A Further Analysis of the Lead-Lag Relationship between the Cash Market and Stock Index Futures Market

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The intraday lead-lag relation between returns of the Major Market cash index and returns of the Major Market Index futures and S&P 500 futures is investigated. Empirical results show strong evidence that the futures leads the cash index and weak evidence that the cash index leads the futures. The asymmetric lead-lag relation holds between the futures and all component stocks, including those that trade in almost every five-minute interval. Evidence indicates that when more stocks move together (market-wide information) the futures leads the cash index to a greater degree. This suggests that the futures market is the main source of market-wide information.

The lead-lag relation between price movements of stock index futures and the underlying cash market illustrates how fast one market reflects new information relative to the other, and how well the two markets are linked. In a perfectly frictionless world,

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price movements of the two markets are contemporaneously correlated and not cross-autocorrelated. However, if one market reacts faster to information, and the other market is slow to react, a lead-lag relation is observed.

Several studies examine the temporal relationship between futures and cash index returns [e.g., Finnerty and Park (1987); Ng (1987); Kawaller, Koch, and Koch (1987); Harris (1989); Stoll and Whaley (1990)]. Their results suggest that futures returns significantly lead cash index returns, although there is weak evidence that cash index returns have some predictive ability about futures returns. For instance, Kawaller, Koch, and Koch (1987) report that the lead from S&P 500 futures to cash prices extends between 20 and 45 minutes, while the lead from cash to futures prices rarely extends beyond one minute. Stoll and Whaley (1990) find that S&P 500 and Major Market Index (MMI) futures returns lead stock index returns by about five minutes on average, and occasionally by as long as 10 minutes or more, but the feedback from the cash market into the futures market is much shorter than that.

Two issues regarding the lead-lag relation between the two markets deserve examination. The first is whether the lead-lag relation is induced by the infrequent trading of component stocks. Many component stocks on the S&P 500 index are not traded frequently enough to allow prices to update information quickly. When the lead-lag relation is analyzed based on intraday price changes, the staleness of component stock prices can cause futures prices to appear to lead cash index prices. Thus, the evidence that futures prices lead the cash index may simply be due to infrequent trading of component stocks, not to a delay in the adjustment of cash index prices. Although Harris (1989) adjusts for the infrequent trading effect, his results pertain only to the 10 days surrounding the 1987 market crash, and are based on a one-factor representation of the value-generating process to estimate the nonsynchronous trading adjustment. Stoll and Whaley (1990) use an ARMA process to purge the effects of infrequent trading, but the parameters of the ARMA model are assumed constant. Therefore, if the effects of infrequent trading are changing, the one-factor model adjustment or ARMA filtering may not adequately eliminate the infrequent trading components.

The second issue to be examined is why, if not because of nonsynchronous trading, futures prices lead cash index prices. The most popular explanation is that the futures market is less costly for traders to utilize than the cash market, so the futures market is dominant in revealing economy-wide information. One implication of this explanation is that if traders prefer to trade futures contracts rather than the component stocks, an asymmetric lead-lag relation should hold between the returns of futures and all individual stocks. A second implication is that the lead-lag relation should change when it becomes more costly or less costly for traders to exploit the information in the cash market.

In this article I study the lead-lag relation in a dataset that avoids spurious conclusions. The MMI is chosen, and the intraday relation between returns of the MM cash index and returns of both MMI and S&P 500 futures are examined. Compared with the underlying stocks of the S&P 500 index, the component stocks of the MMI are more actively traded, so that the infrequent trading problem is less serious. Further, since only 20 stocks compose the MMI, a study of the lead-lag relation can be extended easily beyond that of the futures and cash index to that of the futures and component stocks. By examining the trading frequencies and nontrading probabilities of individual stocks, it also can be determined whether nonsynchronous trading explains the lead-lag relation between the futures and cash index.

I also examine how lead-lag patterns change under different conditions. Specifically, observations are stratified and examined to determine whether the feedback between the two markets becomes higher or lower depending upon (i) bad news versus good news, (ii) the relative intensity of trading activity in the two markets, and (iii) the extent of market-wide movement. These results shed light on the determinant(s) of the lead-lag relation.

Consistent with previous evidence, I find that futures prices lead cash index prices predominantly. The results are robust, even in a more recent sample period when the cash market seems to be faster in processing market-wide information. The asymmetric lead-lag relation is observed for all 20 component stocks. However, the lead-lag pattern cannot be explained completely by nonsynchronous trading of futures and component stocks. Even for stocks traded more actively than MMI futures, the returns are led by futures returns. Also, for stocks that are very actively traded and have nontrading probabilities close to zero, the returns still lag behind futures returns significantly. In addition, the evidence indicates that when more stocks move together (market-wide information), the feedback from the futures market into the cash market is higher. This suggests that the futures market is able to update market-wide information faster than the cash market.

This article is organized as follows. In Section 1, the cash market and the stock index futures market, and the possible reasons for the lead-lag patterns, are discussed. In Section 2, the data are described. Five-minute intraday returns of the futures and cash index are constructed for two sample periods. Transaction frequencies and nontrading probabilities of the component stocks and futures are examined. Serial correlations and cross-autocorrelations of cash index and futures returns are also reported. In Section 3, regression models are estimated to examine the lead-lag patterns between cash index returns and futures returns, as well as between component stock returns and futures returns. Observations are stratified to determine how the lead-lag patterns behave under different circumstances. The conclusion is given in Section 4.

1. Lead-Lag Relation between the Cash and Index Futures Markets

Both futures prices and cash index prices reflect the aggregate values of underlying stocks. Futures and cash prices will differ, however, because of differences in carrying costs.[1] But if interest rates and dividend yields were nonstochastic, contemporaneous price changes in the two markets would be perfectly correlated and no lead-lag relation would exist between them. Various frictions, however, may cause one market to react faster to information than the other, so that the lead-lag relation is observed.[2]

The lead-lag relation between futures prices and cash index prices may be attributed to infrequent trading of stocks within the index. Since component stocks may not be traded in the last instant of each time interval, observed index values, which are the averages of the last transaction prices of component stocks, cannot update actual developments in the stock marker and lag behind "true" index values. If futures prices reflect information instantaneously, cash index prices will lag behind futures prices. Harris (1989) derives an estimator of the underlying index values using a simple one-factor representation of the value-generating process to estimate the nonsynchronous trading adjustment. Stoll and Whaley (1990) use an ARMA process to purge the effects of infrequent trading, and extract the return innovations to proxy for true index returns. However, these adjustments may not be adequate if the effects of nonsynchronous trading are changing.[3]

[1] Index arbitrage opportunities exist if the value of the index futures contract deviates from the cost of buying the individual stocks that make up the index, and then holding them to maturity. Several papers study the frequency of index arbitrage opportunities, including Modest and Sundaresan (1983), MacKinlay and Ramaswamy (1988), and Chung (1991).

[2] In addition to those discussed in the text, other frictions include discreteness of stock prices [Gottlieb and Kalay (1985)]. stabilization activities of specialists (Amihud and Mendelson (1980)], and dual trading practice in the futures market [Fishman and Longstaff (1989)].

[3] Stoll and Whaley (1990) estimate the parameters of the ARMA model each year, thereby allowing the effects of nonsynchronous trading to change every year. However, if the effects of nonsynchronous trading change throughout the day, the ARMA filtering may not completely purge the nonsynchronous trading components.

Lo and MacKinlay (1990) examine the effects of nonsynchronous trading on the cross-autocorrelation pattern. They show that the relative nontrading probabilities of security i and j are given by the ratio of the covariance of past returns of j to current returns of i, and the covariance of past returns of i to current returns of j. In other words, if security i has a higher nontrading probability than security j, security i lags security j more than it leads. This relation suggests that if the lag is only due to nonsynchronous trading, futures returns will be dominant in leading returns of only those component stocks that have higher nontrading probabilities than futures.

Several factors can influence how fast the cash and futures markets reflect information, and thus affect the lead-lag relation. One factor is short-sale constraints in the cash market, such as legal or contractual prohibitions of shorting by certain institutional investors and corporate insiders, the inability to borrow stock to short, and the "no short sale on a down-tick" rule. Diamond and Verrecchia (1987) show that prohibiting traders from shorting slows the adjustment of prices to private information, especially with respect to private bad news. Since there is no short-sale constraint in the futures market, futures prices are symmetric in reflecting private good news and bad news. Therefore, the lead-lag relation would not be the same under bearish and bullish markets, and futures prices should lead the cash index to a greater degree under bad news—if the short-sale constraints are binding. However, if the marginal arbitrageur has long positions in the stocks, and he is not constrained by short-sale restrictions, cash index prices should not lag futures to a greater degree under bad news.

The lead-lag relation also may be affected by the intensity of trading activity in the two markets. Lower trading activity implies that the securities are less frequently traded, so observed prices lag "true" values more. Also, information dissemination may be related to the intensity of trading activity. Admati and Pfleiderer (1988) show that, in general, trades of both discretionary liquidity traders and informed traders cluster, with each group preferring to trade when the market is thick. The clustering of trades causes more information to be released when trading activity is higher. Therefore, the lead-lag relation is expected to vary with the relative intensity of trading activity in the two markets. Stephan and Whaley (1990) study the intraday relation between the stock market and the stock option market. They find that not only do price changes of stocks lead price changes of options, but that trading activity (proxied by the number of transactions and trading volume) in the two markets also bears the same kind of lead-lag relation. This provides evidence that price discovery and trading activity are related.

Lead-lag patterns may also depend on whether the information is market wide or firm specific. Subrahmanyam (1991) suggests that some informed traders are precluded from the cash and futures markets because of fixed costs of trading or budget constraints. Market-wide informed traders are discouraged from trading in individual securities because doing so requires a larger capital outlay than trading in futures contracts. Security-specific informed traders, on the other hand, do not trade index futures because the security-specific information is trivial in determining futures prices. Chan (1990) shows that even in the absence of transaction costs, a market-wide informed trader earns a higher profit by trading in futures contracts than by trading in individual securities.[4] Therefore, if information acquisition is endogenous, futures traders have a higher incentive to collect market-wide information than do cash market traders. As the above discussion suggests, the futures market should reflect market-wide information more quickly than the cash market does. Thus, when there are more stocks moving together (because of market-wide information), futures prices should lead the cash index to a greater degree.

2. Data and Preliminary Statistics

2.1 Data

Two sample periods-August 1984 through June 1985, and January through September 1987—are examined in this article. Froot and Perold (1990) document that the autocorrelation of short-run returns on several broad stock market indexes declines over time, suggesting that new trading practices have improved the processing of market-wide information. By including 1987, the robustness of the lead-lag pattern can be verified. Several sets of data are employed. Transactions data for the 20 component stocks of the MMI are obtained from Francis Emory Fitch, Inc. (for 1984 to 1985) and from the Institute for the Study of Security Markets (for 1987). For each transaction, the date, time, price, and number of shares traded are available. The MM cash index level is computed from these transaction data. The MMI futures price data file,[5] supplied by the Chicago Board of Trade, consists of

[4] Market makers in both the futures and cash markets adjust prices in response to orders submitted by marketwide informed traders, firm-specific informed traders, and liquidity traders. Therefore, the information possessed by informed traders affects the pricing process and, in turn, affects the profits of informed traders. Market-wide informed traders find that it is better to exploit their information in the futures market because the information of firm-specific traders is diversified and has little effect on the pricing process.

[5] The original MMI futures contract is denominated as 100 times the index value. On July 7. 1985, after many market participants showed a preference for a larger contract, the CBOT introduced a Maxi MMI futures contract with a multiplier 250 times the index value. As of September 1986, the original contract was delisted. Therefore, the futures transactions data in 1987 are on the Maxi MMI futures contracts. However, the component stocks remain unchanged.

the time and price records of futures transactions whenever the price differs from that of the previous transaction. Since the nearby contract is usually the most actively traded, only data for nearby futures contracts are used. The S&P 500 futures price data, provided by the Chicago Mercantile Exchange, contain the time and price records of the S&P futures transactions whenever the price differs from the previous one. Again, only nearby futures contracts are examined.

Each day, trading hours are partitioned into five-minute intervals. In each interval, the last price observation for the futures and component stocks is identified. If no price is observed within that five-minute span, the last price in the previous five minutes is recorded for this interval. The cash index is calculated by aggregating prices of 20 stocks and adjusting aggregate prices by a divisor.[6] The price observations are used to compute five-minute returns for the futures and cash index.[7]

In 1984-1985, component stocks were traded on the NYSE between 9:00 A.M. and 3:00 P.M. (Central), while the MMI and S&P 500 futures contracts were traded in Chicago between 8:45 A.M. and 3:15 P.M. (Central). In 1987, both the component stocks and futures contracts were traded half an hour earlier. Since no price observations are available for component stocks when the stock market is closed, this study is confined to NYSE trading hours. Also, since some stocks have delayed openings, examination is delayed until all stocks have started trading. On average, it takes about 25 minutes for all stocks to begin trading. Further, overnight returns are excluded since they span an interval different from the five-minute returns.

2.2 Preliminary statistics

The trading frequencies and nontrading probabilities for MMI and S&P 500 futures contracts and MMI component stocks are reported in Table 1. Trading frequency is the average number of trades in the five-minute interval. Nontrading probability is the proportion of intervals in which there are no trades. Since the futures price dataset records trades only when the price changes, there is a downward bias in the trading frequency and an upward bias in the nontrading probability. In 1984-1985, for the MMI futures contracts, there are 5.3 trades on average (which record price changes) and a 4.9 percent nontrading probability (which records a price change) in the five-minute interval; for the S&P 500 futures contracts, there are 20.2 trades on average and a 0 percent nontrading probability. Therefore, while

[6]MMI is a priceweighted index and can be expressed as $I_t = \Sigma\, P_{i,t}/d$, where $P_{i,t}$ is the price of the i th stock at time t and d is the adjustment divisor. The divisor is adjusted for any stock split or stock dividend.

[7]Since the futures contract requires no investment, its rate of return is formally undefined. It is more appropriate to interpret the return as the percentage price change.

Table 1
Trading frequency and nontrading probability of MMI and S&P 500 futures and MMI component stocks in five-minute intervals

	Aug. 1984–June 1985[1]		Jan.–Sept. 1987[2]	
Futures/stocks	Trading frequency	Nontrading probability (%)	Trading frequency	Nontrading probability (%)
MMI futures	5.29	4.9	19.52	0.05
S&P 500 futures	20.21	0.0	31.57	0.0
American Express (AXP)	3.05	10.5	5.27	2.4
AT&T (T)	4.94	1.9	9.40	0.2
Chevron (CHV)	1.99	18.2	3.09	9.9
Coca-Cola (KO)	1.49	32.3	3.73	8.4
Dow Chemical (DOW)	3.10	8.0	3.83	6.7
Du Pont (DD)	2.15	16.7	3.37	9.1
Eastman Kodak (EK)	2.42	15.6	3.73	7.2
Exxon (XON)	4.91	1.8	3.63	4.4
General Electric (GE)	3.37	7.7	6.28	1.4
General Motors (GM)	3.53	8.8	4.93	6.5
IBM (IBM)	7.58	0.5	10.16	0.1
International Paper (IP)	1.31	35.6	3.48	8.6
Johnson & Johnson (JNJ)	2.77	10.3	3.58	7.5
Merck & Co. (MRK)	1.36	34.6	4.16	5.7
Minnesota Mining & Mfg. (MMM)	1.66	27.2	2.70	14.6
Mobil Oil (MOB)	4.43	4.3	3.72	5.0
Philip Morris (MO)	1.82	24.0	4.32	5.1
Procter & Gamble (PG)	1.56	26.5	3.22	11.8
Sears (S)	3.32	6.6	2.91	12.8
U.S. Steel (X)	1.39	29.5	2.40	19.9

Trading frequency is the average number of trades in the five-minute interval. Nontrading probability is the proportion of intervals in which there is no trade.

[1] 14,246 observations.

[2] 10,312 observations.

there is a minor infrequent trading problem for MMI futures contracts, it does not exist for S&P 500 futures contracts. Among the component stocks, the most actively traded stock is IBM, which has 7.58 trades and a 0.5 percent nontrading probability, followed by Exxon, AT&T, and Mobil Oil, which have 1.8 percent, 1.9 percent, and 4.3 percent nontrading probabilities, respectively. Half of the component stocks have nontrading probabilities higher than 10 percent. Therefore, although the nonsynchronous trading problem associated with the MMI is less serious, there is still a danger that the lead-lag relation is due to this friction. In 1987, the MMI futures shows a drastic increase in trading intensity, as evidenced by a fourfold increase in trading frequency, and a 0.05 percent nontrading probability. Most of the component stocks also experienced increases in trading frequency and decreases in nontrading probability. Therefore, if there is a spurious lead-lag relation induced by nonsynchronous trading, it will be reduced in this sample period.

The autocorrelation structures of five-minute returns of the MM

Table 2
Autocorrelation of five-minute MM cash index and futures price changes

	Aug. 1984–June 1985[1]			Jan.–Sept. 1987[2]		
Lag	MM cash index	MMI futures	S&P 500 futures	MM cash index	MMI futures	S&P 500 futures
1	0.308*	0.023	0.037*	0.124*	0.042*	−0.068*
2	0.124*	−0.010	−0.016	−0.054*	−0.016	0.032*
3	−0.005	−0.047*	−0.042*	−0.037*	−0.030*	−0.021
4	−0.052*	−0.035*	−0.027*	−0.012	−0.033*	0.008
5	−0.044*	−0.013	−0.009	−0.028	−0.025	−0.020
6	−0.033*	0.005	0.009	−0.020	−0.017	−0.004

[1] 14,246 observations.
[2] 10,312 observations.
* Significant at the 0.001 level.

cash and index futures, and the S&P 500 index futures are presented in Table 2. In 1984-1985, the serial correlations of MMI cash returns for the first two lags are reasonably large (0.308 and 0.124) and significant at the 0.1 percent level.[8] In contrast, the serial correlations of MMI and S&P 500 futures returns are relatively small. In the first lag, the coefficient is 0.023 for MMI futures and 0.037 for S&P 500 futures. The difference in the serial correlations between cash index returns and futures returns may be due to nonsynchronous trading of component stocks within the MMI. It may also be due to slow dissemination of market-wide information in the cash market. Consistent with the evidence in Froot and Perold (1990), the serial correlations in the cash returns diminish over time; in 1987, the serial correlation drops to 0.124 at the first lag and turns negative at the second lag. This may imply that there is less nonsynchronous trading of component stocks or that the cash market is faster in processing market-wide information in 1987.

The cross-correlation between returns of the MM cash index and the two index futures is shown in Table 3. This provides a preliminary look at the lead-lag relation between the two markets and suggests the number of leads and lags to be used in the later regression analysis. The first column shows the cross-correlation between MMI cash and futures returns in 1984-1985. The contemporaneous correlations are 0.506, suggesting that the two time series are not perfectly correlated. Correlations between current returns of MMI cash and lagged returns of MMI futures are remarkably high (0.399, 0.184, and 0.061 for the first three lags). In contrast, correlations between current returns of

[8] As Lindley (1957) points out, for large samples lower significance may be required. All the tests in this article use the 0.1 percent level of significance as the rejection criterion, instead of conventional levels of significance.

Table 3
Cross-correlation coefficients of five-minute returns of MMI cash (S_t) and MMI futures ($F_{M,t}$) and S&P 500 futures ($F_{SP,t}$)

	Aug. 1984–June 1985[1]		Jan.–Sept. 1987[2]	
Lag k	$p(S_t,F_{M,t+k})$	$p(S_t,F_{SP,t+k})$	$p(S_t,F_{M,t+k})$	$p(S_t,F_{SP,t+k})$
−6	−0.014	−0.011	−0.018	−0.015
−5	−0.025	−0.029*	−0.025	−0.018
−4	−0.009	−0.006	−0.021	−0.004
−3	0.061*	0.063*	−0.021	−0.011
−2	0.184*	0.202*	−0.011	−0.014
−1	0.399*	0.424*	0.296*	0.419*
0	0.506*	0.456*	0.614*	0.499*
1	0.144*	0.139*	0.060*	0.419*
2	−0.034*	−0.037*	−0.038*	0.045*
3	−0.050*	−0.049*	−0.038*	−0.032*
4	−0.037*	−0.029*	−0.023	−0.016
5	−0.006	−0.006	−0.025	−0.003
6	0.001	0.003	−0.008	−0.019

$p(S_t,F_{M,t+k})$ is the cross-correlation coefficient between current MMI cash returns and past MMI futures returns (for negative lags) and future MMI futures returns (for positive lags). $p(S_t,F_{SP,t+k})$ is the cross-correlation coefficient between current MMI cash returns and past S&P 500 futures returns (for negative lags) and future S&P 500 futures returns (for positive lags). Asymptotic standard errors for the cross-correlation coefficients can be approximated as the square root of the reciprocal of the number of observations (i.e., 0.0084 for 14,246 observations and 0.0098 for 10,312 observations).

[1] 14,246 observations.

[2] 10,312 observations.

* Significant at the 0.001 level.

MMI cash and leading returns of MMI futures are only significantly positive at the first lead (0.144). Cross-correlations between returns of the MM cash index and S&P 500 index futures in 1984-1985, shown in the second column, have a similar pattern. The correlation coefficients at the first three lags are 0.424, 0.202, and 0.063, while the coefficient at the first lead is 0.139. The third and fourth columns show the cross-correlation in 1987. Unlike the 1984-1985 sample period, current returns of the MM cash index are correlated with lagged futures returns only at the first lag. This is consistent with the claim that the cash market reacts faster to market-wide information over time, and therefore lags the futures market less in the latter sample period.

3. Empirical Results

3.1 Lead-lag relation

The lead-lag behavior between the cash and futures markets is examined by estimating the regression

$$R_{S,t} = a + \sum_{k=-3}^{3} b_k R_{F,t+k} + \epsilon_{S,t}, \tag{1}$$

where $R_{S,t}$ are five-minute MM cash index returns and $R_{F,t}$ are returns of either MMI futures or S&P 500 index futures, at time *t*. The coefficients with negative subscripts (b_{-3}, b_{-2}, b_{-1}) are lag coefficients, and those with positive subscripts (b_1, b_2, b_3) are lead coefficients. If the lag coefficients are significant, the cash index lags futures. If the lead coefficients are significant, the cash index leads futures? The choice of three leads and lags is based on Table 3, which shows that cross-correlation coefficients of longer leads and lags are small. Since three leads and lags are required for each observation, six more observations are lost each day.

The model only estimates the intraday relation between cash index and futures returns and does not investigate the variability of the disturbances. There is, however, mounting evidence that the volatilities of stock returns change over time [see French, Schwert, and Stambaugh (1987); Akgiray (1989); Schwert and Seguin (1990)]. Chan, Chan, and Karolyi (1991) estimate a bivariate generalized autoregressive conditional heteroskedastic (GARCH) model for the joint processes governing the intraday stock index and index futures returns, and demonstrate that volatilities in the two markets are not only time varying, but are also related. Based on previous evidence, the error terms ($\epsilon_{s,t}$) in regression (1) are likely to be time-varying heteroskedastic. The dynamics of the conditional variances are not explicitly modeled in this article. However, since heteroskedasticity generally leads to inconsistent estimates of standard errors and invalidates inference, all of the *t*- ratios for the coefficients are adjusted using Hansen's (1982) variance-covariance matrix. An attractive feature of Hansen's correction is that the model does not have to specify the formal structure of heteroskedasticity and autocorrelation, yet the covariance matrix estimator is consistent in the presence of heteroskedastic and autocorrelated errors.

Regression results are presented in Table 4. Model 1 is estimated using the raw cash index returns. The first two columns show regression results based on MMI futures returns. The contemporaneous coefficient b_0, is 0.378 and 0.581 in the two sample periods, and is the largest among all coefficients, suggesting that the two markets react simultaneously to much of the information. In 1984-1985, estimates of lag coefficients (b_{-3}, b_{-2}, b_{-1}) are 0.069, 0.144, and 0.293, and are significant at the 0.1 percent level. In 1987, only b_{-1} remains significant, confirming that the cash index more recently reacts to futures price movement faster. Evidence also indicates that futures lags the cash index less in the more recent sample; the estimate of the lead

[9]Use of the terms "lead" and "lag" does not necessarily mean that price movement in one market causes price movement in the other market. It is more appropriately interpreted as one market reacting faster to information than the other market, which lags and then catches up.

coefficient (b_1) decreases from 0.106 in 1984-1985 to 0.039 in 1987. Regression results based on S&P 500 futures returns, shown in the third and fourth columns, are similar to those based on MMI futures returns. For example, in 1984-1985, the estimates of lag coefficients are 0.070, 0.161, and 0.325, while the first lead coefficient is 0.107. χ_{LAG} and χ_{LEAD} are χ^2- statistics that test that the lag coefficients (b_{-3}, b_{-2}, b_{-1}) and the lead coefficients (b_3, b_2, b_1) are jointly zero, and both of them have p values smaller than 0.1 percent. There is also evidence that the MM cash index lags S&P 500 futures less in 1987.

Model 2 follows Stoll and Whaley (1990) by estimating the regression based on return innovations. In the first stage, an autoregressive process is estimated for cash index returns,[10] and serially uncorrelated return innovations are extracted. In the second stage, the regression is estimated using return innovations. This procedure filters out the portion of cash index price changes due to infrequent trading of component stocks and allows analysis of the lead-lag behavior when the infrequent trading bias is reduced. Results are shown in the fifth through eighth columns. Return innovations are estimated using different autoregressive specifications, but the results are generally similar. Regression results using the return innovations extracted from a parsimonious AR(1) model are reported. Not surprisingly, the lag coefficients are smaller than those in model 1. For example, in 1984-1985, estimates of the lag coefficients (b_{-3}, b_{-2}, b_{-1}) are 0.024, 0.053, and 0.177 for the MMI futures, and 0.019, 0.061, and 0.219 for the S&P 500 index futures. Nevertheless, parameter estimates are significant, indicating that futures prices still lead cash index prices after the infrequent trading component is taken into account.

Overall, there is evidence that there is a lead-lag relation between the MM cash index and the index futures, regardless of whether MMI futures or S&P 500 futures are used. Further, the lead-lag relation is asymmetric-the feedback from the futures market into the cash market is higher than the reverse. Even though the cash market seems to react faster to market-wide information over time, the asymmetric lead-lag relation persists.

3.2 Lead-lag relation between futures and component stocks

Examination of the lead-lag relation between returns of the component stocks and futures provides two kinds of information. First, evidence in the previous section suggests that the futures leads the cash index predominantly. By studying individual stocks, it is possible

[10] Although Stoll and Whaley (1990) show that observed portfolio returns follow an ARMA process, the existence of an MA component is due to the bid-ask spread. Since bid-ask spreads are likely to be canceled out and are insignificant components in the cash index return, only the autoregressive process is considered.

Table 4
Regression of five-minute MMI cash returns ($R_{S,t}$) or return innovations ($R_{\epsilon,t}$) on lags and leads of five-minute MMI futures returns or S&P 500 futures returns ($R_{F,t}$)

Model 1: MMI returns (S_t)

$$R_{S,t} = a + \sum_{k=-3}^{3} b_k R_{F,t+k} + \epsilon_{S,t}$$

Model 2: MMI return innovations (S_t)

$$R_{\epsilon,t} = a + \sum_{k=-3}^{3} b_k R_{F,t+k} + \epsilon_{\epsilon,t}$$

	Model 1 MMI returns (S_t)				Model 2 MMI return innovations (S_t)			
	MMI futures		S&P 500 futures		MMI futures		S&P 500 futures	
	1984–1985	1987	1984–1985	1987	1984–1985	1987	1984–1985	1987
b_{-3}	0.069*	−0.006	0.070*	−0.021	0.024*	−0.005	0.019	−0.022
	(12.53)	(−0.60)	(11.85)	(−1.20)	(4.18)	(−0.46)	(3.06)	(−1.31)
b_{-2}	0.144*	−0.012	0.161*	0.008	0.053*	−0.056*	0.061*	−0.044*
	(26.64)	(−0.78)	(27.08)	(0.72)	(9.06)	(−3.63)	(9.51)	(−3.37)
b_{-1}	0.293*	0.371*	0.325*	0.435*	0.177*	0.303*	0.219*	0.375*
	(49.47)	(30.37)	(48.92)	(14.67)	(30.15)	(24.05)	(32.26)	(11.92)
b_0	0.378*	0.581*	0.349*	0.509*	0.346*	0.576*	0.317*	0.502*
	(57.30)	(51.40)	(50.55)	(22.46)	(50.64)	(48.81)	(44.52)	(21.29)
b_1	0.106*	0.039	0.107*	0.060*	0.107*	0.042	0.109*	0.065*
	(19.80)	(3.12)	(18.07)	(3.45)	(19.08)	(3.23)	(17.34)	(3.49)
b_2	−0.004	−0.018	−0.006	−0.036	−0.002	−0.018	−0.002	−0.034
	(−0.79)	(−1.89)	(−1.13)	(−2.72)	(−0.29)	(−1.77)	(−0.42)	(−2.54)
b_3	−0.007	−0.006	−0.124	−0.013	−0.005	−0.007	−0.010	−0.013
	(−1.42)	(−0.73)	(−2.36)	(−1.15)	(−0.95)	(−0.79)	(−1.86)	(−1.17)
χ_{LAG}	3013.2*	962.2*	2942.5*	260.9*	1063.9*	624.7*	1209.8*	154.2*
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)
χ_{LEAD}	398.9*	15.2	339.1*	15.4*	375.9*	14.9	320.2*	14.9
	($p = 0.000$)	($p = 0.002$)	($p = 0.000$)	($p = 0.001$)	($p = 0.000$)	($p = 0.002$)	($p = 0.000$)	($p = 0.002$)
$\bar{R}^2$	0.48	0.51	0.45	0.45	0.33	0.46	0.30	0.41

Sample periods are August 1984 to June 1985 (14,246 observations) and January to September 1987 (10,312 observations). Values in parentheses are t-ratios, which are based on standard errors adjusted for autocorrelation and heteroskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero.

* Significant at the 0.001 level.

to determine whether such an asymmetric lead-lag relation exists between the futures and all component stocks or just some of the stocks. Second, by examining individual stocks, the nontrading probability of each stock relative to the futures can be compared to determine whether the nonsynchronous trading of futures and component stocks explains the lead-lag relation. If the spurious lead-lag relation is induced by nonsynchronous trading of futures and component stocks, futures should lead only infrequently traded stocks. The regression results for each stock in 1984-1985 are reported in Table 5. The $\bar{R}^2$ varies widely across stocks, ranging from 0.277 for IBM to 0.009 for AT&T. This indicates that the association between the stocks and the futures market differs from one stock to another. Evidence does not suggest that the futures leads only less actively traded stocks. For component stocks like IBM, AT&T, and Exxon, which seem to be more actively traded than the futures in 1984-1985 (in terms of relative nontrading probabilities),[11] their returns are significantly led by futures returns. Further, lag coefficients are much larger than lead coefficients. For instance, estimates of b_{-1}, and b_1 are 0.298 and 0.175 for IBM, and 0.193 and 0.064 for Exxon in 1984-1985. Since IBM and Exxon do not have higher nontrading probabilities than MMI futures, evidence that lag coefficients are larger than lead coefficients is not explained by nonsynchronous trading. Although not reported, results for 1987 show that the cash market reacts faster to information in the futures market; all the component stocks lag the futures less in 1987. However, the coefficient b_{-1} remains significantly positive, and the χ_{LAG} statistic rejects that the lag coefficients are jointly zero for all component stocks. In brief, the evidence indicates that the futures market is faster in updating prices and disseminates that information into the cash market. Although the cash market is faster in processing the information, the results that futures lead all component stocks are robust.

3.3 Lead-lag relation under bad news and good news

To examine whether the lead-lag relation is different under bad news and good news, observations are sorted by the sign and size of cash index returns. Trading hours are partitioned into 30-minute intervals (i.e., each interval contains six observations), and cash index returns are calculated for each interval. The 30-minute intervals are stratified into five quintiles based on cash index returns, and observations are allocated into the five quintiles according to the ranking of the interval. Quintile 1 is the bad news group, containing observations of the

[11] This is still true, even taking into consideration that the futures prices dataset records trades only when the price changes. If buy and sell orders are random, the true nontrading probability of the futures will be a half of 4.9 percent (i.e., 2.5 percent), which is higher than those of active stocks.

smallest returns and downward price movements, which are most likely to be subject to short-sale constraints. Quintile 5 is the good news group, containing observations of the highest returns and upward price movements, which are least likely to be subject to short-sale constraints. The 30-minute interval is chosen to be short enough to avoid many different bits of information, and long enough to allow the information effect to have an impact on the lead-lag relation of some observations. Although a one-hour interval is also used for stratification, results remain the same and are not reported.

After stratification, only observations from quintiles 1 and 5 are retained and pooled in the regression, but a dummy intercept as well as dummy slope coefficients are added for the observations from quintile 1. The dummy slope coefficients measure the differential impact on the lead-lag relation under both bad news and good news. If the short-sale constraints are binding, the cash index lags futures longer, and the dummy slope lag coefficients will be positive.[12] Results based on MMI futures are reported in Table 6.[13] First, the estimate of b_{-1} is positive in both sample periods, and the p value of χ_{LAG} is close to 0 percent. Second, none of the dummy slope lag coefficients $(b'_{-1}, b'_{-2}, b'_{-3})$ are significantly positive in any regression. χ'_{LAG} is the χ^2- statistic that tests whether the dummy slope lag coefficients are jointly zero; it is not significant. Summarizing the results, it does not seem that the futures leads the cash index only under bad news. Neither is there a stronger tendency for the futures to lead the cash index under bad news than under good news. This may suggest that short-sale restrictions are not a constraint to marginal arbitrageurs, who are able to exploit their information by selling stocks under bad news.

3.4 Lead-lag relation under different intensities of trading activity

Since data on intraday futures trading volume are not available, the intensity of trading activity is measured by the number of transactions in the futures and cash market.[14] Because futures transactions are

[12]If the cash index does not lag futures under good news, but lags futures under bad news, the dummy slope lag coefficients are positive. However, if even under good news the cash index falls behind futures by one lag. and lags futures longer under bad news, then the dummy slope coefficient will be negative for the first lag and positive for higher lags.

[13]Results of the following tests based on S&P 500 futures are qualitatively similar to those based on MMI futures and are not reported. These results are available upon request.

[14]Stephan and Whaley (1990) examine the intraday relation between trading activity of the option and stock market. Option and stock market activity in each five-minute interval is measured by the number of transactions and by the number of option contracts and shares traded. It is found that the trading activity of the stock market leads that of the option market, independent of whether the number of transactions or the number of contracts traded is used as the metric. This supports using the number of transactions as a proxy for trading activity.

Table 5
Regression of five-minute returns of component stocks ($R_{i,t}$) on lags and leads of five-minute returns of MMI futures ($R_{F,t}$)

$$R_{i,t} = a + \sum_{k=-3}^{3} b_k R_{F,t+k} + \epsilon_{i,t}$$

Stock symbol	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
AXP	0.109*	0.288*	0.481*	0.553*	0.151*	−0.007	−0.026	556.0*	35.4*	0.078
	(4.04)	(10.71)	(18.55)	(20.48)	(5.81)	(−0.28)	(−1.04)	(p = 0.000)	(p = 0.000)	
T	0.133	0.216*	0.229*	0.298*	0.160*	−0.028	0.030	109.3*	16.1*	0.009
	(3.10)	(5.13)	(5.51)	(6.99)	(3.88)	(−0.69)	(0.74)	(p = 0.000)	(p = 0.001)	
CHV	0.105*	0.136*	0.218*	0.295*	0.063	−0.036	0.021	147.3*	8.1	0.022
	(4.40)	(5.61)	(8.37)	(11.89)	(2.61)	(−1.51)	(0.90)	(p = 0.000)	(p = 0.044)	
KO	0.076*	0.179*	0.263*	0.238*	0.022	0.017	−0.020	543.7*	6.8	0.069
	(5.59)	(12.38)	(18.21)	(16.60)	(1.59)	(1.26)	(−1.49)	(p = 0.000)	(p = 0.078)	
DOW	0.126*	0.150*	0.342*	0.433*	0.027	−0.011	0.006	208.2*	0.9	0.027
	(4.27)	(4.95)	(11.02)	(13.98)	(0.91)	(−0.39)	(0.21)	(p = 0.000)	(p = 0.823)	
DD	0.082*	0.123*	0.252*	0.346*	0.145*	−0.036	−0.037	186.7*	47.9*	0.043
	(3.92)	(5.83)	(10.91)	(14.42)	(6.60)	(−1.72)	(−1.95)	(p = 0.000)	(p = 0.000)	
EK	0.035	0.130*	0.334*	0.419*	0.151*	−0.000	0.006	596.4*	90.7*	0.108
	(2.29)	(8.87)	(22.53)	(26.92)	(9.50)	(−0.01)	(0.41)	(p = 0.000)	(p = 0.000)	
XON	0.095*	0.117*	0.193*	0.240*	0.064*	0.005	−0.022	248.6*	17.4*	0.032
	(5.70)	(6.75)	(10.83)	(13.30)	(3.80)	(0.31)	(−1.35)	(p = 0.000)	(p = 0.001)	
GE	0.044	0.157*	0.393*	0.406*	0.122*	−0.006	−0.018	669.0*	50.9*	0.106
	(2.65)	(9.48)	(23.23)	(21.94)	(6.96)	(−0.37)	(−1.16)	(p = 0.000)	(p = 0.000)	
GM	0.057*	0.148*	0.377*	0.423*	0.142*	−0.009	−0.012	8263*	125.8*	0.160
	(4.43)	(11.52)	(26.84)	(30.18)	(11.13)	(−0.73)	(−0.97)	(p = 0.000)	(p = 0.000)	
IBM	−0.007	0.034	0.298*	0.624*	0.175*	−0.032	−0.007	652.7*	234.9*	0.277
	(−0.63)	(2.99)	(24.58)	(46.54)	(15.23)	(−2.97)	(−0.67)	(p = 0.000)	(p = 0.000)	

Table 5
Continued

Stock symbol	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
IP	0.108*	0.138*	0.267*	0.320*	0.099*	0.017	0.019	319.2*	38.3*	0.060
	(5.85)	(7.91)	(14.65)	(17.51)	(5.93)	(1.10)	(1.13)	(p = 0.000)	(p = 0.000)	
JNJ	0.107*	0.168*	0.310*	0.397*	0.020	0.046	−0.000	197.8*	4.3	0.030
	(3.65)	(5.86)	(10.65)	(13.77)	(0.70)	(1.68)	(−0.01)	(p = 0.000)	(p = 0.232)	
MRK	0.068*	0.134*	0.229*	0.292*	0.066*	0.015	0.006	371.5*	26.2*	0.075
	(4.97)	(9.31)	(16.22)	(21.06)	(4.85)	(1.15)	(0.51)	(p = 0.000)	(p = 0.000)	
MMM	0.071*	0.148*	0.310*	0.354*	0.120*	0.023	−0.007	437.1*	65.5*	0.090
	(4.39)	(8.99)	(18.17)	(20.38)	(7.69)	(1.55)	(−0.44)	(p = 0.000)	(p = 0.000)	
MOB	0.128*	0.237*	0.202*	0.367*	0.058	−0.011	−0.016	135.4*	3.8	0.018
	(3.93)	(7.03)	(6.08)	(10.84)	(1.85)	(−0.33)	(−0.50)	(p = 0.000)	(p = 0.286)	
MO	0.058*	0.166*	0.241*	0.251*	0.052*	0.000	−0.016	348.0*	14.45	0.060
	(3.79)	(10.90)	(15.34)	(15.72)	(3.61)	(0.03)	(−1.19)	(p = 0.000)	(p = 0.002)	
PG	0.093*	0.166*	0.246*	0.321*	0.116*	−0.009	−0.018	266.6*	36.9*	0.044
	(4.67)	(8.41)	(11.73)	(16.04)	(6.01)	(−0.49)	(−0.99)	(p = 0.000)	(p = 0.000)	
S	0.102*	0.191*	0.380*	0.423*	0.111*	−0.014	0.026	340.3*	19.7*	0.044
	(3.96)	(7.49)	(14.47)	(16.38)	(4.35)	(−0.56)	(1.01)	(p = 0.000)	(p = 0.000)	
X	0.075	0.169*	0.262*	0.327*	0.155*	−0.027	−0.019	136.6*	29.6*	0.022
	(2.59)	(5.88)	(8.59)	(11.12)	(5.40)	(−0.94)	(−0.65)	(p = 0.000)	(p = 0.000)	

Sample period is August 1984 to June 1985 (14,246 observations). Values in parentheses are t-ratios, which are based on standard errors adjusted for autocorrelation and heteroskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero.

* Significant at the 0.001 level.

Table 6
Regression of five-minute MMI cash returns ($R_{s,t}$) on lags and leads of five-minute MMI futures returns ($R_{F,t}$), with dummy slope coefficients for observations from quintile of highest cash index returns

$$R_{s,t} = a + a'd_t + \sum_{k=-3}^{3} b_k R_{F,t+k} + \sum_{k=-3}^{3} b'_k d_t R_{F,t+k} + \epsilon_{s,t},$$

$$d_t = \begin{cases} 0, & \text{if from the highest cash index returns quintile,} \\ 1, & \text{if from the lowest cash index returns quintile.} \end{cases}$$

	Aug. 1984–June 1985		Jan.–Sept. 1987	
	Estimate	t-ratio	Estimate	t-ratio
b_{-3}	0.030	2.08	−0.034	−1.91
b_{-2}	0.137*	10.27	−0.031	−1.57
b_{-1}	0.323*	22.41	0.374*	19.29
b_0	0.428*	22.70	0.593*	30.30
b_1	0.083	6.81	0.011	0.62
b_2	−0.029	−2.62	−0.045	−2.61
b_3	−0.016	−1.31	−0.014	−0.87
b'_{-3}	0.009	0.51	0.031	1.05
b'_{-2}	−0.019	−1.10	−0.069	−1.72
b'_{-1}	−0.047	−2.54	−0.007	−0.19
b'_0	−0.088*	−4.39	−0.009	−0.25
b'_1	−0.018	−1.08	0.023	0.65
b'_2	0.014	0.88	0.004	0.15
b'_3	−0.005	−0.30	−0.017	−0.74
Obs.	5785		3798	
$\bar{R}^2$	0.592		0.544	
χ_{LAG}	562.1* ($p = 0.000$)		396.8* ($p = 0.000$)	
χ_{LEAD}	63.9* ($p = 0.000$)		8.3 ($p = 0.039$)	
χ'_{LAG}	8.0 ($p = 0.045$)		4.4 ($p = 0.220$)	
χ'_{LEAD}	2.1 ($p = 0.561$)		0.9 ($p = 0.806$)	

The t-ratios are based on standard errors adjusted for autocorrelation and heteroskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero. χ'_{LAG} (χ'_{LEAD}) is the χ^2-statistic that tests whether the dummy slope lag (lead) coefficients are jointly zero.

* Significant at the 0.001 level.

recorded only when prices are different from those of previous transactions, there is a bias that results from the recorded number of transactions understating the actual number of transactions. However, if the bias were constant over time, changes in the recorded number of transactions could reflect the variation in trading activity intensity. To a certain extent, the bias is not constant over time, but is affected by the volatility level. When volatility is higher, there is a larger price fluctuation, so that there are more transactions being recorded. Therefore, the higher the volatility is, the lower the bias is. However, previous studies [e.g., Karpoff (1987) and Lamoureux and Lastrapes (1990)] indicate that volatility and trading volume are positively correlated. This suggests that the bias is negatively correlated with trading volume, and the bias moves in the right direction to reflect changes in trading activity.

Based on the number of transactions in futures and cash markets, subgroups are formed to reflect relative intensity of trading activity in the two markets. Thirty-minute intervals are first sorted into three main groups based on the total number of transactions of 20 component stocks. The groups reflect low, medium, and high trading activity in the stock market. Within each group, the 30-minute intervals are sorted into three subgroups based on the recorded number of transactions in the futures market, so that there are nine subgroups altogether. Observations are then allocated into one of the nine subgroups according to the ranking of the 30-minute intervals, and only observations from the subgroups of low and high futures trading activity are used. Therefore, although the recorded number of transactions is not a very accurate measure of trading activity, focusing on the subgroups with low and high futures trading activity ensures that there is a difference in the relative trading intensity of the two markets across the two subgroups. Regressions are estimated separately for the three main groups (three different levels of cash trading activity) by including dummy slope coefficients for the observations from the subgroup with high futures trading activity. Therefore, the cash trading activity is held constant, allowing examination of the effect of higher futures trading activity on the lead-lag relation.

Table 7 shows the MMI futures results for the groups of low and high cash trading activity.[15] Whether observations can be stratified to allow futures trading activity to vary, while holding cash trading activity constant, depends on whether trading activity in the two markets is highly correlated. Although not reported in the table, results show that the last group (high cash trading activity) is not successful in controlling cash trading activity across the two subgroups. For example, in 1984-1985, when the number of futures transactions increases, the number of cash transactions also increases (the average number of MMI futures transactions increases from 4 to 11 across the subgroups of low and high futures trading activity, while the average number of total transactions for the 20 component stocks increases from 77 to 89). When moving from low to high cash trading activity, the $\bar{R}^2$ of the regression, or the association between the two markets, increases. This indicates that more common information is generated when trading activity is higher. Most of the dummy slope coefficients are insignificant. The coefficient b'_1 is significantly negative in the group of low cash trading activity in 1984-1985, suggesting there is a weaker tendency for the cash index to lead futures when there is a relative increase in futures trading activity. This may be just because futures prices are less stale when trading activity is higher. In 1987,

[15] Results for the group of medium trading activity are similar. Because of space limitations, they are not reported, but will be furnished upon request.

Table 7
Regression of five-minute MMI cash returns ($R_{s,t}$) on lags and leads of five-minute MMI futures returns ($R_{F,t}$), with dummy slope coefficients for observations from subgroup of high futures trading activity

$$R_{S,t} = a + a'd_t + \sum_{k=-3}^{3} b_k R_{F,t+k} + \sum_{k=-3}^{3} b'_k d_t R_{F,t+k} + \epsilon_{s,t},$$

$$d_t = \begin{cases} 0, & \text{if from the subgroup of low futures trading activity,} \\ 1, & \text{if from the subgroup of high futures trading activity.} \end{cases}$$

	Aug. 1984–June 1985				Jan.–Sept. 1987			
	Low cash trading activity		High cash trading activity		Low cash trading activity		High cash trading activity	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
b_{-3}	0.080*	4.05	0.084*	4.86	0.004	0.18	−0.014	−0.40
b_{-2}	0.140*	7.45	0.128*	7.41	0.098*	3.57	0.184*	5.09
b_{-1}	0.157*	8.20	0.308*	16.59	0.252*	8.87	0.310*	8.99
b_0	0.247*	11.84	0.477*	22.78	0.432*	16.23	0.628*	17.39
b_1	0.150*	8.46	0.142*	7.71	0.055	2.43	0.002	0.06
b_2	−0.005	−0.31	0.003	0.22	−0.024	−1.12	−0.020	−0.71
b_3	−0.006	−0.35	−0.010	−0.63	0.016	0.79	0.034	1.17
b'_{-3}	−0.013	−0.57	−0.032	−1.43	−0.003	−0.10	0.025	0.63
b'_{-2}	−0.029	−1.31	0.004	0.21	−0.051	−1.52	−0.291*	−5.71
b'_{-1}	0.051	2.23	0.044	1.91	0.108	3.15	0.062	1.42
b'_0	0.008	0.33	−0.056	−2.18	0.051	1.55	0.034	0.82
b'_1	−0.080	−3.78	−0.039	−1.77	−0.031	−1.12	0.057	1.34
b'_2	−0.007	−0.36	−0.009	−0.49	0.042	1.57	−0.031	−0.86
b'_3	0.008	0.44	−0.006	−0.32	−0.034	−1.38	−0.053	−1.57
Obs.	2900		3525		2282		1625	
$\bar{R}^2$	0.291		0.592		0.441		0.677	
χ_{LAG}	113.8* ($p = 0.000$)		308.3* ($p = 0.000$)		83.1* ($p = 0.000$)		132.4* ($p = 0.000$)	
χ_{LEAD}	72.1* ($p = 0.000$)		62.0* ($p = 0.000$)		7.2 ($p = 0.065$)		1.6 ($p = 0.649$)	
χ'_{LAG}	7.9 ($p = 0.047$)		6.0 ($p = 0.110$)		13.6 ($p = 0.003$)		33.2* ($p = 0.000$)	
χ'_{LEAD}	14.7 ($p = 0.002$)		3.6 ($p = 0.302$)		4.9 ($p = 0.178$)		5.1 ($p = 0.168$)	

The t-ratios are based on standard errors adjusted for autocorrelation and heterskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero. χ'_{LAG} (χ'_{LEAD}) is the χ^2-statistic that tests whether the dummy slope lag (lead) coefficients are jointly zero.

* Significant at the 0.001 level.

when MMI futures are actively traded so that the infrequent trading problem is not an issue, none of the dummy slope lead coefficients (b_1', b_2', b_3') is significant.

Overall, there is no compelling evidence to suggest that the lead-lag relation may be affected by the relative intensity of trading activity in cash and futures markets. Variation in the infrequent trading component may slightly affect the relation between the two markets. However, if the futures contracts are traded actively enough, changes in the trading intensity will not have a significant impact on the lead-lag pattern.

3.5 Lead-lag relation under market-wide movement

Previous discussion suggests that it is more likely for informed traders to use futures contracts instead of component stocks if there is market-wide information. Although the information content available in the market is unobservable, the arrival of market-wide information can be inferred from the price changes of component stocks. Intuitively, if there is a broad price movement in the cash market, it represents the arrival of market-wide information. I motivate a simple proxy with the following discussion.

An advantage of trading index futures over a portfolio of individual stocks is the lower transaction costs in the futures market. However, the amount of market-wide information determines whether investors prefer to trade in the futures or cash market. Suppose a trader has private information about each component stock, such that he knows the price change of stock i is ΔS_i. He can exploit this information by taking a position in one unit of a futures contract, or one share of each stock in the cash market. The gross profits (before transaction costs) are $|\Sigma_{i=1}^{20} \Delta S_i|$ if he exploits the information in the futures market, and $\Sigma_{i=1}^{20} |\Delta S_i|$ if he exploits the information in the cash market. Therefore, if there is market-wide information that affects all stock prices moving together in the same direction, then $|\Sigma_{i=1}^{20} \Delta S_i|$ equals $\Sigma_{i=1}^{20} |\Delta S_i|$. Under this situation, gross profits earned in the two markets are the same, but the net profit earned in the futures market is higher because the transaction cost is lower. Consequently, futures contracts are more attractive. However, when some stocks move in the opposite direction so that $|\Sigma_{i=1}^{20} \Delta S_i|$ becomes smaller than $\Sigma_{i=1}^{20} |\Delta S_i|$, using futures contracts is less attractive.

Therefore, when the transaction cost is constant over time, the relative advantage of futures contracts can be measured by the RATIO variable $|\Sigma_{i=1}^{20} \Delta S_i| / \Sigma_{i=1}^{20} |\Delta S_i|$. This co-movement ratio measures the extent of market-wide movement. When there are more stocks whose prices move in the same direction, the co-movement ratio is higher and traders prefer to trade in futures contracts. In the extreme, if prices of all component stocks move in the same direction, the co-movement ratio is one.

To investigate the effect of the market-wide movement on the lead-lag pattern, RATIO is first calculated for each 30-minute interval. Observations are then stratified into five quintiles based on the RATIO of 30-minute intervals. The higher the quintile is, the more likely that there is market-wide information affecting the stocks moving together. In Table 8, the lead-lag relation is reported for each quintile using MMI futures. An interesting pattern is that across higher quintiles, the lag and contemporaneous coefficients increase dramatically, while the lead coefficients remain about the same. In 1984-1985, the estimates of b_{-2}, b_{-1}, and b_0, are 0.098, 0.229, and 0.309, respectively, in quintile 1, and increase to 0.152, 0.352, and 0.434 in quintile 5. $\chi_{1,5}$ (χ_{ALL}) is the χ^2– statistic that tests whether the coefficients in quintiles 1 and 5 (all quintiles) are equal; it can be rejected for the lag coefficients at the 0.1 percent level of significance. In contrast, the lead coefficients do not differ significantly across the quintiles, and $\chi_{1,5}$ and χ_{ALL} for these lead coefficients are also not significant. The inference from the results in 1987 in similar. The lead coefficients are statistically small in all quintiles. On the other hand, the lag coefficient b'_{-1} increases from 0.299 in quintile 1 to 0.374 in quintile 5, and the p values for $\chi_{1,5}$ and χ_{ALL} are both close to 0 percent.

A problem associated with the RATIO variable is that it is a price-weighted measure. If a few stocks have much higher share prices than the others, the magnitudes of price changes in these stocks have a decisive impact on the co-movement ratio. Further, RATIO sometimes may be misleading. Suppose there is a piece of firm-specific information for one stock and no information for other stocks; there would be a price change for just one stock. Therefore, RATIO will be equal to unity and will misleadingly imply that there is market-wide information. To mitigate this problem, another proxy is constructed to measure the extent of market-wide movement. This proxy, PROP, is measured by $|N_u - N_d|/(N_u + N_d + N_z)$, where N_u, N_d, and N_Z are the number of stocks moving upward, moving downward, and with no change in the 30-minute interval, respectively. The PROP variable measures the net proportion of stocks moving together. It depends on the direction, not the magnitude, of the price movement of component stocks.[16] Again, the higher the ratio is, the more likely there is market-wide information affecting the stocks moving together.

Observations are stratified into five quintiles based on the PROP of the 30-minute intervals, and regression results for each quintile are

[16] If there is a price change for just one stock, and no price change for the other stocks, as in the previous example, PROP will be equal to 0.05 and will not indicate market-wide information.

presented in Table 9. The lead-lag pattern is similar to that in Table 8. For example, the lag and contemporaneous coefficients increase dramatically across higher quintiles. In both sample periods, results reject that the estimates of b'_{-1} are equal in all quintiles, but do not reject that the estimates of b'_{1} are different. In summary, the evidence is consistent with the hypothesis that futures prices react to market-wide information faster than do cash index prices. When there is market-wide information, the feedback from the futures market to the cash market is higher.

Since construction of the above measures to proxy for market-wide information is ad hoc and is proposed in a heuristic fashion, they are almost surely an approximation. To address this concern, two issues are considered. The first issue involves interpretation, as the above co-movement measures may proxy for some other market characteristics that could influence the lead-lag relation between the two markets. One possibility is that these co-movement measures may merely be reflecting the absolute price movement in the futures market; when there are more component stocks moving together, the absolute future price changes will also be higher. Since the absolute price change is positively correlated with trading volume (Karpoff (1987)], it may be that a higher co-movement ratio simply reflects a higher futures trading volume. Although this conjecture is reasonable, it is not supported by the evidence in the article. Previous results show that there is only a slight variation in the lead-lag pattern when futures trading volume varies. Also, though not reported, a change in the lead-lag pattern is found between the MM cash index and S&P 500 futures when the co-movement ratio varies. Since the co-movement ratios are constructed based on 20 MMI component stocks, a higher co-movement ratio is not necessarily accompanied by a higher S&P 500 futures price change, unless it is really reflecting the arrival of market-wide information.

The second issue involves measurement errors. Even though the proxies are reflecting the arrival of market-wide information, they are noisy measures. The identification of the arrival of market-wide information within the 30-minute interval is ad hoc. Within an interval there could be some other events, such as the release of firm-specific information and portfolio-liquidity trading, which affect price movements. Also, the co-movement proxies do not control other factors that may affect the advantages of using index futures over component stocks (e.g., leverage, transaction costs, and liquidity). If these factors are not constant, they may also influence the lead-lag relation. Therefore, the impact of market-wide information on the lead-lag pattern can be contaminated by other factors. Nevertheless, even though they are noisy, from an econometric point of view, the proxies are used

Table 8

Regression of five-minute MMI cash returns ($R_{s,t}$) on lags and leads of five-minute MMI futures returns ($R_{f,t}$) for five quintiles sorted by the RATIO variable

Quintile	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
Aug. 1984–June 1985										
1	0.057*	0.098*	0.229*	0.309*	0.087*	−0.024	−0.018	277.8*	58.7*	0.28
(Low)	(4.88)	(7.96)	(15.80)	(18.52)	(6.54)	(−2.05)	(−1.61)	(p = 0.000)	(p = 0.000)	
2	0.068*	0.130*	0.219*	0.307*	0.085*	−0.017	−0.029	409.2*	75.2*	0.31
	(6.23)	(11.68)	(17.49)	(24.07)	(7.80)	(−1.62)	(−2.79)	(p = 0.000)	(p = 0.000)	
3	0.067*	0.122*	0.262*	0.340*	0.087*	−0.018	−0.017	521.1*	62.7*	0.38
	(5.87)	(11.23)	(20.53)	(25.14)	(7.40)	(−1.58)	(−1.45)	(p = 0.000)	(p = 0.000)	
4	0.056*	0.146*	0.287*	0.380*	0.095*	−0.015	0.001	700.7*	72.1*	0.49
	(4.73)	(13.42)	(23.33)	(30.10)	(8.40)	(−1.54)	(0.06)	(p = 0.000)	(p = 0.000)	
5	0.050*	0.152*	0.352*	0.434*	0.093*	−0.002	−0.008	1065.0*	74.6*	0.63
(High)	(3.79)	(11.91)	(28.64)	(30.92)	(8.55)	(−0.19)	(−0.77)	(p = 0.000)	(p = 0.000)	
$\chi_{1,5}$	0.2	12.6*	63.3*	65.5*	0.1	2.1	0.5			
	(p = 0.659)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.703)	(p = 0.146)	(p = 0.468)			
χ_{ALL}	2.07	16.1	100.2*	104.6*	0.7	2.5	5.3			
	(p = 0.723)	(p = 0.003)	(p = 0.000)	(p = 0.000)	(p = 0.950)	(p = 0.640)	(p = 0.260)			

Table 8
Continued

Quintile	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
Jan.–Sept. 1987										
1	−0.023	0.026	0.299*	0.533*	−0.030	−0.013	−0.026	222.5*	4.5	0.42
(Low)	(−1.21)	(1.48)	(14.57)	(21.90)	(−1.56)	(−0.71)	(−1.47)	(p = 0.000)	(p = 0.210)	
2	−0.027	0.014	0.372*	0.584*	0.052	−0.019	−0.013	351.3*	6.5	0.53
	(−1.53)	(0.59)	(18.43)	(26.76)	(2.18)	(−1.12)	(−0.61)	(p = 0.000)	(p = 0.091)	
3	0.026	0.048	0.371*	0.524*	0.020	−0.033	−0.034	247.7*	7.1	0.40
	(1.11)	(2.29)	(15.50)	(21.24)	(1.05)	(−1.73)	(−1.57)	(p = 0.000)	(p = 0.067)	
4	−0.020	−0.004	0.408*	0.566*	0.028	−0.011	−0.006	458.2*	2.4	0.55
	(−1.02)	(−0.22)	(21.33)	(28.84)	(1.52)	(−0.63)	(−0.33)	(p = 0.000)	(p = 0.501)	
5	0.039	−0.092	0.374*	0.633*	0.048	−0.034	0.001	227.1*	6.6	0.69
(High)	(1.98)	(−2.45)	(13.22)	(29.49)	(1.93)	(−1.82)	(0.06)	(p = 0.000)	(p = 0.084)	
$\chi_{1,5}$	9.5	32.1*	12.9*	22.8*	13.2*	1.1	1.8			
	(p = 0.002)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.302)	(p = 0.183)			
χ_{ALL}	18.3*	54.5*	26.3*	35.8*	16.7	2.1	4.0			
	(p = 0.001)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.002)	(p = 0.711)	(p = 0.407)			

RATIO is the co-movement ratio measured by $|\Sigma\ 20\Delta S_i| / \Sigma\ |\Delta S_i|$, where ΔS_i is the price change of MMI component stock i within the 30-minute interval. Values in parentheses are t-ratios, which are based on standard errors adjusted for autocorrelation and heteroskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero. $\chi_{1,5}$ (χ_{ALL}) is the χ^2-statistic that tests whether the coefficients in quintiles 1 and 5 (all quintiles) are equal.

* Significant at the 0.001 level.

Table 9

Regression of five-minute MMI cash returns ($R_{S,t}$) on lags and leads of five-minute MMI futures returns ($R_{F,t}$) for five quintiles sorted by the PROP variable

Quintile	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
Aug. 1984–June 1985										
1	0.058*	0.112*	0.206*	0.295*	0.084*	−0.008	−0.027	301.2*	53.7*	0.29
(Low)	(4.82)	(9.66)	(15.41)	(18.90)	(6.47)	(−0.72)	(−2.58)	(p = 0.000)	(p = 0.000)	
2	0.060*	0.107*	0.226*	0294*	0.079*	−0.029	0.000	275.7*	50.2*	0.31
	(5.23)	(8.36)	(15.57)	(20.50)	(6.64)	(−2.43)	(0.04)	(p = 0.000)	(p = 0.000)	
3	0.055*	0.131*	0.271*	0.336*	0.084*	−0.027	−0.020	538.8*	61.3*	0.41
	(4.56)	(11.33)	(20.57)	(22.46)	(7.12)	(−2.27)	(−1.70)	(p = 0.000)	(p = 0.000)	
4	0.067*	0.148*	0.280*	0.377*	0.101*	−0.011	−0.012	643.4*	59.0*	0.47
	(5.48)	(12.69)	(21.20)	(27.71)	(7.60)	(−0.94)	(−1.06)	(p = 0.000)	(p = 0.000)	
5	0.060*	0.155*	0.341*	0.416*	0.089*	0.003	−0.001	961.6*	59.1*	0.64
(High)	(4.20)	(12.09)	(26.36)	(28.58)	(7.62)	(0.24)	(−0.05)	(p = 0.000)	(p = 0.000)	
$\chi_{1,5}$	0.0	6.9	72.5*	57.5*	0.1	0.5	3.3			
	(p = 0.874)	(p = 0.008)	(p = 0.000)	(p = 0.000)	(p = 0.797)	(p = 0.482)	(p = 0.068)			
χ_{ALL}	0.7	13.6	86.9*	88.7*	2.0	6.2	5.4			
	(p = 0.954)	(p = 0.009)	(p = 0.000)	(p = 0.000)	(p = 0.740)	(p = 0.187)	(p = 0.245)			

Table 9
Continued

Quintile	$\hat{b}_{-3}$	$\hat{b}_{-2}$	$\hat{b}_{-1}$	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	χ_{LAG}	χ_{LEAD}	$\bar{R}^2$
Jan.–Sept. 1987										
1	−0.010	0.038	0.312*	0.508*	0.002	−0.013	−0.033	228.2*	4.3	0.41
(Low)	(−0.51)	(1.93)	(14.86)	(21.36)	(0.10)	(−0.72)	(−1.83)	(p = 0.000)	(p = 0.235)	
2	−0.009	0.033	0.356*	0.580*	0.041	−0.012	−0.030	276.3*	5.3	0.52
	(−0.47)	(1.47)	(16.43)	(23.49)	(1.70)	(−0.61)	(−1.80)	(p = 0.000)	(p = 0.148)	
3	0.002	0.031	0.356*	0.553*	0.030	−0.024	−0.006	260.7*	4.1	0.46
	(0.09)	(1.29)	(16.03)	(23.48)	(1.23)	(−1.46)	(−0.25)	(p = 0.000)	(p = 0.255)	
4	−0.021	−0.003	0.412*	0.581*	0.009	−0.020	0.003	447.1*	1.6	0.55
	(−1.02)	(−0.17)	(20.98)	(27.62)	(0.51)	(−1.03)	(0.13)	(p = 0.000)	(p = 0.762)	
5	0.031	−0.095	0.387*	0.628*	0.048	−0.032	−0.000	238.1*	6.3	0.69
(High)	(1.53)	(−2.55)	(13.69)	(28.53)	(1.91)	(−1.71)	(−0.03)	(p = 0.000)	(p = 0.099)	
$\chi_{1,5}$	3.8	36.3*	11.2*	28.5*	4.6	0.8	2.4			
	(p = 0.052)	(p = 0.000)	(p = 0.001)	(p = 0.000)	(p = 0.032)	(p = 0.386)	(p = 0.118)			
χ_{ALL}	6.9	56.1*	21.1*	30.9*	7.1	1.2	4.8			
	(p = 0.137)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.133)	(p = 0.884)	(p = 0.303)			

PROP is the co-movement ratio measured by $|N_u - N_d|/|N_u + N_d + N_z|$, where N_u, N_d, and N_z represent the number of MMI component stocks moving upward, moving downward, and with no change in the 30-minute interval. Values in parentheses are t-ratios, which are based on standard errors adjusted for autocorrelation and heteroskedasticity using Hansen's (1982) correction. χ_{LAG} (χ_{LEAD}) is the χ^2-statistic that tests whether the lag (lead) coefficients are jointly zero. $\chi_{1,5}$ (χ_{ALL}) is the χ^2-statistic that tests whether the coefficients in quintiles 1 and 5 (all quintiles) are equal.

* Significant at the 0.001 level.

simply as a benchmark for stratification and will not lead to inconsistent estimates.

4. Conclusion

In this article the lead-lag relation between the intraday futures and cash index prices over two sample periods, August 1984 through June 1985 and January through September 1987, is investigated. Since infrequent trading of component stocks can cause a spurious lead-lag relation between futures and cash index returns, the MMI, an index that comprises 20 actively traded stocks, is used to examine the intraday relation between the cash and futures market. Transaction frequencies of component stocks and futures are also examined to investigate the extent to which nonsynchronous trading explains the lead-lag relation. The observations are stratified to determine whether the lead-lag pattern changes in accordance with (i) bad news versus good news; (ii) the relative intensity of trading activity in the two markets; and (iii) the extent of market-wide movement.

Empirical results confirm previous findings that there is an asymmetric lead-lag relation between the two markets; there is strong evidence that the futures leads the cash index, and weak evidence that the cash index leads the futures. The results are robust even in 1987, when the cash market seems to be faster in processing market-wide information. Several sets of results suggest that nonsynchronous trading cannot completely explain why futures prices are dominant in leading the cash index. First, an asymmetric lead-lag relation holds between futures and all component stocks, even in 1984-1985 when some stocks are more frequently traded than the futures. Second, even for some stocks that are actively traded and have nontrading probabilities close to zero (e.g., IBM and AT&T), the returns still lag futures returns significantly. Therefore, the lead-lag relation is not well explained by nonsynchronous trading [e.g., Lo and MacKinlay (1990)].

Cash index prices do not lag futures prices longer under bad news. Further, even under good news, cash index prices still lag futures prices. This may indicate that marginal arbitrageurs have long positions in the stocks and are not constrained by shorting stocks under bad news. There is no compelling evidence to suggest that the lead-lag relation may be affected by the relative intensity of trading activity in cash and futures markets. An increase in the level of futures trading, holding the level of cash trading constant, causes futures either to lead cash to a greater degree or to lag cash to a smaller degree. Nevertheless, the marginal impact is small. The most significant result is that the lead-lag pattern varies consistently with the extent of market-wide movement. When there are more stocks moving together (market-wide information), the feedback from the futures market to the cash market is stronger. This provides some support for the hypothesis that the cash and futures markets do not have symmetric access to information. Because of differential transaction costs and expected profits, the futures market becomes the main source of market-wide information, while the cash market is the main source of firm-specific information. Since firm-specific information is diversifiable and market-wide information is systematic, the discovery of market-wide information is more important, so that the feedback from the futures market into the cash market is larger than the reverse.

The asymmetric lead-lag relation between cash and futures markets can be attributed to two forces. First, the futures market is faster than all individual stocks in processing information. Second, futures prices seem to be better at reflecting market-wide information than cash index prices. Certainly, the two forces are interrelated. It may be that because the futures market is better at reflecting market-wide information, it leads all component stocks. If the number of component stocks within the index is higher, the market-wide information component is more important and the feedback from the futures market to the cash market becomes stronger. This may explain why previous studies find a particularly strong asymmetric lead-lag relation between the S&P 500 cash and futures markets.

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