ 0 \ *)$ and $(0 \ 1 \ 0 \ * \ *)$, co-integration between trades and quotes, are accepted for 4 stocks in the NV_t model and 3 stocks in the NT_t model.

⁹The details of all the tests in this section are omitted because of space limitations, but they are available upon request. Estimation results for models with an unrestricted and a fully identified β are also available.

Table 1

Activity during the overlapping interval

Panel A reports the percentage of the trading activity of the 5 Spanish cross-listed stocks (BBV, ELE, REP, STD and TEF) during the overlapping period (15:30–17:30 Spanish Time) that corresponds to the NYSE, both in terms of the volume traded (millions of shares) and number of trades (thousands). Panel B is indicative of the trading activity of the Spanish ADRs listed on the NYSE during the overlapping trading interval between the SSE and the NYSE. The overlapping interval has been divided into equally spaced time intervals of 1, 3 and 5 minutes. Panel B.1 reports the percentage of intervals with at least one new quote register in the TAQ database. Panel B.2 reports the percentage of intervals with at least one new trade register in the TAQ database. Panel C reports the empirical size distribution of the NYSE trades during the overlapping interval with respect to the 25%, 50%, 75%, 90%, 95% and 99% percentiles of the empirical size distribution of the SSE trades during the complete Spanish trading session (3:00–11:30 a.m. NY Time). That is, under the hypothesis of equal distributions, the expected values are 25%, 25%, 25%, 15%, 5%, 4% and 1%, respectively.

<i>Panel A: NYSE Trading shares</i>					<i>Panel B: Trading activity</i>					
Stock	Volume		Trades		B.1. Quotes			B.2. Trades		
	Total	%NYSE	Total	%NYSE	1 min	3 min	5 min	1 min	3 min	5 min
BBV	519	1.35	208	2.07	18.71	40.03	54.28	11.73	27.92	39.97
ELE	283	3.08	166	4.17	29.69	60.07	77.45	18.84	45.6	63.68
REP	315	12.03	170	5.85	45.36	77.03	89	24.66	53.98	71.02
STD	710	2.8	247	3.48	31.06	61.33	78.02	21.05	47.23	64.18
TEF	1,795	23.23	651	5.93	74.19	96.28	98.52	61.82	90.23	96.3

<i>Panel C: Size distribution of the NYSE trades during the overlapping period*</i>									
	Percentile	< = 25	25–50	50–75	75–90	90–95	95–99	> 99	Obs.
BBV	Buys	18.32	32.17	29.47	12.07	2.57	3.92	1.47	1632
	Sells	17.55	27.35	36.48	12.41	2.75	2.29	1.16	2837
ELE	Buys	27.95	26.91	25.05	11.87	3.41	3.51	1.31	3817
	Sells	0.00	47.03	33.91	10.65	3.82	3.40	1.19	3117
REP	Buys	13.91	13.43	27.66	20.58	8.95	9.16	6.31	4758
	Sells	16.42	7.36	33.91	18.38	10.06	8.00	5.88	5190
STD	Buys	28.06	27.34	25.14	10.78	3.17	3.26	2.24	4415
	Sells	13.56	35.72	30.20	14.09	2.07	2.40	1.95	4202
TEF	Buys	0.00	13.57	14.79	26.28	7.79	17.86	19.70	20732
	Sells	0.00	14.87	21.55	20.84	10.90	17.51	14.32	4505

*Trade-size percentiles of reference: complete SSE trading session (9:00–17:30 ST).

(trade) register in the TAQ database. BBV is an infrequently traded stock on the NYSE; TEF can be considered as frequently traded; the remaining stocks are intermediate cases.

Table 1C reports the empirical distribution of the NYSE trade size during the overlapping interval with respect to the percentiles of the empirical distribution of the SSE trade size for the entire Spanish trading session. For TEF and REP the allocation of NYSE trades in the highest size-percentiles of the empirical distribution of the SSE trades is larger than expected under the hypothesis that both trade size distributions are equal. Therefore, NYSE trades for these stocks tend to be large in terms of the SSE standards. The SSE trading activity sharply increases as soon as the NYSE opens. During this period, SSE trades have the largest average size of all the Spanish session.

NYSE specialists of non-US stocks claim, in informal conversations, that the NYSE should be a pure satellite of the SSE. All of them agree that the contribution of the NYSE depends, to a large extent, on the degree of development of the domestic market. When the home market is an illiquid, infrequently traded, or immature market, the NYSE tends to lead or at least remarkably contribute to it. Because the trading activity in Spain concentrates on a small set of stocks, the SSE provides particularly high standards of liquidity and activity for the cross-listed stocks. Besides, the SIBE is a technologically advanced and transparent system. They also assert that, in the case of a strong domestic market, the specialist usually tends to be a passive rather than an active player in price formation. Bacidore and Sofianos (2000) evidence the critical role the specialist plays in providing liquidity for infrequently traded non-US stocks. Therefore, we should expect NYSE quotes to be hardly informative. Nonetheless, using Hasbrouck (1995) methodology, Grammig et al. (2005) and Hupperets et al. (2002) report findings on two Dutch and two German NYSE-listed ADRs that do not necessarily support this view. Grammig et al. obtain 1997–1998 NYSE information shares of 19.6% and 1% for SAP and DT. The NYSE volume shares, for these stocks were 24% and 35%, respectively. Hupperets et al. report 1999 average NYSE information shares of 6.5% and 9% for AHO and KPN, with 2.2% and 2.7% NYSE volume shares respectively. A different issue, however, is whether the SSE traders glean valuable information from the NYSE trades even when the NYSE quotes are uninformative. If this is the case, a quote-based analysis could erroneously characterize the NYSE as a satellite of the SSE.

The VEC model (9) is estimated by SURE using the FGLS algorithm (e.g., Green, 1997). No overnight returns have been considered, and no lags reach back to the previous day. The estimation results are consistent across stocks and the main findings derived are independent of the clock-time interval and the trading proxy used. As an example, Table II summarizes the estimated model for TEF with the 1-min resolution and NT_t as the proxy for trading activity. The lag-length is 3. There are 3 co-integration vectors: the first one is (1 −1 0 0*) and the other two are close to the (1 1 * ***) derived in Section 2. We also report the residual correlation matrix and the Breusch and Pagan (1980) chi-square test for independence.

The identified error correction term (ECT_1) is statistically significant for all stocks and specifications, and the sign of the coefficient is the expected one. If either the NYSE quote or the SSE quote moves away from the long-run equilibrium, a proportion of the disequilibrium is corrected in the next period. The hypothesis $|\alpha_t^{NY}| > |\alpha_t^S|$ cannot be rejected at the 1% level. As the SSE quote responds to deviations from the NYSE quote, the price discovery process may not be completely driven by the Spanish market. Consistently, when $q_{t-1}^S - q_{t-1}^{NY} > 0$, Δx_t^S decreases (pressure to sell) and Δx_t^{NY} increases (pressure to buy), which forces both quotes to move towards convergence.

Table 2 also evidences the usual negative autocorrelation in quote changes, the positive autocorrelation in signed trading, and the strong positive impact of trades on quotes (e.g., Hasbrouck (1991a)). In addition, we observe a significant positive effect of the lagged Δq_t^S values on the Δq_t^{NY} equation, reflecting co-movements of both quotes led by the SSE. That is, Δq_t^{NY} is more sensitive to changes in the lagged values of Δq_t^S than the other way around. Similarly, both quotes adjust upwards following an increase in the other market's signed trading. However, the significance of the effect of the NYSE trading activity on Δq_t^S depends on the time interval considered. Finally, we find evidence of clusters of signed trading activity between the SSE and the NYSE, generally led by the Spanish market; that

Table 2

Estimation of the VEC model

This table shows the estimated coefficients of the following VEC model for the Spanish cross-listed stock TEF,

$$A\Delta y_t = \alpha\beta'y_{t-1} + B(L)\Delta y_{t-1} + \xi_t,$$

with $y'_t = (q_t^D \ q_t^F \ x_t^D \ x_t^F)$, $\xi'_t = (\varepsilon_t^D \ \varepsilon_t^F \ w_t^D \ w_t^F)$, α is the $4 \times r$ co-integration matrix, and β is the $4 \times r$ matrix of long-run coefficients. Finally,

$$A = \begin{bmatrix} 1 & 0 & -\theta_{D,0}^D & -\theta_{F,0}^D \\ 0 & 1 & -\theta_{D,0}^F & -\theta_{F,0}^F \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

We also report the residual correlation matrix with the [Breusch and Pagan \(1980\)](#) chi-square test for independence and the normalized co-integration vectors. *ECT* means error correction term; Δq is a change in quotes; Δx_t is the net trading activity in period t ; ε is a trade-unrelated shock; w is a trade-related shock; *Int.* means intercept; the subscript *S* means Spanish Stock Exchange, and the subscript *NY* means NYSE. The overlapping trading interval between the SSE and the NYSE is divided into 1-minute intervals. The lag length has been determined using the AIC information criterion. We report the coefficients of a VEC model that uses the accumulated net number of trades as the proxy for trading activity. The net number of trades is the difference between the number of buyer-initiated trades and the number of seller-initiated trades executed during the corresponding time interval. The first co-integration vector is restricted to being (1−1 0 0*), where “*” represents an unrestricted intercept.

Obs.:26668	Δ_q^S	Δ_q^{NY}	Δ_x^S	Δ_x^{NY}
$ECT_1(t-1)$	−0.0167*	0.0968*	−0.00049*	0.00045*
$ECT_2(t-1)$	0.00019*	0.0009*	−0.00007*	−6.03E−06*
$ECT_3(t-1)$	0.00047*	−0.0001	−0.00005*	2.20E−06
$\Delta_q^S(t-1)$	−0.1477*	0.1221*	0.00451*	0.00074*
$\Delta_q^S(t-2)$	−0.0613*	0.1090*	−0.0012	0.00044*
$\Delta_q^S(t-3)$	−0.0102*	0.0718*	0.0008*	0.00024*
$\Delta_q^{NY}(t-1)$	−0.0002	−0.3146*	0.0003	−0.0019*
$\Delta_q^{NY}(t-2)$	0.0028	−0.1392*	0.0001	−0.00089*
$\Delta_q^{NY}(t-3)$	0.0042	−0.0566*	−0.0007	−0.00031*
$\Delta_x^S(t)$	3.3233*	0.5643*		
$\Delta_x^S(t-1)$	0.13031*	0.9552*	0.2669*	0.0079*
$\Delta_x^S(t-2)$	−0.4282*	0.2088*	0.1060*	0.0041*
$\Delta_x^S(t-3)$	0.0004	−0.0123*	0.0003	−0.0001
$\Delta_x^{NY}(t)$	0.8787*	6.4607*		
$\Delta_x^{NY}(t-1)$	0.3885*	2.974*	0.0958*	0.0534*
$\Delta_x^{NY}(t-2)$	0.2705	0.8544*	0.0005	0.0234*
$\Delta_x^{NY}(t-3)$	−0.0136	0.2306**	0.0087	−0.0010
R^2	0.1732	0.203	0.1446	0.0328

Table 2 (Continued)

Correlation matrix of residuals

	ε^S	ε^{NY}	w^S	w^{NY}
ε^S	1			
ε^{NY}	0.0463	1		
w^S	0	0	1	
w^{NY}	0	0	0.0297	1

Breusch-Pagan test: $\chi^2(6) = 80793$, $P\text{-value} = 0.0000$

Co-integration vectors

	q^S	q^{NY}	x^S	x^{NY}	Int.
ECT_1	1	−1	0	0	0.0051
ECT_2	1	0.9651	0.3214	−4.265	−6.873
ECT_3	1	0.9684	0.1705	−3.0934	−6.2294

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

is, positive lagged Δx_t^S are followed by positive Δx_t^{NY} . This result suggests trading transmission between markets.

The residual correlation matrix in Table 2 shows that, by assumption, trade-related and trade-unrelated noises are uncorrelated. Additionally, ε_t^S and ε_t^{NY} are slightly but significantly correlated. Since the correlation is weak, the two markets may differ in their ability to judge noisy public disclosures. Similarly, w_t^S and w_t^{NY} are also significantly correlated, suggesting common shocks in the trading processes. These correlations increase with time aggregation. Therefore, we expect the information share bounds described in Section 4 to be tighter as we decrease time aggregation.

Following Watson (1994), we derive the VMA representation (13) directly from the estimated VEC model (9). Table 3 contains the lower and upper information share bounds for the 1-min resolution.¹⁰

The SSE is, as we expected, the leading market in the price discovery process of the five Spanish cross-listed stocks during the overlapping interval. The information shares for the SSE trade-unrelated informational shocks (ε_t^S) are between 62 and 85% depending on the stock and the trading measure. In contrast, the contribution of the NYSE trade-unrelated shocks (ε_t^{NY}) is negligible. Only TEF and REP, with a 6.3–6.6% and 4.1–4.9% shares, generate some doubt about its statistical significance. Even in this case, the contribution is marginal. For the remaining stocks, the ε_t^{NY} contribution approaches zero. In the context of the scenario proposed in Section 2, these results suggest that the SSE generally makes judgments about public disclosures that are more precise and disseminates this information more quickly than the NYSE. However, for the most frequently traded Spanish stocks, the

¹⁰Changes in the US\$/€ exchange rate might cause some distortions in the computation of the information shares. However, Lieberman et al. (1999) conclude that the correlation between the changes in quotes and the changes in the exchange rates is irrelevant. Moreover, Grammig et al. (2005) find that the exchange rate is not a relevant determinant in price discovery. Therefore, we assume that any bias induced by shocks in the exchange rate is negligible.

Table 3

Information shares during the overlapping interval

This table contains SSE and NYSE information shares (in %) corresponding to trade-related (w_t^S , w_t^{NY}) and trade-unrelated (ε_t^S , ε_t^{NY}) shocks for 5 Spanish cross-listed stocks: BBV, ELE, REP, STD, and TEF. The information share is the proportion of variance in the efficient price that is attributable to a given innovation. The table provides both lower the upper (in parenthesis) bounds for each information share. “NV” (“NT”) means that the information shares correspond to a VEC model that uses the net volume traded (net number of trades) as the trading proxy.

	BBV				ELE				REP				STD				TEF			
	ε^S	ε^{NY}	w^S	w^{NY}	ε^S	ε^{NY}	w^S	w^{NY}	ε^S	ε^{NY}	w^S	w^{NY}	ε^S	ε^{NY}	w^S	w^{NY}	ε^S	ε^{NY}	w^S	w^{NY}
NV	82,1 (82,3)	1,0 (1,2)	16,5 (16,6)	0,1 (0,2)	85,0 (85,3)	2,3 (2,6)	12,2 (12,2)	0,2 (0,2)	78,4 (78,7)	4,1 (4,4)	16,7 (16,8)	0,4 (0,4)	83,1 (83,1)	0,9 (0,9)	15,9 (15,9)	0,1 (0,1)	68,8 (71,1)	6,3 (8,6)	20,3 (20,7)	1,9 (2,3)
NT	77,2 (77,2)	0,0 (0,0)	22,7 (22,7)	0,0 (0,1)	78,9 (79,2)	2,2 (2,4)	18,6 (18,6)	0,0 (0,0)	69,6 (69,9)	4,9 (5,2)	24,9 (25,0)	0,2 (0,2)	76,2 (76,2)	0,7 (0,7)	23,0 (23,0)	0,0 (0,0)	61,9 (63,9)	6,6 (8,6)	28,4 (28,7)	0,9 (1,2)

NYSE might have some advantage over the SSE in processing some particular event, such as news that concerns the American investments of these firms, their industries in general, or the US economy in particular.

The trade-related informational shares show a completely different picture. On the one hand, for the 1-min resolution the SSE trade-related shocks (w_t^S) explain between 12.2% and 28.4% of the long-term variance of the Spanish cross-listed stocks, again depending on the stock and trading measure. The information share for the NYSE trade-related shocks (w_t^{NY}), however, is less than 1% in almost all the cases. We define the NYSE relative trade-related informational share (RTRIS) as the trade-related information share of the NYSE over the sum of all the information shares attributed to the trading activity, that is, $RTRIS^{NY} = IS(w_t^{NY}) / (IS(w_t^{NY}) + IS(w_t^S))$. If we compare this measure with the “trading shares” in Table 1, we must conclude that the NYSE trading activity has no information content. Around 23% of TEF and 12% of REP traded volume takes place at the NYSE. However, the corresponding RTRIS is almost zero. Similar results are obtained with the number of trades. To summarize, the NYSE is close to being a pure satellite market of the SSE for all the Spanish cross-listed stocks. The information content of the trading activity in the US market is clearly negligible for all stocks ($\lambda_F \approx 0$).¹¹

¹¹We have estimated several refined versions of the empirical model (9). Firstly, we examined the existence of intra-daily patterns in the information shares, concluding that as the SSE closure approaches the NYSE clearly becomes a satellite. Secondly, we distinguished between non trading periods and perfectly balanced (accumulated net volume equal to zero) trading periods using dummy variables. In our case, no-trading periods provided the same information as balanced periods. Thirdly, we considered the impact of any relevant information revealed before the trading sessions overlap on the residuals of model (9). We found that Spanish returns during the 6½ hour interval preceding the NYSE opening were positively correlated with the initial NYSE trade-unrelated shocks. Despite that, information shares did not differ from those previously reported. Finally, we checked whether our findings depended on the particular trading proxy used in (9). We computed the NVt and NTt proxies discarding, first, small-sized trades (trade-size hypothesis) and, second, small and large-sized trades (stealth-trading hypothesis). We concluded that under the stealth-trading hypothesis (Barclay and Warner, 1993) the NYSE could not be considered as a pure satellite market of the SSE for the most frequently traded cross-listed stock (TEF). Nonetheless, the US contribution was absolutely trade-unrelated. Methodological and empirical details on all these robustness tests can be found in the working paper version (<http://ssrn.com/abstract=309881>).

7. Conclusions

This paper studies the price discovery process of cross-listed securities during the period when their trading sessions overlap. Building on Hasbrouck's (1995) information share approach, we have introduced a methodology that distinguishes two sources of information asymmetries between markets: trade-related and trade-unrelated information. By separating the quote innovations into trade-related and trade-unrelated shocks, we are able to decompose the global information share of each market into its trade-related and trade-unrelated components. By modeling the trading processes of the different markets, we also allow for incremental information contained in trade shocks, beyond that reflected in each market's quotes. This approach improves on previous empirical methodologies in several ways: it considers other information than just the market quotes; it provides a more accurate characterization of a dominant-satellite relationship when it exists; it accounts for alternative sources of information provision and, therefore, information asymmetries; it allows the evaluation of the information content of the trading process of each market; and it is flexible enough to accommodate further extensions, such as introducing liquidity shocks.

As an empirical application of this methodology, we studied the contribution of the NYSE to the price discovery process of the Spanish cross-listed stocks. This study centered on the daily overlapping trading interval between the NYSE and the SSE. Not surprisingly, our results indicate that the SSE leads the price discovery. The SSE trade-related shocks account for 12% to 30% of the long-run variance of the Spanish cross-listed stocks. NYSE trade-related shares, however, are undistinguishable from zero. Indeed, the NYSE global contribution is clearly negligible for almost all the Spanish cross-listed stocks.

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