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Security price adjustment across exchanges: an investigation of common factor components for Dow stocks[☆]

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Abstract

VECMs can detect trades that permanently move the markets in cross-listed stocks. We employ Gonzalo and Granger's (J. Business Econom. Stat. 13 (1995) 1) reduced-rank regressions and Q_{GG} test statistic to analyze the common factor weight attributable to three informationally-linked exchanges for DJIA stocks over 1988–1995. We distinguish this error correction approach to trading price adjustment from the information shares approach to quote price leadership. In 1988, a 72.2% mean common factor weight (f_{NYSE}) approximated the NYSE's 86% share of the trades. However, by 1992 f_{NYSE} had declined precipitously for 27 Dow stocks, averaging only 49.6%, despite an unchanged 86% share of the trades. By 1995, the NYSE's common factor weight had recovered, averaging 62.9% on 84% of the trades. We discuss three alternative microstructure-theoretic hypotheses that can confront this evidence.

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1. Introduction

In this paper, we investigate intermarket price adjustment on the New York, Chicago, and Pacific stock exchanges using 1998, 1992, and 1995 data for the thirty stocks comprising the DJIA. Our work focuses on the adjustment of cointegrated trading prices to any event that causes a divergence from the law of one price. Suppose that there is a trade at the same price on each of three informationally-linked exchanges. Then, as a result of an information event, there is a new trade on each exchange, but at three different prices. Sometimes this divergence reflects differences of opinion in assessing the same information, sometimes differential market frictions, and sometimes differences in depth at the prior quote. In each case, by hypothesis, subsequent arbitrage forces the prices together so that two of the exchanges error-correct to the price posted by the remaining exchange. If the new prices persist, trading prices on this third exchange revealed a common factor innovation that links the stochastic processes in these cointegrated markets, and it is the proportions of this common factor innovation attributable to each market that we measure and test.

Our vector error correction modeling (VECM) approach is based on Harris, McInish, Shoesmith and Wood (HMSW, 1995) and Tse, Lee and Booth (1996) but extends previous VECM work on cross-listed security prices in several ways. First, HMSW's analysis is limited to one stock, IBM, in 1990. Since IBM was the most active stock at the time and since IBM attracts an enormous analyst following and an NYSE crowd, it remains an open question whether IBM results can be generalized to other active stocks. Second, in this paper we formulate a microstructure-theoretic model of a common stochastic trend and employ Gonzalo and Granger (1995) to estimate and test common factor components attributable to each exchange's prices. The higher the normalized factor weight of an exchange, the bigger the contribution to revelation of the innovations underlying the common stochastic trend in that stock. Third, since Lo and MacKinlay (1990) demonstrate that spurious serial correlation may result from taking imperfectly synchronous observations on returns that are serially uncorrelated in continuous time, we investigate the robustness of these common factor results to variations in our MINSPAN data grouping procedure for obtaining synchronous trades. Finally, we test the common factor components for differences across exchanges and over time.

In the last decade, the rapid growth of trading through screen-based electronic communications networks (ECNs) has transformed the equity markets. Competition among the ECNs and the traditional market centers affects the order submission behavior of informed traders and can therefore alter the nature and location of price discovery. Increasingly, institutions are trading directly and anonymously with each other through an ECN without using brokers as intermediaries. For example, rather than using the upstairs market in New York, American Century Fund often now splits large portfolio rebalancing orders into thirty or forty trades that are executed through an ECN or preferenced to a regional exchange. Trading through crossing networks like those operated by Instinet and ASX has also greatly increased. Selective diversion of orders for listed stocks to other trading venues may significantly affect the information content of the order flow remaining in New York.

For eleven of the DJIA stocks in 1995, we find that the common factor weight of all three exchanges is statistically significantly different from zero. We also find that competition for order flow is an evolutionary ebb and flow process (Shapiro, 1993). From a mean of 72% in 1988, the NYSE common factor weights decline in 1992 for twenty-seven DJIA stocks to average only 49.6%. We conjecture that these changes in the common factor weights are associated with the competitiveness of the NYSE's spreads, depths and immediacy. NYSE spreads did widen 1990–1992 (Huang and Stoll, 1996a,b). Then, in response to the emergence of innovative ECNs during 1992–1994, the NYSE spreads retightened (Stoll, 1995). By 1995, NYSE common factor weights had recovered fully to equal or exceed 1988 levels for thirteen DJIA stocks.

1.1. The error correction approach to price discovery

Price discovery is the process by which security markets attempt to identify permanent changes in equilibrium transaction prices. The competition among specialists and other market markers for uninformed order flow based on depth, immediacy, and quoted spreads attracts the informed trades that permanently move the markets.[1] As discussed in Section 3.2 below, the Gonzalo-Granger (GG) common factor components provide a way to detect and calibrate these informed trades. In particular, GG factor weights multiplied by cointegrated prices form a common stochastic trend that is orthogonal to the error-correction process by which each security price adjusts to disparities in the idiosyncratic shocks in order to maintain arbitrage equilibrium.

This common factor approach to price discovery differs in several ways from continuous time modeling of lead–lag relations across security markets. For example, deJong and Nijman (1997) offer an estimation procedure that can handle irregularly-spaced continuous data from both high and low frequency markets. Although much can be learned about the linkage between derivatives and underlying securities from these continuous time lead–lag covariances, our purposes are somewhat different. Most importantly, the error correction approach to price discovery isolates the dynamics following a synchronous event of price divergence (in which all the markets have traded) and the subsequent readjustment to a common stochastic trend. Consequently, in Section 2 below we present a price adjustment model that analyzes each set of synchronous trades rather than inferring lead–lag covariances from the higher frequency markets or imputing prices to intervening periods of non-trading in the lower frequency markets. In this sense, error correction to a common stochastic trend in the synchronous transaction prices differs from

[1] Hasbrouck (1991, 1993), Lee (1993), Harris et al. (1994), Keim and Madhavan (1995), Harris et al. (1995), Blume and Goldstein (1997), and Easley et al. (1996a) have analyzed empirically various aspects of this informed order flow.

questions of price leadership and other short-run dynamics during the intervening quotes or trades.

Our prior cointegration-error correction research on the cross-listings of IBM reveals that 1990 prices on the New York and regional exchanges follow a multi-lateral error correction process to eliminate disparities between NYSE and Pacific or NYSE and Chicago prices (Harris et al., 1995). This multi-lateral resolution of pricing disparities in synchronous trades implies that some permanent price changes are attributable to the satellite markets. Lieberman et al. (1999) and Ding et al. (1999) report that similar multilateral error correction occurs with dual-listings across international stock markets.

In an earlier and related approach to price discovery, Hasbrouck (1991) models the persistent effects of innovations in vector autoregressions of continuous stock prices. Hasbrouck (1993) proposes the proportion of the permanent innovation variance in the implicit efficient price series as a measure of the quality of a security market's price discovery. And in his 1995 paper, Hasbrouck incorporates multiple cointegrated markets as possible sources of innovation variance in a common stochastic trend. A market's "information share", he then defines as the variance of the common trend innovation attributable to that market relative to the total innovation variance in the common trend as a whole. For the DJIA stocks in August–October 1993, Hasbrouck (1995) found a 91% information share for the NYSE quotes, and this proportion exceeded the NYSE's 84% share of the trading volume. The NYSE was therefore characterized as "information dominant". Hasbrouck (2000) addresses the strength (in making quote price leadership inferences) and weakness (in providing non-unique parameters) of this innovation variance approach.

The next section presents a common stochastic trends model that motivates applying Gonzalo and Granger's common factor methodology to transaction stock price series. Section 3 presents the empirical model, discusses estimation procedures, and identifies the two-way and one-way price adjustment hypotheses we test. Section 4 explains the data collection, reports our results for each of the Dow 30 stocks, and discusses alternative hypotheses that can explain the findings. Section 5 offers a summary and conclusion and provides suggested directions for future research.

2. Common stochastic trends representation of an error correction model

To formulate the dynamics of price adjustment across informationally-linked exchanges, consider the following common stochastic trends representation of two price series emanating from the trades executed by the NYSE specialist in the centralized market (P_{c}) and the trades executed by regional market-markers (P_{R}). Three key features of the model we develop are: (1) synchronous trading events that define intervals of trading time, (2) a cointegration-error correction hypothesis reflecting arbitrage across the alternative trading venues, and (3) a testable implication about the contribution of each venue to the common stochastic trend in the realized transaction prices.

In market microstructure applications, cointegration and error correction are linear dynamic properties of non-stationary time series data that share the implicit efficient price as a common stochastic trend. Suppose that for thickly-traded securities the continuous sequence of the implicit efficient price is an $I(1)$ series that can be represented as a random walk

$$P_t = P_{t-1} + w_t, \quad w \overset{\text{iid}}{\sim} \mathrm{N}(0, \sigma_w^2), \tag{1}$$

where t is trading time and w_t is the random information arrival over the interval between P_{t-1} and P_t. Because P_t exhibits no tendency to mean revert, information arrivals lead to permanent shocks that cumulate over the time between synchronous trades into a stochastic trend $\sum w_t$, where all the relevant markets trade at time $t = 1$ and then again at time $t = T$. In an auction theory framework, the $\sum w_t$ public information may be thought of as a common value realizable in a thick resale market with an idealized (zero) spread.

By hypothesis, actual trading prices in both the centralized and regional markets impound the w_t information arrivals but each differs from P_t by a zero-mean, covariance-stationary random disturbance $\varepsilon_{\mathrm{c},t}$ or $\varepsilon_{\mathrm{R},t}$:

$$P_{\mathrm{c},t} = P_t + \varepsilon_{\mathrm{c},t} \quad \text{and} \quad P_{\mathrm{R},t} = P_t + \varepsilon_{\mathrm{R},t}, \tag{2}$$

where $\varepsilon_{\mathrm{c},t}$ and $\varepsilon_{\mathrm{R},t}$ are assumed to be identically distributed through time but may be autocorrelated. The epsilon disturbances are intended to model localized order imbalances attributable solely to transitory shocks in private value (e.g., liquidity-based motives for trade). Consequently, although lagged information arrivals w_{t-s} can plausibly affect ε_t (the market-maker's or limit-order traders' assessment of localized order imbalance), we assume that lagged values of the levels of order imbalance ε_{t-s} cannot improve upon the univariate forecast of w_t. Thus, we allow w_t and ε_t to be correlated, but $\varepsilon_{\mathrm{c},t}$ and $\varepsilon_{\mathrm{R},t}$ do not Granger-cause w_t.[2,3]

Rewriting innovations in (2) as the sum of changes in the implicit efficient price and in private values

$$\Delta P_{\mathrm{c},t} = \Delta P_t + \Delta\varepsilon_{\mathrm{c},t} = w_t + \Delta\varepsilon_{\mathrm{c},t}, \tag{3}$$

$$P_{\mathrm{c},t} = P_{\mathrm{c},t-1} + w_t + \Delta\varepsilon_{\mathrm{c},t} \quad \text{and} \quad P_{\mathrm{R},t} = P_{\mathrm{R},t-1} + w_t + \Delta\varepsilon_{\mathrm{R},t} \tag{3$'$}$$

shows one reason why *realized* prices are not a random walk. Only if order imbalances due to innovations in private values are unchanged ($\Delta\varepsilon_{\mathrm{c},t}$ and $\Delta\varepsilon_{\mathrm{R},t} = 0$), will the trading price sequence of first differences $\Delta P_{\mathrm{c},t}$ or $\Delta P_{\mathrm{R},t}$ exactly mirror the

[2] The empirical orthoganalization implied by Gonzalo and Granger's (1995) common factor estimation procedure imposes this same restriction.

[3] We thank the referee for clarifying the admissibility of these correlations at "possibly all leads and lags."

implicit efficient price sequence of first differences $\Delta P_t = w_t$.[4] Nevertheless, at any realization (e.g., at $t = T$), both trading price sequences impound the stochastic trend in the implicit efficient price as a common factor:

$$P_{c,T} = P_{c,0} + \sum_{t=1}^{T} w_t + \varepsilon_{c,T} \quad \text{and} \quad P_{R,T} = P_{R,0} + \sum_{t=1}^{T} w_t + \varepsilon_{R,T}. \tag{4}$$

Each trading price level can be seen to depend (a) on a non-stochastic initial value (with t_0 chosen so that $P_{c,0} = P_{R,0}$), (b) on the common stochastic trend of the cumulated random information arrivals $\sum w_t$ (identical to the common stochastic trend in Stock and Watson, 1988), and (c) on a zero-mean covariance stationary process that is specific to the trading venue and to time period T and is therefore an idiosyncratic transitory disturbance.[5]

Although both the centralized and regional trading price sequences in Eq. (3′) are non-stationary, the difference between their contemporaneous values is itself a stationary time series:

$$(P_{c,t} - P_{R,t}) = \varepsilon_{c,t} - \varepsilon_{R,t}, \tag{5}$$

i.e., the sum of two zero-mean covariance-stationary random disturbances. When linear combinations of integrated $I(1)$ variables like $P_{c,t}$ and $P_{R,t}$ are themselves $I(0)$, the underlying series are cointegrated $C(1, r)$ where r is the number of cointegrating vectors. Therefore, by the Granger Representation Theorem for cointegrated variables. $\Delta P_{c,t}$ and $\Delta P_{R,t}$ can be estimated as a vector error correction model (VECM) for the ith trading venue

$$\Delta P_{i,t} = \left\{ \sum_{i=1}^{3} \sum_{s=1}^{S} \beta_{i,t-s} \Delta P_{i,t-s} \right\} + \gamma_i Z_{i,t} + u_{i,t}, \tag{6}$$

[4] Trading prices will also differ from the full-information, implicit efficient price by a signed half-spread reflecting bid–ask bounce. With P_t in an equation like (2) taken as the continuous quote midpoint, Hasbrouck (2000) follows Glosten (1987) and Campbell et al. (1997) in modeling the disturbance ε_t as a half-spread times a random indicator variable signifying the trade direction. This bid–ask bounce modeling framework introduces more economic motivation but poses substantial additional complications for empirical implementation. In particular, since spreads incorporate an asymmetric information component to cover the costs of adverse selection, half-spreads and w_t will be jointly determined in contrast to the above situation of no Granger causality from ε_{t-s} to w_t. In addition, Easley and O'Hara (1987) and Bertsimas and Lo (1998) argue that such models of information-based trading must account for serial dependence in the trade direction indicator variable. In Harris et al. (2000) we relate bid–ask bounce to a one-way price discovery hypothesis suggested by Hasbrouck (2000). In the present framework, however, neither bid–ask bounce nor the adverse selection component of the spread are modeled explicitly as the focus here is on the dynamics of adjustment to divergent *synchronous trading prices across markets*, not on the innovations in the continuous efficient price itself. In that sense, again, it is fair to distinguish the present intermarket price adjustment research from price leadership (lead–lag) inferences in continuous data.

[5] Chowdhry and Nanda (1991) found that transitory order imbalance was contemporaneously correlated across venues in times of information trading. We introduce this finding below in our specification of the estimation model.

where $Z_{i,t}$ is an error correction term and S is the optimal lag length that minimises the AIC for the vector autoregressive system of price level equations. Importantly, we expect the u_t disturbances reflecting market frictions to be contemporaneously correlated across the alternative trading venues i and j – i.e., $\mathrm{Cov}(u_{i,t}u_{j,t}) \neq 0$.[6]

3. An empirical model

3.1. The fully-specified VECM

If the error correction terms in Eq. (6) are specified consistent with a no-arbitrage equilibrium as an intermarket price divergence $Z_{i,j,t} = (P_{i,t-1} - P_{j,t-1})$, an analytically useful interpretation of the β and γ parameters in the VECM emerges. Substituting (3) and (5) into the VECM yields for two of the three venues j:

$$\Delta P_{\mathrm{NY},t} = \sum_{j=1}^{3} \beta_{\mathrm{NY},j} \sum_{s=1}^{S} w_{t-s} + \sum_{j=1}^{3} \sum_{s=1}^{S} \beta_{\mathrm{NY},j,t-s} \Delta\varepsilon_{j,t-s} + \sum_{j \neq i}^{2} \gamma_{\mathrm{NY},j}(\varepsilon_{\mathrm{NY},t-1} - \varepsilon_{j,t-1}) + u_{\mathrm{NY},t}, \tag{7}$$

$$\Delta P_{\mathrm{CHI},t} = \sum_{j=1}^{3} \beta_{\mathrm{CHI},j} \sum_{s=1}^{S} w_{t-s} + \sum_{j=1}^{3} \sum_{s=1}^{S} \beta_{\mathrm{CHI},j,t-s} \Delta\varepsilon_{j,t-s} + \sum_{j \neq i}^{2} \gamma_{\mathrm{CHI},j}(\varepsilon_{\mathrm{NY},t-1} - \varepsilon_{j,t-1}) + u_{\mathrm{CHI},t}. \tag{7'}$$

As emphasized by Tse et al. (1996) and Booth et al. (1999), the error correction parameters $\gamma_{i,j}$ reflect idiosyncratic adjustment of $P_{i,t}$ to disparities in shocks to private value that cause cointegrated series to diverge. By virtue of the permanent–transitory decomposition assumed above, no such error correction process can have any permanent effect on the common stochastic trends $\sum w_t$ and therefore no permanent effect on $P_{i,t}$ itself. Our specification for the trading price sequences in Eq. (4) as a random walk of information arrivals plus a covariance-stationary private value ε_t that does not Granger-cause the w_t was inspired by Gonzalo and Granger (1995), whose permanent–transitory decomposition establishes this result.

[6] The possible cross-equation correlation of the disturbances is of particular relevance to our choice of the Gonzalo-Granger (1995) common factor estimation procedure because it is this feature of the empirical model that introduces non-unique parameters into Hasbrouck's (1995) information shares methodology.

3.2. Gonzalo-Granger decomposition and common factor estimation

Gonzalo-Granger (1995) write p cointegrated series as an additively separable function of k common factor(s) $\boldsymbol{f}_t$ and r stationary error correction terms $\boldsymbol{z}_t = \boldsymbol{\alpha}'\boldsymbol{P}_{t-1}$ where $\boldsymbol{\alpha}'$ is an $r \times p$ matrix of the cointegrating vectors and $\boldsymbol{z}_t$ is $I(0)$:

$$\boldsymbol{P}_t = \boldsymbol{A}_1\boldsymbol{f}_t + \boldsymbol{A}_2\boldsymbol{z}_t \tag{8}$$

$$= \boldsymbol{A}_1\boldsymbol{\gamma}'_\perp \boldsymbol{P}_t + \boldsymbol{A}_2\boldsymbol{\alpha}'\boldsymbol{P}_{t-1}. \tag{8$'$}$$

Let $\boldsymbol{P}_t$ be a $p \times 1$ vector of cointegrated prices, $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ are loading matrices, and $\boldsymbol{\gamma}'_\perp$ is a $k \times p$ matrix of common factor weights on the contemporaneous prices in the k common factor vector(s) $\boldsymbol{f}_t$ where $k = (p - r)$. Gonzalo and Granger (1995) show that under the above restrictions, the $p \times k$ matrix $\boldsymbol{A}_1 = \boldsymbol{\alpha}_\perp(\boldsymbol{\gamma}'_\perp\boldsymbol{\alpha}_\perp)^{-1}$ and the $p \times r$ matrix $\boldsymbol{A}_2 = \boldsymbol{\gamma}(\boldsymbol{\alpha}'\boldsymbol{\gamma})^{-1}$ where by definition $\boldsymbol{\gamma}'_\perp\boldsymbol{\gamma} = 0$. Since the vector of common factor weights $\boldsymbol{\gamma}_\perp$ is orthogonal to the coefficient vector $\boldsymbol{\gamma}$ on the error correction terms in a fully-specified VECM, the $\gamma_{i,j}$ estimates in Eq. (7) provide a way to identify the permanent components $\boldsymbol{\gamma}'_\perp\boldsymbol{P}_t$.

For example, consider the special case in which the New York market is totally (100%) responsible for revelation of the common stochastic trend. Here, we anticipate that cointegration tests will reveal two cointegrating vectors ($r = 2$) implying one common factor ($k = 3 - 2$) corresponding to w_t in the foregoing model structure. With $k = 1$, the rank of the $3 \times k$ loading matrix $\boldsymbol{A}_1$ in Eq. (8$'$) is 1 (i.e., each row of $\boldsymbol{A}_1$ is identical), and the elements of $\boldsymbol{\gamma}_\perp$ therefore cumulate the response of each price series to an innovation in the composite common factor. The error correction terms of the VECM in Eq. (6) would then be estimated as

$$\gamma\alpha'\boldsymbol{P}_{t-1} = \begin{bmatrix} \gamma_{\mathrm{NY}} & \gamma_{\mathrm{NY}} \\ \gamma_{\mathrm{CHI}} & \gamma_{\mathrm{CHI}} \\ \gamma_{\mathrm{PAC}} & \gamma_{\mathrm{PAC}} \end{bmatrix} \begin{bmatrix} \Pi_{1\mathrm{NY}} & \Pi_{1\mathrm{CHI}} & \Pi_{1\mathrm{PAC}} \\ \Pi_{2\mathrm{NY}} & \Pi_{2\mathrm{CHI}} & \Pi_{2\mathrm{PAC}} \end{bmatrix} \begin{bmatrix} P_{\mathrm{NY},t-1} \\ P_{\mathrm{CHI},t-1} \\ P_{\mathrm{PAC},t-1} \end{bmatrix}, \tag{9}$$

where $\Pi_{1,i}$ and $\Pi_{2,i}$ are the elements of the cointegrating vectors, and where, by hypothesis, $\gamma_{\mathrm{NY}} = 0$ such that

$$\gamma\alpha'\boldsymbol{P}_{t-1} = \begin{bmatrix} 0 & 0 & 0 \\ \gamma_{\mathrm{CHI}(\Pi_{1\mathrm{NY}}+\Pi_{2\mathrm{NY}})} & \gamma_{\mathrm{CHI}(\Pi_{1\mathrm{CHI}}+\Pi_{2\mathrm{CHI}})} & \gamma_{\mathrm{CHI}(\Pi_{1\mathrm{PAC}}+\Pi_{2\mathrm{PAC}})} \\ \gamma_{\mathrm{PAC}(\Pi_{1\mathrm{NY}}+\Pi_{2\mathrm{NY}})} & \gamma_{\mathrm{PAC}(\Pi_{1\mathrm{CHI}}+\Pi_{2\mathrm{CHI}})} & \gamma_{\mathrm{PAC}(\Pi_{1\mathrm{PAC}}+\Pi_{2\mathrm{PAC}})} \end{bmatrix} \begin{bmatrix} P_{\mathrm{NY},t-1} \\ P_{\mathrm{CHI},t-1} \\ P_{\mathrm{PAC},t-1} \end{bmatrix}. \tag{10}$$

Under this one-way price adjustment hypothesis, NY prices do not error correct to intermarket price divergence whereas both satellite markets do error correct in order to maintain their equilibrium (cointegration) relationship to the permanent stochastic trend in New York. To identify the GG common factor vector $\boldsymbol{\gamma}_\perp$ for this case, one simply applies the orthogonality condition $\boldsymbol{\gamma}'_\perp\boldsymbol{\gamma} = 0$ which here implies $\boldsymbol{\gamma}'_\perp = [1, 0, 0]$. That is, the first price series in Eqs. (8$'$), (9) and (10) – i.e., P_{NY} – is 100% responsible for revealing the common stochastic trend.

3.3. Testing common factor weights

Gonzalo and Granger (1995) prove Eq. (8′) for their permanent–transitory decomposition and show how to estimate $\boldsymbol{\gamma}_{\perp}$ with reduced rank regression and eigenvector computations similar to those used in the Johansen technique for estimating the cointegrating vectors $\boldsymbol{\alpha}'\boldsymbol{P}_t$.[7] Most importantly, Gonzalo and Granger also develop a χ^2 distributed test statistic (Q_{GG}) for the elements of the common factor vector $\gamma_{\perp j}$. Because of the linear combination restriction on the $\gamma_{\perp j}$, these coefficients can be normalized and interpreted as a vector of factor weights on the underlying time series that together are responsible for the multivariate cointegration.

These common factor weights provide a direct test of intermarket price adjustment across cointegrated security markets. To examine the null hypothesis of two-way price adjustment, the common factor weights can be tested separately or in subgroups as significantly greater than zero – i.e., H_0: $\gamma_{\perp j} > 0$ and H_a: $\gamma_{\perp j} = 0$. Thus, one can test whether the NYSE is in fact responsible for revealing 100% of the common factor. As order flow continues to fragment, the comparisons allowed by these Q_{GG} statistical tests take on potentially pivotal meaning in the competition among satellite markets. Here, we use the common factor weights attributable to NYSE versus Pacific and Chicago trades to test for differences across these exchanges over the three years 1988, 1992 and 1995. We then relate these findings to a discussion of market shares and relative spreads over this period.

Other permanent–transitory decompositions and estimation procedures are available but are less well suited to the purpose at hand. King et al. (1991) and Quah (1992) restrict the dynamics of the idiosyncratic transitory components ε_t to be orthogonal to the permanent trend components w_t at all leads and lags. Instead, we have followed the example of Hall et al. (1992) in macroeconomic data, Gonzalo and Granger (1995) in interest rate data, and Tse et al. (1996) in Eurobond data by imposing the much less restrictive condition that no transitory component ε_t can Granger-cause any permanent trend component w_t. One advantage for stock price applications is that lagged information arrivals w_{t-s} (interpreted as lagged changes in the implicit efficient price ΔP_t) *are* allowed to affect the current level of the transitory component ε_t (interpreted as assessments of order imbalance by the specialist or limit order traders).

Another advantage of the Gonzalo-Granger decomposition is that it reproduces a kind of mimicking behavior observed in the actual data. In particular, the $B_{i,j,t-s}$ parameters in the second term of Eq. (7) refer to the short-run sensitivity of $\Delta P_{i,t}$ to lagged changes in idiosyncratic shocks $\Delta\varepsilon_{j,t-s}$ in the jth market. That is, some market participants are observing and imitating the idiosyncratic changes in the private value of other market participants. Autoquote sequences illustrate this mimicking

[7] For detailed accounts of the estimation procedures to obtain common factor results, see Johansen (1995, Chapter 8) and Gonzalo and Granger (1995). Hamilton (1994, Chapters 19 and 20), Enders (1995, Chapter 6), Booth et al. (1999), and Huang (2000) provide useful treatments of the relevant cointegration econometrics.

behavior.[8] Because of their realism, these information feedback and mimicking effects, both of which are defined and limited by Granger causality flowing from public to private assessments of new information, are particularly attractive stochastic processes for stock market microstructure research.[9]

Finally, the GG procedure also provides robust estimation of the common factor weights despite the presence of contemporaneous correlation of cross-equation, cross-market disturbances – i.e, the $u_{i,t}$ in the system of equations (7). Hasbrouck (1995) offers a related measure of the price discovery across cointegrated markets. However, Hasbrouck's information shares methodology depends on the ordering of variables in the Cholesky factorization of the residual covariance matrix, and the discrepancies between the orderings become large when the contemporaneuous correlation of disturbances across the markets increases (Tse, 1999; Huang, 2000). Hasbrouck's (1995) original study is unaffected by this problem because of his extremely high frequency (one second) resolution of quote data which effectively minimizes the cross-equation error covariance. Nevertheless, in other circumstances this non-uniqueness of the parameter estimates can pose a substantial difficulty in testing the relative magnitude of price discovery by one market, channel, or trading

[8] In Table 1 of Hasbrouck (1995) regional market makers mechanically mimic a misprinted NYSE quote one-tenth the normal price level and then revert when the error is corrected. Although this example is extraordinary for the magnitude of the error, the regional autoquote process is really quite routine. Beginning Monday August 28, 2000, seven stocks listed in the New York Stock Exchange (NYSE) started trading in decimals. We developed an algorithm to identify autoquotes that bracket the existing NYSE quote and calculated the percentage of time that each of these seven stocks was autoquoted during the week of August 28, 2000 as follows: APC, 71.3%; FCE/A, 38.3%; FCE/B, 38.8%; FDX, 66.8%; GTW, 72.0%; HUG, 73.5%; and MNS, 63.4%. It is evident that autoquoting is a frequent form of mimicking behavior. Importantly, the second term in Eq. (7) makes clear that such mimicking events are distinct from the question as to whether regional market-making is responsible in part for the common factor that drives *permanent* price moves in these cointegrated markets.

When regional exchanges choose to extract themselves from quote competition in listed stocks, they program a computer to intercept all NYSE/AMEX quotes and immediately update their own quote by adding a small amount to the ask and subtracting a small amount from the bid. Hence, an autoquote signals that the regional exchange is temporarily not competing on price. Autoquotes do not affect trade prices, but are potentially an important source of contamination in the use of quotes. Trades occur on the regional exchanges during periods of autoquoting, but those trades simply match or better the existing BBO.

[9] It is a matter of disputed opinion as to whether these highly desirable information feedback features of the GG decomposition come at too high price. Gonzalo and Granger (1995) promote their restriction of common factor components to contemporaneous prices as abstracting from future unobservables while Hasbrouck (2000) criticizes them for ignoring price history. Stock and Watson (1988) first showed that cointegrated series share common stochastic trends representable as a linear combination of the current *and lagged* permanent components of the underlying series. We are indebted to the referee for showing that the random walk portion of the Gonzalo-Granger common factor is identical to a Stock-Watson (1988) decomposition that incorporates lagged as well as current values of the time series. Indeed, the referee proved that a trading price sequence like our Eq. (4) can be derived by substituting the Stock-Watson decomposition into Gonzalo and Granger's (1995) definition of the common factor.

group versus another. In part for this reason, we adopt the Gonzalo and Granger common factor procedure to estimate and test our model.[10]

4. Empirical results

4.1. Data and cointegration tests

Our transaction data are taken from the Institute for the Study of Security Markets database for the years 1988, 1992, and 1995, where the trades with conditions code C, R, N, and Z are excluded, and the trades are error filtered. In a multi-market setting, because non-synchronicity is an alternative hypothesis explaining the serial dependencies in the data, one must maintain synchronicity in the data collection in order to test for the flow of information from one market to another. To acquire synchronous prices from the New York, Chicago, and Pacific exchanges, we form matched tuple data sets that minimize the span (i.e., the observation interval) between trades.[11] In Appendix A we explain the MINISPAN procedure and demonstrate the robustness of the common factor results across five other data collection procedures designed to simulate possible spurious lead–lag relationships in heavily traded stocks. Table 1 suggests the high frequency of this MINSPAN data collection procedure. For example, Philip Morris traded synchronously across the New York, Chicago, and Pacific exchanges 10,216 times in 1992 with an average span of 83 seconds. Most other DJIA stocks generated several thousand synchronous price tuples and exhibited spans from one-half to five minutes.

Prior to testing for cointegration of the three trading price series, we first determine the order of integration and an optimal lag length for the system of equations formed by the three price series in the levels. High frequency trade-to-trade stock price data are $I(1)$ series. We find the same holds true for our synchronous trading prices. For each of the DJIA stocks, one or two lags are indicated by the minimum Akaike information criterion in a systems estimation of

[10] From another point of view, we adopt a different methodology because intermarket price adjustment in synchronous trades is not the same thing as price leadership inferences in continuous quote data. In the time period of our study, regional exchanges and electronic crossing networks did not compete on quotes because the extant order-handling rules did not require that the market with the best quote receive an order. To investigate the error correcting adjustment dynamics of *trading prices* across venues required that we then narrow the focus to synchronous events – i.e., events in which all the markets report a trade within a minimum time span. In a careful and exhaustive simulation study of our GG estimation and data collection procedure relative to that of Hasbrouck (1995), Tse (2000) finds that the censorship of the sample that results from our excluding intervening observations in the high frequency market (NYSE) in order to focus on synchronous events across all three markets does not bias the common factor results. We investigate further this issue of the robustness of the common factor results to our data collection procedure in Appendix A.

[11] Following Blume and Goldstein (1997), all these studies of intermarket pricing adjust the time stamps in the Chicago and Pacific exchanges 16 and 5 seconds, respectively, to correct for minimum reporting lags.

Table 1
Statistics for tuples constructed using MINSPAN
For each firm each day, we construct tuples of synchronous trades on the New York, Chicago, and Pacific exchanges as follow. Omitting the first trade of the day, we observe the sequence of trades on each exchange. Our first tuple includes the first trade on the third exchange to trade. This tuple also includes the trade from each of the other two exchanges that is the closest in time to the first included trade. We repeat the process until all of the trades are exhausted. This data collection method is identical to that of Harris et al. (1995). Appendix A presents several checks for robostness of the results to these data collection methods.

		1988		1992		1995	
Firm	Symbol	No. Obs.	Span (seconds)	No. Obs.	Span (seconds)	No. Obs.	Span (seconds)
Aluminum Co. of America	AA	1,272	647	1,067	613	970	565
Allied-Signal	ALD	2,016	410	1,955	395	1,207	470
American Express	AXP	3,820	224	5,377	164	3,415	204
Boeing	BA	2,208	375	13,929	62	5,056	105
Bethlehem Steel	BS	2,936	279	1,330	609	2,390	291
Caterpillar	CAT	1,264	569	1,195	649	1,860	233
Chevron	CHV	4,081	216	3,585	240	3,107	206
DuPont	DD	1,995	335	2,638	297	1,628	315
Walt Disney	DIS	2,549	295	11,818	77	5,207	119
Eastman Kodak	EK	5,673	150	4,673	174	2,060	271
General Electric	GE	9,342	101	5,271	154	5,891	100
General Motors	GM	3,431	232	3,961	36	4,644	118
Goodyear Tire & Rubber	GT	1,561	553	1,130	66	2,418	186
International Business Machines	IBM	8,663	93	32,754	51	7,783	74
International Paper	IP	1,096	482	743	866	670	810
J. P. Morgan	JPM	896	700	1,255	507	2,109	807
Coca-Cola	KO	2,173	341	11,157	53	5,934	115
McDonalds	MCD	1,676	345	4,737	44	7,909	68
Minnesota Mining & Mfg.	MMM	1,954	307	2,059	332	4,189	159

Philip Morris	MO	2,682	288	10,216	83	5,816	98
Merck	MKR	2,738	247	21,326	47	8,139	78
Proctor & Gamble	PG	1,676	465	5,174	169	2,603	232
Sears Roebuck	S	5,408	169	3,276	252	2,261	222
AT&T	T	9,548	86	8,749	100	7,652	78
Texaco	TX	9,359	97	4,183	206	2,882	216
Union Carbide	UK	2,990	269	2,336	248	953	463
United Technologies	UT	1,711	501	1,067	606	559	838
Westinghouse	WX	1,970	406	7,639	111	2,395	245
Exxon	XON	6,197	146	6,394	203	2,551	222
Woolworth	Z	1,463	543	1,121	661	1,639	190

the unconstrained VARs. The Johansen cointegration test procedure is then run on the first differences of the logged series with two lags and no intercept. Under the iterated null hypotheses of $r = 0$, $r = 1$ cointegrating vectors we show the maximal eigenvalue test statistics for cointegration against the alternative hypotheses $r = 1$ or $r = 2$. In Table 2, for each of the DJIA stocks, both $r = 0$ and $r = 1$ are rejected at 99% significance. Therefore, $r = 2$, indicating two cointegrating vectors and one common trend.

By the Granger Representation Theorem, Chicago, Pacific, and New York trading prices therefore follow an error correction process whose equilibrium error is defined by the cointegrating vectors $\boldsymbol{\alpha}'$ in Eqs. (8′), (9) and (10). A quick indication of the arbitrage-free equality of these synchronous prices is reported in Table 2 where each of the cointegrating vectors sums to zero to two and three decimal places. While extraordinary, these cointegration results are hardly surprising given the high frequency of the synchronous trading and the impermanence of arbitrage opportunities in these closely watched DJIA stocks.

4.2. Common factor weights and information dominance

Table 3 displays our estimates of the Gonzalo-Granger factor weights $\gamma_{\perp i}$ that reflect the contribution of the Chicago, Pacific, and New York stock exchanges to revelation of the single common factor. The average $\gamma_{\perp i}$ attributable to the NYSE in 1988 is 72.2% and varies from 49% and 58% for Westinghouse and AT&T up to 92% and 95% for Merck and Goodyear. Most of these $\gamma_{\perp i}$ exceed the NYSE's 60–75% share of the trades in DJIA stocks and in some cases exceed the NYSE's 72–90% share of the dollar trading volume in DJIA stocks. Consequently, our 1988 results confirm Hasbrouck's (1995) finding that the NYSE is "information dominant".

However, the fragmentation of equity trading in the early 1990s suggests that competition for order flow is an evolutionary ebb and flow process (Shapiro, 1993). And this may be especially true for informed trades that move the markets since information traders are most likely to transact through markets whose narrow spreads attract liquidity traders (Benveniste et al., 1992). NYSE spreads did rise by an economically significant amount in 1990 and 1991 (Huang and Stoll, 1996a, b). We therefore reestimated the model on 1992 data.

The common factor weights for 1992 for the NYSE in Table 3 indicate a decline in the NYSE's proportion of the price discovery over the period 1988–1992. Some of the declines are enormous (e.g., GM from 82% to 41%, Merck from 92% to 36%, Philip Morris from 76% to 42%, and Union Carbide from 85% to 43%). Since the NYSE's share of the 1992 trading volume remained high (i.e., GM 80%, Merck 88%, Philip Morris 71%, Union Carbide 83%), the centralized market was not "information dominant" in these stocks. On average, among the 27 DJIA stocks that decline, the proportion of the price discovery attributable to the NYSE fell from

71.8% to 49.6%.[12] In the nine stocks with MINSPAN observation intervals of less than 90 seconds (Boeing, Walt Disney, General Motors, Goodyear, IBM, Coca-Cola, McDonald's Philip Morris, and Merck), the decline in the NYSE's price discovery from 1988 to 1992 is even larger – i.e., from 79% to 46%.

Again, recall that this error correction measure of intermarket price adjustment captures the resolution of price disparities after coincident but unequal price changes in synchronous trades. To the extent that the *information content* of the trades accounts for the increased NYSE spreads in the early 1990s, one would expect these spreads not to erode as a result of competitive processes. But to the extent that these increased spreads represent rents in excess of the ever-falling cost of execution, one *would* expect them to erode. Stoll (1995) reports that between 1992 and 1995, NYSE spreads *did* decline precipitously. If supra-competitive spreads in the early 1990s fragmented the order flow and drove off liquidity trades and noise trades, a reduction of NYSE spreads might well bring the uninformed order flow back, and Benveniste et al. (1992) argue that informed trades would soon follow. We therefore investigate whether by 1995 the incidence of NYSE trades that permanently move the markets had indeed returned to the much higher 1988 levels.

Table 3 shows that for thirteen of the DJIA stocks, this is precisely what occurred.[13] For these stocks the 1988–1992 decline in NYSE common factor weights proved temporary, and by 1995 the proportion of the common factor attributable to the NYSE equaled or exceeded its 1988 level. Another six DJIA stocks showed substantial increases in the NYSE's share of price discovery from 1992 to 1995 (Allied-Signal, Boeing, General Motors, Philip Morris, Merck, and Union Carbide), while three DJIA stocks (Eastman Kodak, Goodyear Tire & Rubber, Coca-Cola) increased 4–9 percentage points. Chevron, DuPont, GE, and MacDonald's remained at or near their 1992 lows. In only three cases (Aluminum Co. of America, J.P. Morgan and Exxon) did the NYSE's common factor weight continue to decline from 1988 through 1992 to 1995. For the DJIA stocks as a whole, the mean common factor weights for the NY, Pacific and Chicago exchanges in 1995 are 62.9%, 14.8%, and 22.3%.

4.3. Tests of common factor weights

At the end of this cycle of order flow diverting from the NYSE, competitive discipline eroding NYSE spreads, and then the order flow returning, it is clear that the regionals retain an increased role in revelation of the common factor. Merck

[12] Interestingly, the three stocks with a rising NYSE common factor weight from 1988 to 1992 (i.e., International Paper, Caterpillar, and Bethlehem Steel) have the first, third, and fifth longest MINSPANs in the 1992 DJIA data set at 866, 649, and 609 seconds, respectively. Apparently, when the most recent or next trade on the Chicago or Pacific exchange is 10–15 minutes away, informed trades execute in New York independent of whether higher spreads in New York are currently deterring liquidity trades in that trading venue in those stocks.

[13] American Express, Bethlehem Steel, Caterpillar, Walt Disney, International Business Machines, Minnesota Mining & Mfg., Proctor & Gamble, Sears Roebuck, AT&T, Texaco, United Technologies, Westinghouse, and Woolworth.

Table 2

Estimates and tests of cointegrating vectors

For each firm in our sample, we estimate the cointegrating vectors for the three series of synchronous trade prices. The coefficients sum to approximately 0.0, indicating that these data satisfy the linear no-arbitrage restriction underlying the theoretical and empirical models. These cointegrating vectors define the equilibrium errors that we employ subsequently in the estimation of the error correction version of the model. For each firm, we also present results of the maximum eigenvalue test of $r = 0$ against $r = 1$ and of $r = 1$ against $r = 2$. The 99% critical values for rejecting the null hypotheses are 26.15 and 18.78, respectively (Enders, 1995). To conserve space, we present results only for 1995. Test results and the confirmation of the linear restriction are essentially identical for the years 1988 and 1992.

Firm symbol	AA	ALD	AXP	BA	BS	CAT	CHV	DD	DIS	EK
First cointegrating vector: Sum of coefficients of equilibrium error	−0.013	0.043	0.010	0.008	−0.012	−0.016	0.018	−0.021	0.051	−0.008
Second cointegrating vector: Sum of coefficients of equilibrium error	0.027	0.004	0.006	0.014	−0.025	−0.055	−0.068	−0.024	0.009	−0.033
Test of $r = 0$ against $r = 1$	77.28*	74.98*	65.66*	65.08*	74.07*	66.93*	67.90*	67.82*	72.16*	69.18*
Test of $r = 1$ against $r = 2$	69.47*	67.23*	61.47*	62.16*	60.19*	54.67*	65.19*	64.23*	57.16*	61.85*

Firm symbol	GE	GM	GT	IBM	IP	JPM	KO	MCD	MMM	MO
First cointegrating vector: Sum of coefficients of equilibrium error	0.002	−0.002	−0.058	−0.05	−0.021	0.047	0.001	0.012	−0.029	0.000
Second cointegrating vector: Sum of coefficients of equilibrium error	0.021	−0.027	0.081	0.000	−0.011	−0.021	−5.217	0.007	−0.052	0.000
Test of $r = 0$ against $r = 1$	69.35*	67.50*	62.49*	59.20*	78.18*	70.64*	67.56*	64.76*	67.93*	58.80*
Test of $r = 1$ against $r = 2$	62.13*	62.01*	60.52*	52.40*	65.73*	64.45*	66.71*	63.19*	61.35*	56.70*

Firm symbol	MRK	PG	S	T	TX	UK	UT	WX	XON	Z
First cointegrating vector: Sum of coefficients of equilibrium error	0.000	−0.009	0.001	−0.017	−0.069	0.009	−0.030	−0.035	0.050	−0.027
Second cointegrating vector: Sum of coefficients of equilibrium error	−0.002	0.006	−0.025	−0.026	−0.007	−0.005	0.013	0.000	−0.032	0.063
Test of $r = 0$ against $r = 1$	66.52*	71.59*	67.25*	66.17*	73.55*	70.86*	71.48*	69.48*	69.24*	73.12*
Test of $r = 1$ against $r = 2$	57.59*	67.81*	64.30*	62.14*	63.96*	68.76*	57.14*	59.12*	68.46*	50.77*

*Significant at the 0.01 level.

Table 3
Proportion of price discovery, by exchange by year
For each of the three exchanges in our study for each year, we present the common-long memory factor weights (in percent), which are normalized so that for a given firm for a given year, the weights sum to 100%, except for rounding errors. Since we have three series ($n = 3$) and two cointegrating vectors ($r = 2$) there is only one common factor – i.e., one relevant vector of the common factor matrix orthogonal to the adjustment vectors. We test the elements of this last eigenvector of the common factor matrix for significance using the methodology developed by Gonzalo and Granger (1995). In each case the null hypothesis is that the factor weight for the indicated exchange is 0. The test statistic is distributed chi-squared with one degree of freedom.

	Chicago			Pacific			New York		
Firm	1988	1992	1995	1998	1992	1995	1988	1992	1995
Aluminum Co. of America	1	9	22	24	9	21	76	67	57
Allied-Signal	16*	38**	20	11	38**	16	72**	51*	64*
American Express	17*	33**	16*	19*	33**	21**	64*	43*	63*
Boeing	1	33**	34*	26**	33**	6	73**	44*	60**
Bethlehem Steel	15	12	23*	22	12	4	63	64	73**
Caterpillar	18*	26**	11	17*	26**	8	65*	70*	81**
Chevron	14*	35**	29*	16*	35**	20	70*	49*	51*
DuPont	8	31**	28	10	31**	21	82**	49*	51*
Walt Disney	8	25**	13**	13	25**	10*	79**	44*	77**
Eastman Kodak	13*	26**	43*	9	26**	1	78	49*	56*
General Electric	17*	23**	22*	17*	23*	20*	65*	58*	58**
General Motors	11	34**	31**	8	34**	2	82**	41*	67**
Goodyear Tire & Rubber	2	38**	16	3	38**	14	95*	61*	70**
International Business Machines	6	26**	12**	10	26**	3*	84**	43*	85**
International Paper	3	7	15	16	7	22	80	85	63
J. P. Morgan	30*	33	30	1	10	17	69**	57	53*
Coca-Cola	15*	27**	22**	15*	19*	20**	70**	54*	58*
McDonalds	18*	26**	29**	21*	25**	23**	60*	49*	48**
Minnesota Mining & Mfg.	3	26**	25*	28**	28**	7	69**	46*	68**
Philip Morris	9	33**	23*	15*	25**	17	76**	42*	60**

Merck	4	47**	17**	3	17*	15**	92**	36*	68**
Proctor & Gamble	9	33**	26*	23*	16*	6	68*	52*	68**
Sears Roebuck	25**	26**	10	12	26**	16	63*	48	74
AT&T	22*	27**	23**	20*	23**	20*	58*	50*	57**
Texaco	17*	20**	18**	22*	17*	12	65*	63**	70**
Union Carbide	8	36**	2	7	21*	35*	85**	43*	63*
United Technologies	14	10	30	17	37	1	68	55	69
Westinghouse	25*	33**	22*	26**	28**	31**	49*	40**	47**
Exxon	8	16*	31	10	23*	15	82**	61*	54**
Woolworth	23*	39	25	13	17	21*	64*	44	64**
Mean	12.6	27.5	22.3	15.2	20.6	14.8	72.2	51.9	62.9

*Significant at the 0.10 level.

**Significant at the 0.05 level.

trading is perhaps the most spectacular example of this phenomenon where the Pacific and Chicago exchanges barely contributed at all to revelation of the common factor in 1988 with common factor weights of 3% and 4%, and yet by 1992 their respective weights increased to 17% and 47%, respectively. In the most recent 1995 data, the common factor weights for Merck are NYSE 68%, Pacific 17% and Chicago 15%. We tested each common factor weight in Table 3. The null hypothesis is that prices revealed in trades on only two of the three markets contribute to the permanent components of prices; the tested market introduces only transitory components and will therefore exhibit a normalized common factor weight that is insignificantly different from zero. The five and ten percent significance levels reported in Table 3 are based on critical values for the Gonzalo-Granger Q_{GG} test statistic distributed χ^2 with one degree of freedom.

Focusing on the most recent 1995 data, the Pacific exchange exhibits a mean common factor weight in twelve DJIA stocks of 20% and a range from 3% in IBM to 35% in Union Carbide. The Chicago exchange has a mean common factor weight of 24% in twenty DJIA stocks ranging from 12% in IBM to 43% in Kodak. The NYSE has significant 1995 common factor weights in twenty-seven DJIA stocks from 48% in MacDonald's to 85% in IBM, averaging 63%. The 1995 common factor weights are all statistically significantly different from zero for all three exchanges in nine stocks, and one of the two regional market contributes statistically significantly to revelation of the common factor alongside the NYSE in twelve other stocks. These results confirm an independent role in revelation of the common factor for both regional exchanges.

To further assess the role of the regionals in this intermarket price adjustment process, we tested the joint hypothesis that neither of the regional markets contributes to revelation of the common factor. Table 4 lists the chi-square Q_{GG} test statistic and p-values for this test. We can reject the null hypothesis for six stocks in 1988, for nineteen stocks in 1992, and for eleven stocks in 1995.[14] Hence, again, the test results support the view that the regionals contribute significantly to revelation of the common factor.

Next, for each exchange, we investigate whether the changes in factor weights over time are statistically significant using a paired t-test. First we compare the years 1988/1992 for the Chicago exchange. For each firm we subtract the observations for the first year from those of the second, and calculate the mean (M) and standard deviation (S) of these differences. The test statistic, $(M/(S(n-1)^{0.5}),\ n = 30)$ has a t-distribution. We replicate this test for the Chicago exchange comparing the years 1992/1995 and 1988/1995, in turn. Then we replicate the entire analysis for the Pacific and New York exchanges, so that we have (3 exchanges $\times$ 3 pairs of years) nine test statistics, which are reported in Table 5. As we saw earlier, over the entire

[14] Aluminum Co. of America, American Express, Chevron, GE, Coca-Cola, AT&T, McDonald's Philip Morris, Merck, Westinghouse, and Exxon.

Table 4
Test of the null hypothesis that 100% of the price discovery occurs on the NYSE
Using the Gonzalo and Granger (1995) Q_{GG} statistic, we test the null hypothesis that the factor weight for the NYSE is 1 and that the factor weights of the other two exchanges are both 0. The test statistic is distributed chi-squared with two degrees of freedom.

	1988		1992		1995	
Firm	χ^2	p-Value	χ^2	p-Value	χ^2	p-Value
Aluminum Co. of America	0.70	0.40	1.06	0.30	6.39**	0.01
Allied-Signal	1.01	0.32	2.55	0.11	1.23	0.27
American Express	2.65*	0.10	12.69**	0.01	2.94*	0.09
Boeing	1.04	0.31	21.89**	0.01	2.27	0.13
Bethlehem Steel	2.24	0.13	2.79*	0.10	1.97	0.16
Caterpillar	0.79	0.40	1.22	0.27	0.30	0.58
Chevron	1.48	0.22	5.75*	0.02	3.86*	0.05
DuPont	0.21	0.64	3.56*	0.06	2.08	0.15
Walt Disney	0.44	0.51	0.19	0.66	0.70	0.40
Eastman Kodak	0.67	0.41	8.99**	0.01	1.85	0.17
General Electric	3.09*	0.08	4.94**	0.03	4.56*	0.03
General Motors	0.46	0.50	13.49**	0.01	2.09	0.15
Goodyear Tire & Rubber	0.02	0.87	0.87	0.35	1.17	0.28
International Business Machines	0.52	0.47	60.11**	0.01	0.24	0.63
International Paper	0.26	0.61	0.56	0.36	0.05	0.82
J. P. Morgan	1.02	0.31	1.49	0.22	1.71	0.19
Coca-Cola	0.95	0.33	0.56	0.45	4.43*	0.04
McDonalds	1.79	0.18	5.12**	0.02	10.93**	0.00
Minnesota Mining & Mfg.	1.03	0.31	4.10**	0.04	1.17	0.19
Philip Morris	0.49	0.48	9.05**	0.01	2.83*	0.09
Merck	0.01	0.97	0.64	0.42*	3.81	0.05
Proctor & Gamble	0.99	0.32	0.64	0.42	1.52	0.22
Sears Roebuck	2.95*	0.09	5.77**	0.01	0.06	0.81
AT&T	7.37**	0.01	15.54**	0.01	4.66*	0.03
Texaco	3.04*	0.08	3.31*	0.07	1.61	0.20
Union Carbide	0.23	0.63	1.47	0.22	1.33	0.25
United Technologies	0.85	0.35	2.68*	0.10	0.60	0.46
Westinghouse	2.20	0.14	20.98**	0.01	8.76**	0.00
Exxon	0.74	0.39	2.72*	0.01	3.62*	0.06
Woolworth	0.65	0.42	3.03*	0.08	2.20	0.14

* Significant at the 0.10 level.
** Significant at the 0.05 level.

1988–1995 period, we cannot reject the hypothesis that the NYSE factor weights are the same. However, we do reject the null hypothesis that the differences are zero at the 0.01 level for both regional exchanges for all pairwise comparisons and for the NYSE over 1988–1992 and 1992–1995. Hence, the contribution of the NYSE and satellite trading venues to revelation of the common stochastic trend in Dow stock prices does vary over time.

Table 5
Results of tests for variability of common factor weights over time
Consider first the coefficients for the Chicago exchange. For the first pair of years (1988/1992), we subtract the observations for the first year from those for the second, giving thirty paired differences ($n = 30$). Denote the mean and standard deviation of these differences by M and S, respectively. We calculate a t-statistic as follows: $M/(S/(n-1)^{0.5})$. This procedure is repeated for the remaining pairs of years for the Chicago exchange and for all three pairs of years for each of the other two exchanges, producing nine test statistics.

	Chicago	Pacific	New York
1988/1992	7.07*	−7.45*	4.34*
1992/1995	−2.23*	−4.52*	−3.88*
1988/1995	4.71*	−4.02*	−0.14

*Significant at the 0.01 level.

4.4. Discussion of results

4.4.1. Related theoretical literature on centralized versus decentralized security markets

The low-cost matching of buyers and sellers with selective execution on electronic trading systems (ETSs) contrasts with the reputation of centralized exchange specialists for price improvement in specific segments and differential execution quality at specific depths (Easley et al., 1996a). Immediacy, reliability, and price impact do vary both across trading venues and intraday, and these characteristics may not be verifiable to the trader at the time of placing an order. Institutional traders therefore routinely perform retrospective (backcasting) studies to rank each dealer or specialist's execution quality, and reputations therefore become pivotally important. In any such market-making regime with unobservable or unverifiable execution quality, price premiums for some execution services are required in competitive equilibrium (Klein and Leffler, 1981). By hypothesis, such price differentials correlate with sustained high execution quality and exist even if all customer segments trade and search with equal skill and frequency. Aitken et al. (1995) show that broker reputations for high quality facilitation services earn price premiums in decentralized, competitive security markets with adverse selection and long-lived traders.

Other theoretical research on market-making has emphasized the distinct role played by centralized intermediaries (e.g., Mookherjee and Reichelstein, 1992; Rock, 1996). Benveniste et al. (1992) argue that the greatest advantage of a centralized exchange specialist arises when informed traders are most likely to meet liquidity traders who are sensitive to the size of the spread. In that case, reducing competition in specialist trading and concentrating the uninformed order flow in the centralized exchange lowers the cost-covering asymmetric information component of the equilibrium spread. In addition, relative to matching buyers with decentralized sellers on ETSs or in satellite markets, a monopoly intermediary invests in more quality-assurance monitoring mechanisms in order to secure a reputation for high execution quality. Centralized intermediaries can therefore reduce the price premium necessary to sustain high-quality transactions under adverse selection (Biglaiser, 1995).[15] This implies that, for any given level of asymmetric information, the equilibrium cost-covering spread can be lower on a centralized exchange. However, with some market power, centralized market-makers are likely to raise and lower these spreads over time in response to market pressures and reputational objectives.

4.4.2. Three hypotheses about informed trades and the competition for order flow

The NYSE, Pacific and Chicago Stock Exchanges compete against NASDAQ dealers and electronic trading systems (ETS) such as ASX, Instinet, Medoff, and Posit. The centralized market offers a higher execution reliability in posted price transactions, while the matching systems offer a better price albeit for narrowly selective executions (Easley et al., 1996a). Yavas (1992) and Gehrig (1993) argue that the ‘‘match-makers’’ execute for buyers and sellers whose reservation price and willingness to pay fall within the market-maker's equilibrium bid–ask spread. One hypothesis is that these within-the-spread transactions represent uninformed liquidity trades or noise trades. ‘‘Cream skimming’’ such transactions from the centralized exchange would result in an NYSE specialist, with obligations to trade, having fewer pooling opportunities over which to spread the risk of being uniformed. Equilibrium spreads on the NYSE would then increase as the specialist (and uninformed investors on the NYSE) raised their intraday required return to recoup expected losses from trading against superior information (Brennan and Subrahmanyam, 1996).[16]

As ASX, Instinet, Medoff, and Posit emerged in the early 1990s, both NYSE and NASDAQ spreads did rise substantially (Huang and Stoll, 1996a,b). Since these increases were economically significant, they could well have made the screen-based ETSs as well as some regional markets a lower transaction cost alternative. If there were no other systematic differences in the costs of executing on the various exchanges,[17] one would expect spread-sensitive uninformed NYSE order flow to decline. And Benveniste et al. (1992) argue the NYSE specialists would then be less likely to attract information traders. This *Spread-sensitive-uninformed-order-flow hypothesis* can therefore explain our results showing the reduced incidence 1988–1992 of NYSE trades that permanently move the markets.

To further investigate the relationship between diversion of uninformed order flow and a decline in information-based trading, we calculated the NYSE share of the trading volume for each DJIA stock for each year. These results are displayed in

[15] In Biglaiser's (1995) model most high-quality transactions are traded through the centralized intermediary, and most low-quality transactions are traded through the matching market.

[16] Spreads may also rise in the presence of cream skimming because of an increase in the specialist's inventory holding costs.

[17] Differential spreads could of course reflect differential price impact for various trade sizes (i.e., differential market depth). We agree with Hasbrouck (1995) that the issue of market depth and relative liquidity for a given price innovation are fertile areas for future research on price discovery. They are, however, beyond the scope of the present study.

Table 6
NYSE market share, by year
For each year for each stock in the DJIA, this table shows the ratio of NYSE dollar volume of trading to the sum of NYSE + Midwest + Pacific dollar volume of trading multiplied by 100.

Firm	1988	1992	1995
Aluminum Co. of America	89	91	89
Allied-Signal	87	89	89
American Express	88	87	86
Boeing	90	80	83
Bethlehem Steel	83	87	80
Caterpillar	85	87	82
Chevron	85	91	89
DuPont	85	85	83
Walt Disney	85	87	82
Eastman Kodak	89	84	83
General Electric	87	89	82
General Motors	86	80	84
Goodyear Tire & Rubber	88	92	89
International Bus. Machines	85	83	82
International Paper	88	87	88
J. P. Morgan	87	87	87
Coca-Cola	86	87	82
McDonalds	88	89	83
Minnesota Mining & Mfg.	86	80	80
Philip Morris	72	71	77
Merck	88	88	95
Proctor & Gamble	87	85	83
Sears Roebuck	81	89	85
AT&T	86	86	84
Texaco	83	83	83
Union Carbide	88	83	83
United Technologies	89	91	90
Westinghouse	89	78	76
Exxon	78	84	84
Woolworth	88	90	76
Mean	85.9	85.7	84.0

Table 6. Only six DJIA stocks (in boldface) exhibit the substantial decline in 1992 order flow indicative of the *spread-sensitive-uninformed-order-flow hypothesis* – i.e., Boeing, Eastman Kodak, General Motors, Minnesota Mining & Mfg., Union Carbide, and Westinghouse. In each instance, we correlated the time series of NYSE market shares with the NYSE's common factor weight for that year. The *spread-sensitive-uninformed-order-flow hypothesis* implies a positive relationship. Pooling the three-year time series for the six stocks, the correlation coefficient is 0.687, significant with a p-value of 0.003. Including in the pooled time-series cross-section analysis all eleven securities whose market shares declined from 1988 to 1992, the correlation is

0.383, significant with a p-value of 0.04. Given that we have only three years for observation, the results in favor of Benveniste, Marcus, and Wilhelm's hypothesis are surprisingly strong for these eleven stocks. Of course, as the referee points out, other securities have very different market share time paths, and in some cases, a negative correlation between the NYSE's share of the trading volume and the common factor weight. The overall correlation coefficients for all thirty stocks is insignificantly different form zero – i.e., 0.011 (p-value, 0.313).

A second hypothesis consistent with our findings is that the declining price discovery on the NYSE may reflect an exodus of institutional trades from (and a later return to) New York's upstairs matching market. Institutions do search for price improvement being offered to other segments of the NYSE order flow or available on other trading venues, especially on quote-driven ETSs and to a lesser extent on regional exchanges. Keim and Madhavan (1995, 1996) analyze this aspect of the competition for order flow with a rich data set on equity institutional trades. Remember that our error correction approach to price discovery focuses on the resolution of price disparities after coincident but unequal changes in synchronous *trading* prices. Screen-based ETSs may be where this type of price arbitrage activity by uninformed institutional traders can operate most efficiently. At the same time, the updating of *quotes* to incorporate permanent innovations in the price discovery process could proves quicker and more efficient on the NYSE, consistent with Hasbrouck's (1995) results.

Under this *allowed-trading-practices hypothesis*, price discovery in the synchronous *trades* would return to the New York exchange only after differential price improvement for other segments of the NYSE order flow ceased. Hidden limit orders and some stopped order practices *were* curtailed by the NYSE in June 1995. Uninformed institutional order flow would then reappear thereby attracting trades that permanently move the markets. In addition, the unbundling of trade reporting between 1992 and 1993 partially explains the increased NYSE share of the trades towards the end of our time period. Rule 144 bloc trades also may have contributed to this return of the institutional order flow to New York. Under this rule change, blocs of a sufficient size can now cross on the NYSE without clearing out the order book. Changes in the allowed trading practices on the centralized exchange are therefore consistent with the inception by 1995 of the return of institutional order flow volume and informed trading to New York.

Finally, a third hypothesis consistent with our findings is that asymmetric information differs in predictable ways across trading venues and across trade size or other customer segments within a venue (Barclay and Warner, 1993). Easley et al. (1996b), for example, develop a method for estimating the probability of information-based trading across ninety randomly-selected active and inactive NYSE stocks. By rerouting less informed orders eligible for selective execution at low spreads to ETSs or regional specialists, trading practices like preferencing and payment for order flow, which might differ over time, may have concentrated informationally-advantaged trades in the centralized market (Easley et al., 1996a). To the extent such trades reflect innovations in the *permanent* component of the pricing process, the NYSE's proportionate weight in the common factor would rise from 1992 to 1995, *independent of a falling overall level of spreads*.[18] Nevertheless, this *institutions-of-trading hypothesis* has the distinguishable implication that supra-competitive NYSE spreads (in excess of specialist cost) could erode at the same time that the probability of informed NYSE trading and the NYSE's common factor weight increased. This prediction is consistent with our 1992–1995 common factor findings for twenty-five of the DJIA stocks reported in Table 3 and with Stoll's (1995) result that NYSE and NASDAQ spreads did decline precipitously 1992–1995. Battalio et al. (1997) provide specific evidence of declining 1995 spreads in NYSE-listed stocks subject to preferencing.

5. Summary and conclusions

This paper models the resolution of coincident but unequal price changes in synchronous trades (i.e., trading price discrepancies) on the New York, Chicago, and Pacific stock exchanges for the years 1998, 1992, and 1995. We estimate common factor weights that indicate the proportion of the permanent component of DJIA stock price adjustments attributable to the three most active specialist exchanges. The common factor weights signify the incidence of trades that permanently move prices on these three markets.

For many DJIA stocks our 1988 common factor results confirm Hasbrouck's (1995) finding that the NYSE was "information dominant" in discovering DJIA stock prices with factor weights from 63% to 95% (averaging 72.2%) and market shares of the trading volume from 72% to 90%. However, competition for informed and uninformed order flow is an ebb and flow, dynamic process. Estimating these same factor weights attributable to the NYSE's price discovery for 1992 reveals very different results. Across twenty-seven of the DJIA thirty stocks, the NYSE common factor weight declined. For sixteen of the DJIA stocks, the NYSE factor weight declined below 50%, and the average common factor weight attributable to the NYSE dropped to 51.9%. By 1995, the NYSE's common factor weight had returned to its historical level for thirteen Dow stocks and partially recovered for nine others. Notably, however, even after the return of much of the informed order flow to New York, in 1995 the regional exchanges continued to make a statistically significant contribution to revelation of the common factor for eleven of the 30 DJIA stocks.

Examining several hypotheses to explain the temporary decline in NYSE common factor weights between 1988 and 1992, we identify supra-competitive NYSE spreads as one possible cause. By 1995, NYSE spreads eroded to more competitive levels, and the common factor weights for DJIA stocks indicate that a majority of the revelation of the common stochastic trend (62.9%) was again attributable to the NYSE, 14.8% was attributable to the Pacific Exchange, and 22.3% was attributable

[18] Directly estimating the asymmetric information component of NYSE and regional spreads here is prevented by the clock time interruptions between synchronous trading events implemented through our MINSPAN procedure.

to the Chicago Exchange. In 1992, the data reveal that the regional exchanges attracted a substantially greater proportion of the trades that move the markets.

In future research using this error correction approach to intermarket price adjustment, we hope to identify what cross-sectional factors determine whether a particular security's common factor becomes revealed primarily in the centralized as opposed to the satellite markets. In addition, we have begun a time series analysis of the common factors for various trading venues over several decades from the origins of the NTIS system to the onslaught of the ECNs in the late 1990s. Finally, an exciting new direction is the application of these error correction techniques to modeling depth at the quote and other measures of liquidity.

Appendix A

In this Data Appendix, we first describe the MINSPAN data collection procedure and five alternative procedures that can be used to check MINSPAN for robustness, each simulating the possible effect of spurious lead–lag correlations on our results. In Section A.2, we report the results of estimating the common factor weights with each of these data collection procedures for several stocks in our sample.

A.1. Data collection procedures

Suppose we have three markets, designated a, b, and c, on which trading is conducted. In every case we omit the first trade of the day. Assume that we collect data at very small clock time intervals so that there is at most only one trade per period. Each such period is represented by a separate frame in the diagram below. For a given market, we signify the first trade using the subscript 1, the second trade using the subscript 2, and so forth. Our goal is to collect tuples comprising one trade on each market, where the trades are matched in time as closely as possible. Assume the following sequence of trades:

a_1	b_1	c_1	c_2	c_3			b_2	a_2	c_4	b_3	b_4	a_3		c_5	b_5	a_4	c_6	b_6

1. MINSPAN: Our primary data collection procedure, which we call MINSPAN, attempts to minimize the number of periods (or more generally, the time) between trades. We begin our analysis with the first trade of the day on each market, omitting the opening trade. The third market to trade is included in our first tuple. We also include the trade in each of the other two markets that is closest in time to this trade. Hence, the trades on the other two markets can occur before or after the first trade included. Once a tuple is collected, we begin the procedure again. For the sequence of trades above, the MINSPAN procedure results in the following tuples: $a_1b_1c_1$, $b_2a_2c_4$, $c_5b_5a_3$. In this example, $c_5b_5a_3$ and $c_5b_5a_4$ have the same span. Our procedure retains the first tuple $c_5b_5a_3$. When we measure

span in seconds rather than in periods, the number of times that we have two adjacent observations that give exactly the same span is very small.

Modified MINSPAN. By limiting MINSPAN to a specified length, we can limit our analysis to fast markets.

2. REPLACEALL: In this procedure, after all three markets have traded, we create a tuple from the most recent trade on each market and then begin the process again. For the sequence of trades given above, this procedure leads to the following tuples: $a_1b_1c_1$, $c_3b_2a_2$, $c_4b_4a_3$, $c_5b_5a_4$.
3. XFIRST: This procedure forces a trade on market X to be the first trade of every tuple. Once a trade on market X has occurred, the next trade on each of the other two markets are collected to form a tuple. For the trading sequence given above, this procedure results in the following tuples with a, b, and c first, in turn: AFIRST, $a_1b_1c_1$, $a_2c_4b_3$, $a_3c_5b_5$, $a_4c_6b_6$; BFIRST, $b_1c_1a_2$, $b_4a_3c_5$, $b_5a_4c_6$; CFIRST, $c_3b_2a_2$, $c_4b_3a_3$, $c_5b_5a_4$.

A.2. Robustness of results

In Table 7 we report the results of a robustness check on the MINSPAN using these five data collection procedures. The stocks we use for this exercise were as follows: two of the DJIA most thickly traded, shortest span (1–2 minutes) stocks – IBM and Coca-Cola (KO), two moderate span (4–5 minutes) stocks – Caterpillar (CAT) and Eastman Kodak (EK), and one of the DJIA's longest span (9–10 minutes) stocks – Aluminium Company of America (AA). For all five stocks, MINSPAN results from Table 3 are repeated in the first column of Table 7 for convenience in making comparisons.

To address concerns about the spurious serial correlation that could result from MINSPAN tuples containing a price (for the less active market) from a previous tuple, we reestimated the common factors with REPLACEALL, which replaces all the trades before capturing another observation. In the second column of Table 7, the spans, significance tests, and even the common factor estimates themselves are virtually identical to the results for MINSPAN for IBM and KO. REPLACEALL does increase the common factor weight for the high frequency market (NYSE) for the moderate span stocks. In the case of Caterpillar, the parameter for NYSE price discovery rises by approximately ten percent (from 0.81 to 0.91). The conclusions from the significance tests remain identical however. The statistical insignificance of both regional common factors here in the REPLACEALL results is consistent with their statistical insignificance in the MINSPAN results. Notice, in addition, that the joint test of whether the regionals do not contribute to price discovery in 1995 trading of Caterpillar (reported in Table 4) is consistent with these single parameter estimates. In the case of Eastman Kodak, the NYSE factor weight rises from 0.56 to 0.72. In both MINSPAN and REPLACEALL, the significance tests confirm the role of the Chicago Exchange and the NYSE. Even in the longest span stock – AA, the parameter results for MINSPAN and REPLACEALL are virtually identical. We conclude therefore that no substantial spurious correlation arises from looking back

Table 7
Alternative synchronous tuple collection procedures
We present the results of the estimation of the Gonzalo and Granger (1995) common-long memory factor weights for five alternative data collection procedures using data for 1995. As explained in Appendix A, REPLACEALL, CHICAGOFIRST, PACFIRST, NYSEFIRST are alternatives to MINSPAN for sampling these data.

		MINSPAN	REPLACEALL	CHICAGOFIRST	PACFIRST	NYSEFIRST
IBM.95	Obs	7,783	9,408	7,048	8,120	8,838
	Span	74	73	75	76	79
	CHI	0.12**	0.12 * *	0.13 * *	0.11 * *	0.12 * *
	PAC	0.03*	0.03*	0.06*	0.02*	0.03*
	NYSE	0.85 * *	0.85 * *	0.81 * *	0.87 * *	0.85 * *
KO.95	Obs	5,934	8,136	6,187	6,576	7,414
	Span	115	111	104	108	113
	CHI	0.22*	0.21*	0.14*	0.18	0.18*
	PAC	0.20*	0.20 * *	0.19 * *	0.26 * *	0.24 * *
	NYSE	0.58 * *	0.59 * *	0.67 * *	0.56 * *	0.58 * *
CAT.95	Obs	1,860	2,747	1,967	2,381	2,593
	Span	266	211	204	207	210
	CHI	0.11	0.06	0.04	0.05	0.03
	PAC	0.80	0.03	0.02	0.02*	0.05
	NYSE	0.81*	0.91 * *	0.94 * *	0.93 * *	0.92 * *
EK.95	Obs	2,060	2,724	2,232	2,034	2,588
	Span	271	274	265	264	273
	CHI	0.43 * *	0.22*	0.34*	0.31	0.26*
	PAC	0.06	0.06	0.04	0.05	0.06
	NYSE	0.56 * *	0.72 * *	0.62 * *	0.64 * *	0.68 * *
AA.95	Obs	970	1,296	1,043	1,008	1,255
	Span	565	567	523	561	564
	CHI	0.22	0.28	0.37	0.40	0.26
	PAC	0.21	0.12	0.13	0.02	0.16
	NYSE	0.59	0.60	0.50	0.58	0.58

*Significant at the 0.10 level.
**Significant at the 0.05 level.

to capture a recent trade in a less frequent market, even if that trade appeared in the previous tuple.

To address concerns about the spurious serial correlation that could result from systematic patterns of bid–ask bounce across the central and regional markets, we reestimated the common factors with each market's trades initiating the collection of a data tuple. Remember that in our trading price framework, fast updating of the quotes to reflect an information event does not result in price discovery. If the NYSE leads on quote revision, and the regionals update more slowly but match the BBO quote when they trade, no trading price divergence is ever observed, no error correction is necessiated, and no price discovery occurs. Only when the market makers (or their limit order placers) assess the information differently enough to actually execute a trade at a divergent price can the error correction approach to price discovery come into play. Conceivably, under the one way price discovery hypothesis, a quick trade at a new price on the satellite markets could preceed any trades in the centralized market even though the latter had first updated the quotes. To account for this possibility, we recollected the data forcing each market to be the first price in the tuple. The results are reported in the last three columns of Table 7.

Again, the parameter estimates are very similar. Some patterns do emerge. Resampling each time the NYSE trades (in NYSEFIRST) results in more observations but virtually identical spans to MINSPAN. In the two cases where the NYSE common factor is different (in Caterpillar and Eastman Kodak), it is larger with NYSEFIRST. But in two other cases, the common factor for the centralized market in the first and last columns is identical (i.e., 0.85 for IBM and 0.58 for KO). Relative to MINSPAN, the centralized market common factor is generally *higher* when the lower frequency markets are sampled first. Compare the NYSE parameter 0.67 for Coca-Cola in CHICAGOFIRST to 0.58 with MINSPAN; compare the 0.94 and 0.93 for Caterpillar with CHICAGOFIRST and PACFIRST to 0.81 for MINSPAN; compare the 0.62 and 0.64 for Kodak with CHICAGOFIRST and PACFIRST to 0.56 for MINSPAN. These results would appear to suggest that some bias results from the ordering within tuples. We have the most confidence in data collection procedures like MINSPAN that do not ignore intervening trades in order to wait for a particular market to trade first.

Finally, we are indebted to the referee for suggesting that as trading thins out, the ordering of trades in a synchronous trades sampling procedure can result in spurious serial correlation. We managed to capture this effect in the PACFIRST simulation with one of our sample stocks. In Eastman Kodak, when the lowest frequency market (PACIFIC) is forced to be the first price collected in each tuple, the otherwise consistently significant role of the Chicago exchange in price discovery is misestimated to be insignificantly different from zero. When one also notes that many of the common factor parameters in Aluminium Company of America (9–10 minutes spans) exhibit instability and statistical insignificance, it is fair to point out that the error correction approach we adopt may well be limited in its applicability to more thickly-trades stocks. At the 1–5 minute spans that characterize most DJIA stock trading and arbitrage activities, however, the MINSPAN procedures we propose appear sound. Again, Tse (2000) imputes trading prices to one-second intervals of non-trading using our entire data set and finds no stock for which our MINSPAN procedure introduces censorship bias.

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