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Departamento de Estadística y Econometría
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 91 624-96-08

Cross-listing, Price Discovery and the Informativeness of the Trading Process.*

Roberto Pascual¹, Bartolomé Pascual-Fuste² and Francisco Climent³

Abstract

This paper analyzes the price discovery process of a set of Spanish stocks cross-listed at the NYSE. Our methodology distinguishes between two sources of information asymmetries. Market-specific information that is revealed through the trading process and public disclosures simultaneously revealed to both markets but subject to informed judgments. We compute the information share of the Spanish and U.S. trading activity during the daily 2-hour overlapping interval. Empirical results show that the NYSE contribution to the price discovery process is not negligible. But the NYSE information is basically trade-unrelated.

Keywords: Cross-listing, price discovery, trade-related information, ADRs.

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¹ Departamento de Economía y Empresa Universidad de las Islas Baleares and Departamento de Economía de la Empresa Universidad Carlos III de Madrid

²Departamento de Economía y Empresa Universidad de las Islas Baleares

³ Departamento de Economía Financiera y Matemática Universidad de Valencia

^{*} Corresponding author: Roberto Pascual, Departamento de Economía y Empresa, Universidad de las Islas Baleares, Ctra. Valldemossa Km 7.5, 07071 Palma de Mallorca, Islas Baleares, SPAIN, Phone: +34-971-17-28-45, Fax: +34-971-17-34-26. R. Pascual is grateful for the hospitality of the Business Department of the Universidad Carlos III of Madrid and for their cooperation during the development of this research project.

I. Introduction

When an asset is traded at multiple markets, a crucial question naturally arises: which market does contribute more to the discovery of the efficient price. A large part of the research on this issue has been focused on discerning whether U.S. regional markets are informationally relevant for the NYSE-listed stocks (e.g., Chordia and Subrahmanyam, 1995; Lin et al., 1995; Blume and Goldstein, 1997). However, the increasing importance of non U.S. companies listed on the NYSE (see Palatkonak and Sofianos, 1999) has also motivated a growing interest in the role that the U.S. stock exchanges play in finding out the efficient value of the international dually-listed stocks (e.g. Werner and Kleidon, 1996; Chan et al., 1996). This paper presents an empirical analysis that makes use of intra-daily data on a set of Spanish stocks traded as ADRs on the NYSE during the year 2000. The study centers the attention on the daily overlapping trading interval between both the NYSE and the Continuous Trading System of the Spanish Stock Exchange (SSE). Our main concern is to determine how much of a change in the efficient price is related to the Spanish and to he U.S. trading activity. The procedure we propose allows to discern to what extend the NYSE contributes to price discovery and whether the information provided by this market is trade-related or trade-unrelated information.

Harris et al. (1995) use a Vector Error Correction Model (VECM) to study the adjustment mechanism of the NYSE and regional prices towards the common underlying efficient price. A significant error correction mechanism in the NYSE price equation indicates that regional markets do contribute to the price discovery of NYSE-listed stocks. Hasbrouck (1995) proposes a common trend representation to model the NYSE and regional quotes. In this model, the fraction of the long-term variance (the variance of the common factor) that is explained by each market is used to measure its information share. Hasbrouck finds that the information share of the regional markets is relatively unimportant. Tse (2000) argues that these two econometric models are equivalent and the empirical differences are due to methodological issues. Recently, Harris et al. (2000) uses the common factor estimation method proposed by Gonzalo and Granger (1995) to evaluate each market's proportion of the price discovery. In this 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. Their findings show changes in the location of price discovery over time. Hupperets and Menkveld (2000) and Grammig et al. (2000)

adapt the Hasbrouck (1995) model to the analysis of non U.S. NYSE-listed stocks. Lieberman et al. (1999), Ding et al. (1999) and Eun and Sabherwal (2000) do the same with the Harris et al. (1995) methodology. These studies report mixed findings.

Previous papers do not differentiate between alternative sources of information because the trading activity is not openly modeled. In this paper we consider two possible causes of information asymmetries between markets. First, the presence of informed agents endowed with superior information about the true value of the stock (e.g., O'Hara, 1995). This information, we assume, is revealed through trading. Because informed agents must decide where to exploit their information advantage (e.g., Chowdhry and Nanda, 1991), trade-related information becomes market-specific. So, it may cause transitory differences in the markets' expectations about the true value of the stock. Trade-related information becomes public as soon as it is revealed in some market. Following Subrhamanyam (1997), we measure the trade-related shocks as the unexpected component of the SSE and NYSE trading processes.

Second, public announcements, characterized as noisy signals (e.g., Harris and Raviv, 1993), may also cause information asymmetries. This trade-unrelated information is simultaneously exposed to all markets. However, markets differ in their ability to process public disclosures. Kim and Verrecchia (1994) develop a model in which some agents process public information into private information resulting in superior judgments. In our context, we expect the agents in the home market (the SSE) to perform more accurate assessments and to respond more quickly to public disclosures than the foreign market (the NYSE). But, since an important part of the Spanish cross-listed firms' business activity takes place in America, some public shocks might be disseminated sooner in the NYSE prices. A given public announcement provides the market with superior capacity to process it with a temporary advantage over the other market. Public disclosures are reflected in the trade-unrelated unexpected components of the SSE and the NYSE quotes.

We motivate our empirical analysis by means of a structural model for two markets that simultaneously trade one stock. Each market forms its sequence of conditional expectations about the security's ultimate value drawing on the revisions of their available information set. These information sets are updated because of trade-related and trade-unrelated information shocks. A pure satellite market has an uninformative trading process and is incapable of interpreting public announcements. It is shown that the natural

empirical counterpart of this model is a vector error correction (VEC) model that explicitly models the informative unexpected component of the trading process.

The corresponding common trend representation of the VEC model allows to measure the contribution of the trading activity in each market to the long-term volatility of the internationally cross-listed stock. Hasbrouck (2000) contrasts the information share approach in Hasbrouck (1995) with the permanent-transitory approach in Harris et al. (2000). Hasbrouck shows that in the case of a two markets 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 estimation error) the true value. This cannot be said for the permanent-transitory approach. Therefore, we slightly modify the information share approach in Hasbrouck (1995) to differentiate between the information share that corresponds to each market's trade-related information and to their relative capacity to evaluate and quickly disseminate public information.

The empirical findings show that the NYSE contribution to price discovery is not negligible. The SSE quotes and the NYSE quotes are cointegrated, so they share a common long-run component. Both markets react to any deviation between their quotes, signifying that we are facing a two-way price discovery process (see Harris et al., 1995). The trading activity at the SSE significantly affects to the quotes posted by the two markets. After a period of positive net volume (more buyer-initiated than seller-initiated volume) or positive net trading (more buyer-initiated than seller-initiated trades) NYSE and SSE quotes increase. Similarly, the NYSE trading activity significantly affects to the NYSE quotes even when the Spanish activity is taken into account. Its impact on the SSE quotes, however, is weaker and depends on the trading frequency of the stock. These findings suggest that the information brought in by the NYSE market is mainly tradeunrelated. The information shares computed confirm this intuition. The 70-90% of the efficient price's long-run variance is due to non trade-related shocks first disseminated in the SSE quotes. Between 10-20% is due to SSE trade-related information and less than the 0.5% is due to NYSE trade-related information. The information share due to public announcements disseminated first at the NYSE varies between the 1% and the 3% depending on the stock and the trading proxy used. Globally, we conclude that the NYSE is not a pure satellite market for the Spanish cross-listed stocks, but its contribution to price discovery is mainly due to public announcements probably originated at America and disseminated sooner in the NYSE quoted prices than in the SSE quoted prices. We also provide strong evidence that for the SSE the volume transacted is more informative that the number of trades. On the contrary, for the NYSE we report weak evidence that it is the occurrence of transactions per se and not the volume traded that contributes to the price discovery of the Spanish cross-listed stocks.

The paper is organized as follows. In section II we motivate the analysis describing a framework for the quote formation of a cross-listed stock that distinguishes between trade-related and trade-unrelated informational shocks. In section III we introduce the empirical VEC model. In section IV we define the information share measure for the U.S. and the SSE trading process. In section V we describe the data set. In section VI we summarize the results of estimating the econometric model. In section VII we provide the information shares for each market. Finally, in section VIII we conclude.

II. Motivation

This section presents a useful framework to motivate and interpret our posterior empirical analysis. Consider a stock that is traded at two different markets with trading sessions that overlap during a given time interval. Indeed, this is the case for the Spanish stocks cross-listed at the NYSE. First, we develop a model in which public disclosures are not noisy signals. Public disclosures may not lead to different interpretations. The two markets adjust quoted prices at the same time and by the same amount after a trade-unrelated shock. Thus, the unique source of information asymmetries between markets is the trade-inferred information. Consider first how expectations are formed. Let m_t be the expectation about the true value of the stock given the full information set at moment t. That is,

$$m_{t} = E[\mathbf{y}_{t} \mid \mathbf{f}_{t}],$$
 [1]

where E[.|.] is the conditional expectation, \mathbf{y}_t is the true value of the stock in a future reference moment \mathbf{t} (for example, the end of trading at the NYSE) and \mathbf{f}_t is the total information available in both markets at moment t. We assume that this information is fully inferred from the time series of previous quotes and trades. The common information set (\mathbf{f}_t^c) includes the current and all previous trade-unrelated shocks and the whole history of trade-related shocks till period t-1. The trade-related (market-specific) information is

initially revealed either at the SSE (\mathbf{f}_{t}^{S}) or at the NYSE (\mathbf{f}_{t}^{NY}). Under this structure we have that $\mathbf{f}_{t} = \{\mathbf{f}_{t}^{S}, \mathbf{f}_{t}^{S}, \mathbf{f}_{t}^{NY}\}$.

Given that, at some point in time, the information sets available at the NYSE and SSE markets may differ, the expectation about \mathbf{y}_{τ} in each market may also be different. Therefore, let the expectation about the true value of the stock at market $i=\{NY, S\}$ at period t be

$$m_t^i = E[\mathbf{y}_t \mid \mathbf{f}_t^{\mathcal{E}}, \mathbf{f}_t^{\mathcal{E}}] . \tag{2}$$

The market i's expectations follow the process in equation [3],

$$m_t^i = m_t^* + \boldsymbol{l}_i w_t^i, \tag{3}$$

where m_t^* represents the expectation about the true value of the stock when only the common information set is available, that is $m_t^* = E[\mathbf{y}_t \mid \mathbf{f}_t^{\epsilon}]$. The stochastic process w_t^i in [3], with $E[w_t^i] = 0$, $E[(w_t^i)^2] = \mathbf{s}_t^2$ and $E[w_t^i w_{t-j}^i] = 0$ $\forall j \neq 0$, characterizes a traderelated innovation that updates the market i's information set. The parameter \mathbf{I}_i measures how much of this trade-related shock is new information (e.g., Hasbrouck, 1991).

The expectation based on the common information set (m_t^*) follows the random walk process [4],

$$m_{t}^{*} = m_{t-1} + w_{t} , \qquad [4]$$

with w_t being a zero-mean uncorrelated stochastic process representing an innovation in the common information set \mathbf{f}_t^{ϵ} , i.e. $\mathbf{f}_t^{\epsilon} = \{\mathbf{f}_{t-1}^{\epsilon}, w_t\}$, due to a public disclosure at period t. Notice that equation [4] implies that any specific information given away at period t-1, either at the SSE or at the NYSE, becomes common information the next period $(\{\mathbf{f}_{t-1}^{s}, \mathbf{f}_{t-1}^{NY}\} \subset \mathbf{f}_t^{\epsilon})$. This imposes a short-term convergence in expectations between both markets. Thus,

$$m_{t}^{i} = m_{t-1} + (\mathbf{I}_{i} w_{t}^{i} + w_{t}).$$
 [5]

Consequently, the revisions in the expectations about the true value of the stock at both markets have a common component (w_t) and an idiosyncratic component $(\boldsymbol{I}_i w_t^i, i=\{NY,$

S}). For example, if $w_t^{NY} = 0$ and $w_t^S \neq 0$ we have that $m_t^{NY} = m_t^* = m_{t-1} + w_t$ and $m_t^S = m_t$. That is, the Spanish market has a more precise expectation at period t than the NYSE. In this scenery, the NY would behave as a pure satellite market if all the traderelated information were disseminated through the SSE trading activity (i.e. $I_{NY} = 0$). We impose the restriction that w_t^{NY} , w_t^S and w_t are mutually uncorrelated processes. This implies that the trade-related shocks are uncorrelated with the shocks motivated by public announcements: $E[w_t^i w_{t-j}] = 0$, $\forall j \geq 0.^2$ By definition, idiosyncratic shocks at different markets are also uncorrelated, $E[w_t^i w_{t-j}^{-i}] = 0$ $\forall j \geq 0$ and $i = \{NY, S\}$, with -i representing the complement of i.

In what follows we describe the quote formation process. Quotes in both markets are the result of the firm demand and offer positions by liquidity providers. In the NYSE the best quotes may represent the interests of the specialist, the floor brokers and the limit orders in the specialist's Display Book. On the contrary, the SSE is a pure electronic order driven market and, consequently, the quotes represent the best prices at the offer and demand sides of the electronic limit order book. In this paper, we average quotes using the quote midpoint of the bid-ask spread,

$$q_t^i = \frac{(a_t^i + b_t^i)}{2},$$

where a_t^i and b_t^i represent the best ask and bid quotes in market $i=\{NY,S\}$. These quotes incorporate all the information revealed up to period t, both specific and common. The change in quotes at period t will be $\Delta q_t^i = q_t^i - q_{t-1}^i$. Let

$$q_t^i = m_t^i + S_t^i, ag{6}$$

where the process S_t^i satisfies that $E(S_t^i) = 0$, $E(S_t^i S_{t-k}^i) = \mathbf{S}_k \ \forall k \geq 0$. Therefore, the term S_t^i represents a covariance-stationary or weak-stationary stochastic component of quoted prices.³ It captures transitory deviations between the quote midpoint and the efficient price. The size of $S_t^i - S_t^{-i}$ depends on disparities in market making costs, market frictions (like the tick size), and other specific features of the microstructures of both markets.

Equation [6] implies that q_t^i is a non-stationary process since it depends on a long-run component (m_t^*) that is integrated of order 1, I(1). Nevertheless, as this non stationary component is common to the U.S. and the Spanish quotes, there exists a linear combination of both quotes that does is stationary,

$$q_{t}^{NY} - q_{t}^{S} = (m_{t}^{NY} - m_{t}^{S}) + (S_{t}^{NY} - S_{t}^{S}) =$$

$$= (\mathbf{I}_{NY} w_{t}^{NY} - \mathbf{I}_{S} w_{t}^{S}) + (S_{t}^{NY} - S_{t}^{S}).$$
[7]

As a consequence, the difference between the quote midpoints is a stationary stochastic process, meaning that both prices are cointegrated with a theoretical cointegration vector [1, -1]. The cointegration condition is necessary to avoid profitable arbitrage opportunities.

In the previous specification it is assumed that both markets simultaneously react to public announcements. Consider an extreme case in which all public signals are first observed by the home market (the SSE) and transmitted to the foreign market (the NYSE) with some lag. To incorporate this possibility, let the NYSE quote be given by

$$m_{t}^{NY} = m_{t-1} + \mathbf{I}_{t} w_{t}^{NY}. {8}$$

Equation [8] explicitly indicates that the NYSE expectations at period t do not account for w_t . Under this specification both prices are still cointegrated. Moreover, under the convenient assumption that $(S_t^{NY} - S_t^S)$ is very close to zero,

$$q_t^{NY} \approx q_{t-1}^S + \mathbf{I}_{NY} w_t^{NY}$$
. [9]

Equation [9] shows that, also in this case, if $\mathbf{I}_{NY} = 0$ (the trading activity is not informative) the NYSE would be a pure satellite market for the Spanish cross-listed stocks.

We relax the previous assumption that public disclosures are not noisy signals. Hence, we allow for a second source of information asymmetries between markets: their respective ability to evaluate public signals. Public disclosures constitute imperfect information, in the sense that the valuable information is communicated with some distortion. One market may have more capacity to recognize the useful information either because it more closely monitors the firm or because it has access to more complete

information about the public signal. Therefore, markets differ in the quality of their judgments. Kim and Verrecchia (1994) develop a model in which earning announcements provide information that may lead to different interpretations (see also Harris and Raviv, 1993, and Bamber et al., 1999). Certain traders posses special capabilities that allow them to make (informed) judgments that are superior to the judgments of other traders. We just adapt Kim and Verrecchia's framework here. Consider that the public signal is

$$\widetilde{w}_{t} = w_{t} + \boldsymbol{d}_{t}, \tag{10}$$

where \mathbf{d}_t is a stochastic process that represents a distortion in the announcement, $E[\mathbf{d}_t] = 0$, $E[(\mathbf{d}_t)^2] = \mathbf{s}_d^2$ and $E[\mathbf{d}_t \mathbf{d}_{t-j}] = 0$ $\forall j \geq 0$. We assume that \mathbf{d}_t and w_t are mutually uncorrelated. Simultaneously to the dissemination of \widetilde{w}_t each market observes

$$J_{t}^{i} = \boldsymbol{d}_{t} + \boldsymbol{z}_{t}^{i}, \qquad [11]$$

where \mathbf{z}_{t}^{i} measures the information a market gleans about the random error by more closely studying the firm, its financial reports and businesses.⁴ Let $E[\mathbf{z}_t^i] = 0$, $E[(\mathbf{z}_{t}^{i})^{2}] = \mathbf{s}_{\mathbf{z},i}^{2}$ and $E[\mathbf{z}_{t}^{i}\mathbf{z}_{t-j}^{i}] = 0 \quad \forall j \geq 0, i = \{S,NY\}.$ Again, we assume that \mathbf{d}_{t} and \mathbf{z}_{t}^{i} are mutually uncorrelated. The quality of the markets' judgment depends on the precision of J_t^i . If $\mathbf{S}_{\mathbf{z},i}^2 = 0$ for all *i* this specification is equivalent to the one in equations [1]-[5]: the two markets perfectly isolate the noise (\boldsymbol{d}_{t}) from the valuable information (w_{t}) . Hence, both market adjust their expectations simultaneously and there are not differences in their interpretations. It follows that, ceteris paribus, the NYSE behavior will approximate more that of a satellite market (equations [8]-[9]) if $\mathbf{s}_{\mathbf{z},S}^2/\mathbf{s}_{\mathbf{z},NY}^2$ tends to zero. The judgments of the NYSE agents would be so imprecise that the revision in the NYSE expectations (m_t^{NY}) would be unreliable and, hence, transitory. We assume that the realization w_t becomes public knowledge the period after the announcement. Therefore, public signals only provide a temporary advantage to the market with the most accurate information about the signal. The period after the signal markets' expectations will converge if there are no additional trade-related or trade-unrelated shocks. The market i's expectations are updated following equation [12],

$$m_{t}^{i} = m_{t}^{*} + \mathbf{I}_{i} w_{t}^{i} + (\widetilde{w}_{t} - J_{t}^{i}),$$
 [12]

where the common-knowledge conditional expectation (m_t^*) is now given by $m_t^* = m_{t-1}^* + \mathbf{I}_i w_{t-1}^i + \mathbf{I}_{-i} w_{t-1}^{-i} + w_{t-1}$. Notice that if $\mathbf{S}_{\mathbf{z},i}^2 \neq 0$ the change in the expectation of market i has a distorting component that will be corrected the next period.

Let ρ be the correlation coefficient between $(\mathfrak{N}_t - J_t^S)$ and $(\mathfrak{N}_t - J_t^{NY})$ and assume that $1 \ge \rho \ge 0$. If $\rho = 1$ both markets observe the same information and have the same posterior beliefs. If $\rho = 0$ the two market will have posterior fully heterogeneous beliefs. Therefore, the empirical correlation between the trade-unrelated unexpected components of the SSE and the NYSE quotes will help to discern which one of the previous frameworks is more realistic. Given the greatest relative importance of the Spanish cross-listed stocks in the SSE, it seems reasonable to expect that the agents in the home market will make more precise judgments than the agents in the foreign market. If this is the case, public disclosures would be disseminated first in the SSE quotes. But when the public signal concerns the firm's activity in America or general news about the American economy, the advantage might be for the agents in the foreign market.

The cointegration result between the SSE and the NYSE quote midpoints still holds for this alternative scenario, meaning that the appropriate empirical counterpart to our framework is an error correction model. Next section develops our empirical specification.

III. The empirical model

The most common efficient parameterization of a vector of cointegrated variables is, from the Granger's Representation Theorem in Engle and Granger (1987), a VECM. Equation [13] represents the error correction representation of the NYSE and SSE quotes for the theoretical model of the previous section,

$$\Delta q_t^i = \mathbf{a}^i (q_{t-1}^i - \mathbf{b} q_{t-1}^{-i}) + \Phi_i^i(L) \Delta q_{t-1}^i + \Phi_{-i}^i(L) \Delta q_{t-1}^{-i} + u_t^i,$$
 [13]

with $i=\{NY, S\}$ and $\Delta=(1-L)$, that is $\Delta q_t^i=(q_t^i-q_{t-1}^i)$. The terms $\Phi_k^i(L)$, for $k=\{i,-i\}$, are autoregressive polynomials in the lag operator L ($L^k y_t=y_{t-k}$) having all their roots outside the unit circle. The component $(q_{t-1}^i-\boldsymbol{b}_{l-1}^{i})$ is the normalized error correction term. Presumably, \boldsymbol{b} is equal to 1. The parameter \boldsymbol{a}^i measures how faster does market i respond to a divergence between the U.S. and the Spanish quote midpoints. If these parameters are significant for both quote midpoints, it would signal that we are facing a two-way price

discovery process (see Harris et al., 1995) and, hence, that the NYSE is not a pure satellite market for the Spanish cross-listed stocks.

The vector of innovations $u' = (u_t^s, u_t^{NY})$ in [13] includes both the innovations associated to the trading process and the innovations associated to the public announcements. Explicitly, let u_t^i be given by

$$u_t^i = \widetilde{\boldsymbol{q}}_i^i(L)w_t^i + \widetilde{\boldsymbol{q}}_i^i(L)w_t^j + \boldsymbol{e}_t^i,$$
 [14]

where $\tilde{\boldsymbol{q}}_k^i(L)$, $k=\{i,j\}$, are finite lag polynomials with all roots outside the unit circle. Equation [14] is specified general enough as to capture usual features of intra-daily data caused by market frictions and specific trading rules. Equation [14] suggests that because of market frictions all the information the trades release at period t may not be reflected instantaneously into market quotes.⁵ Thus, the unexpected component of trades may have lagged effects on the quote midpoint (e.g., Hasbrouck, 1991a, and Pascual et al., 2000). The vector of trade-unrelated shocks $\boldsymbol{e}^i = (\boldsymbol{e}_t^S, \boldsymbol{e}_t^{NY})$ incorporates the information inferred from the public signal, $(w_t - J_t^S)$ and $(w_t - J_t^{NY})$ respectively, but also idiosyncratic features of each market that we do not model explicitly, like the tick size. Under the assumption that both markets have the same ability to judge the public announcement $(w_t \neq 0)$, \boldsymbol{e}_t^S and \boldsymbol{e}_t^{NY} should be highly correlated (see the discussion at the end of the previous section). Hence, we expect $E(\boldsymbol{e}_t^S \boldsymbol{e}_t^{NY}) \neq 0$ due to a common factor.

In order to identify the components in [14], we modify the empirical model [13]-[14] by allowing the quote process be given by,

$$\Delta q_{t}^{i} = \mathbf{a}^{i} (q_{t-1}^{i} - \mathbf{b} q_{t-1}^{-i}) + \Phi_{i}^{i}(L) \Delta q_{t-1}^{i} + \Phi_{-i}^{i}(L) \Delta q_{t-1}^{-i} + \mathbf{q}_{i}^{i}(L) x_{t}^{i} + \mathbf{q}_{-i}^{i}(L) x_{t}^{-i} + \mathbf{e}_{t}^{i}$$
[15]

where x_t^i is defined as a stationary stochastic process representing the net traded volume in period t and market i. A positive value of x_t^i ($x_t^i > 0$) implies more buyer-initiated volume traded than seller-initiated volume. On the contrary, if $x_t^i < 0$ it means that the seller-initiated traded volume is larger than the buyer-initiated one. The generating process of x_t^i is given by,

$$x_{t}^{i} = \prod_{x,i}^{i}(L)x_{t-1}^{i} + \prod_{x,-i}^{i}(L)x_{t-1}^{-i} + \prod_{q,i}^{i}(L)\Delta q_{t-1}^{i} + \prod_{q,-i}^{i}(L)\Delta q_{t-1}^{-i} + w_{t}^{i}$$
[16]

where $\Pi_{h,k}^{i}(L)$, for $h=\{x, q\}$, $i=\{NY,S\}$ and $k=\{i, -i\}$, are lag polynomials with all roots outside the unit circle. The new information inferred from the trading process, $\{w_t^{NY}, w_t^S\}$, is interpreted as the unpredictable component of the net volume traded. By substituting recursively [16] into [15], it is straightforward to see that [15]-[16] and [13]-[14] are equivalent empirical specifications. Notice that in [16] the trading process does not depend on the contemporaneous change in market quotes. This is because in our model causality flows from the trading process to the revision of market quotes.

We end with an empirical model with four equations, two for the NYSE and the SSE quotes and two for their respective trading processes,

$$A \begin{bmatrix} \Delta q_t^S \\ \Delta q_t^{NY} \\ x_t^S \\ x_t^{NY} \end{bmatrix} = \begin{bmatrix} \mathbf{a}^S \\ \mathbf{a}^{NY} \\ 0 \\ 0 \end{bmatrix} (q_{t-1}^S - \mathbf{b} q_{t-1}^{NY}) + B(L) \begin{bmatrix} \Delta q_{t-1}^S \\ \Delta q_{t-1}^{NY} \\ x_{t-1}^S \\ x_{t-1}^{NY} \\ x_{t-1}^{NY} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_t^S \\ \mathbf{e}_t^{NY} \\ w_t^S \\ w_t^{NY} \end{bmatrix},$$
[17]

with

$$A = \begin{bmatrix} 1 & 0 & -\boldsymbol{q}_{S,0}^{S} & -\boldsymbol{q}_{NY,0}^{S} \\ 0 & 1 & -\boldsymbol{q}_{S,0}^{NY} & -\boldsymbol{q}_{NY,0}^{NY} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{ and } B(L) = \begin{bmatrix} \Phi_{S}^{S}(L) & \Phi_{NY}^{S}(L) & \boldsymbol{q}_{S}^{*S}(L) & \boldsymbol{q}_{NY}^{*S}(L) \\ \Phi_{S}^{NY}(L) & \Phi_{NY}^{NY}(L) & \boldsymbol{q}_{S}^{*NY}(L) & \boldsymbol{q}_{NY}^{*NY}(L) \\ \Pi_{q,S}^{S}(L) & \Pi_{q,NY}^{S}(L) & \Pi_{x,S}^{S}(L) & \Pi_{x,NY}^{S}(L) \\ \Pi_{q,S}^{NY}(L) & \Pi_{q,NY}^{NY}(L) & \Pi_{x,S}^{NY}(L) & \Pi_{x,NY}^{NY}(L) \end{bmatrix},$$

where $\mathbf{q}_{j}^{*i}(L) = (\mathbf{q}_{j}^{i}(L) - \mathbf{q}_{j,0}^{i})L^{-1}$. Given that we expect $E(\mathbf{e}_{i}^{S}\mathbf{e}_{i}^{NY}) \neq 0$, we have a system of seemingly unrelated equations that could be efficiently estimated by SURE (Zellner, 1962).

IV. The information content of trades

IV.A. Information share

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

$$Var\left(E\left[\Delta m_{t} \mid x_{t}^{i} - E\left[x_{t}^{i} \mid \mathbf{f}_{t-1}^{*}\right]\right]\right),$$
 [18]

where again $i=\{NY,S\}$. Expression [18] is an absolute measure of the amount of specific information provided by the trading activity at market i to form the expectation about the efficient price. From [16],

$$x_t^i - E[x_t^i \mid \mathbf{f}_{t-1}^i] = w_t^i. {19}$$

Therefore, equation [18] is equivalent to

$$I^{i} = Var(E[\Delta m_{i} \mid w_{i}^{i}]) .$$
[20]

Under the testable assumption that w_i , w_t^{NY} and w_t^{S} are mutually uncorrelated, equation [20] is an appropriate absolute measure of the portion of the price discovery attributable to the trading activity at market i. But we can also measure the informativeness of the market i's trading process as its contribution to all the information (trade-related and trade-unrelated) set available for the revision of the expectation about the true value of the stock,

$$SIS^{j} = \frac{Var(E[\Delta m_{t} \mid w_{t}^{j}])}{Var(\Delta m_{t})}.$$
 [21]

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

IV.B. Empirical measure

As Hasbrouck (1995) remarks, every VECM has an associated common trend model representation implied by the cointegration relationships. So, the empirical approaches in Harris et al. (1995) and Hasbrouck (1995) are equivalent (see Tse, 2000). In our case, the empirical specification [17], has the following vector moving average (VMA) representation,

$$y_{t} = \Psi(L)\mathbf{x}_{t}, \qquad [22]$$

with $\Psi(L)$ being a lag polynomial, $y_t' = \left[\Delta q_t^S \ \Delta q_t^{NY} \ x_t^S \ x_t^{NY}\right]$ and $\mathbf{x}_t' = \left[\mathbf{e}_t^S \ \mathbf{e}_t^{NY} \ w_t^S \ w_t^{NY}\right]$. Following Hasbrouck (1995), consider the two first equations in [22], i.e. the equations that correspond to the changes in the quote midpoint of the U.S. and Spanish exchanges, $\Delta q_t = \mathbf{y}(L)\mathbf{x}_t$, where $\Delta q_t' = \left[\Delta q_t^S \ \Delta q_t^{NY}\right]$ and $\mathbf{y}(L)$ represent the two first files in the matrix $\Psi(L)$. By recursive substitution,

$$q_{t} = \mathbf{y}(L) \sum_{t=1}^{t} \mathbf{x}_{t} , \qquad [23]$$

and using that $\mathbf{y}(L) = \mathbf{y}(1) + (1 - L)\mathbf{y}^*(L)$, with $\mathbf{y}^*(L) = (\mathbf{y}(L) - \mathbf{y}(1))(1 - L)^{-1}$ it is obtained that,

$$q_{t} = \mathbf{y}(1) \sum_{t=1}^{t} \mathbf{x}_{t} + \mathbf{y}^{*}(L) \mathbf{x}_{t}, \qquad [24]$$

where the first term on the right hand side (RHS) of [24] is the long-run (permanent) component, common to both quotes because of the theoretical cointegration relationship between the U.S. and the SSE quotes. The second term on the RHS of [24], $\mathbf{y}^*(L)\mathbf{x}_i$, is a zero-mean weakly stationary (transitory) component. The cointegration relationship between the quotes entails that $\mathbf{d}'\Psi(1)=0$, where $\mathbf{d}'=(1-1\ 0\ 0)$ is the theoretical cointegration vector. This cointegration structure implies that $\mathbf{y}_1(1)=\mathbf{y}_2(1)=\mathbf{y}_{(1x4)}$, with $\mathbf{y}_k(1)$ representing the k-th file in $\Psi(1)$. Intuitively, the existence of a common long-run component implies that the long-run impact of a new shock on either the U.S. or the Spanish market should have the same permanent impact on both quotes. It follows that $\mathbf{y}\mathbf{x}_i$ measure the impact of a shock on the informationally efficient price. Therefore, if $Var(\mathbf{x}_i) = \Omega_{(4x4)}$, the long-run variance will be given by

$$Var(\Delta m_{t}) = \mathbf{y}\Omega \mathbf{y}^{t}.$$
 [25]

Our aim is to identify the part of this total long-run variance that is explained by each market's information. Given the hypothesis of no correlation between the innovations in the trading activity (w_t^{NY}, w_t^S) and with the common informative shocks $(\mathbf{e}_t^{NY}, \mathbf{e}_t^S)$, a proper measure of [23], the information share attributable to the market i's trading activity, would be

$$SIS^{i} = \frac{\mathbf{y}_{i}^{2} \mathbf{s}_{w^{i}}^{2}}{\mathbf{v} \Omega \mathbf{v}^{i}},$$
 [26]

where $Var(E[\Delta m_t \mid w_t^i]) = \mathbf{y}_i^2 \mathbf{s}_{w^i}^2$ and \mathbf{y}_i is the *i*-th component of the row vector \mathbf{y} . The numerator of [21] is the variance of the impulse-response function of model [22] after a

trade-related shock. If the innovations in $\mathbf{x}_t' = [\mathbf{e}_t^S \ \mathbf{e}_t^{NY} \ w_t^S \ w_t^{NY}]$ are correlated, the covariance terms in Ω could be attributed to any shock. In this paper we follow the Hasbrouck suggestion of constructing upper and lower bounds for the information shares. In order to do that, 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 (see Hasbrouck, 1995 and 2000). These bounds will be tighter as the correlation between the innovations approaches zero.

V. Data

A. Databases

U.S. data is obtained from the TAQ (*Trade and Quote*) database corresponding to the year 2000. We consider consolidated trades and quotes, that is, all trades and quotes from the primary (NYSE), NASD and regional markets. All quote and trade registers previous to the opening quote are dropped. Trades not codified as "regula discarded. Trades performed at the same market, 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 quoted depth equal to zero have also been eliminated. U.S. trades are classified as buyer or seller initiated trades using the Lee and Ready's (1991) algorithm. When trades and quotes must be considered together, the so-called "five seconds rule" has been applied. This rule assigns to each trade the first quote stamped at least five seconds before the trade itself (see Lee and Ready, 1991).8

The Spanish data is supplied by *Sociedad de Bolsas* (SB). This organization was established by the four Spanish Stock Exchanges (Madrid, Barcelona, Bilbao and Valencia) and is responsible for the technical management of the computerized trading system that operates at a national level, the Spanish Stock Exchange Interconnection System (SIBE). The SIBE is an electronic order-driven market similar to those of the Paris Bourse and the Toronto Stock Exchange, where the most liquid Spanish stocks trade. Drawing in a leading-edge technology, the SIBE enables large trading volumes to be handled efficiently and transparently. The SIBE also provides real time information and immediate dissemination of trading data. Since 17 January 2000, SIBE operates in continuous trading between 9:00 a.m. to 5:30 p.m. Spanish time (ST) with an auction between 8:30 a.m. and 9:00 a.m. that determines the opening price of the continuous

session. Hence, there is a two-hour overlapping interval (see Figure 1) between the SSE and NYSE sessions from 15:30 to 17:30 ST (9:30-11:30 a.m. New York time (NYT)).

FIGURE 1
The overlapping trading interval

New York time

3:00 9:30 11:30 16:00

SSE open NYSE open SSE close NYSE close

Spanish time

9:00 15:30 17:30 22:00

SSE close

NYSE close

NYSE open

SSE open

As in the TAQ database, the Spanish database includes trade and quote files. The quote file provides all the adjustments of the five best quotes at the bid and offer side of the electronic limit order book, time stamped at the nearest second. Additionally, the quote file includes the quoted depth at each of the ten quoted prices and the number of orders registered at each level. The trade file includes information about all trades executed, again, time stamped to at the nearest second. Some staff members of the SB confirmed us that, due to both the electronic network that manages trading and the real time dissemination of all the information, there are no lags between the reporting time of the updated quotes and the transactions that triggered them. Therefore, the trades are classified as buyer or seller-initiated, depending on the initiator of the trade (see Odders-White, 2000). Stocks at the SSE are quoted in euros and the tick is based on the share price: €0.01 for prices of less than €0 and €0.05 for prices of more than €0. We will transform the SSE quotes into US\$ applying the corresponding intra-daily exchange rate series provided by Reuters. This time series has a 1-minute resolution and contains the last exchange rate quoted each minute.

The sample consists of 5 Spanish stocks traded at the NYSE as American Depositary Receipts: Telefónica (TEF), a telephone service provider; Banco Bilbao Vizcaya Argentaria (BBV) and Banco Santander Central Hispano (STD), two financial groups; Repsol YPF (REP), an oil, gas and chemical company; and Endesa (ELE), an electricity generator. Henceforth, we will denote the stocks by its ticker symbol. All five stocks are permanently among the 35 most liquid stocks in the SSE. They embody a very important part of the total trading activity of the Spanish market. The five stocks were admitted to

trade at the NYSE before 1990 and an important part of their 2000 revenues come from their business activity at America (BBV 47.16%, ELE 32.68%, REP 28%, STD 58.58% and TEF 50% approximately). The SSE, as the home market, is expected to contribute substantially to price discovery. However, given the importance of the previous figures about the American activity of the dually listed Spanish securities and the dominance of U.S. stock exchanges as leading indicators for the other exchanges around the world, we also expect the NYSE to significantly contribute to price discovery. The issue to discern is whether the NYSE information comes from its trading activity or from public signals first disseminated in the US quotes. Table I shows the percentage of volume traded and of trades executed during the overlapping interval at each stock exchange. If SSE and NYSE trades are equally informative we would expect the information shares corresponding to the trading activity in each market to be close to the percentages shown in that table. Table I reports important differences between TEF and the remaining stocks.

[Table I]

B. Variables

Table II provides additional information about the trading activity at the NYSE of the five Spanish cross-listed stocks. The overlapping period (9:30-11:30 NYT) is divided into equally spaced time intervals from 1 to 5 minutes. Panel A (B) shows the percentage with at least one new quote (trade) register at the TAQ database. BBV is an infrequently traded stock at the NYSE; TEF can be considered as frequently traded; the remaining stocks are intermediate cases.

[Table II]

Given the important differences in the NYSE trading intensity between the five Spanish ADRs, we construct the time series for the previous five clock-time periodicities. Hence, we estimate five empirical models [18] for each of the five stocks. A change in quotes is computed as the difference between the logarithm of the quote midpoint at the end and at the beginning of each time interval. The trading process is represented either by the net volume (NV_t) transferred or by the net number of trades (NT_t) executed during each interval. The NV_t is defined as the difference between the buyer-initiated volume and the seller-initiated volume at the interval t. In this case x_t^i is computed as,

$$x_{t}^{i} = sign_{t} \left(\ln \left| \sum_{k=1}^{z} v_{k} \right| \right)$$
 [27]

where $NV_t = \sum_{k=1}^{z} v_k$ and $sign_t$ equals 1 if $NV_t > 0$ and -1 if $NV_t < 0$. The NT_t is defined as the difference between the number of buyer-initiated trades and the number of seller-initiated trades, and x_t^i is computed analogously to [27]. Jones, Kaul and Lipson (1994) suggest that it is the occurrence of transactions per se and not the volume traded that generates volatility. Therefore, the net volume could not have information beyond that contained in the number of trades of the same sign. Hence, we have estimated [17] using these two alternative trading activity measures. Differences in the information shares obtained with each specification will help to discern whether the volume traded or the trading frequency are more important for the price discovery process of the set of cross-listed stocks.

C. Order of integration and cointegration.

In order to proceed with the estimation of the empirical model [18] it is necessary to confirm that (1) the vector of dependent variables $(\Delta q_t^S, \Delta q_t^{NY}, x_t^S, x_t^{NY})$ is stationary and (2) the SSE and the NYSE quotes are cointegrated and with cointegrating vector (1,-1). We employ the augmented Dickey-Fuller (1979) and the Phillips-Perron (1988) procedures to determine the order of integration of the time series of the log of the quote midpoint in levels, the NV measure in [27] and the analog measure for the NT. In general, for all stocks and for all clock-time intervals we cannot reject the null hypotheses of a unit root for the quote series and we cannot accept it for all the trade series. Regarding cointegration, using both the Engle and Granger (1987) and the Johansen (1988, 1991) methodologies, we obtain that the SSE and the NYSE quotes are cointegrated for all stocks and trading intervals, and the normalized cointegrating vector is, as expected, (1,-1). These results are not reported because of space limitation but they are available upon request.

VI. Estimation results

This section summarizes the estimation of the VECM [17] for the five Spanish cross-listed stocks. The appropriate lag length of the empirical model has been determined using the Schwartz Bayesian Criterion (SBC).¹⁰ For all stocks, trading proxies, and time intervals, the maximum number of lags has been 6. No overnight returns have been

considered and no lags reached back to the previous day. If, for example, the optimal number of lags is four, the dependent vector begins with the fifth observation each overlapping interval. Table III reports the estimated model for TEF with the 1-minute time series. Panel A shows the estimated coefficients when the transformation [27] of the NTt is employed to proxy for trading activity. The lag length is 3. Panel B contains the estimated coefficients when the transformation [27] of the NVt is used to proxy for trading activity. The lag length is 4. Both panels also report the residual correlation matrix and the Breusch and Pagan (1980) chi-square test for independence. The model is estimated by SURE using the FGLS algorithm (e.g., Green, 1997, pg. 511-513). In general, the estimation results are consistent across stocks and the main findings derived are independent of the clock-time interval and the trading proxy used. Hence, the following comments refer not only to Table III but also to the other stocks in the sample, all the time intervals considered, and the two trading proxies. Remarkable differences will be explicitly mentioned.

[Table III]

A first relevant finding is that the error correction term (ECT) in the two quote equations is statistically significant for all stocks and specifications, and the sign of the coefficient is the expected one. If there is a movement in either the NYSE or the SSE away from the long-run equilibrium in a given period, a proportion of the disequilibrium is corrected the next period. Thus, if the ECT $q_{t-1}^S - q_{t-1}^{NY} > 0$ the next period Δq_t^S will decrease and Δq_t^{NY} will increase, rectifying (at least partially) the deviation between both markets. As the SSE quotes also respond to deviations from the NYSE quotes, this result evidences that the price discovery process is not completely driven by the Spanish market. Another consistent result across stocks is that the magnitude of the coefficient associated to the ECT of the Δq_t^S equation (\mathbf{a}_t^{NY}) is always smaller in absolute terms than the coefficient associated to the ECT of the Δq_t^N equation (\mathbf{a}_t^{NY}) . Statistical tests performed over the estimated coefficients of [17] confirm that $|\mathbf{a}_t^{NY}| > |\mathbf{a}_t^N|$ cannot be rejected at the 1% level. This result provides additional insights into the error correction process, suggesting that the reaction of the NYSE to the price differentials is faster and larger than that of the SSE.

Examining the coefficients of the lagged values of Δq_t^S and Δq_t^{NY} on the quote equations we observe, on the one hand, a significant negative autocorrelation in quotes. This finding could evidence a correction process that starts after an uninformative or transitory change of the quotes posted in a given market. On the other hand, there is a significant positive effect of the lagged Δq_t^S values on the Δq_t^{NY} equation, reflecting comovements of both quotes leaded by the SSE. The opposite relationship is also true for TEF (for all time intervals): the lagged values of Δq_t^{NY} also affect positively to Δq_t^S . However, statistical tests confirm that $\left|\sum \mathbf{f}_{NY,j}^{NY}\right| > \left|\sum \mathbf{f}_{NY,j}^{S}\right|$, that is, Δq_t^{NY} is more sensitive to changes in the lagged values of Δq_t^S is not usually significant.

The trading activity has an strong positive effect on quotes, independently of the proxy used. Table III evidences that an increase in the NV_t or in NT_t either at the SSE or at the NYSE produces an upward adjustment of both quotes. This finding is very important because indicates that the trading activity at the NYSE provides some information to both markets, even when the trading activity at the SSE has been taken into account. For the other stocks in the sample we obtain consistent results, although the significance of the effect of the trading activity at the NYSE on Δq_t^s depends on the time interval considered.

From the trade equations we report an expected and an unexpected finding. On the one hand, the expected result is a strong positive autocorrelation in x_i^i independently of the proxy used, either NV_t or NT_t. This finding is consistent with Hasbrouck's (1991a) findings that buyer-initiated trades tend to be followed by additional buyer-initiated trades. Additionally, we find evidence of clusters of signed trading activity between the SSE and the NYSE, generally leaded by the Spanish market. Thus, positive lagged values of x_i^s (more buyer-initiated than seller-initiated trading) are associated with posterior positive values in x_i^{NY} . This result suggests trading transmission between markets. For the most frequently traded stocks at the NYSE (TEF and REP) we also found evidence of trading transmission from the NYSE to the SSE. On the other hand, positive lagged values of Δq_i^s increase x_i^i , i={S, NY}. That is, after a period where the value of the stock at the SSE has increased, both markets experiment a larger pressure to buy. However, and this is the unexpected finding, for the NYSE we obtain the opposite effect. Lagged positive values of

 Δq_t^{NY} increase the pressure in the NYSE to sell (decreases x_t^{NY}). This relationship is not observed for the SSE trading activity. Hence, our explanation is that this result captures the marginal effect of inventory control by the specialist at the NYSE. Periods of intense demand $(x_t^{NY} > 0)$ are linked to increases in the value of the stock $(\Delta q_t^{NY} > 0)$, as we have observed before. During these periods, the NYSE specialist will be forced to provide liquidity in order to maintain stable market conditions. This is especially true for infrequently trade stocks (see Madhavan and Sofianos, 1998, and Kavajezc, 1999) and non-US stocks (see Bacidore and Sofianos, 2000). As a consequence the specialist could be forced to hold an undesired negative inventory position in the cross-listed stock. During the next period, the specialist will try to motivate traders to introduce market orders to sell in order to restate their preferred inventory position. This is also consistent with the negative autocorrelation of Δq_t^{NY} previously commented.

In general, the estimation results suggest that the SSE leads the price discovery process of the Spanish cross-listed stocks, but the role of the NYSE is not merely to be a satellite of the Spanish market. The relevant question is to determine whether the NYSE contribution to price discovery is due to their trading activity or to trade-unrelated shocks first incorporated to the NYSE quotes. This is the aim of the next section.

VII. Information shares

Table III reports the residual correlation matrix for the VECM [17] estimated using TEF data and with a 1-minute resolution. As we assumed in the theoretical scenarios in section II, trade-related and trade-unrelated noises are uncorrelated. This result is consistent across stocks and across time intervals. Additionally, \mathbf{e}_{t}^{S} and \mathbf{e}_{t}^{NY} are significantly correlated and, of course, this correlation increases with time aggregation. Similarly, w_{t}^{S} and w_{t}^{NY} are also significantly correlated, suggesting common shocks in the trading process. This correlation also increases but less with time aggregation. Therefore, we expect the information share bounds described in section IV to be tighter as we decrease time aggregation. The residual correlation matrices reported also indicate that the scenario with noisy trade-unrelated shocks described in section II better characterizes the underlying price discovery process. The simultaneous trade-unrelated shocks are not perfectly correlated, suggesting that both markets differ in their ability to judge noisy

public disclosures. This section will also discern which market usually makes the more accurate assessments.

A prior step needed to proceed with the computation of the information shares is to obtain the VMA representation of the VECM in [17]. Hasbrouck (1995) uses simulation methods to derive the VMA representation of his empirical model. We derive it directly from the estimated VECM (e.g., Watson, 1994). The changes in the US\$/€ exchange rate might cause some distortions in the computation of the informational shares. However, Liberman et al. (1999) conclude that the correlation between the changes in quotes and the exchange rates is negligible. Moreover, Grammig et al. (2000) measure the informational share attributable to shocks in the exchange rate, modeled as a random walk process. Their findings suggest that the exchange rate is not a significant determinant in price discovery. So, we assume that the possible biases induced by shocks in the exchange rate are also irrelevant.

Table IV contains the lower and upper bounds of the informational shares estimated for the five cross-listed stocks (hence, the values in a given row do not sum to 100%). The table reports the information shares for all models estimated: for the five clock time resolutions (1 to 5 minutes) and for the two possible trade indicators (NT_t and VT_t with the transformation in (27)).

[Table IV]

Table IV evidences that the SSE is, as we expected, the leading market in the price discovery process of the five Spanish cross-listed stocks. The information shares for the SSE trade-unrelated informational shocks (\mathbf{e}_i^s) are between 70% and 90% depending on the stock and the clock time resolution. But Table IV also indicates that the contribution of the NYSE is not negligible. The NYSE trade-unrelated informational shocks (\mathbf{e}_i^{NY}) account for 1% (TEF, STD, BBV) to 3% (REP, ELE) of the variance of the efficient price. This informational share is the most variable across stocks. It is also very sensitive to time aggregation for BBV, the less frequently traded Spanish cross-listed stock at the NYSE (see Table II). In the scenario presented in section II, these information shares imply that the SSE generally does more precise judgments about the information content of public signals and disseminates this information quicker than the NYSE. However, for some news, probably news that concern the business activity of the Spanish stocks at America or the American economy in general, the NYSE seem to have an advantage over the SEE.

The trade-related informational shares show a completely different picture. On the one hand, the SSE trade-related shocks (w_t^S) explain between 10% and 20% of the long-term variance of the Spanish cross-listed stocks, again depending on the stock and the clock time resolution. An interesting result is that the informational share of w_t^S is larger when the NV_t measure is used to proxy for trading activity. These differences suggest that the volume transferred at the SSE is more informative for the price discovery process of the Spanish cross-listed stocks than the occurrence of trades per se. This finding contrasts with Jones, Kaul and Lipson (1994) conclusions. On the other hand, the information share for the NYSE trade-related shocks (w_t^{NY}) is less than 0.5% in almost all the cases. Additionally, the Panel B of Table IV indicates that the w_t^S 's information share that is lost when we use the NT_t proxy is not gained by the NYSE trade-related shocks.

A more accurate assessment of the NYSE trading activity's contribution during the overlapping period would be to compare the relative trade-related informational shares with the "trading shares" in Table I. The relative trade-related informational shares are computed as the information share of the market i's trading activity over the sum of all the information shares attributed to trading activity. The results when the volume (in shares) is used as a proxy for trading activity are very conclusive: the number of shares transacted at the NYSE is not informative. For example, 23% of the TEF traded volume takes place at the NYSE. However, the corresponding relative trade-related informational share (using lower bounds) is only the 1-2%. Similarly, for REP the NYSE "volume sh and the relative trade-related informational share is between 1-3%. If we consider the number of trades as the appropriated source of information results are not so conclusive. For TEF and ELE the "trade shares" (5.93% and 4.17% respectively) are usually inferior to the corresponding relative trade-related informational shares for all time resolutions (1.88-14.04% and 6.06%-9.73% respectively). This result provides weak evidence that, for the NYSE, it is the occurrence of transactions per se and not the volume traded that contributes to the price discovery of the Spanish cross-listed stocks. This result seems reasonable: in the market with the highest trading frequency, the volume traded is what provides new information. But in the market with the lowest trading frequency, the information is inferred from unusual short durations (e.g., Easley and O'Hara, 1992) between trades.

VII. Conclusions

This paper has studied the role played by the NYSE in the price discovery process of four Spanish cross-listed stocks traded as ADR's in the US market. Our methodological contribution resides in distinguishing between two alternative sources of information asymmetries: trade-related shocks and noisy public disclosures. The study centers on the daily overlapping trading interval between both the NYSE and the SSE.

Our main conclusion is that the NYSE cannot be characterized as a pure satellite market of the SSE. Both SSE and the NYSE react to any deviation between their quotes. This indicates that we are facing a two-way price discovery process. Moreover, we conclude that the NYSE contribution to price discovery is mainly due to trade-unrelated shocks that are earliest disseminated at the US market than at the SSE. The information shares of both markets confirm that the SSE leads the price discovery process of the Spanish cross-listed stocks. The information share due to public announcements first disseminated at the NYSE is, however, remarkable. It varies between the 1% and the 3% depending on the stock and the trading proxy used. On the contrary, less than the 0.5% of the long-run variance is due to NYSE trade-related information. For the SSE we evidence that the volume traded is more informative than the number of trades. On the contrary, for the NYSE we find weak evidence that it is the occurrence of transactions per se that matters.

Footnotes

- 1. The future reference period t can be taken as the end of trading either at the SSE or at the NYSE. In the first case we do not impose the full convergence in expectations at the end of the overlapping period. If $w_{t-j}^{NY} \neq 0$, with j close to zero, the specific information generated at the U.S. may not be completely incorporated to the SSE quotes at moment t.
- 2. This is a strong assumption because it implies that the trading activity motivated by the announcement does not provide any additional information. We will see that this assumption is not strictly necessary, but it is adopted for simplicity of exposition and is tested in the empirical sections.
- 3. An alternative specification would be to assume that the public announcement provides each market with a different signal, for example $w_t^i = w_t + \mathbf{d}_t^i$. In this case, a market may be provided with an inferior signal than the other.
- 4. Empirically, the homokedastic characterization of the transitory component is not strictly necessary for our purposes, but it is assumed to simplify the exposition.
- 5. The NYSE rules state that the specialist should maintain a fair and orderly market. This includes the responsibility of stabilizing prices in their assigned stocks. The specialist ensures that trading in the stocks moves smoothly throughout the day (e.g. Hasbrouck et al., 1993). In the SSE there is no specialist or figure alike. However, the existence of hidden orders and stopped orders may also delay the full revelation of the information behind the trades. Alternatively, traders with heterogeneous priors and private information may take some intervals of trading to have their expectational differences resolved (e.g., Kyle, 1985; Harris and Raviv, 1993).
- 6. Chiang and Lin (1999) shows that the existence of a minimum price variation and the bid-ask bounce may induce a bias in the estimation of a VECM using high-frequency transaction price data. However, the authors also show that by using quote midpoints this bias in considerably reduced.
- 7. Hasbrouck (1995) pointed out that the information shares depend on the ordering of the variables in the Cholesky factorization of the residual covariance matrix. The first (last) variable in the ordering will tend to have a higher (lower) information share. The discrepancy could be large if the residuals across markets are highly contemporaneously correlated.
- 8. Recently, two contemporaneous studies, Ellis et al. (2000) and Odders-White (2000), have compared alternative classification rules. On the one hand, Ellis et al. and Odders-White have found that the Lee and Ready's algorithm outperform 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 (2000) observes that the biases introduced by the classification rules are more relevant for large and frequently traded stocks. The Spanish NYSE-listed stocks are neither large nor frequently traded compared with the largest stocks listed in the U.S. market. On the other hand, Blume and Goldstein (1997) showed that the "five-seconds rule" could not be generalized to all sample periods and markets. However, Odders-White (2000) also shows that the "five-seconds rule" does not seem to explain much of the bias induced by the Lee and Ready's algorithm.
- 9. Before 17 January 2000 continuous trading was from 9:30 to 17:00 ST; therefore, the overlapping trading period with the NYSE was just one hour and a half. Additionally, the beginning of the daylight saving time in October for Spain and US coincides. However, the end of this 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 overlapping trading period reduces to one hour.
- 10. This criterion is chosen because it tends to pick up more parsimonious specifications and because it has superior large sample properties than other procedures, for example the Akaike information criterion (e.g., Enders, 1995, pg. 88-89 and 315).
- 11. For example, the TEF residual correlation matrix for the 5 minute case and using NT_t as the proxy for trading activity shows that $Corr(\boldsymbol{e}_{t}^{S}, \boldsymbol{e}_{t}^{NY})=0.3608$ and 0.3303 when NV_t is used. Additionally, $Corr(\boldsymbol{w}_{t}^{S}, \boldsymbol{w}_{t}^{NY})=0.099$ and 0.108 for the NT_t and the NV_t specification, respectively.

References

Bacidore, Jeffrey M. and George Sofianos, NYSE specialist trading in non-US stocks, NYSE Working Paper, #00-05.

Bamber, Linda Smith, Orie E. Barron and Thomas L. Stober, 1999, Differential interpretations and trading volume, *Journal of Financial and Quantitative Analysis*, 34, 3, 369-386.

Blume, Marshall E., and Michael A. Goldstein, 1997, Quotes, order flow, and price discovery, *The Journal of Finance*, 52, 221-244.

Breusch, T. and A. Pagan, 1980, The LM test and its implications to model specification in econometrics, *Review of Economic Studies*, 47, 239-254.

Chan, K.C., Wai-Ming Fong, Bong-Chan Kho and René Stulz, 1996, Information, trading and stock returns: lessons from dually listed securities, *Journal of Banking and Finance*, 1161-1187.

Chiang, Kevin C.H. and Ji-Chai Lin, 1999, Inferring price discovery from frictional markets, *Working Paper*, E.J. Ourso College of Business Administration, Louisiana State University.

Chordia, Tarun, and Advanidhar Subrahmanyam, 1995, Market making, the tick size, and payment-for-order flow: theory and evidence, *Journal of Business*, 68, 4, 543-575.

Chowdhry, Bhagwan and Vikram Nanda, 1991, Multimarket trading and market liquidity, *Review of Financial Studies*, 4, 3, 483-511.

Dickey, D.A. and W.A. Fuller, 1979, Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, 427-431.

Ding, D., Frederick H. deB. Harris, S.T. Lau and Thomas H. McInish, 1999, An investigation of price discovery in informationally-linked markets: equity trading in Malasia and Singapore, *Journal of Multinational Financial Management*, 9, 317-329.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *The Journal of Finance*, 47, 2, 577-605.

Ellis, Katrina, Roni Michaely and Maureen O'Hara, 2000, The accuracy of trade classification rules: evidence from Nasdaq, *Journal of Financial and Quantitative Analysis*, 35, 4, 529-551.

Enders, Walter, 1995, *Applied Econometric Time Series*, Wiley Series in Probability and Mathematical Statistics, John Wiley and Sons.

Engle, Robert, and C. Granger, 1987, Co-integration and error correction: Representation, estimation and testing, *Econometrica*, 35, 251-276.

Eun, Cheol S. and Sanjiv Sabherwal, 2000, Price discovery for internationally traded securities: evidence from the U.S.-listed Canadian stocks, *Working Paper*, DuPree College of Management, Georgia Tech, Atlanta.

Foster, F. Douglas, and S. Viswanathan, 1993, Variations in trading volume, return volatility, and trading costs: evidence on recent price formation models, *The Journal of Finance*, 48, 187-211.

Gonzalo, Jesus and C. Granger, 1995, Estimation of common long-memory components in cointegrated systems, *Journal of Business and Economic Statistics*, 13, 1-9.

Grammig, Joachim, Michael Melvin and Christian Schlag, 2000, Price discovery in international equity trading, *Working Paper*, CORE, Université Catholique de Louvain la Neuve.

Green, William H., 1997, Econometric Analysis, Prentice-Hall, New Jersey.

Harris, Milton, and Arthur Raviv, 1993, Differences of opinion make a horse race, *The Review of Financial Studies*, 6, 473-506.

Harris, Frederick H. deB, Thomas H. McInish, Gary L. Shoesmith, and Robert A. Wood, 1995, Cointegration, error correction, and price discovery on internationally linked security markets, *Journal of Financial and Quantitative Analysis*, 30, 4, 563-579.

Harris, Frederick H. deB, Thomas H. McInish and Robert A. Wood, 2000, The dynamics of price adjustment across exchanges: an investigation of price discovery for Dow stocks, *Working Paper*, Babcock Graduate School of Management, Wake Forest University.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *The Journal of Finance*, 46, 179-207.

Hasbrouck, Joel, 1991b, The summary informativeness of stock trades: An econometric analysis, *The Review of Financial Studies*, 4, 571-595.

Hasbrouck, Joel, 1995, One security, many markets: determining the contributions to price discovery, *The Journal of Finance*, 50, 4, 1175-1199.

Hasbrouck, Joel, 2000, Stalking the "efficient price" in market microstructure specifications: An overview, *Working Paper*, Stern School of Business, New York University.

Hasbrouck, Joel, 1993, Assessing the quality of a security market: a new approach to measuring transaction costs, *Review of Financial Studies*, 6, 191-212.

Hasbrouck, Joel, George Sofianos, and Deborah Sosebee, 1993, New York Stock Exchange systems and trading procedures, NYSE *Working Paper* #93-01.

Hupperets, Erik and Bert Menkveld, 2000, Intra-daily analysis of market integration: Dutch blue chips traded in Amsterdam and New York, *Working Paper*, The Warton School, University of Pennsylvania.

Johansen, S., 1988, Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, 12, 231-254.

Johansen, S., 1991, Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica*, 59, 1551-1580.

Jones, Charles M., Gautam Kaul and Mark L. Lipson, 1995, Transactions, volume, and volatility, *Review of Financial Studies*, 7, 4, 631-651.

Kavajecz, Kenneth A., 1999, A specialist's quoted depth and the limit order book, *The Journal of Finance*, 54, 747-771.

Kim, Oliver, and Robert E. Verrecchia, 1994, Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics*, 17, 41-67.

Kyle, Albert S., 1985, Continuos auctions and insider trading, *Econometrica*, 53, 1315-1335.

Lee, Charles M., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *The Journal of Finance*, 46, 733-746.

Lieberman, Offer, Uri Ben-Zion and Schmuel Hauser, 1999, A characterization of the price behavior of international dual stocks: an error correction approach, *Journal of International Money and Finance*, 18, 2, 289-304.

Lin, Ji-Chai C., Gary C. Sanger, and G. Geoffrey Booth, 1995, Trade size and components of the bid-ask spread, *Review of Financial Studies*, 8, 1153-1183.

Madhavan, Ananth, and George Sofianos, 1998, An empirical analysis of NYSE specialist trading, *Journal of Financial Economics*, 48, 189-210.

Odders-White, Elizabeth R., 2000, On the occurrence and consequences of inaccurate trade classification, *Journal of Financial Markets*, 3, 3, 259-286.

O'Hara, Maureen, 1995, Market Microstructure Theory, Blackwell, Cambridge.

Pascual, Roberto, Alvaro Escribano, and Mikel Tapia, 2000, "Adverse Selection Costs, Trading Activity and Liquidity in the NYSE: An Empirical Analysis in a Dynamic Context", *Working Paper* #00-90, Universidad Carlos III de Madrid.

Phillips, P.C.B., and P. Perron, 1988, Testing for a unit root in time series regression, *Biometrika*, 75, 335–346.

Pulatkonak, Melek and George Sofianos, 1999, The distribution of global trading in NYSE-listed non-US stocks, *NYSE Working Paper*, 99-03.

Subrahmanyam, Advanidhar, 1997, Multi-market trading and the informativeness of stock trades: an empirical intra-daily analysis, *Journal of Economics and Business*, 49, 515-531.

Tse, Yiuman, 2000, Further examination of price discovery on the NYSE and regional exchanges, *The Journal of Financial Research*, 23, 3, 331-351.

Werner, Ingrid M., and Allan W. Kleidon, 1996, U.K. and U.S. trading of British cross-listed stocks: An intra-daily analysis of market integration, *Review of Financial Studies*, 9, 619-664.

Zellner, Arnold, 1962, An efficient method of estimating Seemingly Unrelated Regressions and tests for aggregation bias, *Journal of the American Statistical Association*, 57, 348-368.

TABLE I
Trading shares during the overlapping interval

This table reports the percentage of the trading activity of the Spanish cross-listed stocks during the overlapping period (15:30-17:30 ST) that corresponds to the Spanish Stock Exchange (SSE) and to the NYSE. The Panel A reports the percentages of the volume traded (measured in thousand of shares) and Panel B the percentages of the number of trades completed.

Stock	SSE	NYSE	% SSE	% NYSE							
	Panel A: Volume (thousands of shares)										
BBV	512094.86	7014.9	98.65	1.35							
ELE	274826.5	8724.5	96.92	3.08							
REP	277895.95	37996.9	87.97	12.03							
STD	690320.59	19857	97.20	2.80							
TEF	1378373.9	417107.1	76.77	23.23							
		Panel B: Num	ber of trades								
BBV	203.722	4.301	97.93	2.07							
ELE	159.311	6.934	95.83	4.17							
REP	160.228	9.948	94.15	5.85							
STD	238.671	8.617	96.52	3.48							
TEF	612.823	38.665	94.07	5.93							

TABLE II
Activity during the overlapping interval

This table is indicative of the trading activity of the Spanish ADRs listed at the NYSE during the overlapping trading interval between the SIBE and the NYSE (9:30:00-11:30:00, New York time). The overlapping interval has been divided into equally spaced time intervals from 1 to 5 minutes. The Panel A reports the percentage of those intervals with at least one new quote register at the TAQ database. The Panel B reports the percentage of those intervals with at least one trade register at the TAQ database.

Stock	Stock 1 min 2 min		3 min	4 min	5 min						
	Panel A: Quotes										
BBV	18.71	30.71	40.03	47.81	54.28						
ELE	29.69	47.74	60.07	69.85	77.45						
REP	45.36	65.67	77.03	84.17	89						
STD	31.06	49.15	61.33	70.96	78.02						
TEF	74.19	92.01	96.28	97.84	98.52						
_		Pa	anel B: Trades								
BBV	11.73	20.49	27.92	34.11	39.97						
ELE	18.84	33.56	45.6	55.68	63.68						
REP	24.66	41.49	53.98	63.04	71.02						
STD	21.05	36.09	47.23	56.59	64.18						
TEF	61.82	82.14	90.23	94.41	96.3						

TABLE III Estimation of the VECM

This table reports the estimated coefficients of the VECM [17] for TEF. To construct the time series, the overlapping trading interval between the SSE and the NYSE is divided in 1-minute intervals. For the definition of the variables see section VI.C in the paper. The lag length has been determined using the BSC information criterion. Panel A shows the coefficients of the VECM model that uses the transformation [27] of the 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. PanelB shows the coefficients of the VECM that uses the transformation [27] of the net volume as the proxy for trading activity. Net volume is defined as the difference between the buyer-initiated volume (in shares) and the seller-initiated volume in a given time interval. Both panels also report the residual correlation matrix and the Breusch and Pagan (1980) chi-square test for independence.

Panel A: Net number of trades

	Δq^{S}	$\Delta q^{\scriptscriptstyle NY}$	x^{s}	x ^{NY}
ECT (t-1)	-0.00856*	0.06732*		
Δq^{S} (t-1)	-0.11192*	0.16711*	1041.13*	46.27*
Δq^{S} (t-2)	-0.06495*	0.13449*	607.08*	32.67*
Δq^{S} (t-3)	-0.01248*	0.05319*	160.78***	19.04*
Δq^{NY} (t-1)	0.00969*	-0.33566*	89.29*	-97.85*
Δq^{NY} (t-2)	0.01048*	-0.14352*	175.102	-45.68*
Δq^{NY} (t-3)	0.00643*	-0.05147*	4.89*	-18.19*
$x^{s}(t)$	0.000011*	0.00000338*		
x^{s} (t-1)	1.34E-06*	0.00000335*	0.1822134*	0.0011792*
x^{S} (t-2)	-3.01E-07	9.14E-07	0.0104644*	-0.0001318
x^{S} (t-3)	-1.01E-06*	1.04E-07	0.0192556*	0.0007438**
$x^{NY}(t)$	0.000035*	0.0002703*		
x^{NY} (t-1)	0.000012***	0.0001239*	0.7103537*	0.0930372*
x^{NY} (t-2)	-4.13E-07	0.0000457*	0.0006557	0.0484854*
x^{NY} (t-3)	-0.0000129	1.31E-07	0.4375214*	0.0423458*
R2	0.1574	0.2014	0.0478	0.0456
	_	N.Obs.: 2664	8	

^{*, **, ***} Significance at the 1%, 5% and 10% level respectively.

Correlation matrix of residuals

	\boldsymbol{e}_{t}^{S}	\boldsymbol{e}_{t}^{NY}	W_t^S	w_t^{NY}
\boldsymbol{e}_{t}^{S}	1			
$oldsymbol{e}_{t}^{NY}$	0.0494	1		
w_t^S	0	0	1	
w_t^{NY}	0	0	0.0235	1

Breusch-Pagan test: $chi^2(6) = 79.715$, Pr = 0.0000

TABLE III Estimation of the VECM (Cont.)

Panel B: Net volume

	Δq^{S}	$\Delta q^{\scriptscriptstyle NY}$	x^{s}	x^{NY}
ECT (t-1)	-0.00393*	0.06309*		
Δq^{S} (t-1)	-0.14013*	0.15637*	267.95*	198.41*
Δq^{S} (t-2)	-0.07719*	0.12907*	27.965	141.48*
Δq^{s} (t-3)	-0.02919*	0.06141*	-41.454	86.61**
Δq^{S} (t-4)	-0.01921*	0.01091	-109.07*	43.784*
Δq^{NY} (t-1)	0.01299*	-0.35525*	25.540	-480.71*
Δq^{NY} (t-2)	0.01646*	-0.17106*	-27.719	-261.36*
Δq^{NY} (t-3)	0.01395*	-0.07553*	-59.65*	-129.04*
Δq^{NY} (t-4)	0.01129**	-0.02913*	-0.35382	-54.57*
$x^{s}(t)$	0.000011*	0.0000105*		
x^{S} (t-1)	0.000001*	0.0000142*	0.15318*	0.02788*
x^{S} (t-2)	-4.42E-07	0.0000085*	0.05550*	0.01126*
x^{S} (t-3)	-3.60E-06*	0.000004**	0.02576*	0.00971**
x^{S} (t-4)	-2.36E-06*	0.00000198	0.04848*	0.001518
$x^{NY}(t)$	6.22E-06*	0.0000624*		
x^{NY} (t-1)	2.23E-06	0.0000277*	0.02842*	0.07585*
x^{NY} (t-2)	-1.23E-06	0.0000131*	0.003095	0.04650*
x^{NY} (t-3)	-1.32E-06	0.0000036	0.03645*	0.03135*
x^{NY} (t-4)	-2.32E-06	0.0000039	0.010929	0.02397*
R2	0.1136	0.2166	0.0443	0.0494
		N.Obs.: 26413		

*, **, *** Significance at the 1%, 5% and 10% level respectively.

Correlation matrix of residuals

	\boldsymbol{e}_{t}^{S}	\boldsymbol{e}_{t}^{NY}	w_t^S	w_t^{NY}
\boldsymbol{e}_{t}^{S}	1	•		•
\boldsymbol{e}_{t}^{NY}	0.0465	1		
W_t^S	0	0	1	
w_t^{NY}	0	0	0.0361	1

TABLE IV
Information shares during the overlapping interval

This table contains the estimated information shares (in %) for trade-related and trade-unrelated shocks originated at the NYSE and the SSE. The information share is the proportion of variance in the efficient price of the stock that is attributable to a given innovation, either trade-related (\boldsymbol{w}_{t}^{S} , \boldsymbol{w}_{t}^{NY}) or trade-unrelated (\boldsymbol{e}_{t}^{S} , \boldsymbol{e}_{t}^{NY}). The table provides the lower bound and the upper bounds (in parenthesis) based on the estimation of the VECM [17]. The table shows the results of the VECM estimated with different clock time resolutions (1 minute to 5 minutes).

					Panel	A: Net vo	olume (in s	hares)					
		В	BV			ELE				REP			
	\boldsymbol{e}_{t}^{S}	$oldsymbol{e}_{t}^{NY}$	w_t^S	W_t^{NY}	\boldsymbol{e}_{t}^{S}	$oldsymbol{e}_{t}^{NY}$	w_t^S	w_t^{NY}	$\boldsymbol{e}_{\scriptscriptstyle t}^{\scriptscriptstyle S}$	$oldsymbol{e}_{\scriptscriptstyle t}^{\scriptscriptstyle NY}$	w_t^S	W_t^{NY}	
1m	82.328	0.890	16.474	0.134	83.875	2.634	12.920	0.366	79.436	3.243	16.861	0.344	
	(82.448)	(1.010)	(16.528)	(0.188)	(84.061)	(2.820)	(12.939)	(0.385)	(79.522)	(3.330)	(16.890)	(0.374)	
2m	81.765	1.210	16.547	0.199	85.112	2.065	11.789	0.259	80.659	3.232	15.149	0.349	
	(82.019)	(1.463)	(16.573)	(0.224)	(85.870)	(2.823)	(11.806)	(0.276)	(81.177)	(3.750)	(15.242)	(0.441)	
3m	81.478	0.000	18.343	0.133	77.678	1.723	18.824	0.078	80.630	3.326	14.224	0.164	
	(81.511)	(0.033)	(18.356)	(0.146)	(79.345)	(3.390)	(18.854)	(0.108)	(82.221)	(4.918)	(14.289)	(0.229)	
4m	80.004	0.000	19.693	0.208	77.819	2.448	17.822	0.156	79.477	2.660	14.989	0.156	
	(80.037)	(0.033)	(19.755)	(0.270)	(79.497)	(4.126)	(17.899)	(0.234)	(82.079)	(5.262)	(15.105)	(0.272)	
5m	82.274	0.000	16.595	0.924	75.055	2.624	20.065	0.089	75.359	3.416	17.588	0.508	
	(82.298)	(0.025)	(16.778)	(1.106)	(77.112)	(4.681)	(20.174)	(0.199)	(78.357)	(6.414)	(17.718)	(0.639)	
					Panel	B: Net n	umber of t	rades					
	e_t^S	\boldsymbol{e}_{t}^{NY}	w_t^S	w_t^{NY}	\boldsymbol{e}_{t}^{S}	\boldsymbol{e}_{t}^{NY}	w_t^S	W_t^{NY}	\boldsymbol{e}_{t}^{S}	\boldsymbol{e}_{t}^{NY}	w_t^S	w_t^{NY}	
1m	81.750	2.098	15.913	0.113	94.937	2.721	1.975	0.189	84.009	3.955	11.398	0.438	
	(81.880)	(2.229)	(15.909)	(0.109)	(95.116)	(2.901)	(1.974)	(0.187)	(84.171)	(4.117)	(11.436)	(0.476)	
2m	79.402	3.184	16.988	0.126	93.053	2.563	3.138	0.203	83.558	3.672	11.679	0.358	
	(79.668)	(3.450)	(17.021)	(0.160)	(94.092)	(3.602)	(3.142)	(0.207)	(84.224)	(4.338)	(11.747)	(0.425)	
3m	80.763	0.740	18.137	0.027	92.121	2.663	2.576	0.216	81.721	3.966	12.253	0.114	
	(81.060)	(1.037)	(18.173)	(0.063)	(94.541)	(5.083)	(2.580)	(0.221)	(83.596)	(5.841)	(12.323)	(0.185)	
4m	75.171	0.000	24.792	0.000	88.357	4.054	4.439	0.405	77.405	2.887	16.855	0.176	
	(75.203)	(0.032)	(24.797)	(0.005)	(91.010)	(6.706)	(4.531)	(0.497)	(79.959)	(5.448)	(16.975)	(0.297)	
5m	78.237	0.000	21.669	0.066	87.411	5.198	3.756	0.405	80.519	3.067	12.985	0.123	
	(78.288)	(0.052)	(21.646)	(0.042)	(90.623)	(8.409)	(3.775)	(0.423)	(83.628)	(6.162)	(13.202)	(0.315)	

TABLE IV
Information shares during the overlapping interval (Cont.)

			Pan	el A: Net v	olu	me (in sh	ares)			
		S	ΓD			TEF				
	\boldsymbol{e}_{t}^{S}	\boldsymbol{e}_{t}^{NY}	w_t^S	w_t^{NY}		\boldsymbol{e}_{t}^{S}	$oldsymbol{e}_{t}^{NY}$	w_t^S	W_t^{NY}	
1 m	81.517	1.012	17.287	0.156		77.605	0.811	19.771	0.622	
	(81.532)	(1.027)	(17.300)	(0.169)		(78.516)	(1.722)	(20.051)	(0.902)	
2m	82.884	1.195	15.548	0.249		75.772	1.019	18.502	0.130	
	(82.988)	(1.299)	(15.568)	(0.269)		(80.107)	(5.353)	(18.745)	(0.373)	
3m	82.589	1.108	15.347	0.264		70.651	0.978	19.942	0.160	
	(83.194)	(1.713)	(15.435)	(0.352)		(78.431)	(8.758)	(20.431)	(0.649)	
4m	84.671	0.855	13.672	0.042		66.720	1.299	20.134	0.193	
	(85.406)	(1.590)	(13.697)	(0.067)		(77.817)	(12.396)	(20.691)	(0.750)	
5m	83.227	0.869	14.789	0.162		68.273	0.387	19.040	0.033	
	(84.158)	(1.800)	(14.811)	(0.185)		(80.488)	(12.601)	(19.093)	(0.086)	
			Par	nel B: Net	nun	ber of tra	des			
	e_t^S	\boldsymbol{e}_{t}^{NY}	w_t^S	w_t^{NY}		\boldsymbol{e}_{t}^{S}	$\boldsymbol{e}_{\scriptscriptstyle t}^{\scriptscriptstyle NY}$	w_t^S	w_t^{NY}	
1 m	89.256	1.643	9.045	0.026		85.491	3.707	7.456	1.218	
	(89.288)	(1.675)	(9.043)	(0.024)		(87.473)	(5.690)	(7.602)	(1.364)	
2m	87.864	1.645	10.315	0.066		81.020	2.585	9.046	0.599	
	(87.957)	(1.738)	(10.332)	(0.083)		(87.469)	(9.033)	(9.348)	(0.901)	
3m	86.304	1.054	11.631	0.396		73.776	3.116	8.674	0.828	
	(86.822)	(1.572)	(11.729)	(0.494)		(86.953)	(16.292)	(9.103)	(1.258)	
4m	87.105	1.241	10.462	0.314		71.388	2.594	9.658	0.542	
	(87.922)	(2.079)	(10.502)	(0.376)		(86.845)	(18.057)	(10.011)	(0.903)	
5m	86.047	1.554	11.384	0.034	•	68.115	1.641	10.437	0.200	
	(86.977)	(2.495)	(11.426)	(0.083)		(87.325)	(20.851)	(10.836)	(0.597)	