THE DYNAMICS OF PRICE ADJUSTMENT ACROSS EXCHANGES:

AN INVESTIGATION OF PRICE DISCOVERY FOR DOW STOCKS

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ABSTRACT

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This paper employs error correction techniques to detect trades that permanently move the markets by estimating the location and magnitude of price discovery across three informationally-linked stock exchanges. We argue that after coincident but unequal price changes in synchronous trades, discovery of the new equilibrium price occurs in that trading venue to which other markets error correct. Common factor estimation (Gonzalo and Granger, 1995) summarizes each market's proportion of the price discovery in this error correction sense.

Across the DJIA stocks in 1988, the average common factor weight for the NYSE (72%) closely matched its share of the trades. The centralized market was "information dominant." However, by 1992 the proportion of the price discovery attributable to the NYSE had declined precipitously for 27 of the DJIA stocks, averaging only 49.6%. The NYSE's share of price discovery recovered substantially by 1995. Our tests confirm that these changes in the location of price discovery over time are statistically significant.

JEL Classification: G12

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1.1. Introduction

In this paper, we investigate price discovery on the New York, Chicago, and Pacific stock exchanges using 1988-1995 data for the thirty stocks comprising the DJIA. Our work focuses on the dynamics of adjustment of 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 the divergence reflects differences of opinion, sometimes market frictions, and sometimes differences in depth at the prior quote. In any event, subsequent arbitrage forces the prices together so that two of the exchanges error-correct to the price first posted by the remaining exchange. If the new prices persist, this third exchange provided price discovery, and it is this error correction that we measure and test.

Our error correction modeling (ECM) approach to price discovery is based on Harris, McInish, Shoesmith, and Wood (HMSW, 1995) and Tse, Lee and Booth (1996), but extends previous ECM work on price discovery 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, it remains an open question whether their results can be generalized to other active stocks. Second, to isolate the common factor(s) attributable to each of the three competing exchanges, we employ a synchronous data collection procedure for multi-market trading (i.e., MINSPAN) and investigate the robustness of our price discovery results to several changes in that procedure. Third, we formulate for each of the stocks a Stock-Watson (1988) common stochastic trend as a weighted average of the contemporaneous observed price series. Specifically, we employ the reduced-rank Johansen estimation procedure of Gonzalo and Granger (1995) to estimate and test the components of the common factor undelying the permanent trend in each stock. The higher the component weight of an exchange, the bigger the contribution to price discovery of that exchange. Finally, we test these common factor components for statistical 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 now often splits large portfolio rebalancing orders into thirty or forty trades that are executed through an ECN. Trading through crossing networks like those operated by Instinet and ASX has also greatly increased. Selective diversion of orders for NYSE-listed securities to off-NYSE venues may significantly affect the information content reflected in the order flow remaining on the floor.

For many of the DJIA stocks, we find that the contribution to price discovery of all three exchanges is statistically significant. We also find that competition for order flow is an evolutionary ebb and flow process (Shapiro, 1993). For example, in 1988, the NYSE's proportionate weight in the common factor for GM and Kodak, is 82% and 78%. Estimating the common factor weights for 1992 reveals a very different result. The NYSE common factor weight for GM and Kodak falls to 41% and 49%, respectively. These results mirror the NYSE's decline over the same period for IBM from 84% to 43%. Declining common factor weights emerge for twenty-seven of the 30 DJIA stocks between 1988 and 1992 with a mean factor weight in 1992 of 49.6%. For the DJIA stocks as a whole, the proportion of price discovery attributable to the NYSE fell from 72% to 52%. By 1995, however, common factor weights for the NYSE recovered fully to equal or exceed 1988 levels for thirteen DJIA stocks. For example, the NYSE’s proportion of the price discovery for GM, Kodak, and IBM recovered to 67%, 56%, and 85%, respectively. We conjecture that these changes in the location of price discovery are associated with the competitiveness of the NYSE’s spreads, depths and immediacy. NYSE spreads did widen 1990-1992 (Huang and Stoll, 1996a and 1996b). Then, in response to the success of the innovative ECNs during 1992-1995, the NYSE spreads retightened (Stoll, 1995).

1.2. 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; i.e., trades that permanently move the markets. In a multi-market microstructure setting, after coincident but unequal price changes in synchronous trades, discovery of the new equilibrium price occurs in that trading venue to which other markets error correct. Our primary reason for an interest in cointegrated stock price series exhibiting error-correcting adjustments is that their common factors can be used to estimate and test the relative magnitude of price discovery attributable to any given market. As shown by Gonzalo and Granger (1995) and discussed below (in Section 2), the common factors are permanent trend components orthogonal to the error-correcting adjustments and can be estimated as linear combinations of the underlying observable price series. For each of the DJIA stocks, this paper estimates the proportionate factor weight of the common long-memory component attributable to the New York, Chicago, and Pacific exchanges for 1988, 1992, and 1995.

This error correction 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 their subsequent readjustment to a common stochastic trend. Consequently, we move on to analyze the next 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 new common trend differs from short-run dynamics during the intervening trades. In addition, Lo and MacKinlay (1990) demonstrate that spurious serial correlation may result from taking non-synchronous observations on returns that are serially uncorrelated in continuous time. We therefore devote considerable effort to checking the robustness of the results to our MINSPAN data grouping procedure that seeks to minimize the spurious lead-lag relations that could result from observing imperfectly synchronous trades. For all these reasons, we present in section 2 below a model of *synchronous* trading price adjustment across informationally-linked markets that exhibit common stochastic trends.

The competition among specialists and other market makers for uninformed order flow based on depth, immediacy, and spreads attracts trades that permanently move the markets. Hasbrouck (1991, 1993, 1995), Lee (1993), Harris, McInish, and Wood (1994), Keim and Madhavan (1995), Harris, McInish, Shoesmith and Wood (1995), Blume and Goldstein (1996), and Easley, Kiefer and O'Hara (1996) have analyzed empirically various aspects of this informed order flow. Hasbrouck (1991) modeled the persistent effects of trade innovations on vector autoregressions of stock prices. Hasbrouck (1993) proposed 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. Hasbrouck (1995) incorporated multiple cointegrated markets as possible sources of a common innovation variance in NYSE-listed *quotes*. For the DJIA stocks in August-October 1993, he found 91% of the price discovery attributable to the NYSE quotes, and this proportion exceeded the NYSE's 84% share of the August-October 1993 trading volume. The NYSE was therefore characterized as "information dominant."

Other recent cointegration-error correction research reveals the adjustment dynamics of the *trading price process*. Using careful time matching of the trades on the New York, Chicago, and Pacific stock exchanges, Harris, McInish, Shoesmith and Wood (1995) show that 1990 IBM prices on these three informationally-linked markets are cointegrated and follow a multi-lateral error correction process. That is, prices on the NYSE as well as the satellite specialist markets error correct to eliminate disparities between NYSE and Pacific or NYSE and Chicago prices. This multi-lateral resolution of pricing disparities in synchronous trades implies that some permanent price changes are attributable to price discovery on the satellite exchanges. Lieberman (1999) and Ding, Harris, Lau and McInish (1999) report that similar multilateral error correction also occurs with dual-listed stocks across international stock markets.

The next section presents a multivariate time-series model of the common factor methodology applied to transaction stock price series. Section 3 discusses estimation procedures and identifies the price discovery 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 factor representation of an error correction model of price discovery

To formulate the dynamics of price adjustment across informationally-linked exchanges, consider the following common factor model of two price series emanating from the trades executed by the NYSE specialist in the centralized market (P_c) and the trades executed by market-makers in other trading venues (P_R). Three key features we develop in this model are 1) synchronous trading events that define intervals of trading time, 2) an explicit arbitrage-based motivation for cointegration in individual security returns across informationally-linked exchanges, and 3) a testable implication about the impounding of a common trend in realized transaction prices.

Cointegration and error correction are linear dynamic properties of non-stationary time series data that share common stochastic trends. Suppose that for thickly-traded securities the continuous sequence of implicit efficient prices is an I(1) series that can be represented as a random walk,

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

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 $\sum_{t=1}^{T} w_t$, where all the relevant markets trade at time t=1 and then again at time t=T. Our model focuses primarily on which markets "move first" to incorporate these stochastic trends in their trading prices.

By hypothesis, trading prices in the centralized market will also reflect the w_t information arrivals but will differ from P_t by a zero-mean, covariance-stationary random disturbance in liquidity demand $\varepsilon_{c,t}$ reflecting localized order imbalance:

$$(2) \qquad P_{c,t} = P_t + \varepsilon_{c,t}$$

where $\varepsilon_{c,t}$ is assumed to be identically distributed through time but may be autocorrelated. Since the $\varepsilon_{c,t}$ shocks can be thought of as isolating liquidity-based motives for trade and market frictions, it is plausible to also assume that w_t can not be forecasted from prior knowledge of $\varepsilon_{c,t}$ - - i.e., that $E(w_t \varepsilon_{c,t-s}) = 0$; w_t and $\varepsilon_{c,t-s}$ are independent for all t and s. Rewriting (2) as

$$(3) \qquad \Delta P_{c,t} = \Delta P_t + \Delta\varepsilon_{c,t}$$

yields an MA(1) expression

$$(3') \qquad P_{c,t} = P_{c,t-1} + w_t + \Delta\varepsilon_{c,t}$$

that shows one reason why trading prices are not a random walk. Only if order imbalance is unchanged ($\Delta\varepsilon_{c,t}= 0$) will the trading price sequence of first differences $\Delta P_{c,t}$ exactly mirror the implicit efficient price sequence of first differences ΔP_t.[1] Nevertheless, the trading price is itself I(1), and at any realization (e.g., at t=T), both price sequences impound the stochastic trend as a common factor:[2]

(4) $$P_T = P_0 + \sum_{t=1}^{T} w_t$$

(5) $$P_{c,T} = P_{c,0} + \sum_{t=1}^{T} w_t + \varepsilon_{c,T} .$$

That is, each price level is seen to depend on non-stochastic initial values, a zero-mean covariance-stationary process that is transitory ($\varepsilon_{c,t}$), and the permanent trend of the cumulated random information arrivals $\sum_{t=1}^{T} w_t$. Across competing exchanges, it is the first market to impound this Stock-Watson (1988) common stochastic trend into actual trading prices that we associate with an event of price discovery.

Given informationally-linked markets, if the w_t are directly observable to regional specialists or limit order traders as well as to the NYSE specialist and floor traders, continuous trading prices in the regional exchanges $P_{R,t}$ will also differ from P_t by a localized index of liquidity demand $\varepsilon_{R,t}$:

(6) $$P_{R,t} = P_t + \varepsilon_{R,t} ,$$

which is an MA(1) sequence analogous to (2"),

(6') $$P_{R,t} = P_{R,t-1} + w_t + \Delta\varepsilon_{R,t}.$$

Again, $\varepsilon_{R,t}$ is assumed to be identically distributed through time but may be autocorrelated. Importantly, we expect these liquidity demand shocks or other market frictions in the alternative trading venues to be contemporaneously correlated- - i.e., $\text{Cov}(\varepsilon_{c,t}\ \varepsilon_{R,t}) \neq 0$ (see Chowdhry and Nanda, 1991).

[1]Trading prices will also differ from the full-information, implicit efficient price by a signed half spread (positive for buyer-initiated trades and negative for seller-initiated trades) reflecting bid-ask bounce and by an asymmetric information premium that market-makers require to cover the costs of adverse selection. See Glosten (1987). Easley and O'Hara (1987) and Bertsimas and Lo (1998) also argue for models of information-based trading that can account for non-spurious serial dependence in the data. In the present model, 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 trading prices *across markets,* not on the innovations in the continuous efficient price itself.

[2] After demonstrating other reasons why Glosten's (1987) model of strategic trading under asymmetric information is inconsistent with a random walk, Campbell, Lo, and MacKinlay (1997, chap. 3) also specify a common-factor representation of individual security returns.

Although both the centralized and regional trading prices in equations (3') and (6') are non-stationary, the difference between their contemporaneous values, subtracting equation (2) from (6),

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

is itself a stationary time series--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 stationary, the underlying series are cointegrated C(1). 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) that includes lagged changes in the underlying price series plus error correction terms:

(8) $$\Delta P_{NY,t} = \alpha_{NY} + \sum_{j=1}^{3}\sum_{t=1}^{S} \beta_{NY\,j,\,t-s}\,\Delta P_{j,\,t-s} + \sum_{j\neq k}^{2} d_{NY,\,k}\,(P_{NY,\,t-1} - P_{k,\,t-1}) + u_{NY,\,t}$$

(8') $$\Delta P_{PAC,t} = \alpha_{PAC} + \sum_{j=1}^{3}\sum_{t=1}^{S} \beta_{PAC\,j,\,t-s}\,\Delta P_{j,\,t-s} + \sum_{j\neq k}^{2} d_{PAC,\,k}\,(P_{NY,\,t-1} - P_{k,\,t-1}) + u_{PAC,\,t}$$

(8'') $$\Delta P_{CHI,t} = \alpha_{CHI} + \sum_{j=1}^{3}\sum_{t=1}^{S} \beta_{CHI\,j,\,t-s}\,\Delta P_{j,\,t-s} + \sum_{j\neq k}^{2} d_{CHI,\,k}\,(P_{NY,\,t-1} - P_{k,\,t-1}) + u_{CHI,\,t}$$

where j, k are the number of competing markets, S is the optimal lag length that minimizes the AIC information criterion for the corresponding VAR system of price level equations, and $u_{j,\,t}$ is an unrestricted error term.[3]

If the error correction terms are specified as the lagged difference in the underlying price levels (as in our case, the lagged deviation of the Pacific (PAC) and Chicago (CHI) regional prices from NYSE prices in equations (8) -(8'')), an illuminating and analytically useful variance decomposition interpretation of the β and d parameters in the VECM is available. Making use of the common trends specification of cointegrated asset prices in (2) and (6) to simplify the error correction terms and rearranging equations (3') and (6') as $\Delta P_{j,\,t-s} = w_{t-s} + \Delta\varepsilon_{j,\,t-s}$ and then substituting for the $\Delta P_{j,\,t-s}$ in the VECM yields (for one of the three price series, the NYSE case),

(9) $$\Delta P_{NY,\,t} = \alpha_{NY} + \sum_{j=1}^{3}\sum_{t=1}^{S} \beta_{NY\,j}\; w_{t-s} + \sum_{j=1}^{3}\sum_{t=1}^{S} \beta_{NY\,j,\,t-s}\,\Delta\varepsilon_{j,\,t-s} + \sum_{j\neq k}^{2} d_{NY,\,k}\,(\varepsilon_{NY,\,t-1} - \varepsilon_{k,\,t-1}) + u_{NY,\,t}$$

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[3] In general, the error term is unrestricted, but of particular relevance to our estimation procedure is the possible correlation of the u_t across equations.

Following Tse, Lee and Booth (1996) and Booth, So, and Tse (1999), Equation (9) makes clear that the error correction parameter d in a standard VECM reflects the adjustment to long-run arbitrage equilibrium between the markets necessitated by transitory shocks idiosyncratic to each market $\varepsilon_{j,\,t}$,whereas the betas in a standard VECM reflect changes in both common factor permanent components P_t and transitory components $\varepsilon_{j,\,t}$. Specifically, the $\Sigma\, B_{NY\ j}$ refers to the long-run equilibrium impounding in $P_{NY,\ t}$ of lagged innovations in the common factor, whereas $B_{NY\ j\ ,\ t\text{-}s}$ refers to the short-run sensitivity of $P_{NY,\,t}$ to particular (transitory) idiosyncratic shocks $\Delta\varepsilon_{j,\ t\text{-}s}$. In a two-variable model the VECM is just identified, so knowing the d parameters is sufficient to derive the $\Sigma\, B_{k\ j}$ and $B_{kj,\ t\text{-}s}$ and separate the permanent and transitory effects. In a VECM with three or more variables, overidentification necessitates other more complex estimation methods to decompose these effects.

Stock and Watson (1988) first showed that cointegrated series share common stochastic trends representable as a linear combination of the permanent components of the underlying series. Therefore, not only should $w_{t\text{-}s}$, the lagged change in the common factor P_t, appear in the specification of all three equations like (9), but in addition, if $w_{t\text{-}s}$ and each $\varepsilon_{j,\ t\text{-}s}$ are independent (as we assumed above), the lagged change in the common factor can be written as

$$(10) \qquad w_{t\text{-}s} \;=\; \Delta P_{t\text{-}s} \;=\; \Delta\,(\,f_{NY}\, P_{NY,\,t\text{-}s} + f_{PAC}\, P_{PAC,\,t\text{-}s} + f_{CHI}\, P_{CHI,\,t\text{-}s}\,) \;=\; \Delta\,(A_{\perp}'\,\mathbf{P}_{j,\,t\text{-}s})$$

where $A_{\perp}$ is a loading matrix of common factor permanent components f_j that is orthogonal to the short-run dynamics of the idiosyncratic transitory factors $\varepsilon_{j,\ t\text{-}s}$ that cause these three security prices to diverge. So, the implicit efficient price can be written as a linear function of the observable contemporaneous security prices, and Gonzalo and Granger (1995) showed how the parameters f_j could be estimated and tested, as discussed below.

3.1. Price Discovery Hypotheses

It is convenient to state what we shall call the one-way and two-way price discovery hypotheses in the framework of equations (9) and (10). Under the two-way price discovery null hypothesis, innovations in the implicit efficient price $\Delta P_t = w_t$ are impounded into the permanent stochastic trend of the trading prices in all three markets, and $\Sigma\, B_{NY\ j}$, $\Sigma\, B_{PAC\ j}$, and $\Sigma\, B_{CHI\ j}$ or equivalently the common factor components f_{NY} , f_{PAC} , and f_{CHI} are all statistically significant. This multilateral price adjustment to new information occurs in the above theoretical framework because the arrival of new information is observable not only to the NYSE specialist and floor traders but also to regional market-makers and off-floor broker dealers (or their clients). However, NYSE specialists and floor traders glean insights useful in assessing the probable price impact of the w_t arrivals by observing the composition of the order flow and the order execution strategy of particular participants both on and off the floor. This is information not generally available to other market participants off the floor. Although they have no new w_t information themselves, NYSE floor traders employ their informational advantage in the trading process to trade ahead of and impound more quickly than other traders any permanent price moves.

Under the one-way price discovery alternative hypothesis, then, regional exchanges may follow the lead of the centralized market in updating trading prices to reflect the likely price impact of new w_t information. In our modeling framework, this lead-lag relationship would certainly follow if the regional exchange participants were unable to observe w_t directly, but instead had to form price expectations based on delayed official (NTIS) reports from the NYSE floor. One plausible model of this lead-lag process asserts that regional trading prices are determined by lagged centralized market trading prices ($P_{c,\, t-n}$), by liquidity demand disturbances among regional participants, and by any observed deviation between the most recent trading prices in the alternative venues:[4]

$$P_{R,\, t} = f\,(P_{c,\, t-n},\ \varepsilon_{R,\, t}\ , (P_{c,\, t-1} - P_{R,\, t-1})) \qquad (11)$$

Here the Stock-Watson VAR solutions at t=T would again display the stochastic trend as a common factor, and the difference between the prices on the NYSE and regionals could well be stationary depending on whether or not arbitrage allows past deviations between the NYSE's and regionals' prices to persist. If, as expected, arbitrage between the trading venues quickly removes any deviations in the most recent trading prices $P_{c,\, t-1} - P_{R,\, t-1}$, then we expect $P_{c,\, t}$ and $P_{R,\, t}$ to be cointegrated--i.e., to error correct to long-run no-arbitrage relationships.

To confirm the appropriateness of these stationarity restrictions for DJIA stocks, we will test the order of integration and the hypothesized cointegration of these NYSE and regional price series using the augmented Dickey-Fuller and Johansen tests. Having confirmed cointegrated series, our principal purpose is to provide a measure of the proportion of common stochastic trends emanating from the NYSE's versus regionals' trades.

[4] One reason off-floor trading prices might reflect lagged official trade reports from the floor as well as the most recent pricing differentials is because order imbalance is seldom cleared immediately. That is, trading prices do not instantaneously reflect Walrasian, market-clearing prices from sequential batch auctions. Instead, a lagged series of recent floor trades is needed for off-floor market-makers to assess the information content of the order flow on the floor (e.g., the depth at any given price). Harris, McInish, and Chakravarty (1995) model the continuous auction in a specialist market as a non-Walrasian queue-service rationing mechanism.

Cointegration therefore proves to be a restriction that allows us to specify error correction modeling for the ΔP equations and move on to Gonzalo-Granger's common trends estimation procedure (GG procedure) for the common factor weights.

Although the functional form of the error correction is non-unique (and therefore one cannot argue for any particular normalization in equations (8) - (8"), see Hasbrouck (1995)), the modeling implications of the foregoing discussion for regression relations are clear. First, any specification of the empirical ECM for price changes ΔP_j in any trading venue should include lagged ΔP_js as well as lagged fractional adjustment error correction terms such as $d_j\ (P_{j,\,t-1} - P_{k,\,t-1})$. One then tests the one-way price discovery hypothesis by testing the parameters d_j in each price change equation. Under the one-way price discovery hypothesis, $\Delta P_{R,t}$ error corrects to equilibrium deviations between the NYSE and regional prices, but not the other way around. With the NYSE trading price P_c as theoretically the sole source of price discovery, one-way impounding of new information implies one-way error correction. Alternatively, statistically significant error correction terms in all VECM equations rejects the hypothesis of one-way price discovery in favor of the two-way null. Harris, McInish, Shoesmith, and Wood (1995) and Ding, Harris, Lau, and McInish (1999) proceed in this manner.

Using error correction techniques, Harris, McInish, Shoesmith, and Wood (1995) find evidence to support the two-way price discovery hypothesis in the 1990 NYSE and regional trading of IBM. However, IBM trading is unique, attracting an enormous following in the analyst community, and attracting the largest crowd of NYSE floor traders. For thinly-traded securities or even for the more typical thickly-traded security, we have no reason to believe that the price discovery process is identical to that for IBM. In addition, price discovery is an ebb and flow process; we wish to investigate the contribution of the NYSE and regionals to price discovery over several years; we investigate 1988-95. Finally, we follow the example of Hall, Anderson, and Granger (1992) in macroeconomic data, Gonzalo and Granger (1995) in interest rate data, and Tse, Lee, and Booth (1996) in Eurobond data by applying to stock markets the duality between ECMs and common trends estimation and testing procedures. In particular, we employ Gonzalo and Granger's reduced-rank regressions and Q_{GG} test statistic for testing the common factor components.

3.2. Common Trends Estimation and Testing

In several recent papers, Gonzalo (1994) and Gonzalo and Granger (1995) have proposed a new approach to decomposing a vector of cointegrated time series. Rather than imposing a random walk on the transitory components or restricting the transitory components to be orthogonal to the permanent components at all leads and lags as in Quah (1992), Gonzalo and Granger impose the less restrictive condition that no transitory components ε_t can Granger-cause any permanent, "common long-memory" components w_t.[5] With r cointegrating vectors, there are $k = n - r$ common factors corresponding to the $n - r$ common stochastic trends. Here, we anticipate the maximal eigenvalue and trace tests for cointegration will reveal two cointegrating vectors and imply therefore one common stochastic trend corresponding to $\sum_{t=1}^{T} w_t$ in our foregoing model structure.

Referring to equation (10), the common factor components f_j in the loading matrix $A_\perp$ are estimated with reduced rank regression and eigenvector computations similar to those used in the Johansen technique.[6] Gonzalo and Granger (1995) proved equation (10), and they developed a χ^2 distributed test statistic (Q_{GG}) for the coefficients of the common factor vector f_j. Because of the linear combination restriction on the f_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 price discovery across cointegrated security markets. Under the null hypothesis of two-way price discovery, each of the common factor weights are statistically significantly greater than zero --i.e., $H_0 : f_{NY}, f_{PAC}$, and $f_{CHI} > 0$ and $H_a : f_{NY}, f_{PAC}$, or $f_{CHI} = 0$. We employ the Gonzalo and Granger procedure to estimate the proportion of actual price discovery attributable to NYSE trades versus regional trades for each of the DJIA stocks over three years of intraday trading in 1988, 1992 and 1995.

There are several other econometric procedures for estimating common trends models. King, Plosser, Stock, and Watson (1991) offered an early empirical implementation of the idea. Their research focused on structural equation specification and identifying restrictions for separating permanent and transitory components

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[5]One advantage for stock price applications is that lagged changes in the permanent component interpreted as new public information arrivals w_t can still affect the level of the transitory component ε_t interpreted as new assessments of liquidity demand. These information feedback effects which are defined and limited by Granger causality flowing from public to private assessments of new information are especially attractive in a stock market microstructure setting.

[6]For detailed accounts of the computations required to obtain the common long-memory factor results, see Johansen (1995, chapter 8) and Gonzalo and Granger (1995). Campbell and Perron (1991), Enders (1995, chapter 6) and Huang (2000) provide detailed treatments of the relevant cointegration econometrics.

in VECM models. As we have seen, Gonzalo and Granger's (1995) common long-memory estimation procedure offers convenient hypothesis testing on the common factor weights. In addition, the GG procedure provides robust estimation of the loading matrix of weights despite contemporaneous correlation of cross-equation, cross-market disturbances, the u_t in the system of equations (8). Hasbrouck (1995) offers a related common factor measure of the price discovery across informationally-linked markets. However, Hasbrouck's information shares methodology depends on the ordering of variables in the Cholesky factorization of the residual covariance matrix (Hasbrouck, p. 1183), and the discrepancies between the orderings may be large as the contemporaneous correlation of disturbances across the markets increases (Tse 1999 and Huang 2000).[7] For this reason, we adopt the Gonzalo and Granger procedure to estimate our model.

Like Hasbrouck (1995), we view price discovery in terms of innovations in the permanent components of the stochastic process underlying cointegrated price series. But we differ from Hasbrouck (1995) in the way we apply error correction methodology and in the measurement of the prices themselves. Hasbrouck’s research highlights the asymmetry in trading frequency in various venues by analyzing continuous quote data at one-second intervals. Truly stale quotes on one market can provide evidence that another market has moved first to incorporate permanent innovations in the stock price. Thus, Hasbrouck’s (1995) impulse response functions and impact multipliers demonstrate the relative speed of short-run *quote price* adjustment across trading venues. In contrast, because of the presence of autoquotes and quotes with little or no depth in the intermarket quote data, we focus on the resolution of coincident but unequal price changes in synchronous *trades*. In short, our position is that the competition for order flow between the centralized and regional exchanges takes place in trades and not in quotes. Regional exchanges do not compete on quotes because the current order-handling rules do not require that the market with the best quote receive an order. To investigate the longer-run error correction adjustment dynamics of trading prices across venues requires 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.[8]

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[7] By using an extremely high frequency (one second) resolution of quote data where the cross-equation error covariance is minimized, Hasbrouck's (1995) results are robust to a reordering of the input variables (Tse 2000).

[8]Following Blume and Goldstein (1996), all these studies of intermarket pricing adjust the time stamps in the Chicago and Pacific exchanges 16 seconds and 5 seconds, respectively, to correct for minimum reporting lags.

In particular, we estimate the components of the GG common factor(s) attributable to each of three trading venues in order to capture both the location and magnitude of the price discovery reflected in the actual trades. The difference in our two approaches is not a permanent versus transitory components issue. Both approaches ignore transitory innovations attributable to factors like bid-ask bounce, market imperfections, or reporting errors. The difference in the two approaches is that Hasbrouck's approach addresses permanent innovations in the quotes in continuous clock time while ours addresses permanent innovations in trading prices in synchronous trading time.

Both our approach and Hasbrouck's approach have important implications for public policy--in particular, the 1996 National Securities Markets Improvement Act and the SEC's Market 2000 study regarding the desirability of promoting a centralized market. Again, Hasbrouck (1995) finds the NYSE "information dominant" in his study of continuous quotes in 1993. If the NYSE remains information dominant in our synchronous trades setting over 1988-1995, then that finding would strengthen the argument that the satellite markets are free-riding on the price discovery of the NYSE. If, on the other hand, the Chicago and Pacific exchanges prove to be information dominant in synchronous trades in some stocks, then the satellite markets should not be seen by regulators as merely "derivative markets--i.e., markets whose [pricing and execution services] derive from price discovery elsewhere."

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 price

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In a careful and exhaustive simulation study of our GG estimation and data collection procedure relative to that of Hasbrouck (1995), Tse (2000) found 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. Tse also investigated the close relationship between the GG common factor estimation procedure and Hasbrouck's information shares estimation method for investigating short-run dynamics with impulse response functions. He therefore concludes that all differences in our results are attributable to the choice of trades versus quotes.

We investigate further this issue of the robustness of the results to our data collection procedure in the Data Appendix.

discovery hypotheses relating to 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 which minimize the span (i.e., the observation interval) between trades. After the open each day, we wait for a trade in each of the three markets and then acquire the most recent trade in the other two, looking both forward and backward in time. The MINSPAN price tuple recorded on those three trades is then saved, and a new synchronous trade tuple is formed in the same manner. Each observation therefore reflects three new trades and may entail zero, one, two, or three new prices. In the Data Appendix we demonstrate the robustness of the MINSPAN common factor results across five different data collection procedures designed to simulate possible spurious lead-lag relationships in heavily traded stocks.[9]

Table 1 suggests the high frequency of this MINSPAN synchronous price data. In 1992, IBM and Merck traded synchronously across the New York, Chicago, and Pacific exchanges 32,754 and 21,326 times. The average time in seconds over which we observe these IBM and Merck price tuples was 51 and 44 seconds, respectively. Most other DJIA stocks generated several thousand synchronous price tuples and exhibited spans from two to five minutes. The shortest average span was for General Motors (36 seconds) in 3,961 price tuples while the longest was for International Paper (866 seconds) in 743 price tuples.[10] For the Dow 30 stocks as a whole, mean MINSPAN averaged 121 seconds in 5,281 tuples. As expected, across securities the span was inversely correlated with the number of synchronous price tuples observed (r = - 0.56).

An important indication that the competition for order flow is an evolutionary, dynamic process is presented by the contrast between 1992 and 1995 data shown in table 1. Although the mean number of synchronous trade transactions for DJIA stocks declined from 1992 to 1995 (from 5,940 to 3,527) the mean MINSPAN increased only slightly (from 269 seconds to 270 seconds). However, the particulars are quite different for some individual stocks. Woolworth and Caterpillar MINSPANs tightened in 1995 to just one-third of their 1992 levels on increased synchronous trading. Synchronous trading also increased at Bethlehem Steel

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[9]Further, Tse (2000) replicates our results with imputed observations on the thin-trading market and continuously sampled data. He concludes that our common factor estimates do not result from censorship biases of the data collection method.

[10]The cointegration results for International Paper (IP) with the longest (fifteen minute) mean observation interval are virtually identical to those for GM with the shortest (half minute) mean observation interval. Although IP's span may be long relative to an agent's reaction times, the multi-market price adjustments required to restore arbitrage equilibrium are

and MMM where the MINSPANs halved between 1992 and 1995. However, other stocks like GM and Goodyear experienced a two-fold increase in MINSPANs despite more synchronous trading from 1992 to 1995. Overall, the span of the synchronous trade tuples in 1995 was again inversely correlated with the number of synchronous trades observed (r = - 0. 71).

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 three equations formed by the price series in levels. High frequency trade-to-trade stock price data are I(1) series. We find the same holds true for our synchronous trading tuples. For each of the DJIA stocks, one or two lags are indicated by the minimum Akaike information criterion in our systems estimation procedure (TSULMAR). The Johansen cointegration test procedure is then run on the natural logs of the series in levels with two lags and no intercept. The first two eigenvectors for the Chicago, Pacific, and New York price series for each of the DJIA stocks are presented in table 2. 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. For each of the DJIA stocks, both r = 0 and r = 1 are rejected at 99% statistical significance. Therefore, r = 2, indicating two cointegrating vectors and one common trend in each case. Hence, for all the DJIA stocks the Chicago, Pacific and New York trading price series *are* cointegrated, and by the Granger Representation Theorem, their first differences will therefore follow an error correction process.

The cointegrating vectors in each case are given by the first two eigenvectors of the system of price adjustment equations. For example, forming the equilibrium error relationships implied by the cointegrating vectors for General Electric for 1995 we obtain for each trading period t: $z_{1,t} = 14.969\ P_{NY,t} - 1.224\ P_{CHI,t} - 13.743\ P_{PAC,t}$ and $z_{2,t} = 7.349\ P_{NY,t} - 15.531\ P_{CHI,t} + 8.203\ P_{PAC,t}$. Under the maintained hypothesis of long-run equilibrium, where the equilibrium errors equate to zero, solving simultaneously yields $P_{chi} = P_{pac} = P_{ny}$ to three decimal places. This arbitrage-free equality of the three prices in synchronous trading on informationally-linked specialist exchanges is also present for each of the other Dow stocks. A quick indication of this finding is reported in Table 2 where literally each of the cointegrating vectors sums to approximately zero.[11] The same is true for the 1988 and 1992 data as well; the cointegrating vectors sum to zero to two and three significant digits in

unpredictable in the case of IP--i.e., the IP common factor weights are insignificant. Similar results apply to Aluminum Company of America, and United Technologies in 1995.

[11] In the case of GE.95, the estimated cointegrating vectors reported above in the text sum to 0.002 and 0.021, respectively.

most cases and to at least one significant digit in every case. 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 long-memory factor weights and information dominance

These powerful cointegration results allow the application of the Gonzalo-Granger common factor estimation procedure to the DJIA stock prices. For each of three years for each DJIA stock, table 3 displays our estimates of the common factor weights that reflect the permanent contribution to price discovery of the Chicago, Pacific and New York stock exchanges. For three cointegrated price series, these common factor weights are derived from the (normalized) third eigenvector orthogonal to the transitory price adjustment vector (Gonzalo and Granger, 1995).

The average proportion of the common long-memory components attributable to the NYSE in 1988 is 72.2% across the DJIA stocks and varies from 49% and 58% for Westinghouse and AT&T up to 92% and 95% for Merck and Goodyear. Most of these common factor weights are 65-85% exceeding the NYSE's 60-75% share of the trades in DJIA stocks and in some cases exceeding the NYSE's 72-90% share of the dollar trading volume in DJIA stocks. Consequently, these 1988 results confirm Hasbrouck's (1995) finding that the NYSE is "information dominant."

However, the fragmentation of equity trades 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 a centralized intermediary whose reduced spreads attract liquidity traders (Benveniste, Marcus, and Wilhelm 1992). NYSE spreads did rise by an economically significant amount in 1990 and 1991 (Huang and Stoll 1996). 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 for most DJIA stocks. 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%. The lowest NYSE market share of the trading volume for 1992 DJIA stocks was 71%, so in many stocks the NYSE was not "information dominant" at this time.

Across all DJIA stocks, the decline in the long-memory component was from 72.2% in 1988 to 51.9% in 1992. 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 is even larger--i.e., from 79% to 46%. Interestingly, the three stocks with a rising proportion of NYSE price discovery from 1988 to 1992 (i.e., International Paper, Caterpillar and Bethlehem Steel) have the first, third and fifth longest MINSPANs in the 1992 data set at 866, 649 and 609 seconds, respectively. When the most recent or next trade on the Chicago or Pacific exchange is ten to fifteen minutes away, informed trades appear to execute in New York independent of whether higher spreads in New York are dissuading liquidity trades in that trading venue in those stocks. Synchronicity issues and thinness of trading appear to affect the competition for order flow between the centralized and satellite markets even before one leaves the DJIA stocks.

Again, recall that this error correction measure of price discovery 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 the 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, Marcus, and Wilhelm (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.[12] The 1988 to 1992

12American Express, Bethlehem Steel, Caterpillar, Walt Disney, International Business Machines, Minnesota Mining & Mfg., Proctor & Gamble, Sears Roebuck, AT&T, Texaco, United Technologies, Westinghouse, and Woolworth.

decline in NYSE price discovery proved temporary, and by 1995 the NYSE's proportion of price discovery exceeded or approximated its 1988 level. Another six DJIA stocks showed substantial increases in the NYSE's share of price discovery from 1992 to 1995.[13] Three additional DJIA stocks (Eastman Kodak, Goodyear Tire & Rubber, Coca-Cola) increased 4-9 percentage points. Four stocks (Chevron, DuPont, GE, and MacDonald's) remained at or near their 1992 lows. Altogether, the NYSE's proportion of the price discovery rose for twenty-four stocks from 1992 to 1995. And in only three cases (Aluminum Co. of America, J.P. Morgan and Exxon) did the NYSE's proportion of price discovery continue to decline from 1988 thru 1992 to 1995. International Paper, which had actually increased from 1988 to 1992, declined substantially from 1992 to 1995. For the DJIA stocks as a whole in 1995, the average common factor weight for the NYSE is 62.9%, for the Pacific Exchange 14.8%, and for the Chicago Exchange 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 price discovery. Merck trading is perhaps the most spectacular example of this phenomenon where the Pacific and Chicago exchanges barely contributed at all to price discovery in 1988 with common factor weights of 3% and 4%, and yet by 1992 their respective weights increased to 17% and 47%. In the most recent 1995 data, the proportion of price discovery results for Merck are NYSE 68%, Pacific 17%, and Chicago 15%. We tested whether each common long memory factor weight in Table 3 was statistically different from zero. The null hypothesis is that prices revealed in trades on only two of the three markets contribute to the permanent components of price adjustment. That is, under the null, the tested market introduces only transitory innovations into the synchronous trading price series and will therefore exhibit a normalized common factor weight that is insignificantly different from zero. The significance levels reported in table 3 are based on critical values for the chi-square test statistic with one degree of freedom (Gonzalo and Granger, 1995).

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[13] Allied-Signal, Boeing, General Motors, Philip Morris, Merck, and Union Carbide.

Focusing on the common factor weights that are statistically significantly different from zero in 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 and 10% in Disney to 35% in Union Carbide. The Chicago exchange has a mean common factor weight of 24% in twenty DJIA stocks ranging from significant weights of 12% in IBM and 31% in GM and Exxon, to 34% in Boeing and 43% in Kodak. The NYSE has significant 1995 common factor weights in twenty-seven of the DJIA stocks averaging 62%. These 1995 NYSE weights range from 48% in MacDonald's and 51% in DuPont and Chevron to 85% in IBM.

The 1995 Chicago, Pacific and NYSE common factor weights are all statistically significantly different from zero for nine stocks.[14] Rejection of the null hypothesis confirms an independent role in price discovery for both regional exchanges. In twelve other stocks, one regional market contributes statistically significantly to price discovery along with the NYSE. And in five stocks (Allied-Signal, Caterpillar, DuPont, Goodyear, and J.P. Morgan) in 1995 the NYSE's price discovery alone is statistically significant.

To further assess the role of the regionals in price discovery, we test the joint hypothesis that neither of the regional markets contributes to price discovery. The null hypothesis is that synchronous trading prices on these three informationally-linked markets have one and only one common factor--namely, NYSE trading prices. Table 4 lists the chi-square 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.[15] Hence, again, the test results support the view that the regionals contribute significantly to price discovery.

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 x 3 pairs of years =) nine

[14]American Express, Walt Disney, GE, IBM, Coca-Cola, MacDonald's, Merck, AT&T, and Westinghouse.

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

test statistics, which are reported in Table 5. For the NYSE for 1988/1995, we cannot reject the hypothesis that the factor weights are the same. We do reject the null hypothesis that the differences are zero at the 0.01 level for each of the other cases. Hence, we strongly confirm that the contribution of alternative trading venues to price discovery varies over time.

4.4. Discussion of Hypotheses

4.4.1 Related Literature

Several previous papers have analyzed the implications of centralized versus decentralized security market design. The matching of buyers and sellers with selective execution on ECNs has highlighted the reputation of centralized exchange specialists not only for price improvement in specific segments but also for differential execution quality at given depths (Easley, Keifer, and O'Hara, 1996). Execution reliability or immediacy at depth does vary intraday and across trading venues, and these characteristics of the execution may not be verifiable to the trader placing an order. Institutional trades therefore routinely perform retrospective studies to rank each dealer or specialist's execution quality. In any such market-making regime where the spread can signal, ex ante, the unobservable or unverifiable quality of the execution, 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, Garvey and Swan (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.,Yavas (1992), Mookherjee and Reichelstein (1992), Gehrig (1993), Easley, Keifer, and O'Hara (1996) and Rock (1995)). Benveniste, Marcus and Wilhelm (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 screen-based

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's, 1993).[16] This implies that, for any given level of asymmetric information, the equilibrium spread can be lower on a centralized exchange. With some market power in an asymmetric information environment, centralized market-makers are likely to raise and lower these spreads over time in response to market pressures and reputational objectives.

4.4.2 Alternative Hypotheses

The NYSE, Pacific and Chicago stock exchanges and NASDAQ dealers compete against alternative trading venues 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, Keifer and O'Hara, 1996). 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 required return to recoup expected losses from trading against superior information (Brennan and Subrahmanyam, 1996).[17]

As ASX, Instinet, Medoff, and Posit emerged in the early 1990s, both NYSE and NASDAQ spreads did rise substantially (Huang and Stoll, 1996). 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,[18] one would expect

[16]In Biglaiser's (1993) model most high-quality transactions are traded through the centralized intermediary and most low-quality transactions are traded through the matching market.

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

[18]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 issues 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.

spread-sensitive uninformed NYSE order flow to decline. And Benveniste, Marcus, and Wilhelm (1992) argue the NYSE specialists would then be less likely to attract information traders. This *spread-sensitive-uninformed-order-flow hypothesis* can therefore explain the diminishing incidence1988-'92 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 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 share declines 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 for these declining market share stocks are surprisingly strong. 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 coefficient for all thirty stocks is insignificantly different from 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 ECNs and to a lesser extent on regional exchanges. Keim and Madhavan (1995 and 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 ECNs 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 innovations in the permanent component of that price discovery process could prove quicker and more efficient on the NYSE, consistent with Hasbrouck's (1995) results.

Under this *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 by 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 order flow to New York. Under this recent 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 return of order flow volume and price discovery 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, Keifer, O'Hara and Paperman (1995), 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 ECNs 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, Kiefer and O'Hara, 1996). To the extent such trades reflect innovations in the *permanent* component of the pricing process, the NYSE's proportionate weight of the common factor would rise from 1992 to 1995, *independent of the overall level of spreads*. Directly estimating the information content of NYSE and regional trades here is prevented by the clock time interruptions between synchronous trading events on the three exchanges. 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 a measure of NYSE price discovery 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, Greene, and Jennings (1995) 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 long-memory components of DJIA stock prices 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 long-memory results confirm Hasbrouck's (1995) finding that the NYSE was information dominant in discovering DJIA stock prices with factor weights from 63-95% (averaging 72.2%) and market shares of the trading volume from 72-90% (averaging 86.3%). 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 factor weight of the common long-memory component declined. For sixteen of the DJIA, 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 proportion of the price discovery 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 price discovery for eleven of the 30 DJIA stocks.

Examining several hypotheses to explain the temporary decline in NYSE price discovery 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 price discovery (62.9%) was again attributable to the NYSE. In 1995, on average across the DJIA, 14.8% of the price discovery was attributable to the Pacific Exchange, and 22.3% of the price discovery was attributable to the Chicago Exchange. In the interim, 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 price discovery, we hope to identify what cross-sectional factors determine whether a particular security's price discovery occurs 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.

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Data Appendix

In this Data Appendix, we first describe five data collection procedures that can be used to check MINSPAN for robustness and simulate the effect of spurious lead-lag correlations on our results. In the second section, 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:[19] a_1 b_1 $c_{1,}$, b_2 a_2 $c_{4,}$ c_5 b_5 a_3.

   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_1 b_1 c_1, c_3 b_2 a_2, c_4 b_4 a_3 , c_5 b_5 a_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_1 b_1 c_1, a_2 c_4 b_3, a_3 c_5 b_5, a_4 c_6 b_6; BFIRST, b_1 c_1 a_2, b_4 a_3 c_5, b_5 a_4 c_6; CFIRST, c_3 b_2 a_2, c_4 b_3 a_3, c_5 b_5 a_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 minute) 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--Aluminun 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

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[19]In this example, c_5 b_5 a_3 and c_5 b_5 a_4 have the same span. Our procedure retains the first tuple c_5 b_5 a_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.

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 siginificance 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 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 necessitated, 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 three other cases, including the least thickly-traded, longest span stock, the common factor for the centralized market in the first and last columns is identical (i.e., 0.85 for IBM, 0.58 for KO, and 0.59 for AA)[20]. 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 Aluminum Company of America (9-10 minute 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-traded 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.

[20] Of course, all the common factor estimates for AA are statistically insignificantly different from zero.

Table 1. Statistics for tuples constructed using MINSPAN. For each firm for 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 the all of the trades are exhausted. This data collection method is identical to that of Harris, McInish, Shoesmith, and Wood (1995).

		1988		1992		1995	
Firm	Symbol	No. Obs.	Span (secs.)	No. Obs.	Span (secs.)	No. Obs.	Span (secs.)
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	IBM	8,663	93	32,754	51	7,783	74
Machines	IP	1,096	482	743	866	670	810
International Paper	JPM	896	700	1,255	507	2,109	807
J. P. Morgan	KO	2,173	341	11,157	53	5,934	115
Coca-Cola	MCD	1,676	345	4,737	44	7,909	68
McDonalds	MMM	1,954	307	2,059	332	4,189	159
Minnesota Mining & Mfg.	MO	2,682	288	10,216	83	5,816	98
Philip Morris	MKR	2,738	247	21,326	47	8,139	78
Merck	PG	1,676	465	5,174	169	2,603	232
Proctor & Gamble	S	5,408	169	3,276	252	2,261	222
Sears Roebuck	T	9,548	86	8,749	100	7,652	78
AT&T	TX	9,359	97	4,183	206	2,882	216
Texaco	UK	2,990	269	2,336	248	953	463
Union Carbide	UT	1,711	501	1,067	606	559	838
United Technologies	WX	1,970	406	7,639	111	2,395	245
Westinghouse	XON	6,197	146	6,394	203	2,551	222
Exxon	Z	1,463	543	1,121	661	1,639	190
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	1988	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.

Table 4. Test of the null hypothesis that 100% of the price discovery occurs on the NYSE. 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). The null hypothesis is 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	*	0.10	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.

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 in toto.

	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.

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 Business	85	83	82
Machines	88	87	88
International Paper	87	87	87
J. P. Morgan	86	87	82
Coca-Cola	88	89	83
McDonalds	86	80	80
Minnesota Mining & Mfg.	72	71	77
Philip Morris	88	88	95
Merck	87	85	83
Proctor & Gamble	81	89	85
Sears Roebuck	86	86	84
AT&T	83	83	83
Texaco	88	83	83
Union Carbide	89	91	90
United Technologies	89	78	76
Westinghouse	78	84	84
Exxon	88	90	76
Woolworth			
Mean	89	89	88

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 the appendix, 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