財務管理硏究 第十二卷 第二號(1995. 12), 239~271

The Dynamics of Intraday Price Transmisson Across the Stock Index Futures Markets: The Standard & Poor's 500, the New York Stock Exchange Composite, and the Major Market Index Futures

Minho Kim*

<요 약>

본 연구는 현재 미국에서 거래되고 있는 세 가지 주가지수선물 상호간의 일중(intradaily) 가격선도(price leadership) 관계에 관한 실증분석이다. 본 연구가 기존의 연구와 다른 점은, 기존의 연구가 주가지수선물과 그 기준이 되는 현물 가격사이의 가격 선도 관계에 초점을 두고 있는데 반하여 본 연구는 주가지수선물 시장 사이에서 존재하는 가격선도관계를 분석하고 있다는 점이다. 실증분석의 대상이 된 주가지수선물들은 Chicago Mercantile Exchange의 Standard and Poor's 500 Index(S&P 500), New York Futures Exchange의 New York Stock Exchange Composit Index (NYSE), 그리고 Chicago Board of Trade 의 Major Market Index(MMI)이다. 만약 이들 시장들이 정보의 전달에 있어서 효율적(informationally efficient) 이라면 이들 가격간에 선도-지연(lead-lag) 현상은 존재하지 않을 것이다. 그러나 어느 한 시장이 새로운 정보를 선물가격에 반영하는데 다른 시장에 비해 상대적으로 느리다면, 이들 시장 상호간에는 가격의 전이(transmission)현상이 존재하게 될 것이다. 이들 선물간의 일중 가격선도 관계 연구는 이러한 시장의 효율성 문제를 밝히는데 의의가 있을 뿐만 아니라, 시장간의 단기적 가격 괴리를 이용하려는 차익거래자들에게도 유용하게 쓰일 수 있을 것이다.

본 연구는 위에서 언급한 각각의 주가지수선물들이 가격 선도성을 가질 수 있는 이유와 관련된 다음과 같은 세 가지 가설을 설정하였다. 첫째 가설은, 가격의 선도성은 거래량과 관련이 있다는 것이다. 즉, 이들 주가지수선물 중 가장 거래량이 많은 S&P 500 선물이 다른 선물을 선도할 것이라는 가설이다. 둘째, 가격의 선도성은 주가지수를 구성하는 주식의 수에 비례한다는 가설이다. 다시 말하면, 보다 많은 수로 구성된 주가지수일수록 정보처리 속도가 빠르다는 가설이다.

따라서, 본 연구에 포함된 주가지수선물 중 가장 많은 수의 주식을 대상으로 하는 NYSE 선물이

---

* Chonbuk National University

**본 논문은 1995년도 전북대학교 학술 장학재단의 연구비 지원에 의하여 작성되었음.

다른 선물을 선도할 것이다. 마지막 가설은 정보의 처리는 대형주 혹은 기관선호주(institutionally-favored)들이 주도한다는 것이다. 따라서, 주로 이와 같은 주식들로 구성된 MMI 선물이 선도성을 가질 수 있다는 것이다.

위의 가설들을 검증하고 시장간의 가격 선도관계를 분석하기 위하여 본 연구는 vector autoregressive(VAR) 모형을 이용하여 충격-반응 함수(impulse response functions)를 계산하고, 분산분해(variance decomposition)를 수행하였다. 또한 가격상호간에 존재할지도 모르는 공적분(cointegration)관계를 Johansen(1991)과 Johansen and Juselius (1992) 등이 제시한 다변량 공적분 검정(multivariate cointegration test)를 통하여 분석하였다. 분석기간은 1986년 1월부터 1990년 7월까지이며, 각 주가지수선물들의 5분 간격 data를 사용하였다.

연구결과, 충격-반응 분석은 어느 한 시장에서의 충격(shock)은 다른 시장으로 매우 빠르게 전달되고 있음을 보여 주었다. 그러나 충격의 지속정도는 그 충격의 진원지에 따라 달랐다. 즉, NYSE나 MMI 선물로부터 발생한 충격은 다른 시장의 가격에 5분 안에 반영을 끝냈지만 S&P 500 선물에서 발생한 shock은 그 이상 지속되었다. 또한, 분산분해 결과 S&P 500 선물이 자기자신 뿐만 아니라 다른 시장의 예상하지 못했던 움직임(unexpected movements)을 설명하는데 가장 큰 설명력(explanatory power)을 가지고 있었다. 결론적으로 S&P 500 선물이 다른 선물을 약 5분 간격으로 선도하였다. 이는 가격의 선도가 거래량과 밀접한 관계가 있음을 보여 주는 것이다.

I . INTRODUCTION

This study examines the dynamics of the price transmissions across the stock index futures contracts currently traded in the United States. The majority of prior studies on stock index futures examine the temporal relationship between the futures and their corresponding underlying cash markets [e.g., Kawaller, Koch, and Koch (1987), Stoll and Whaley (1990), Chan (1992)]. The basis of these studies is that in perfectly efficient futures and cash markets with no transactions costs, informed investors are indifferent between trading in one market or the other. Thus, new information would be reflected in both markets simultaneously. Accordingly, contemporaneous returns of each market would be perfectly correlated while non-contemporaneous returns would not be correlated. In short, there would be no lead-lag relation between the prices of futures and cash. Many empirical studies, however, have documented the mispricing between futures and cash markets from their theoretical price relationship. The consensus is that the futures market generally leads the cash market.

The infrequent trading of the component stocks in the index is one plausible reason for this asymmetric relationship. When new information arrives in the market, the futures contract, as a single claim, is able to update the new information immediately. For the cash index price to reflect new information fully, every stock within the index must be traded. This staleness in the index cash price may make cash prices lag behind futures prices. Empirical findings, however, do not seem to support this line of reasoning as a source of the asymmetric relationship between the futures and cash prices.[1] The nature of new information may also be related to the observed asymmetric relationship. Chan (1992) finds that when the market has information of a general nature, futures prices lead cash prices to a greater extent. He argues that firm-specific information, which is diversifiable, is mainly reflected in the cash index prices while the futures market is the main source of market-wide information which is systematic. Consequently, futures prices contain more information so that there exists a feedback from futures to cash prices.

This paper differs from previous studies on the stock index market in that we examine possible mispricings across the index futures, rather than between futures and their associated cash markets. Specifically, we examine the intraday price leadership among the futures markets of the Standard & Poor's 500 index, the New York Stock Exchange Composite index, and the Major Market index. If these markets are informationally efficient and all information is fully reflected in the prices of these markets, then there will be no systematic lead-lag pattern among the prices. If, however, for some reason, one market is slow in reacting to a piece of new information, it will lag behind the other markets, possibly showing price transmission channels from one market to the other markets.

In addition to the market efficiency issue, studying the intradaily price relationship among futures contracts is important to the arbitrage traders who take advantage of

---

1) For example, Stoll and Whaley (1990) use an ARMA (2,3) process on the Standard & Poor's 500 cash return series to control for the infrequent trading effect. The results show that even after the infrequent trading effect is removed the cash price still lags behind the future price. Moreover, Chan's (1992) study on the Major Market index shows that the futures return even leads the returns of component stocks traded more heavily than the futures itself.

extremely short-term price deviations between futures prices.[2] Particularly, this type of short-term intermarket arbitrage activity is popular between the S&P 500 and NYSE composite futures contracts because of their close correlation.[3] An arbitrager with knowledge of the historical correlation between two futures contracts can simultaneously take a short position in the overvalued futures contract and a long position in the undervalued futures. If the aberration is temporary and the price relationship returns to normal, the arbitrager will realize a risk-less profit. This intermarket arbitrage coupled with cash-future arbitrage will force the index future prices back into line.

To study the dynamics of the intradaily price transmission 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 the 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. In addition, we test possible cointegration relationships among the prices of futures markets by the multivariate procedures outlined by Johansen (1991) and Johansen and Juselius (1992). The cointegrating constraints are explicitly considered in the analysis of the impulse response functions to capture the long-as well as the short-run price dynamics among the variables.

Ⅱ. The Stock Index and Index Futures Markets.

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

---

[2] This type of arbitrage is different from inter-market spreading, in which speculators usually take short or long positions in different futures markets over several weeks or months.

[3] Historically, there has been an extremely high correlation between the two futures contracts. During our sample period from 1986 to 1991, the correlation was 99.53% on a daily basis and 65.62% on a five-minute interval. This is because the S&P 500 index represents about 80 percent of the value of NYSE index, and they use the same method to calculate the indices. According to Byrne (1987) about thirty-five percent of the trading activity on the NYSE composite future contract is related to the short-term arbitrage against the S&P 500 contract.

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 them are listed on the NYSE and the market value of these stocks equals about 80 percent of the total value of securities traded on the NYSE. The rest of the securities are from the American Stock Exchange and the NASDAQ. To reflect a cross-section of industry groups, the firms are selected on the basis that they represent a particular industry as well as on capitalization. Therefore, the S&P 500 firms do not match the capitalization-based Fortune 500 firms, and the stock prices of the component firms are sensitive to changes in their respective industry. 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 it is comprised of 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 indices 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 represent 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 currently 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 State 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 then it has been the most actively traded, dominating other stock index futures contract in terms of trading volume. (Table 1 shows the annual trading volume of the three index futures contracts included in this study for the period of 1986-1991.) The NYSE Composite

---

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

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. This is the reason we do not include the Value Line Index futures contract in this study.

Table 1
Annual Volumes of the Stock Index Futures Contracts(1986~1991)

Unit: 1,000 Contracts

Futures Contracts	Year					
	1986	1987	1988	1989	1990	1991
S & P 500	19.506	18.983	11.353	10.560	12.134	12,330
NYSE Compostite	3.132	2.910	1.648	1,556	1,572	1,486
Major Market Index	1.736	2,625	1,174	1.085	948	702

Source: Each annual volume is the sum of daily volume provided by Knight Ridder Financial Publishing, Inc.

Index futures contract was introduced by the NYFE in May 1982. The MMI futures were introduced in July 1984 by the CBOT. The trading volume of MMI futures is roughly equal to that of NYSE index futures.

Like most other futures contracts, stock index futures represent a legal commitment to buy or sell the standardized units of the specific index at a fixed price at a pre-determined delivery date. 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 feature of cash settlement has made trading of stock index futures more efficient and less costly because market participants do not need to construct proxy portfolios for delivery at maturity. 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.

Another unique point of index futures is the contract multiplier which is used to calculate the contract value. Each contract has a value equal to its quoted price times respective dollar multiple. All the above futures contracts use $500 as a multiplier. On October 11, 1991 the CBOT doubled the multiplier from $250 for its MMI futures contract. The contract value, however, remained the same because the MMI index level was halved. The multiplier is important because it determines the contract size. Typically, the MMI and the NYSE futures represent about 80 percent and 50 percent of value of the S&P 500 futures, respectively.6)

Ⅲ. Literature Review

1. The Relationship Between Stock Index Futures and Index Cash

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 the intradaily data is that the futures leads the cash by a few minutes. For example, Kawaller, Koch, and Koch (1987, 1988) use Granger's (1969) causality model to test leads and lags between the cash and futures prices for the S&P 500. They use minute-by-minute transactions prices over the period 1984 to 1985. They find that contemporaneous prices are most significantly related although there is some evidence of a twenty to forty-five minute leadership on the futures prices over the cash prices. The influence of cash price movements on the futures hardly extends beyond one minute.

Using a simultaneous equations model of Garbade and Silber (1983), Laatsch and Schwarz (1988) examine minute-to-minute as well as daily data for the MMI futures and cash index from July 1984 to September 1986. They find that during the initiation period of MMI futures markets the futures-cash relationship is unstable while the futures clearly leads cash prices as the market has become mature. Cheung and Ng (1990) utilize Pierce and Haugh (1977) test for Granger causality in the mean for the fifteen-minute interval futures and cash prices of S&P 500 over the period of June 1983 to June 1987. They use a moving average process to purge autocorrelations in the index cash price and the GARCH process to control the time-varying variance of residuals for both the futures and cash prices. They then use the standardized residuals from the

---

6) For example. as of July 19. 1991 the S&P 500 futures was selling at 386.65. or a value of $193,400 (386.65 × 00). MMI and NYSE futures priced at 633.70 and 211.70. respectively. Therefore the value of the MMI contract was $158,412 (633.70 × 50) and that of the NYSE futures was $105,800 (211.70 × 00).

GARCH process to perform cross-correlations based test for causality in the mean. They find that futures prices lead cash prices by about fifteen minutes while the evidence of causality from the cash to futures prices is rather weak.

Stoll and Whaley (1990) also find that the S&P 500 and the MMI futures over the period of 1982 to 1987 tend to lead the cash index returns by about five minutes on average even after the index returns are purged of infrequent trading and bid/ask price effects by an ARMA model. The futures returns lead even the returns of highly actively traded IBM stock. They argue that infrequent trading only partially explains the asymmetric relations between futures and cash markets. They support the hypothesis that the futures market plays a leading role in the price discovery process by reflecting the new information faster than the cash market. Chan, Chan, and Karolyi (1991) use five minute interval data for the S&P 500 for the period 1984 to 1989. Using a bivariate GARCH model, they find futures returns leads the cash returns by about five minutes.

Chan (1992) examines the relationship not only between the MMI futures and cash but also between the MMI futures and all 20 component stocks within the index. He uses five-minute interval data over two sample periods - August 1984 to June 1985, and January to September 1987. The results show that futures prices consistently lead cash prices. The MMI futures return even leads the returns of components stocks that are traded more heavily than the futures itself. He also finds that when the market has information of a general nature, futures prices lead cash prices to a greater extent. He concludes that futures prices lead cash index prices because firm-specific information, which is diversifiable, is mainly reflected in the index cash prices while the futures market is the main source of market-wide information, which is systematic.

A group of studies has examined the impact of the Crash of 1987 on the futures-cash relationships. For example, Harris (1989) analyses five-minute data for the S&P 500 index cash and futures prices over a ten-day period surrounding the Crash. He finds that the degree of price leadership of the futures market significantly increases during the week after the Crash, and that the large negative basis during the Crash period is partly due to the nonsynchronous trading. Using minute-by-minute prices for the S&P 500 from August and December 1987, Kutner and Sweeney (1991) also find that after the Crash the extent of price leadership on the futures over the cash index increases to about fourteen minutes from about seven minutes before the Crash period. In a study of MMI futures and cash prices, Schwarz and Laatsch (1991) use a simultaneous equations model over different measurement intervals (one week, one day, five minutes, and one minute) and different subperiods from September 1985 to March 1988. They find that in the early years of MMI futures cash prices lead futures prices but the trend is reversed as the market has evolved. They, however, find that the extent of leadership of the futures market was reduced slightly after the Crash.

Empirical evidence from the FT-SE 100 by Abhyankar (1993) also supports the price leadership of the futures market. With hourly data he performs cross-correlation-based tests with an AR(2)-GARCH(1,1) filter as well as regression-based tests. He finds that futures leads the cash index by an hour although there exists a strong contemporaneous relationship between the two markets. He also finds that lower transactions costs in the London cash market after the Big Bang have dampened the lead of futures significantly while short sale restrictions in the equity market have increased the lead of futures.

Recently, some of studies have focused on a long-run equilibrium relationship between the futures and cash prices by using Engle and Granger's (1987) concept of cointegration and error correction mechanism.[7] 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) also find that the S&P 500 and the FT-SE 100 index futures and cash prices are cointegrated.[8] Before testing different versions of error correction models, they use an MA(1) process to purge serial correlations of the price series. They find that futures and cash prices are mostly simultaneously related on a daily basis. They also compare the mean absolute forecast errors from one of their error correction models with those from the standard vector autoregressive model (without the error correction term) to show that their error correction specification decreases forecast errors sig-

---

[7] Engle and Granger's (1987) cointegration concept has been extensively utilized in other areas of finance and economics: interest rates (Engle and Granger 1987, and Hall, Anderson, and Granger 1992); foreign exchange rates (Hakkio and Rush 1989, and Barnhart and Szakmary 1991); equity markets of different countries (Taylor and Tonks 1989, and Arshanapalli and Doukas 1993); live cattle futures (Bessler and Covey 1991); crude oil futures(Quan 1992, and Schwarz and Szakmary 1994).

[8] Unlike the above studies, however, they employ daily rather than intraday data.

nificantly.

2. The Relationship Between Stock Indices.

Studies on the relationship between stock indices have focused on the lead-lag structure among international equity market indices. For example, Hilliard (1979) examines daily data on stock indices from ten major world equity markets. His results show that in general world indices move independently although there is evidence of some co-movement of stock indices within the same geographical areas. Other than the New York vs. Amsterdam, he finds no lead-lag relationship among the national indices. Using ARIMA-based models, Khoury, Dodin, and Takada (1987) and Schollhammer and Sand (1987), however, find some evidence of lead-lag relationships among national stock indices. They also find that the U.S. stock indices generally lead indices of other countries.

Utilizing a vector autoregressive (VAR) system, Eun and Shim (1989) also find a substantial degree of interdependencies among national stock indices for the period 1980 to 1985. In addition, they find that innovations in the U.S. equity market index are transmitted to indices of other countries by one trading day. Koch and Koch (1991) use a simultaneous equations model and generally confirm the findings of Eun and Shim. They especially report a growing leadership of the Japanese equity market. In contrast, recently Arshanapalli and Doukas (1993) find no linkages among national stock indices during the period 1980 to September 1987. Their cointegration and error correction models show that France, Germany, and UK stock indices are not related to the U.S. market for the pre-Crash period. They, however, find a growing trend of international co-movement after the Crash.9)10)

---

9) Jeon and von Furstenberg (1990), and Le (1991), also report a growing trend of co-movement of international equity indices after the Crash. Studies by Roll (1988), Aderhold, Cumming, and Harwood (1988), and Bennet and Kelleher (1988) also provide evidence of strong international equity market linkages around the Crash period.

10) In a study of the Scandinavian stock indices, Mathur and Subrahmanyam (1991) find that the causality runs from Sweden to Denmark, Finland, and Norway, and from Norway to Sweden and Denmark.

Ⅳ. Hypotheses

Given the empirical findings of an asymmetric relationship between the futures and cash markets, especially for short time periods within a day, and that the source of the mispricing is related to the information reflection process, we expect to find a similar type of intradaily informational inefficiency among the index futures. Based on prior theoretical as well as empirical studies we set up the following three hypotheses.

First, we hypothesize that price leadership is related to trading volume. A theoretical link between the intensity of trading and information dissemination is provided by the models of Admati and Pfleiderer (1988) and Foster and Viswanathan (1990). The models show that trading tends to concentrate in particular time periods within a trading day or within a week, and that prices at these clustering periods contain more information. Stephan and Whaley (1990) and Lamoureux and Lastrapes (1990) provide empirical evidence of a possible link between price discovery and trading intensity. Besides the price discovery role of trading volume, arbitrage and the difference in trading volume among the futures contracts may cause a lead-lag pattern in the intraday futures prices. Consider a situation where both market participants of the S&P 500 and the NYSE composite futures are actively involved in short-term arbitrage between two futures markets. The influence of this arbitrage on the price of the S&P 500 futures will be minor due to its far higher volume, while the short-term price of the NYSE composite futures is relatively heavily influenced. This may cause the NYSE futures to lag behind the S&P 500 futures [Byrne (1987)]. Thus, in this study, the first hypothesis is that the S&P 500 futures, with a dominant trading volume over other index futures contracts, would be a price leader.

The second hypothesis is derived from Chan's (1992) study. He argues that because the futures market processes market-wide information more rapidly than the cash market, futures prices tend to lead cash prices. He also argues that as the number of component stocks within an index grows, market-wide information becomes more important and the degree of price leadership from futures to cash becomes stronger. This is because information specific to a few firms is unsystematic while market-wide information is systematic. Chan's argument implies that as the number of component stocks grows, an index futures contract will contain more market-wide information and has a better chance of reflecting the information in its price. Thus, it is possible that an index futures contract with a larger number of component stocks shows a price leadership over other futures contracts. Within the context of this study, the second hypothesis is therefore that the NYSE futures (whose index has the largest number of underlying component stocks) is the fastest in processing new information, and thus shows price leadership over the other futures contracts.

The last hypothesis is derived from the studies of Lo and Mackinlay (1990) and Conrad, Gultekin, and Kaul (1991). Lo and Mackinlay emphasize the cross-sectional interaction among security returns in explaining positive expected profits from the contrarian strategy. They show that an asymmetric cross effect occurs when trading intensities differ among securities. By grouping the firms according to their size, they find that the returns of larger stocks almost always lead those of smaller ones. Conrad, et. al. also documented asymmetric volatility spillover effects. The return volatility of larger firms significantly explains the future return volatility of smaller firms. In an effort to identify sources of this lead-lag structure, Badrinath, Kale, and Noe (1992) find that institutional ownership, rather than firm size, is the determining factor of the asymmetric relationship. 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. One implication of these findings is that new information (be it market-wide or firm-specific) is first impounded in prices of the larger and/or institutionally-favored firms and then the shocks are transmitted to smaller firms. Thus, the last hypothesis is that the Major Market Index futures (whose index contains the largest and most institutionally-favored stocks) is the first to react to new information, and thus leads the others.

V. Data.

The data set comprises transaction prices on the S&P 500, the NYSE composite, and the MMI futures contracts 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. Within each interval the first and the last prices are recorded. 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 [Pt-Pt-1] using the last transactions price within each interval, expect for the overnight case where Pt is substituted by the first price within the interval.

All futures prices used in this study are always those of 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), while the MMI futures open fifteen minutes earlier. Thus, the first three five-minute interval observations 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 observations are 114,048 for each of the futures contracts.

Ⅵ. Methodology.

1. Test of Stationarity

Given the time series nature of the data, an initial step in the analysis is to test whether each price series is integrated or stationary. An integrated, or non-stationary, time series is said to have a unit root and any shock to the series is permanent. This implies that an integrated time series will not revert back to its mean after the shock while a stationary series will revert to its preshock level. As shown by Sims, Stock, and Watson (1990) and Balke (1991), any econometric model with a non-stationary time series will be misspecified and potentially lead to a spurious inference about the estimated parameters. To identify the unit root of each series we apply the following Augmented Dickey-Fuller (ADF) tests, i.e.:

$$\Delta y_t = \delta_1 + \eta_1 y_{t-1} + \sum_{i-1}^{K} \phi_{1,i} \Delta y_{t-1} + \varepsilon_{1,t}. \tag{1a}$$

$$\Delta^2 y_t = \delta_2 + \eta_2 y_{t-1} + \sum_{i=1}^{K} \phi_{2,i} \Delta^2 y_{t-i} + \varepsilon_{2,t}, \tag{1b}$$

where y_t is each index series, and Δ and Δ^2 are the first and second difference operator, respectively. A sufficient number of lagged differences is included so that the residual series is approximately white noise. The null hypothesis for model (1a) is that each index contains a unit root. A significant value on the t-statistic of η_1 will reject the null hypothesis in favor of the alternative that the variable is stationary. These "pseudo" t-statistics do not have a t-distribution and the critical values of the test are tabulated by Davidson and Mackinnon (1993). Similarly, a significant value on the t-statistic of η_2 in model (1b) will reject the null of two unit roots in favor of the alternative of one unit root.

2. Test of Multivariate Cointegration

We expect to find that each variable is integrated of order one, denoted I(1), because all previous studies of asset prices have obtained this result. Once we determine that each variable is I(1), the next step would be 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 may easily obtain stationarity of the time series data. However, returns data tends to ignore information about long-run relationships by only taking first differences. The main idea of Engle and Granger's (E-G) (1987) cointegration and error correction specification is to test a common long-run trend and to incorporate the trend in the model building. If one or more cointegration relations exist among the variables and they are not explicitly accounted for in the model, the model could be misspecified and the parameter estimates could be inefficient [Engle and Yoo (1987)].

Suppose there exist some linear relations among the variables α, β, and γ:

$$\alpha_t = \psi_0 + \psi_1 \beta_t + \psi_2 \gamma_t + \mu_t \tag{2}$$

The variables are said to be cointegrated of order (1,1) if they are all integrated of order one and the residual μ_t has no unit roots. To test for the cointegration, one can apply the ADF regression to the residuals from regression (2). This is the same regression used to test the unit roots of each series. This test is based on the cointegration concept developed by E-G. The E-G type cointegration approach, however, has some problems in dealing with more than two variables. In case of N non-stationary variables, there may exist at most N-1 distinct cointegrating relationships among the variables. Therefore, when N>2, a cointegrating vector from the E-G approach may not be unique. That is, more than one cointegrating relationship may exist. In addition, the estimated cointegration parameters may be sensitive to the choice of dependent variables.

An alternative test for the cointegration has been provided by Johansen (1988, 1991) and Johansen and Juselius (1990, 1992). It is based on maximum-likelihood estimation, and is designed to test for the number of linearly independent cointegrating vectors existing among the variables. Consequently, in this study, we utilize the multivariate Johansen procedure to test the cointegration among the variables.[11] It is based on the estimation of the following vector autoregressive system of equations.

$$Y_t = H + \Pi_1 Y_{t-1} + \cdots + \Pi_k Y_{t-k} + U_t \tag{3}$$

where H 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, the NYSE futures, and MMI futures, respectively. Π is a 3×3 vector of coefficients, and U_t is a 3×1 column vector of error processes. By using the first difference operator, Δ, we can rewrite equation (3) as

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{k-1} \Delta Y_{t-k+1} + \Pi Y_{t-k} + H + U_t, \tag{4}$$

where

---

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

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

and

$$\Pi = -(I - \Pi_1 -, \cdots, \Pi_k).$$

Equation (4) is in the form of a traditional VAR model of Sims (1980) with first differences except for the ΠY_{t-k} term. The Π term determines whether or not, and to what extent, the systems 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 Π is full rank, then any linear combination of Yt is stationary. If the rank(Π) = 0, the matrix Π is a null matrix and the equation (4) collapses to the traditional VAR model with first differences. In the case of $0<[\text{rank}(\Pi)]=r<p$, 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 Π matrix by testing whether the eigenvalues of Π', the estimate of Π, are significantly different from zero.

To test the null hypothesis that there are at most r cointegrating vectors in a set of p variables, first we need to run the regressions of ΔY_t and Y_{t-1} on lagged ΔY_{t-1} and constant terms, yielding residuals of R0t and R1t, respectively, and then to compute the canonical correlations between two residuals, denoting them as $\omega i(\omega 1 > \omega 2 > \cdots > \omega i)$. The likelihood-ratio test of the null hypothesis is obtained by the trace test defined as

$$\textit{Trace Test} = -T \sum_{i=r+1}^{p} \ln(1-\omega_i^2). \tag{4a}$$

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

$$\textit{Maximal Eigen alue Test} = -T \ln(1-\omega_{r+1}^2). \tag{4b}$$

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

3. The Estimation of Vector Autoregressive (VAR) Model.

After determining the cointegrating relationships among the variables, we calculate the impulse response function (IRF) of the VAR system under the cointegrating constraints. The IRF traces the impact of a shock in a variable onto the system over a time period. Thus, we can measure how rapidly information is transmitted across different index futures markets. The IRF is derived from the moving average representation of the autoregressive system. For example, in a moving average form Equation (4) can be expressed as

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

where At is 3×3 matrix of coefficients of the 3 variables in the system. Y_t vector is expressed in terms of accumulation of both current and past residuals, U's, which are called 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 ith variable in k periods to an innovation in jth 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. This also makes it ambiguous to decompose variance in the variables into components attributable to each innovation. Thus, we need to make some transformation of the error terms to make them contemporaneously uncorrelated. The transformation is often done by orthogonalizing the innovations so that the orthogonalized innovations form an identity covariance matrix and are uncorrelated both serially and contemporaneously.

The orthogonalization is obtained from $U_t = V \times \xi_t$, where V is a lower triangular matrix. Equation (5) can be expressed as follows with the transformed error terms:

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

where $B_k = V \times A_k$. With (i,j)th component of B_k matrix, we now can single out the impact of a shock in the jth variable in period t to the value of the ith variable because the orthogonalized innovations in the ξ matrix are uncorrelated both serially and contemporaneously. Specifically, by an unit shock in the jth variable in time t, the value of ith variable changes by $B_{ij,t+1}$ in the next period and $B_{ij,t+2}$, and $B_{ji,t+3}$ and so on in the subsequent future time 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

$$[\sum_{k=0}^{t-1} B^2_{ii,k} \,/\, \sum_{j=0}^{m} \sum_{k=0}^{t-1} B^2_{ii,k}], \tag{7}$$

where m is the number of variables in the system. This shows the fraction of t time period ahead forecast error variance of variable i explained by innovations in variable j. In the context of this study, if ,for example, the MMI has a true price leadership over 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.

Ⅶ. Empirical Results.

1. Stationarity and Multivariate Cointegration Tests.

We estimate the stationarity property of each index series by the Augmented Dickey-Fuller test described in equations (1a) and (1b). Table 2 summarizes the results. Each number in the table denotes the t-statistic for the hypothesis that $\eta=0$ in the regression equations. The lag length of the ADF tests is selected such that the Ljung-Box Q-statistic at 36 lags indicates absence of autocorrelation in the residuals. The asymptotic critical values for the ADF tests are provided by Davidson and Mackinnon (1993). For the

Table 2

Augmented Dickey-Fuller Unit Root Tests[1)]

One Unit Root : $\Delta y_t = \delta_1 + \eta_1 y_{t-1} + \sum_{t=1}^{K} \phi_{1,\,i} \Delta y_{t-1} + \varepsilon_{1,t}$,

Two Unit Root : $\Delta^2 y_t = \delta_2 + \eta_2 y_{t-1} + \sum_{t=1}^{K} \phi_{2,\,i} \Delta^2 y_{t-1} + \varepsilon_{2,t}$,

Indices[2)]	One Unit Root	Two Unit Root
SP	-1.832	-21.133***
YX	-2.197	-21.229***
BC	-1.701	-20.924***

1. Each number represents the t-statistics for the hypothesis that $\eta=0$ in the regressions listed. Asymptotic critical values are from Davidson and Mackinnon (1993). Lag length K is chosen such that the Q-statistic at 36 lags indicates absence of autocorrelation in the residuals. We use 5-minute interval data from December, 1985 to July 1991 with total observations of 114,048 for each of the index futures contracts.
2. Each entry represents the Standard & Poor 500 Index, the New York Stock Exchange Composite Index, and the Major Market Index, respectively.

*** indicates significance at the 1% level.

test to identify the presence of one unit root, we fail to reject the null hypothesis that each index series is I(1). For the tests using the second difference as the dependent variable to check for two unit roots, the null is rejected for all index series at the 1% significance level. These results are fairly consistent with the findings of many previous studies which have documented that in a reasonably efficient market asset prices are not mean-reverting. Given this finding we take the first difference of each index series to obtain stationarity.

The next step is to check whether there are any cointegration relationships among the three index futures series. This is to recapture any long-run trend, which might be lost because of the first differencing of the variables. We perform Johansen multivariate cointegration test, which is specified in equation (4). For this test, we use the daily closing observations for each index series,[12)] and a lag length of six is chosen by the Sims likelihood method. Table 3 reports the results. Both the trace and maximal eigenvalue tests indicate there are no cointegration relationships among the stock index

---

[12)] 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 assumethat with daily data we can reasonably detect any cointegration relationship, if it exists.

Table 3
Johansen Multivariate Cointegration Tests[1]

	$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{k-1} \Delta Y_{t-k+1} + \Pi Y_{t-k} + H + U_t$,					
	Trace Test[2]			Maximal Eigenvalue Test[3]		
	$\Pi=0$	$\Pi\leq 1$	$\Pi\leq 2$	$\Pi=0$	$\Pi=1$	$\Pi=2$
Futures	28.85	10.33	0.54	13.52	9.81	0.54

1. The cointegration equation is based on three variables of SP, YX, and BC. 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 from December 1986 to July 1991.
2. The trace statistic is defined as

$$-T \sum_{i=r+1}^{p} \ln(1-\omega_i^2).$$

where T is the number of time periods and ωi is the correlations between residuals.

3. The maximal eigenvalue test statistic is defined as

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

futures series of the S&P 500, NYSE index, and Major Market index. Consequently, we estimate the VAR model with the first differenced five-minute interval data without cointegration constraints.

2. Vector Autoregressive Model Estimation

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 an hour; We fail to reject the hypothesis that all coefficients of lags 13 through 18 are zero at the 5 percent significance level. A lag length of 12 would be sufficient enough to capture any feedback from lagged prices in that the index futures are actively traded.

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. But in our study no clear a priori ordering exists. In addition, when the variables are highly correlated, the empirical results may depend on the ordering of the variables. To some extent, this is the case in our sample. In the 5-minute interval futures sample, the correlation between variables are; SP vs YX: 0.656, SP vs. BC: 0.641, and YX vs. BC: 0.576.

The 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 system 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. These three different orderings are also consistent with our three hypotheses which provide plausible reasons that each one of the index futures contracts would lead the other two contracts. Specifically, we use the following three orderings: 1) SP−YX−BC, 2) YX−BC−SP, and 3) BC−SP−YX such that the first ordering is to test the price leadership for the S&P 500 index futures, the second for NYSE index futures and the last for MMI futures.

Table 4 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 other two markets explained by the innovation in the variables on the top. The results show that the S&P 500 index futures has the highest explanatory power over the other two contracts. That is, 93.62% 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). The comparable percentages for the NYSE and Major Market index futures are 85.87% and 79.48%, respectively. This is the case when each variable is put in the first place. Regardless of ordering, the S&P 500 index futures turns out to have highest explanatory power. For instance, when variables are put in the second position, the cumulative percentages that the S&P 500 futures explains other two variables are 19.18% while 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 SP YX, and BC, respectively. The results imply that in predicting unexpected future movements among stock index futures contracts, the S&P 500 index futures has the highest predictive power.

The analysis of impulse response functions provides additional insights by showing the time path of these transmission channel from one market to the others. Table 5

Table 4

Decomposition of 1-Hour Ahead forecast Error Variance[1]

Variables EXplained	Panel A: Ordering -- SP, YX, BC By Innovations in		
	SP	YX	BC
SP	96.76	0.78	0.79
YX	49.62	50.09	0.21
BC	44.00	4.05	51.95
Sum[2]	93.62	4.83	1.00

Variables EXplained	Panel B: Ordering -- YX, BC, SP By Innovations in		
	YX	BC	SP
SP	94.72	1.03	2.78
YX	36.41	62.19	1.39
BC	49.46	8.82	41.72
Sum[2]	85.87	9.85	4.17

Variables EXplained	Panel C: Ordering -- BC, SP, YX By Innovations in		
	BC	SP	YX
SP	94.47	1.86	0.34
YX	43.72	55.88	0.39
BC	35.76	17.32	46.88
Sum[2]	79.48	19.18	0.73

1. The number 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

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

where Bij.k is calculated from the orthogonalized moving average transformation of 3×3 vector. We use 5-minute interval data from December, 1985 to July 1991 with total observations of 114,048 for each index futures.

2. 'Sum' represents the cumulative percentage of forecast error variance of 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 variances of the NYSE and Major Market Index futures explained by the innovation in the S&P 500 index futures.

summarize the impulse responses for the index futures contracts. The orderings are the same as before and the results are presented in each panel. We also plot the time path of responses in Figure 1 based on the estimations in each panel of Table 5. Each impulse response represents the moving average coefficient in equation (6), and is nor-

Table 5
Impulse Responses of the Index Futures1)

Panel A: Impulse Response to an Unit Innovation in SP

Responses	Minutes after Shock											
in	0	5	10	15	20	25	30	35	40	45	50	55
YX	0.71	0.14	0.01	-0.03	0.01	-0.05	-0.01	-0.01	0.02	-0.02	-0.02	-0.02
BC	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 Response to an Unit Innovation in YX

Responses	Minutes after Shock											
in	0	5	10	15	20	25	30	35	40	45	50	55
BC	0.61	0.08	0.01	-0.02	0.04	-0.02	0.01	-0.01	0.03	0.01	-0.01	0.03
SP	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 Response to an Unit Innovation in BC

Responses	Minutes after Shock											
in	0	5	10	15	20	25	30	35	40	45	50	55
SP	0.66	0.07	0.04	-0.01	0.01	0.02	0.06	-0.00	0.03	0.00	-0.02	0.01
YX	0.61	0.08	-0.02	-0.05	0.01	-0.04	-0.03	0.01	0.02	0.00	-0.01	0.00

1. 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 :

$$\Delta Y_t = \sum_{k=0}^{\infty} B_k \xi_{t-k}$$

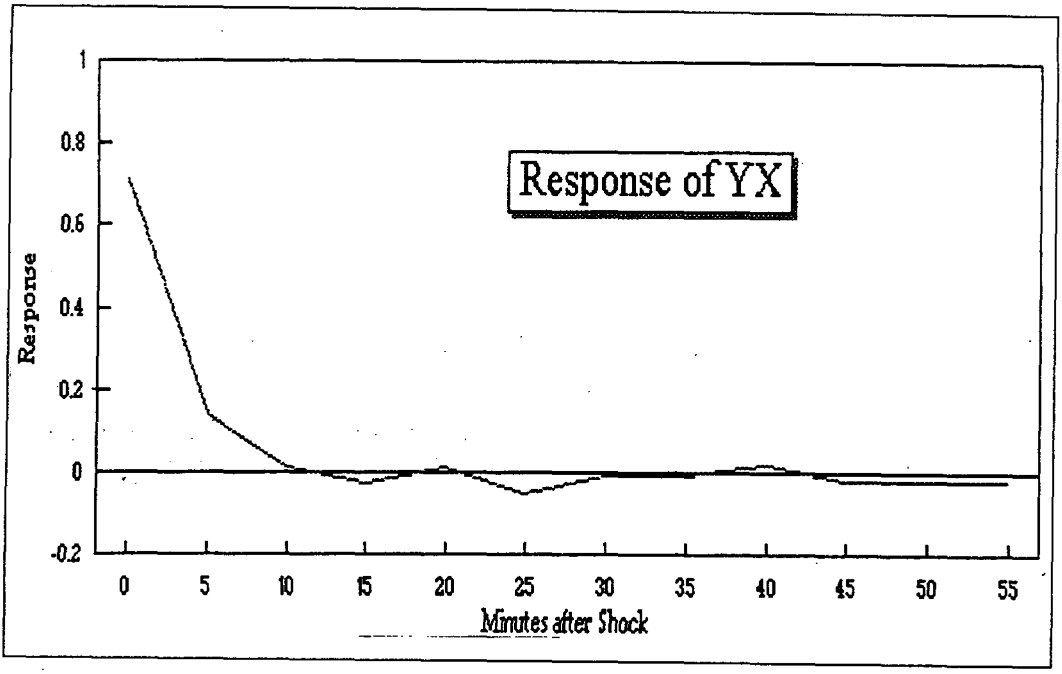
where Y_t is a vector of three variables in the VAR system. Each Bij is divided by its standard error for proper comparison. We use 5-minute interval data from December, 1985 to July 1991 with total observations of 114,048 for each index futures.

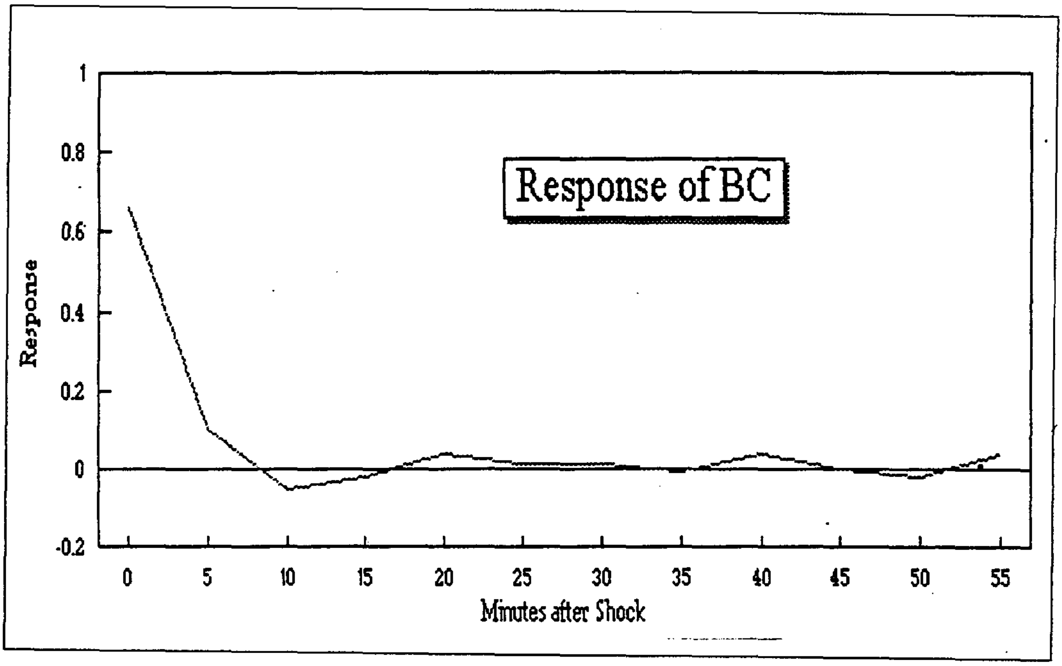
malized by its standard error. This normalization is needed to compare the impulse responses across variables which have different variations.

Panel A of the Table 5 and Figure 1 illustrates that any shocks given in the S&P 500 index futures are transmitted to the other two futures contracts, and each transmission process is completed by about 10 minutes after the shocks. Panel B shows the influence of NYSE index futures over other two contracts. Shocks from the NYSE futures are transmitted to the other two, but do not seem to persist beyond 5 minutes after the shocks. This is especially true.on the response of S&P 500 index futures. Response of S&P 500 to the shocks from the MMI futures is also quite marginal after 5 minutes since the shocks are given. In short, the impulse response analysis shows that shocks

Figure 1. Impulse Responses[1)]

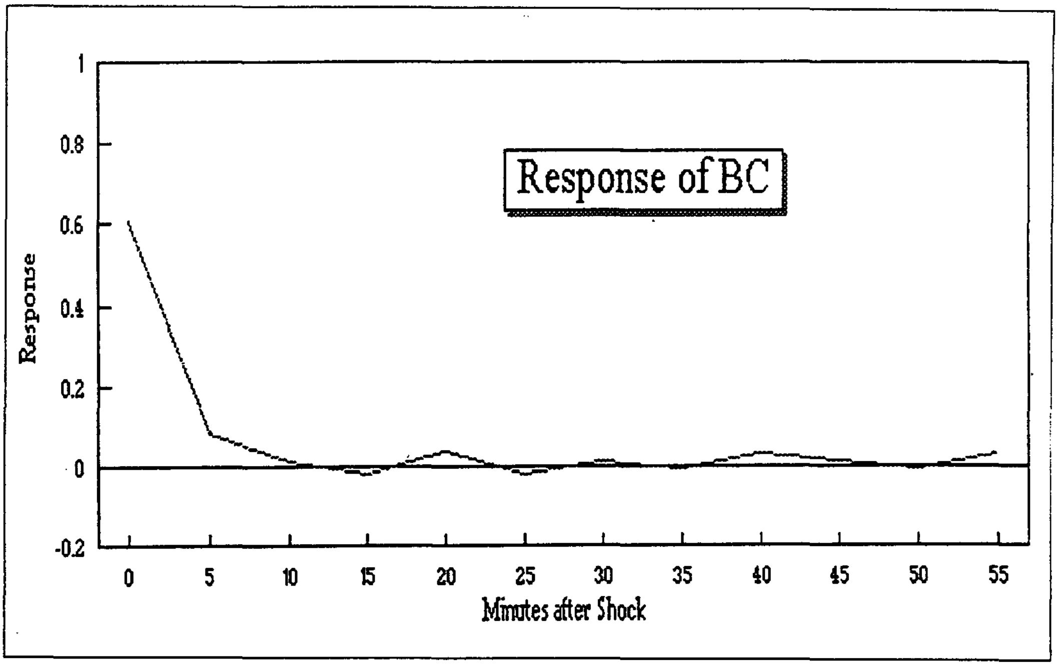
Panel A: Impulse Responses to an Unit Innovation in SP

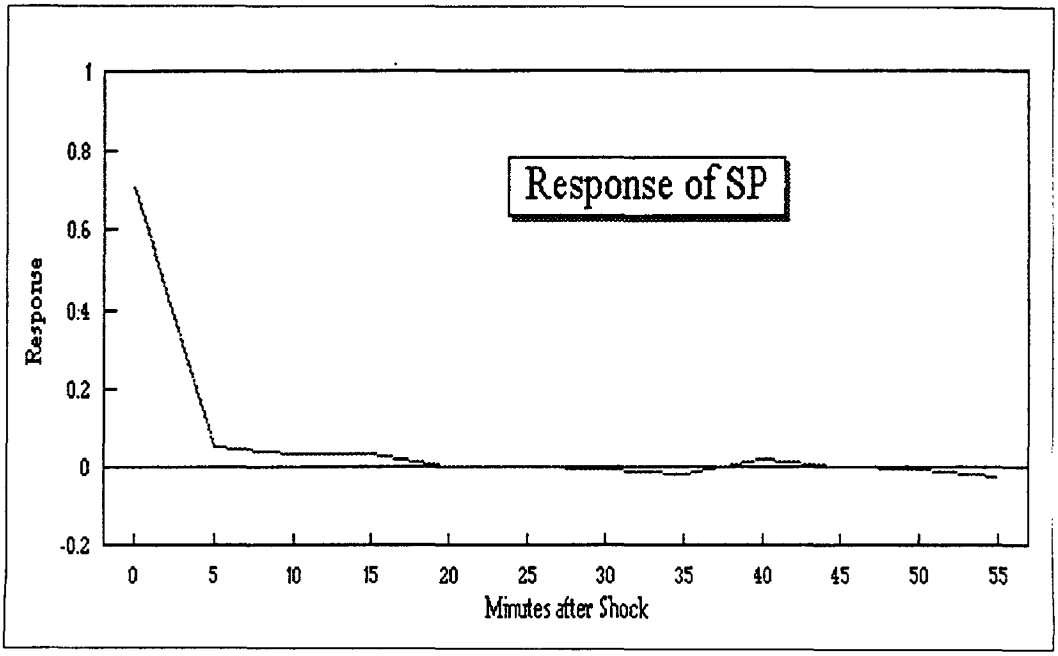




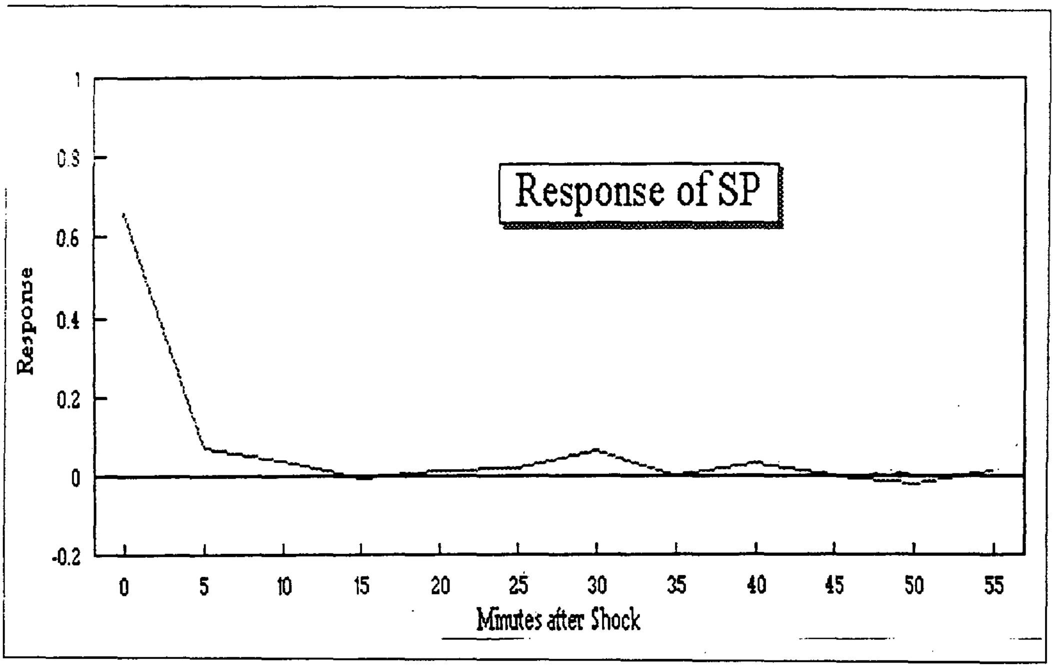
1. The graphs illustrates the time path of the normalized impulse responses and are based on the estimations in Table 5.

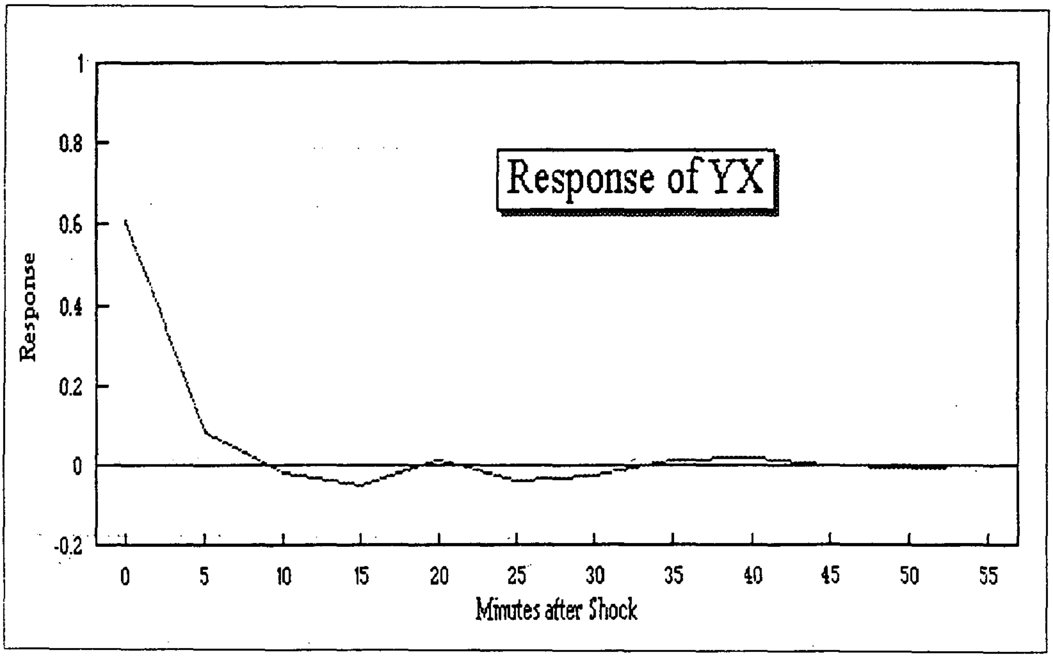
Panel B: Impulse Responses to an Unit Innovation in YX





Panel C: Impulse Responses to an Unit Innovation in BC





from any one market are rapidly transmitted to other markets, but the persistent of the shocks differs depending on the origin of shocks. We find that the S&P 500 index futures leads other two futures by about five minutes.

This finding confirms our first hypothesis which predicts that the S&P 500 index futures, with a dominant trading volume over other index futures contracts, would have price leadership. Therefore, information transfer may be related to the intensity of trading. In this sense, the result in this paper is consistent with the theoretical models of Admati and Pfleiderer (1988) and Foster Viswanathan (1990).

Ⅷ. Conclusions

The focus of this paper is to examine possible mispricing across index futures as well as across cash indices. We study intraday price leadership among the Standard & Poor 500, the New York Stock Exchange Composite, and the Major Market indices. If these markets are informationally efficient and all information is fully reflected in the prices of these markets, then there will be no systematic lead-lag pattern among the prices. If, however, for some reason, one market is slow in reacting to a piece of new information, it will lag behind the other markets, possibly showing price transmission channels from one market to the other markets.

Our three hypotheses provide plausible reasons that each one of futures market would have price leadership over the others. The first hypothesis predicts price leadership by the S&P 500 index futures, which have dominant trading volume over the other index futures. The second hypothesis argues that the NYSE futures (whose index has the largest number of underlying component stocks) will be the fastest in processing new information, and thus show price leadership. The last hypothesis maintains that the Major Market index futures is the first to react to new information, and thus leads the others because the MMI's underlying index contains the largest and most institutionally-favored stocks.

Each one of these hypotheses 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, while 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. This finding is consistent with the first hypothesis, which specifies that price leadership is related to the trading volume.

References

Abhyankar, A.H. "Return and Volatility Dynamics in the FT-SE 100 Stock Index and Stock Index Futures Markets. *WP*, 1993.

Aderhold, Robert, Christine Cumming, and Alion Harwood. "International Linkages among Equities Markets and the October 1987 Market Break," *Federal Reserve Bank of New York Quarterly Review*, Summer, 1988, 34-46.

Admati, Anat R. and Paul Pfleiderer. "A Theory Of Intraday Patterns: Volume And Price Variability," *Review of Financial Studies*, 1988, v1(1), 3-40.

Arshanapalli, Bala and John Doukas. "International Stock Market Linkages: Evidence From the Pre- and Post-October 1987 Period," *Journal of Banking and Finance*. 1993 v17. 193-208.

Ahmed, Shaghil, "Money and Output: The Relative Importance of Real and Nominal Shocks," *Federal Reserve Bank of Philadelphia*, WP, 1993, No.93-20

Badrinath, S.G., Jayrant R. Kale, and Thomas H. Noe, "Of Shepherds, Sheep and the Cross-Autocorrelation in Equity Returns," *WP*, 1992.

Baillie, Richard T. and Tim Bollerslev, "Common Stochastic Trends in a System of Exchange Rates," *Journal of Finance*.1989. v44(1), 167-181.

Balke, Nathan S. "Modeling Trends in Macroeconomic Time Series," *Federal Reserve Bank of Dallas Economic Review*. May. 19-33.

Barnhart, Scott W. and Andrew C. Szakmary. "Testing The Unbiased Forward Rate Hypothesis: Evidence On Unit Roots. Co-Integration. And Stochastic Coefficients," *Journal of Financial and Quantitative Analysis*. 1991, v26(2). 245-268.

Bennett, Paul and Jeanette Keller. "The International Transmission of Stock Price Disruption in October 1987," *Federal Reserve Bank of New York Quarterly Review*. Summer. 1988, 17-33.

Bessler, D.A. and Covey, T. 'Cointegration: Some Results on U.S. Cattle Prices," *Journal of Futures Markets*. 11(4). 461-474.

Byrne, Thomas B. *The Stock Index Futures Market: A Trader's Insights and Strategies*. Probus Publishing Co.. Chicago. IL. 1987.

Chan, Kalok. "A Further Analysis Of The Lead-Lag Relationship Between The Cash Market

And Stock Index Futures Market," *Review of Financial Studies*, 1992, v5(1), 123-151.

Chan, Kalok. "Imperfect Information and Cross-autocorrelation Among Stock Prices," *Journal of Finance*, 1993 v48(4), 1211-1230.

Chan, Kalok, K. C. Chan and G. Andrew Karolyi. "Intraday Volatility In The Stock Index And Stock Index Futures Markets," *Review of Financial Studies*, 1991, v4(4), 657-684.

Cheung, Yin-Wong and Lilian K. Ng. "The Dynamics Of S&P 500 Index And S&P 500 Futures Intraday Price Volatilities," *Review of Futures Markets*, 1990, v9(2), 458-486.

Conrad, Jennifer, Mustafa N. Gultekin and Gautam Kaul. "Asymmetric Predictability Of Conditional Variances," *Review of Financial Studies*, 1991, v4(4), 597-622.

Davidson, Russell and James G. Mackinnon. *Estimation and Inference in Econometrics*, Oxford University Press, 1993.

Diebold, Francis, Javier Gardeazabal, and Kamil Yilmaz, "On Cointegration and Exchange Rate Dynamics," *Federal Reserve Bank of Philadelphia*, WP, 1993, No. 93-2.

Doan, Thomas A. Rats: Users Maual, *Version 4*, Estima, 1992.

Engle, Robert F. and C. W. J. Granger. "Co-Integration And Error Correction: Representation, Estimation And Testing," *Econometrica*, 1987, v55(2), 251-276.

Engle, Robert F. and Byung Sam Yoo. "Forecasting And Testing In Co-Integrated Systems," *Journal of Econometrics*, 1987, v35(1), 143-161.

Eun, Cheol S. and Sangdal Shim. "International Transmission Of Stock Market Movements," *Journal of Financial and Quantitative Analysis*, 1989, v24(2), 241-256.

Foster, F. Douglas and S. Viswanathan. "A Theory Of The Interday Variations In Volume, Variance, And Trading Costs In Securities Markets," *Review of Financial Studies*, 1990, v3(4), 593-624.

Fung, Hung-Gay and Wai-Chung Lo, "Deviations From Purchasing Power Parity," *Financial Review*, 1992, v27(4), 553-570.

Garbade, Kenneth D. and William L. Silber. "Price Movements And Price Discovery In Futures And Cash Markets," *Review of Economics and Statistics*, 1983, v65(2), 289-297.

Granger, C. W. J. "Investigating Causal Relations By Econometric Models And Cross-Spectral Methods," *Econometrica*, 1969, v37(3), 424-438.

Ghosh, Asim. "Cointegration and Error Correction Models: Intertemporal Causality Between Index and Futures Prices," *Journal of Futures Markets*, 1993, v13(2), 193-198.

Hakkio, Crag S. and Mark Rush. "Market Efficiency And Cointegration: An Application To The Sterling And Deutschemark Exchange Markets," *Journal of International Money And Finance*, 1989, v8(1), 75-88.

Hakkio, Crag S. and Mark Rush. "Cointegration: How Short is the Long Run?," *Journal of International Money And Finance*, 1991, v10(1), 571-581.

Hall, Anthony D., Heather M. Anderson and Clive W. J. Granger. "A Cointegration Analysis Of Treasury Bill Yields," *Review of Economics and Statistics*, 1992, v74(1), 116-126.

Harris, Lawrence. "The October 1987 S&P 500 Stock-Futures Basis," *Journal of Finance*, 1989, v44(1), 77-100.

Hilliard, Jimmy E. "The Relationship Between Equity Indices On World Exchanges," *Journal of Finance*, 1979, v34(1), 103-114.

Hung, Wansing, Yoonbai Kim, and Kenichi Ohno, "Pricing Exports: A Cross-Country Study," *Journal of International Money and Finance*, 1993, v12, 3-28.

Jeon, Bang Nam and George M. Von Furstenberg. "Growing International Co-Movement In Stock Price Indexes," *Quarterly Review Of Economics And Business*, 1990, v30(3), 15-30.

Johansen, Soren. "Statistical Analysis Of Cointegration Vectors," *Journal of Economic Dynamics and Control*, 1988, v12(2/3), 231-254.

Johansen, Soren. "Estimation And Hypothesis Testing Of Cointegration Vectors In Gaussian Vector Autoregressive Models," *Econometrica*, 1991, v59(6), 1551-1580.

Johansen, Soren and Katarina Juselius. "Maximum Likelihood Estimation And Inference On Cointegration - With Applications To The Demand For Money," *Oxford Bulletin of Economics and Statistics*, 1990, v52(2), 169-21.

Johansen, Soren and Katarina Juselius. "Testing Structural Hypotheses In A Multivariate Cointegration Analysis Of The PPP And The UIP For UK," *Journal of Econometrics*, 1992, v53(1/2/3), 211-244.

Kasa, Kenneth, "Common Stochastic Trends in International Stock Markets," *Journal of Monetary Economics*, 1992, v29, 95-124.

Kawaller, Ira G., Paul D. Koch and Timothy W. Koch. "The Temporal Price Relationship

Between S&P 500 Futures And The S&P 500 Index," *Journal of Finance*, 1987, v42(5), 1309-1329.

Kawaller, Ira G., Paul D. Koch and Timothy W. Koch. "The Relationship Between The S&P 500 Index And S&P 500 Index Futures Prices," FRB Atlanta - *Economic Review*, 1988, v73(3), 2-11.

Khoury, Sarkis J., Bajis Dodin and Hirokazu Takada. "Multiple Time Series Analysis Of National Stock Markets And Their Structure: Some Implications," *Recent Developments in Banking and Finance*, 1987, v1, 169-186.

Koch, Paul D. and Timothy W. Koch. "Evolution In Dynamic Linkages Across Daily National Stock Indexes," *Journal of International Money And Finance*, 1991, v10(2), 231-251.

Kutner, George W. and Robert J. Sweeney. "Causality Test Between The S&P 500 Cash And Futures Markets," *Quarterly Journal of Business and Economics*, 1991, v30(2), 51-74.

Laatsch, Francis E. and Thomas V. Schwarz. "Price Discovery And Risk Transfer In Stock Index Cash And Futures Markets," *Review of Futures Markets*, 1988, v7(2), 272-289.

Lamoureux, Christopher G. and William D. Lastrapes. "Heteroskedasticity In Stock Return Data: Volume Versus GARCH Effects," *Journal of Finance*, 1990, v45(1), 221-230.

Le, S.V. "International Investment Diversification Before and After the October 19, 1987 Stock Market Crisis," *Journal of Business Research*, 1991, v22, 305-310.

Lo, Andrew W. and A. Craig MacKinlay. "When Are Contrarian Profits Due To Stock Market Overreaction?," *Review of Financial Studies*, 1990, v3(2), 175-206.

Sims, Christopher A. "Macroeconomics And Reality," *Econometrica*, 1980, v48(1), 1-48.

Mathur, Ike and Vijaya, Subrahmanyam. "An Analysis of the Scandinavian Stock Indices," *Journal of International Financial Markets, Institutions & Money*, 1991 v1(1), 91-114.

Mills, Terrence and Alessandra Mills, "The International Transmission of Bond Market Movements," *Bulletin o Economic Research*, 1991, v43(3), 273-281.

Pierce, David A. and Larry D. Haugh. "Causality In Temporal Systems: Characterizations And A Survey," *Journal of Econometrics*, 1977, v5(3), 265-294.

Quan, J. "Two Step Testing Procedure for Price Discovery Role of Futures Prices," *Journal of Futures Markets*, v12(2), 139-149.

Roll, Richard. "The International Crash Of October 1987," *Financial Analyst Journal*. 1988. v44(5), 19-35.

Schollhammer, Hans and Ole Christian Sand. "Lead-Lag Relationships Among National Equity Markets: An Empirical Investigation," *Recent Developments in Banking and Finance*, 1987, v1, 149-168.

Schwarz, Thomas V. and Francis E. Laatsch. "Dynamic Efficiency and Price Leadership in Stock Index Cash and Futures Markets," *Journal of Futures Markets*, 1991, v11(6), 669-683.

Schwarz, Thomas V. and Andrew C. Szakmary. "Price Discovery in Petroleum Markets: Arbitrage, Cointegration, and the Time Interval of Analysis," *Journal of Futures Market*, 1994, v14(2),

Sephton, Peter S. and Hans K. Larsen. "Tests Of Exchange Market Efficiency: Fragile Evidence From Cointegration Tests," *Journal of International Money And Finance*. 1991, v10(4), 561-570.

Sims, Christopher A. "Macroeconomics And Reality," *Econometrica*, 1980, v48(1), 1-48.

Sims, Christopher A., James H. Stock and Mark W. Watson. "Inference In Linear Time Series Models With Some Unit Roots," *Econometrica*, 1990, v58(1), 113-144.

Stephan, Jens A. and Robert E. Whaley. "Intraday Price Changes And Trading Volume Relations In The Stock And Stock Option Markets," *Journal of Finance*. 1990. v45(1), 191-220.

Stoll, Hans R. and Robert E. Whaley. "The Dynamics Of Stock Index And Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis*. 1990. v25(4). 441-468.

Taylor, Mark P. and Ian Tonks. "The Internationalisation Of Stock Markets And The Abolition Of U.K. Exchange Control," *Review of Economics and Statistics*. 1989. v71(2). 332-336.

Wahab, Mahmoud and Malek Lashgari. "Price Dynamics and Error Correction In Stock Index and Stock Index Futures Markets: A Cointegration Approach," *Journal of Futures Markets*, 1993. v13(7). 711-742.