Trading Costs and Price Discovery across Stock Index Futures and Cash Markets

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The focus of this article is to test the trading cost hypothesis of price leadership, which predicts that the market with the lowest overall trading costs will react most quickly to new information. In an attempt to hold market microstructure effects constant and in contrast to previous studies, we examine intraday price leadership *across* the S&P 500, NYSE Composite, and MMI futures, and across the respective cash indexes—rather than between each futures and its associated cash index. We find that, among the futures, the S&P 500 exhibits price leadership over the other index futures, whereas among the cash indexes the MMI leads. Both findings are consistent with the trading cost hypothesis. © 1999 John Wiley & Sons, Inc. Jrl Fut Mark 19: 475–498, 1999

Note: We would like to thank Dave Davidson, Ike Mathur, Subhash Sharma, Karyn Williams, and two anonymous referees for helpful comments and suggestions. Any errors that remain are our own responsibility.
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The Journal of Futures Markets, Vol. 19, No. 4, 475–498 (1999)

CCC 0270-7314/99/040475-24

INTRODUCTION

The majority of prior studies on stock index futures examine the temporal relationship between a futures and its underlying cash market. The basis for these studies is that in perfectly efficient futures and cash markets, informed investors are indifferent between trading in either market, and new information is reflected in both simultaneously. Accordingly, the contemporaneous returns of the two markets would be perfectly correlated, whereas noncontemporaneous returns would be uncorrelated. The majority of empirical evidence, however, has documented some mispricing between the futures and cash markets, with the consensus view that futures generally lead cash markets.

One plausible reason for this asymmetric relationship is infrequent trading of the component stocks in an index, although empirical findings do not seem to support this line of reasoning. For example, Stoll and Whaley (1990) show that, even after removing the infrequent trading effect, the cash price lags behind the futures price. Moreover, in Chan's (1992) study of the Major Market Index (MMI), futures returns lead even the returns of the component stocks that are more actively traded than the futures itself.

Several recent studies suggest that the cost of trading, combined with the nature of new information, is the underlying cause of the observed asymmetric relationship between futures and cash markets. Fleming, Ostdiek, and Whaley (1996) introduce what they call the *trading cost hypothesis,* which predicts that the market with the lowest overall trading costs will react most quickly to new information. They examine price leadership among options on individual stocks, stocks, stock index options, and stock index futures (in order of total trading costs from high to low) and find that, in comparing any two of these markets, the one with lower transactions costs exhibits price leadership. Along similar lines Chan (1992) finds that, when the market has information of a general nature, futures lead cash to a greater extent. Thus, probably because of dramatically lower trading costs, the futures market is likely to be the main source of systematic, marketwide information, whereas the cash index prices may mainly reflect firm-specific diversifiable information. If so, futures prices may temporarily contain more information until such information flows from futures to cash prices.

Another way to test the trading cost hypothesis is to examine price leadership *among* futures and/or among cash indexes—something which to date has not been done. The key motivation for examining price leadership across futures and across cash indexes, rather than *between* futures and cash (as is conventionally done in the literature) is to study the flow of information in markets of similar microstructure. By holding these microstructure effects constant, we can more accurately measure the initiation and response of prices to new information. In particular, when focusing only on the futures, we will be able to bypass the relatively greater illiquidity and bid–ask problems of cash indexes.

Our study should shed substantial further light on the trading cost hypothesis. If price leadership is determined by low relative transactions costs, then we should see the most liquid index futures contract, with the lowest bid–ask spread, lead the other futures. Specifically, we should observe that the S&P 500 index futures lead the NYSE and MMI futures. We also examine price leadership among the cash indexes underlying these futures contracts, using an approach pioneered by Stoll and Whaley (1990) to purge the cash indexes of the effects of bid–ask spreads and infrequent trading of the component stocks. It is interesting to note that, if the trading cost hypothesis is correct, we would not expect to find the same price leadership among the cash indexes as among the futures. Because transactions costs in the cash market are largely determined by firm size, with the stocks of larger market capitalization firms having lower trading costs, we would expect the MMI cash index, which contains the largest underlying stocks, to lead the S&P 500 and NYSE cash indexes.

To study the dynamics of intraday price transmissions we utilize a vector autoregressive (VAR) model. Specifically, we calculate the impulse response functions to examine how an innovation in one market transmits across different markets. Through variance decomposition, the VAR model also allows us to assess the relative weight of each variable in the system in generating unexpected variations of its own and other variables.[1]

REVIEW OF THE LITERATURE

The Relationship between Stock Index Futures and Their Associated Cash Indexes

A number of empirical studies find an asymmetric relationship between prices of futures and cash markets. Despite different markets and different methodologies used, the general finding with intraday data is that the futures lead the cash. For example, Kawaller, Koch, and Koch (1987, 1988) find that, whereas contemporaneous prices are most strongly re-

[1]In addition, we test possible cointegration relationships among the prices of the three futures markets via the multivariate procedures outlined by Johansen (1991) and Johansen and Juselius (1992). If they exist, the cointegrating constraints can be explicitly considered in the impulse response functions to capture long- and short-run price dynamics among the variables.

lated, there is evidence of a twenty- to forty-five-minute leadership of S&P 500 futures prices over cash prices. On the other hand, the influence of cash price movements on the futures hardly extends beyond one minute. Cheung and Ng (1990) and Chan, Chan, and Karolyi (1991) also find that S&P 500 futures returns lead cash returns, albeit with a shorter lags, whereas Laatsch and Schwarz (1988) examine the Major Market Index (MMI) and find that the futures clearly lead cash once the market matures.

Stoll and Whaley (1990) and Chan (1992) similarly find that the S&P 500 and MMI futures tend to lead their respective cash index returns, even after index returns are purged of infrequent trading and bid–ask price effects. Both studies show that the futures also lead highly actively traded stocks (such as IBM), thus illustrating that infrequent trading only partially explains the asymmetric relations between futures and cash markets. These results support the hypothesis that the futures market plays a leading role in the price discovery process by reflecting new information faster than the cash market—but they do not tell us why futures play such a role. However, empirical evidence pertaining to the FT-SE 100 by Abhyankar (1995) does contain some insight regarding ultimate causes. Abhyankar also supports the price leadership of the futures market, finding that futures lead cash by an hour on average. More interestingly, Abhyankar finds that lower transactions costs in the London cash market after the Big Bang have dampened the lead of futures, whereas short sale restrictions in the cash market have increased this lead. These findings, as well as those of Fleming, Ostdiek, and Whaley (1996) discussed earlier, are consistent with the hypothesis that price leadership is strongly influenced by relative transactions costs.

Many recent studies have focused on a long-run equilibrium relationship between futures and cash prices via Engle and Granger's (1987) cointegration and error correction methodologies.[2] For example, Ghosh (1993) finds that fifteen-minute prices of the S&P 500 index futures and cash markets are cointegrated. His error correction specifications provide evidence that more information flows from futures prices to cash index prices. In a more extensive study, Wahab and Lashgari (1993) find that the S&P 500 and the FT-SE 100 index futures and cash prices are cointegrated, and that error correction models result in significantly lower forecast errors than standard VAR models.[3]

[2]Engle and Granger's (1987) cointegration methodology has been extensively utilized in other areas of finance and economics: interest rates (Engle & Granger, 1987; Hall, Anderson, & Granger, 1992); foreign exchange rates (Hakkio & Rush, 1989; Barnhart & Szakmary, 1991); equity markets of different countries (Taylor & Tonks, 1989; Arshanapalli & Doukas, 1993); live cattle futures (Bessler & Covey, 1991); crude oil futures (Quan, 1992; Schwarz & Szakmary, 1994).
[3]Unlike the above studies, however, they employ daily rather than intraday data.

THE RELATIONSHIP BETWEEN STOCK GROUPS AND INDEXES

Several studies have documented asymmetric relationships among various groups of U.S. stocks. Lo and MacKinlay (1990) show that weekly returns on the stocks of small firms and lagged weekly returns of large firms are positively correlated. Conrad, Gultekin, and Kaul (1991) find that the volatility of large firm returns leads return volatility for small firms. Chan (1993) assumes that the quality of signals from large firms are better than those from small firms, and shows that this difference in quality induces the lead–lag pattern between large and small firms. Badrinath, Kale, and Noe (1995) argue that the lead–lag relationships are primarily determined by institutional ownership rather than firm size, although the two effects are difficult to disentangle because they are highly correlated. The returns of institutionally favored stocks lead the returns on those that are neglected by institutions by as much as two months, even when firm size and return autocorrelation are controlled for.

Studies of the relationships among stock indexes have also focused on the lead–lag structure among international indexes. Khoury, Dodin, and Takada (1987), Schollhammer and Sand (1987), Eun and Shim (1989), Koch and Koch (1991), and Arshanapalli and Doukas (1993) all find that U.S. stock indexes generally lead the indexes of other countries, particularly in the period following the October 1987 crash, although Koch and Koch also report growing leadership by the Japanese equity market. Because transactions costs are lower in large capitalization stocks than in small capitalizations, and generally lower in U.S. equity markets than in other countries, the results of previous studies using cash indexes are broadly consistent with the conjecture that price leadership and low transactions cost are related.

THE STOCK INDEX AND INDEX FUTURES MARKETS

There are three actively traded stock index futures contracts in the United States. They are Standard and Poor's 500 (S&P 500) of the Chicago Mercantile Exchange, the New York Stock Exchange (NYSE) Composite Index of the New York Futures Exchange, and the Major Market Index (MMI) of the Chicago Mercantile Exchange.[4]

[4]The MMI traded on the Chicago Board of Trade (CBOT) until 1992. As our data period ends with July 1991, the prices of the MMI we are using are the ones that traded on the CBOT.

The S&P 500 index is most widely used as a basis of institutional investment management. It is based on the market value of 500 blue-chip stocks including industrial, utility, transportation, and financial firms. Most of the firms are listed on the NYSE, and the market value of these stocks equals about 80% of the total value of securities traded on the NYSE. The rest of the securities are from the American Stock Exchange and the NASDAQ. Each stock in the index is market-value weighted so that larger firm stocks have greater importance on the value of index. The NYSE Composite Index is also value weighted but is broader than the S&P 500 index because comprises the market value of all outstanding stocks (1996 common stocks as of August 1992) on the NYSE.

The MMI is different from the above two indexes in that it is a price-weighted index of twenty blue-chip stocks listed on the NYSE. It is calculated by adding the price of each component stock and dividing the sum by the MMI divisor. The divisor changes over time to reflect stock splits, stock dividends, mergers, and so on. The MMI has a near perfect correlation (98.86 % on a daily basis for the period 1987 to 1991) with the Dow Jones Industrial Index, because they share seventeen blue-chip stocks and a similar method of calculating the index.

The Kansas City Board of Trade introduced the first stock index futures contract in the United States in February 1982. The contract is based on the Value Line Index.[5] Two months later the CME initiated the S&P 500 futures contract. Since that time, the S&P contract has been the most actively traded, dominating other stock index futures contracts in terms of trading volume (Figure 1 shows the annual trading volume of the three index futures contracts included in this study for the period of 1986 to 1991). The NYSE Composite Index futures contract was introduced by the NYFE in May 1982. The MMI futures were introduced in July 1984 by the CBOT (recently, the CME has taken over trading of the MMI). The trading volume of MMI futures is roughly equal to that of NYSE index futures.

The most considerable difference between traditional futures contracts and stock index futures is the replacement of the traditional delivery mechanism by cash settlement. When stock index futures contracts expire, they are settled in cash by transferring funds into or out of the contract holder's margin account based on the value of underlying index. This cash settlement feature has made trading of stock index futures more

[5]This contract traded actively in the early years. However, the trading volume has fallen drastically during the late 1980s, especially after the crash of 1987. By 1990, average daily trading volume was a few hundred contracts. For this reason, we do not include the Value Line Index futures contract in this study.

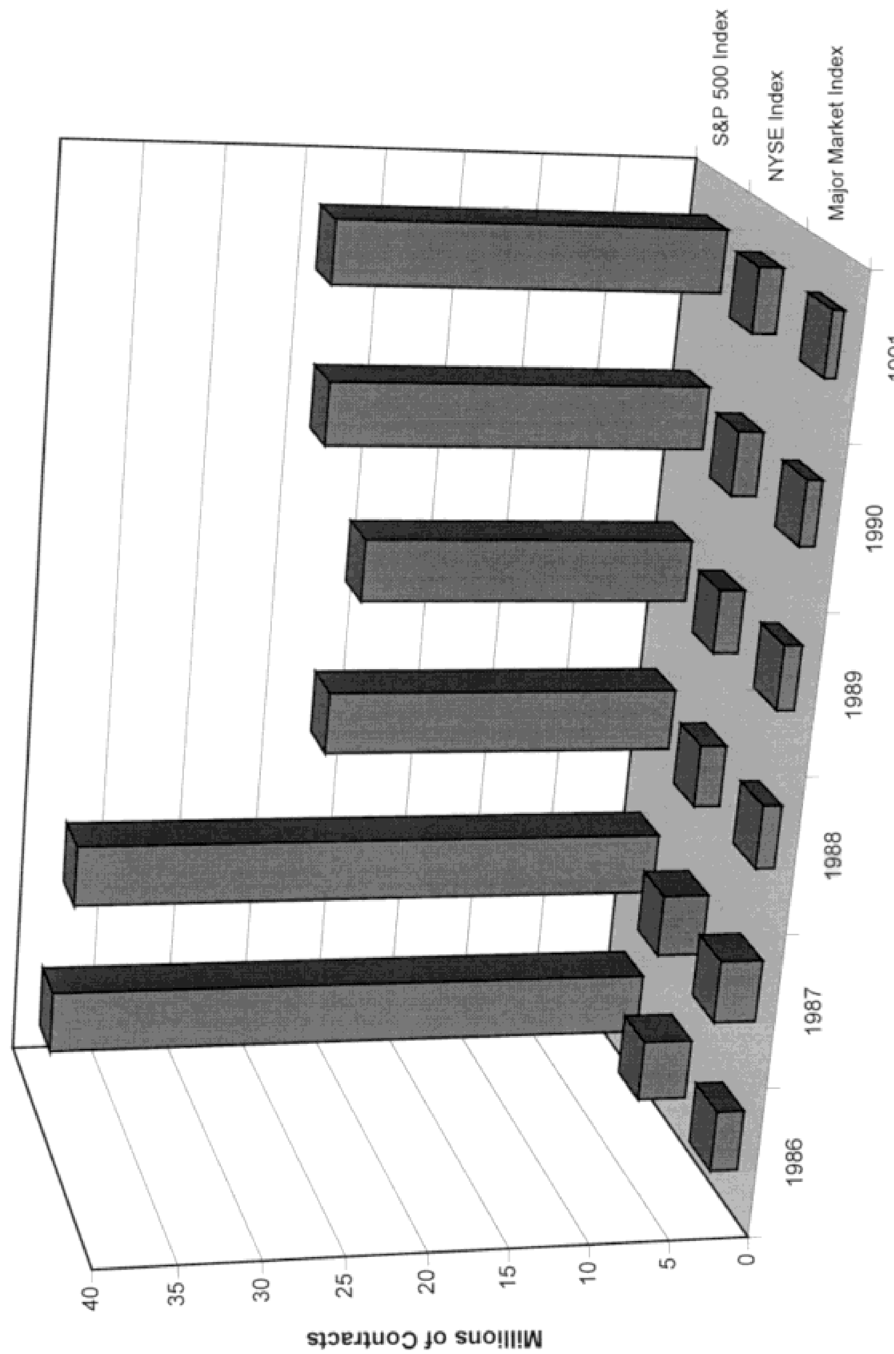

FIGURE 1
Annual trading volume in stock index futures, 1986–1991

efficient and less costly, because market participants do not need to construct proxy portfolios for delivery at maturity.[6]

Trading costs in stock index futures are quite low. Kuserk and Locke (1993) and Fleming, Ostdiek, and Whaley (1996) estimate the effective bid–ask spread in the highly active S&P 500 futures to be about $19 and $30 (respectively) per contract, which is close to the $25 value of one tick. Given that as of 19 July 1991 the S&P 500 futures was selling at 386.65, or a total contract value of $193,400 (386.65 $\times$ 500), the bid–ask spread represents between .010% and .016% of the total contract value.[7] Trading costs in the other stock index futures contracts are higher for two reasons. First, as Laux and Senchack (1992) show, bid–ask spreads are inversely related to trading activity, which is much lower in the case of the MMI and NYSE futures. Second, several studies have found that bid–ask spreads are seldom less than the value of one tick. In dollar terms, the tick size is the same in all three index futures markets ($25), but the contract size is larger for S&P futures: Typically the MMI and NYSE futures represent 80% and 50% of the value of S&P 500 futures, respectively.

In the cash indexes, trading costs are orders of magnitude higher than in the futures. For example, Fleming, Ostdiek, and Whaley (1996) estimate that trading S&P futures costs about 3% as much as trading an equivalent portfolio of index stocks. For our purposes, however, what matters is the relative cost of trading one cash index versus another. Based on exhaustive studies by Stoll and Whaley (1983) and Bhardwaj and Brooks (1992), it is clear that effective bid–ask spreads are substantially lower for relatively high price, large market capitalization stocks such as those that make up the MMI index than for the smaller, lower share price firms that compose a larger portion of the S&P and NYSE indexes.

DATA

The data comprises transaction prices on the S&P 500, the NYSE composite, and the MMI futures contracts (and associated cash indexes) from January 1986 to July 1991. Following Stoll and Whaley (1990) and Chan (1992), we use five-minute interval data for prices of all three futures and cash markets. Within each interval the first and the last prices are re-

[6]For the MMI futures the final cash settlement price is the closing value of the spot MMI on the third Friday of the contract month with maturities available every month. In contrast, the final settlement price of the S&P 500 and NYSE futures is the opening value of the index on the third Friday of the delivery month with quarterly maturities of March, June, September, and December.
[7]During the period covered by this study, the contract value of the S&P 500 futures was 500 times the index. Recently, the CME lowered the contract multiplier to 250 times the index.

corded. If there is no price change during the five-minute interval, the last price from the previous interval is substituted. The first differenced price is defined as $[P_t - P_{t-1}]$ using the last transactions price within each interval, except for the first interval within each day where the first (opening) price within the interval is used as P_{t-1}, in place of the previous day's closing price.

All futures prices used in this study are those on nearby contracts. The rollover within each contract is made 14 days before the last trading day to avoid any expiration effects. During our sample period, the S&P 500 and NYSE index futures market open at 8:30 am and close at 3:15 pm (CST), whereas the MMI futures open fifteen minutes earlier. Thus the first three five-minute intervals are skipped in the MMI futures. Also, if any one of the three markets is closed for a whole day or has delayed openings and/or early closings, the observations of all three markets are skipped for a proper comparison. The total remaining observations are 114,048 for the futures contracts and 118,176 for the cash indexes.

In order to avoid discontinuities associated with the daily cessation of trading between 3:15 pm on the previous trading day and 8:30 am on the current day, as well as with the quarterly rollover of futures contracts, all of the VAR models in this study are estimated using data from 9:30 am to 3:15 pm, which allows for 69 five-minute intervals on each normal trading day. The first 12 five minute intervals (that is, the 8:30–9:30 am periods) are dropped in order to allow lags in the VAR to be estimated solely using data from the same calendar day.

METHODOLOGY

Multivariate Cointegration Tests

Given the time series nature of the data, an initial step in the analysis is to test whether each price series is integrated [denoted I(1)] or stationary [denoted I(0)]. An I(1) time series is said to have a unit root and any shock to the series is permanent. As shown by Sims, Stock, and Watson (1990) and Balke (1991), any econometric model with I(1) series will be misspecified and potentially lead to spurious inferences concerning the estimated parameters. To identify whether our series are I(1), we conduct Augmented Dickey-Fuller (ADF) unit root tests as described in Davidson and MacKinnon (1993).

If each price series is I(1), the next step is to test for cointegration among the variables. As Kasa (1992) points out, most equity market studies have focused on equity returns, rather than on equity prices. With returns one can more easily obtain stationarity of the time series data. However, returns data may ignore information about long-run relationships. The main idea of Engle and Granger's (E-G) (1987) cointegration and error correction specifications is to test for a common long-run trend and to incorporate that trend within the model. If one or more cointegration relations exist among the variables and they are not explicitly accounted for, the model would be misspecified and the parameter estimates would be inefficient (Engle & Yoo, 1987).

As an illustration, assume some linear relations among the variables α, β, and γ:

$$\alpha_t = \psi_0 + \psi_1\beta_t + \psi_2\gamma_t + u_t. \tag{1}$$

The variables are said to be cointegrated of order (1,1) if they are all I(1) and the residual u_t is I(0). To test for cointegration, one can apply the ADF regression to the residuals from regression (1). This is the same regression used to test for the unit roots of each series and is based on the methodology developed by E-G. The E-G approach, however, has some problems in dealing with more than two variables. In the case of N nonstationary variables, there may exist at most N-1 distinct cointegrating relationships among the variables. Thus, when $N > 2$, a cointegrating vector from the E-G approach may not be unique. In addition, the estimated cointegration parameters may be sensitive to the choice of dependent variables. An alternative test for cointegration has been provided by Johansen (1988, 1991) and Johansen and Juselius (1990, 1992). This test is based on maximum-likelihood estimation, and is designed to test for the number of linearly independent cointegrating vectors existing among the variables. We utilize this multivariate procedure to test for cointegration among the prices.[8] This involves estimation of the following VAR system of equations:

$$Y_t = \mu + \Pi_1 Y_{t-1} + \ldots + \Pi_k Y_{t-k} + U_t \tag{2}$$

where μ is a vector of constants, $Y_t = (y_{1,t}, y_{2,t}, y_{3,t})'$, a 3×1 column vector of the variables, the S&P 500 futures (cash), the NYSE futures (cash), and MMI futures (cash), respectively. II_l through II_k are 3×3 matrices of coefficients, and U_t is a 3×1 column vector of error processes. By using the first difference operator, Δ, we can rewrite eq. (2) as

[8]Many studies have utilized Johansen's procedure to test the long-run cointegrating relationships among financial and economic variables: foreign exchange rates (Baillie & Bollerslev, 1989; Sephton & Larsen, 1991; Diebold, Gardeazabal, & Yilmaz, 1993); equity markets (Kasa, 1992); purchasing power parity (Johansen & Juselius, 1992; Fung & Lo, 1992); money and output (Ahmed, 1993); export pricing (Hung, Kim, & Ohno, 1993); international bond market (Mills & Mills, 1991).

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{k-1} \Delta Y_{t-k+1} + \Pi Y_{t-k} + \mu + U_t \quad (3)$$

where

$$\Gamma_i = -(I - \Pi_1 - \ldots - \Pi_i), \ (i = 1, \ldots, k - 1),$$

and

$$\Pi = -(I - \Pi_1 - \ldots - \Pi_k).$$

Eq. (3) is in the form of the traditional VAR model of Sims (1980) with first differences except for the IIY_{t-k} term. The II term determines whether and to what extent the system of equations is cointegrated, and is known as the *cointegrating constraint* in the VAR system. By imposing the cointegrating constraint in the first-differenced VAR model, we can recapture long-run information, which is eliminated by taking first differences to achieve stationarity.

If the matrix II is of full rank, then any linear combination of Y_t is stationary. If the rank(II) = 0, the matrix II is a null matrix and eq. (3) collapses to the traditional VAR model with first differences. In the case of 0 < [rank(II) = r] < p, where r is the rank of the matrix and p is the number of variables in the system, there exist one or more cointegrating relationships among the variables. Johansen's procedure is to determine the rank of the II matrix by testing whether the eigenvalues of $\hat{\Pi}$, the estimate of II, are significantly different from zero.

To test the null hypothesis that there are at most r cointegrating vectors in a set of p variables, we first run the regressions of ΔY_t and Y_{t-1} on lagged ΔY_{t-1} and constant terms, yielding residuals of R_{0t} and R_{1t}, respectively, and then compute the canonical correlations between the two residuals, denoting them as Q_i ($Q_1 > Q_2 > \ldots > Q_I$). The likelihood-ratio test of the null hypothesis is obtained via the trace test, defined as

$$\textit{Trace Test} = -T \sum_{i=r+1}^{p} \ln(1 - Q_i^2), \quad (4a)$$

where T is the number of time periods. We can also use the maximal eigenvalue test, positing that there are r cointegrating vectors in a set of p variables against r + 1. It is defined as

$$\textit{Maximal Eigenvalue Test} = -T \ln(1 - Q_{r+1}^2), \quad (4b)$$

Johansen and Juselius (1990) provide the critical values for the above two tests.

Estimation of the Vector Autoregressive (VAR) Model

After determining whether there are any cointegrating relationships among the variables, we calculate the impulse response function (IRF) of the VAR system, incorporating cointegration constraints if necessary. The IRF traces the impact of a shock in a variable onto the system over time. Thus we can measure how rapidly information is transmitted across different index futures (cash) markets. The IRF is derived from the moving average representation of the autoregressive system. For example, in moving average form, eq. (3) can be expressed as

$$\Delta Y_t = \sum_{k=0}^{\infty} A_k U_{t-k} \tag{5}$$

where A_t is 3×3 matrix of coefficients of the 3 variables in the system. ΔY_t vector is expressed in terms of accumulation of both current and past residuals, U's, which are innovations in that they represent the unexpected portion of the system. The (i,j)th component of matrix A_k represents the dynamic responses of i'th variable in k periods to an innovation in j'th variable, $U_{j(t-k)}$.

By construction of the VAR equations, the error terms are serially uncorrelated but they may be contemporaneously correlated. This implies that an innovation in one variable may also work through the contemporaneous correlations of innovations of different series, rendering the decomposition of variance in the variables into components attributable to each innovation ambiguous. Thus a transformation of the error terms that makes them contemporaneously uncorrelated is required. This transformation is accomplished by orthogonalizing the innovations so that they form an identity covariance matrix and are uncorrelated both serially and contemporaneously. The orthogonalization is obtained from $U_t = V \times \zeta_t$, where V is a lower triangular matrix. Eq. (5) can be expressed as follows with the transformed error terms:

$$\Delta Y_t = \sum_{k=0}^{\infty} B_k \zeta_{t-k} \tag{6}$$

where $B_k = V \times A_k$. With the (i,j)th component of the B_k matrix, we now can single out the impact of a shock in the j'th variable in period t to the value of the i'th variable because the orthogonalized innovations in the ζ matrix are uncorrelated serially and contemporaneously. Specifically, by a unit shock in the j'th variable in time t, the value of i'th variable changes by $B_{ij,t+1}$ in the next period and $B_{ij,t+2}$, $B_{ji,t+3}$, etc. in subsequent periods.

The orthogonalization also lets us decompose the forecast error variance into two parts: the forecast error variance accounted for by its own innovations and by the innovations of other variables within the system. This can be expressed as

$$\left[\sum_{k=0}^{t-1} B_{ij,k}^2 \Big/ \sum_{j=0}^{m} \sum_{k=0}^{t-1} B_{ij,k}^2 \right], \tag{7}$$

where m is the number of variables in the system. This shows the fraction of the t-period ahead forecast error variance of variable I explained by innovations in variable j. Thus, for example, in the context of this study, if the MMI has a true price leadership over the other markets, MMI's own innovations will explain much of the future innovations in the MMI market as well as substantial portions of the forecast error variances of the other markets.

EMPIRICAL RESULTS

Stationarity and Multivariate Cointegration Tests

We examine the stationarity properties of each futures and cash index series via ADF unit root tests. As expected, these tests indicate that all of the price series contain a single unit root.[9] The Johansen multivariate cointegration test results are reported in Table I. For this test, we use the daily closing observations for each index series,[10] and a lag length of six as indicated by the Sims likelihood method. Both the trace and maximal eigenvalue tests indicate that there are no cointegration relationships among the stock index futures series of the S&P 500, NYSE index, and Major Market Index. Similar results are obtained for the cash series. Consequently, we estimate the VAR model without any cointegration constraints.[11]

[9]These results are not reported but are available from the authors upon request.

[10]Unfortunately, we are unable to run the Johansen cointegration test with our 5-minute interval data with more than 100,000 observations for each index series. However, Hakkio and Rush (1991) argue and empirically show that switching to high frequency data from low frequency adds little power to detect cointegration relationships among variables because basically cointegration is a long-run property of the data. Consequently we assume that with daily data we can reasonably detect any cointegration relationship, if it exists.

[11]An additional issue in the cointegration tests, which are performed in part using price levels, is possible discontinuities in the futures price series induced by the quarterly rollover of futures contracts Because the cointegration results for the cash indices, which are not affected by the rollover problem, are similar to those obtained with futures prices, it is unlikely that contract rollovers have a material affect on the futures results. In any case, the VAR results below, which are estimated using only first-differenced data without cointegration constraints, are not affected by the rollover problem.

TABLE I

Johansen Multivariate Cointegration Tests[a]

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{k-1} \Delta Y_{t-k+1} + \Pi Y_{t-k} + \mu + U_t$$

	Trace Test[b]			Maximal Eigenvalue Test[c]		
	$\Pi = 0$	$\Pi \leq 1$	$\Pi \leq 2$	$\Pi = 0$	$\Pi = 1$	$\Pi = 2$
Futures	23.85	10.33	0.54	13.52	9.81	0.54
Cash	23.39	9.78	0.81	12.61	8.97	0.82

[a]The cointegration equation is based on the three variables SP, YX, and BC for both futures and cash markets. The lag length K is chosen by the Sims likelihood method and set to be six. For these cointegration tests, we take the daily closing observations from the intradaily series. The estimation period is December 1986 to July 1991 for both futures and cash.

[b]The trace statistic is defined as

$$-T \sum_{i=r+1}^{p} \ln\,(1 - \hat{Q}_i^2).$$

where T is the number of time periods and $\hat{Q}_i$ is the correlations between residuals.

[c]The maximal eigenvalue test statistic is defined as

$$-T \ln(1 - Q_{r+1}^2).$$

Vector Autoregressive Model Estimation

For the VAR estimation, we use the full data set of five minute interval price changes. Following Stoll and Whaley (1990), before estimation, we purge from each index series the effects of bid–ask spread and infrequent trading via the following regression:

$$\Delta y_t = \alpha + \sum_{l=1}^{N} \Omega_1 \Delta y_{t-1} + \mu_t, \tag{8}$$

where Δy_t is the first differenced 5-minute interval data for each index series and lag length N is selected by the Schwarz criterion. The residuals, μ_t's, are then used to estimate a VAR model. Cash prices are more severely affected by the effects of bid–ask spreads and infrequent trading, although we apply the same procedure for both futures and cash index series. In fact, we find little difference in results between the unpurged and purged series for the futures, but there are some differences for the cash series. Details will be discussed below as appropriate.

Throughout the VAR estimation, we use the Sims likelihood method to choose the lag length. The optimum lag length appears to be 12, which represents one hour, because we fail to reject the hypothesis that all coefficients of lags 13 through 18 are zero at the 5% significance level. A lag length of 12 should be sufficient to capture any feedback from lagged prices, because these markets are actively traded within this period of lag The same lag length is used for the cash indexes.

By construction, the orthogonalization of innovations from the VAR model makes the innovation in the first variable influence all other variables in the system, the innovation in the second variable influence all other variables save the first variable, and so on. Ideally one should order the variables based on a priori expectations of predictive power. Our conjecture concerning the importance of transactions costs notwithstanding, because our study is the first to examine price leadership among futures markets, it is doubtful that an a priori ordering can be justified. Moreover, if the variables are highly correlated, the empirical results depend on the ordering of the variables, and this is the case in our sample. In the 5-minute interval futures sample, the correlation between variables are S&P versus NYSE: 0.656; S&P versus MMI: 0.641; and NYSE versus MMI: 0.576. Those of cash indices are 0.945, 0.798, and 0.771, respectively.

In this situation, one recommended procedure is to change the order of variables and check the relative differences in forecasting power [Doan, (1991)]. Thus we estimate three separate VAR systems of equations by putting each variable in the first place, assuming that innovations from the first variable have the most explanatory power over those from the other two variables. Specifically, we use the following three orderings: (i) S&P-NYSE-MMI; (ii) NYSE-MMI-S&P; and (iii) MMI-S&P-NYSE. The first ordering is to test price leadership for the S&P 500 index futures, the second for NYSE index futures, and the last for MMI futures. We apply the same orderings for the cash indexes.

Dynamics of Information Transfer across Index Futures

Table II reports the decomposition of 1-hour ahead forecast error variance for the three index futures contracts with the three different orderings described above. The last rows of each panel denote the cumulative percentage of forecast error variance of the other two markets explained by innovations in the variables on the top. The results show that the S&P 500 has the highest explanatory power over the other two contracts. That is, the cumulative percentage of 1-hour-ahead forecast error variances of the NYSE and MMI futures explained by the S&P 500 index futures (the second column of Panel A) is 93.62%. The comparable percentages for the NYSE and MMI futures are 85.87% and 78.48%, respectively. This is the case when each variable is put in the first place. Therefore, regard-

TABLE II

Decomposition of 1-Hour Ahead Forecast Error Variance—Index Futures[a]

Panel A: Ordering—S&P, NYSE, MMI

	By Innovations in		
Variables Explained	*S&P*	*NYSE*	*MMI*
S&P	96.76	0.78	0.79
NYSE	49.62	50.09	0.21
MMI	44.00	4.05	51.95
Sum[b]	93.62	4.83	1.00

Panel B: Ordering—NYSE, MMI, S&P

	By Innovations in		
Variables Explained	*NYSE*	*MMI*	*S&P*
NYSE	94.72	1.03	2.78
MMI	36.41	62.19	1.39
S&P	49.46	8.82	41.72
Sum[b]	85.87	9.85	4.17

Panel C: Ordering—MMI, S&P, NYSE

	By Innovations in		
Variables Explained	*MMI*	*S&P*	*NYSE*
MMI	94.47	1.86	0.34
S&P	43.72	55.88	0.39
NYSE	35.76	17.32	46.88
Sum[b]	79.48	19.18	0.73

[a]The numbers reported denote the percentage of 1-hour forecast error variance of the left-hand side variables (i) explained by innovations in the variables (j) on the top. They are

$$\left[\sum_{k=0}^{12} B_{ij,k} \Big/ \sum_{j=0}^{3} \sum_{k=0}^{12} B^2_{ij,k}\right] \times 100,$$

where $B_{ij,k}$ is calculated from the orthogonalized moving average transformation of 3×1 vector. The estimations reported here are from the purged data. The same estimations from the unpurged data do not materially differ. We use 5-minute interval data from December 1985 to July 1991 with total observations of 114,048 for each index futures.

[b]"Sum" represents the cumulative percentage of the forecast error variance of the other two markets explained by the innovation in the variable on the top. For example, 93.62 is the cumulative percentage of 1-hour ahead forecast error variance of the NYSE and MMI futures explained by the innovation in the S&P 500 index futures.

less of ordering, the S&P 500 index futures turn out to have the highest explanatory power. For instance, when variables are put in the second position, the cumulative percentages that the S&P 500 futures explains of the other two variables are 19.18%, whereas those of NYSE and MMI are 4.83% and 9.85%, respectively. In the last position, they are 4.17%, 0.73%, and 1.00% for S&P, NYSE, and MMI, respectively. The results

TABLE III

Impulse Responses—Index Futures[a]

Panel A: Impulse Responses to a Unit Innovation in S&P

Responses in	*Minutes after Shock* 0	5	10	15	20	25	30	35	40	45	50	55
NYSE	0.71	0.14	0.01	−0.03	0.01	−0.05	−0.01	−0.01	0.02	−0.02	−0.02	−0.02
MMI	0.66	0.10	−0.05	−0.02	0.04	0.01	0.01	−0.01	0.04	0.00	−0.02	0.04

Panel B: Impulse Responses to a Unit Innovation in NYSE

Responses in	*Minutes after Shock* 0	5	10	15	20	25	30	35	40	45	50	55
MMI	0.61	0.08	0.01	−0.02	0.04	−0.02	0.01	−0.01	0.03	0.01	−0.01	0.03
S&P	0.71	0.05	0.03	0.03	−0.00	−0.00	−0.01	−0.02	0.02	−0.00	−0.01	−0.03

Panel C: Impulse Responses to a Unit Innovation in MMI

Responses in	*Minutes after Shock* 0	5	10	15	20	25	30	35	40	45	50	55
S&P	0.66	0.07	0.04	−0.01	0.01	0.02	0.06	−0.00	0.03	0.00	−0.02	0.01
NYSE	0.61	0.08	−0.02	−0.05	0.01	−0.04	−0.03	0.01	0.02	0.00	−0.01	0.00

[a]The numbers reported are the normalized impulse responses of each variable for the kth minute after the shock. They are represented by B_{ij} in the orthogonalized moving average transformation of Y_t:

$$\Delta Y_t = \sum_{k=o}^{\infty} B_k \xi_{t-k}$$

where Y_t is a vector of three variables in the VAR system. Each B_{ij} is divided by its standard error for proper comparison. The estimations reported here are from the purged data. The same estimations from the unpurged data are not materially different. We use 5-mimute interval data from December 1985 to July 1991 with total observations of 114,048 for each index futures.

imply that in predicting unexpected movements among stock index futures contracts, the S&P index futures has the highest predictive power.

The analysis of impulse response functions provides additional insights by showing the time path of these transmission channels from one market to the others. Table III summarizes the impulse responses for the index futures contracts. The orderings are the same as before. Each impulse response represents the moving average coefficient in eq. (6) and is normalized by its standard error. This normalization is needed to compare the impulse responses across variables that have different variances.

Panel A of Table III illustrates that any shocks in the S&P 500 index futures are transmitted to the other two futures contracts, and each transmission process is completed in about 10 minutes. Panel B shows the influence of NYSE index futures over the other two contracts. Shocks from the NYSE futures are transmitted to the other two, but do not seem to persist to the same degree beyond 5 minutes after the shocks. This is especially true concerning the response of S&P 500 index futures. The response of S&P 500 futures to shocks from the MMI futures is also quite marginal after 5 minutes. In short, the impulse response analysis shows that shocks from any one market are rapidly transmitted to other markets, but the persistence of the shocks differs somewhat depending on their origin. We find that the S&P 500 index futures leads the other two futures by about five minutes.[12]

Both the VAR decomposition and impulse response findings are consistent with our conjecture that the S&P 500 index futures, with a dominant trading volume and lower trading costs, would have price leadership over other stock index futures. In the next section, we investigate whether the results obtained for futures hold for the cash index series.

Dynamics of Information Transfer across Cash Indexes

Table IV reports the decomposition of 1-hour ahead forecast error variance for the cash indexes. Each index series is purged of the effects of infrequent trading and bid–ask spread by the regression filter described previously. We use the same orderings as in the futures contracts presented in each panel of Table II. One thing to note about the cash indexes is that, because of near perfect correlation between the S&P 500 and NYSE index cash (0.945), any variable that comes first in the VAR system explains most of the other variable's forecast error. For instance, in the second row and second column in Panel A, S&P explains 82.68% of NYSE's forecast error variance. This is much higher than NYSE's forecast error variance explained by its own innovation, which is 12.76%. This makes the cumulative influence of MMI somewhat lower compared to those of S&P and NYSE. Thus interpretation of the results is focused on the individual influence of MMI on S&P and NYSE, and vice versa.

In the first row of Panel A, we can see that when the S&P is put in the first place (that is, when we let S&P influence the other two variables), 94.69% of S&P's forecast error is explained by its own innovation; the rest is explained by MMI (4.99%), and the influence of NYSE is negligible (0.32%). The influence of MMI on NYSE is almost the same (4.55% on

[12]The result is obtained by using the 5-minute interval data that is filtered by the regression described above to purge the effects of bid–ask spread and infrequent trading. The result from the unpurged data does not materially change that from the purged one.

TABLE IV

Decomposition of 1-Hour Ahead Forecast Error Variance—Index Cash[a]

Panel A: Ordering—S&P, NYSE, MMI

	By Innovations in		
Variables Explained	*S&P*	*NYSE*	*MMI*
S&P	94.69	0.32	4.99
NYSE	82.68	12.76	4.55
MMI	63.49	0.41	36.10
Sum[2]	146.17	0.73	9.54

Panel B: Ordering—NYSE, MMI, S&P

	By Innovations in		
Variables Explained	*NYSE*	*MMI*	*S&P*
NYSE	91.10	6.98	1.92
MMI	60.33	39.61	0.06
S&P	85.71	4.61	9.68
Sum[b]	146.04	11.59	1.98

Panel C: Ordering—MMI, S&P, NYSE

	By Innovations in		
Variables Explained	*MMI*	*S&P*	*NYSE*
MMI	99.92	0.03	0.04
S&P	61.48	38.40	0.13
NYSE	57.06	29.42	13.52
Sum[b]	118.54	29.45	0.17

[a]The numbers reported denote the percentage of 1-hour forecast error variance of the left-hand side variables (i) explained by innovations in the variables (j) on the top. They are

$$\left[\sum_{k=0}^{12} B_{ij,k} \Big/ \sum_{j=0}^{3} \sum_{k=0}^{12} B^2_{ij,k}\right] \times 100,$$

where $B_{ij,k}$ is calculated from the orthogonalized moving average transformation of 3 × 1 vector. The estimations reported here are from the purged data. We use 5-minute interval data from December 1985 to July 1991 with total observations of 118,176 for each cash index series.

[b]"Sum" represents the cumulative percentage of the forecast error variance of the other two markets explained by the innovation in the variable on the top. For example, 146.17 is the cumulative percentage of 1-hour ahead forecast error variance of the NYSE and MMI cash indexes explained by the innovation in the S&P 500 index cash.

the second row of the last column). A similar pattern is found in the first row of Panel B. The influence of MMI on NYSE is much higher than that of S&P on NYSE (6.98% versus 1.92%). The first row of Panel C also confirms this pattern. That is, most of MMI's forecast error variance is explained by MMI's own innovation. The influences of S&P and NYSE on MMI are negligible; 0.03% and 0.04%, respectively. Thus we conclude

TABLE V

Impulse Responses—Index Cash[a]

Panel A: Impulse Responses to a Unit Innovation in S&P

	Minutes after Shock											
Responses in	*0*	*5*	*10*	*15*	*20*	*25*	*30*	*35*	*40*	*45*	*50*	*55*
NYSE	0.95	0.04	−0.05	0.01	0.01	0.03	0.02	0.01	0.01	0.01	0.00	0.01
MMI	0.80	−0.03	−0.01	0.00	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.01

Panel B: Impulse Responses to a Unit Innovation in NYSE

	Minutes after Shock											
Responses in	*0*	*5*	*10*	*15*	*20*	*25*	*30*	*35*	*40*	*45*	*50*	*55*
MMI	0.78	−0.03	−0.01	0.01	0.03	0.00	0.00	0.01	0.02	0.02	0.01	0.00
S&P	0.95	−0.01	−0.02	0.00	0.01	0.02	0.01	0.01	0.02	0.01	0.01	0.00

Panel C: Impulse Responses to a Unit Innovation in MMI

	Minutes after Shock											
Responses in	*0*	*5*	*10*	*15*	*20*	*25*	*30*	*35*	*40*	*45*	*50*	*55*
S&P	0.80	0.12	−0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00	−0.01
NYSE	0.78	0.15	−0.03	0.02	0.01	0.02	0.01	0.01	0.01	0.01	−0.00	0.00

[a]The numbers reported are the normalized impulse responses of each variable on the kth minutes after shock. They are represented by B_{ij} in the orthogonalized moving average transformation of Y_t:

$$\Delta Y_t = \sum_{k=o}^{\infty} B_k \xi_{t-k}$$

where Y_t is a vector of three variables in the VAR system. Each B_{ij} is divided by its standard error for proper comparison. The estimations reported here are from the purged data. We use 5-minute interval data from December 1985 to July 1991 with total observations of 118,176 for each cash index series.

that unlike in the futures, the MMI cash index has more predictive power over the other two cash indexes.

This result is confirmed by the analysis of impulse response functions. Table V presents the impulse responses of each cash index. Notice that the response patterns in Panel A and B are almost identical. Given a unit shock in S&P (NYSE), the responses of MMI are 0.80 (0.78) and −0.03 (−0.03) during the first two intervals. In the second interval (5 minutes after shock), shocks from S&P to the NYSE seem to have more persistency than shocks in reverse (0.04 versus −0.01). Panel A and B of Table V show that the responses of the other two markets to a unit shock in S&P (NYSE) are completed in about 5 minutes. The responses of S&P and NYSE to a unit shock in MMI, however, exhibit a noticeable difference. Panel C of Table V shows that any shock originating from the

MMI is fully reflected in the prices of the S&P 500 and NYSE indexes only after 10 minutes.

In sum, we find that in the cash market, the MMI consistently leads the S&P 500 and NYSE indexes by 5 minutes. This result is consistent with previous findings indicating that the stocks of large institutionally favored firms exhibit price leadership. Because these stocks have relatively lower transactions costs than those of less actively traded smaller firms, it is also consistent with the conjecture that price leadership and transactions costs are linked.

CONCLUSIONS

The focus of this article is to test the trading cost hypothesis of price leadership, which predicts that the market with the lowest overall trading costs will react most quickly to new information. In an attempt to hold market microstructure effects constant and in contrast to previous studies, we examine intraday price leadership across the S&P 500, NYSE Composite and MMI futures, and across the respective cash indexes, rather than between each futures and its associated cash index.

Price leadership is examined by the decomposition of forecast error variance and impulse response functions from a vector autoregressive (VAR) model. Among the index futures contracts, we find that the S&P 500 index futures has the highest power in explaining unexpected future movements of the other markets (as well as its own). The impulse response analysis shows that shocks from any one market are rapidly transmitted to other markets, but the persistence of the shocks differs depending on their origin. Shocks from either the NYSE or the MMI futures are reflected in prices of the other markets within five minutes, whereas shocks from the S&P 500 futures persist for ten minutes. In short, we find that the S&P 500 index futures leads the other two futures by about five minutes. Because transaction costs in the S&P futures are lower than in the other index futures, this finding is consistent with the trading cost hypothesis.

In the cash market, we find evidence of leadership by the Major Market Index, in that the MMI has the highest predictive power over the others, and is least explained by the others. The responses of the other markets to shocks from either the S&P 500 or the NYSE index last up to five minutes, whereas the responses of other markets to shocks from the MMI persist up to ten minutes. As in the case of the index futures, we find one market leads the others by about five minutes—but in the cash market, it is the Major Market Index that leads. Again, this finding is consistent with the trading cost hypothesis because earlier research has shown that transactions costs in the large capitalization stocks underlying the MMI index are lower, on average, than in those comprising the broader S&P 500 and NYSE composite indexes. Thus, we conclude that even in markets of similar microstructure, price leadership and trading cost appear to be linked.

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