INDEX FUTURES LEADERSHIP, BASIS BEHAVIOR, AND TRADER SELECTIVITY

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Employing intraday data for futures and cash values for the S&P 500 over the 1993–1996 period, we attempt to characterize the lead–lag relationship between these two markets and their basis behavior. Our findings show evidence of pronounced futures leadership when markets are rising, with no feedback from the cash market. However, when markets are falling, futures leadership is less evident and significant feedback from the cash market is noted. We also provide evidence of a positive relationship

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between the basis and return volatility. We offer an explanation, based on trader selectivity, for the leadership-asymmetry and the basis–volatility relationship. Jrl Fut Mark 22:649–677, 2002

INTRODUCTION

Conventional wisdom suggests that the reason for the observed leadership of stock index futures markets over the underlying equities is that traders in stock index futures face lower transaction costs and reduced liquidity constraints, and are more readily able to trade on new information. We contend that stock index futures leadership can arise in the absence of such advantages. We suggest a framework in which large traders, deriving value from holding customized stock portfolios, systematically select between index futures and spot markets when their portfolios are highly tilted, that is, when their portfolios are very different from a benchmark portfolio. Our framework has roots in the literature and can be compared with models presented by Subrahmanyam (1991) and Chen, Cuny, and Haugen (1995) in that a knife-edge equilibrium is proposed where these traders suddenly might prefer transacting in futures contracts over transacting in stocks or *vice versa*.

We employ intraday data for the S&P 500 futures and cash index over the period January 1993 through December 1996 to examine the implied relationships between index futures and the underlying cash market. Our examination is motivated by two important objectives. The first is to examine if index futures leadership still can arise in the absence of lower transaction costs and other well-known factors found to contribute to futures leadership. The second is to determine the role portfolio tilt plays in the basis–volatility dynamic. Such an examination provides important evidence to market participants and regulators as it determines if factors—other than those already documented—play a role in index futures leadership. Thus, our study is closely related to the literature that examines the causes of index futures leadership (e.g., Chan, 1992; Stoll & Whaley, 1990).

The results from our empirical investigation may be summarized as follows:

i) index futures leadership is asymmetric; in rising markets, futures returns lead spot returns, with no feedback from the cash market; in contrast, there is less evidence of futures leadership in falling markets, but strong evidence of feedback from the cash market;

ii) almost all of the lead–lag influence between futures and spot markets is evidenced during periods of high volatility, which is consistent with the notion that the leadership is information driven;

iii) leadership is weakest at the open and at the close of trading, periods typically associated with high-frequency trading and large bid-ask spreads;[1] and

iv) the difference between the futures and cash index prices, with and without adjustments for interest rates, dividends, and time to expiration, is related positively to market volatility over our sampling interval.

This article is organized as follows. The next section reviews prior arguments on index futures leadership and introduces several new interpretations. A theoretical motivation for the joint study of leadership and basis behavior is presented in the following section. We then describe the data and the results of diagnostic tests and follow up with a report of the empirical results. We end with some concluding remarks.

BACKGROUND

Several studies have demonstrated that stock index futures price changes systematically lead cash price changes (especially for the S&P 500 index) by surprisingly large time intervals. For example, Kawaller, Koch, and Koch (1987) presented evidence suggesting that the S&P 500 futures contract leads the underlying cash index by twenty to forty-five min. Cheung and Ng (1990) and Chan, Chan, and Karolyi (1991) provided similar evidence. Two explanations—infrequent trading and transactions costs—often are put forth to explain index futures leadership.[2] While these explanations provide excellent insight into futures leadership, they fall short of completely describing the lead–lag phenomenon. Consider, for instance, the findings related to infrequent trading. Stoll and Whaley

[1]McNish and Wood (1992) documented that the bid–ask spreads for NYSE stocks follow a reverse-J pattern. The spreads are at their highest at the beginning of the trading day, declining until about 1:30 pm CST, and climbing thereafter.

[2]Miller, Muthuswamy, and Whaley (1994) suggested that imperfections in the relationship between futures and cash returns arise from infrequent trading of the stocks in the cash index. The authors also suggested that the widely documented pattern of mean reversion in the basis may be the result of delays in the trading of some stocks in the index. Fleming, Ostdiek, and Whaley (1996) focused on the role of transaction costs in explaining equity futures leadership. They examined the empirical relationship between the prices of options on individual stocks, stocks, options on stock indexes, and stock index futures, and documented that the market with the lower transaction cost led the market with the higher transaction cost.

(1990) found that the S&P 500 futures contract tends to lead the cash index even after adjusting the index price changes to account for the impact of infrequent trading. Similarly, Chan (1992) documented that the MMI futures leads the underlying index despite the constituent stocks being traded more actively than the futures contract.

The evidence in this article suggests that the transaction costs argument also falls short of fully describing index futures leadership. We demonstrate that the stock index futures leadership is asymmetric across rising and falling markets. We uncover clear evidence of futures leadership, without feedback from the cash market, only when markets are rising. On the other hand, there is positive feedback from the cash market when markets are falling. Thus, we can reasonably infer that futures leadership is driven by factors other than differences in transaction costs alone: intramarket transaction costs are fairly symmetric across rising and falling markets.[3]

The trader-selectivity-based arguments we put forth to explain the asymmetric-leadership patterns evolve from contemporary studies on trader behavior, as well as from casual observation of commercial trading in index futures. For instance, Odean (1998) and Grinblatt and Keloharju (2001) presented evidence that investors in the stock market suffer from a disposition effect, a reluctance to realize their losses. Such behavior would imply that stock price changes display pronounced serial correlation when prices are falling. However, it should be noted that the findings in Odean and Grinblatt and Keloharju relate primarily to individual traders. Related more closely to institutional traders is the explanation suggested by Chen et al. (1995). Chen et al. suggested that some traders derive a value from holding customized stock portfolios rather than indexes. To temporarily reduce exposure, these traders will sell index futures contracts rather than stock.

It is noteworthy that the Odean and Chen et al. frameworks implicitly predict an asymmetry in leadership between index futures and the underlying markets. In both frameworks, futures contract leadership should be more evident in falling markets.[4] For instance, the disposition effect in stocks noted by Odean should not be expected in futures markets because futures contracts have a limited time horizon, arguably only one day. In

[3]Based on our results, it is important to note that the subject of market leadership is better examined using disaggregated data (for instance, based on market direction). Easley, O'Hara, and Srinivas (1998) also noted that an incomplete and even biased picture on leadership could emerge when employing aggregate data.

[4]A subtle yet important difference between Chen et al. and our study is the *raison d'etre* that leads to falling markets. In Chen et al., the driver is market volatility, whereas in ours, the driver is the arrival of negative news (discussed later).

the Chen et al. framework, discretionary traders seeking to preserve portfolio customization will prefer trading futures contracts when markets are falling. Chen et al. also predicted a negative relationship between the basis and volatility and provided supporting evidence for the period of 1986 through 1990. These studies led us to suggest that the actions of traders have substantial effects on index futures leadership. However, our results are not consistent with some of their implications. We find little support for index futures leadership in falling markets. Moreover, the suggested negative basis–volatility relationship is not supported for our sample.

Our findings raise the obvious question: what explains the leadership asymmetry and the changing basis–volatility relationship? As in Chen et al., we suggest that trader selectivity and portfolio customization play an important role in explaining these patterns. In our framework, the commercial or institutional trader's reward/punishment is tied to the performance of an endogenously determined portfolio against a benchmark index. Under certain conditions, for instance, when the expected portfolio tracking error is high, this trader will opt to reduce portfolio customization by selling stock. At other times, the trader will prefer to maintain portfolio customization and transact in futures markets. Thus, trading will be concentrated in one or the other market. We propose that the basis–volatility relationship and the lead–lag relationship across the two markets is an artifact of this initial concentration of large, informed trading in either the futures contract or the stock portfolio. Ultimately, our framework implies that the nature of the basis–volatility and lead–lag relationships will change depending on whether these traders have a predisposition to trade in one market over the other.

Given our characterization of the institutional trader's role in price behavior, it is important that we consider the patterns in the participation of this group. Figure 1 traces the open interest of commercial traders (mainly large, institutional traders), small traders, and noncommercial traders (large futures speculators) for the S&P 500 contract over the April 1983–December 1996 period.[5] It readily is apparent that

[5]The CFTC defines commercial traders as large bonafide hedgers or traders who hold positions representing a substitute for transactions to be made at a later time in the cash market, and whose positions exceed the reporting levels established for that contract. Noncommercial traders are large speculators whose holdings exceed the CFTC reporting levels. Small traders are traders whose holdings do not exceed the reporting levels, and no distinction is made regarding their motives, hedging, or speculation. Spread traders, the fourth group of traders, take opposite positions on contracts with different maturities. Given their very small representation in the total open interest, they are excluded from Figure 1. The sum of long contracts across the various trader types should be equal to the sum of short contracts.

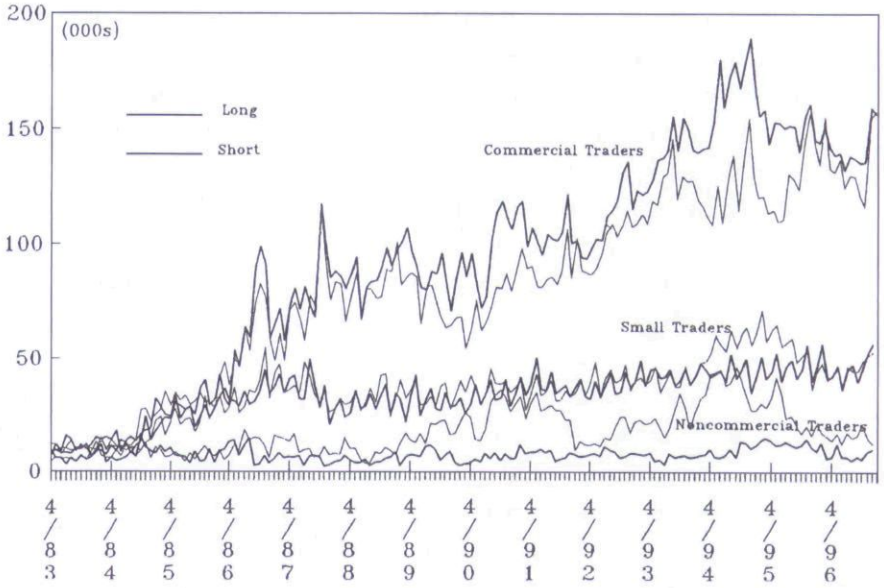

FIGURE 1

Commitment of traders in the S&P 500 futures contracts. The plots represent the long and short positions of three groups of traders in the S&P 500 futures contracts (over all expirations) over the interval 4/1983–12/1996. Commercial traders are defined by the CFTC guidelines as large bonafide hedgers or traders who hold positions representing a substitute for transactions to be made at a later time in the cash market, and whose positions exceed the reporting levels established for that contract. Mainly, they represent institutional traders. Noncommercial traders are large speculators whose holding exceed the CFTC reporting levels. Small traders are traders whose portions do not exceed the reporting levels, and no distinction is made regarding their motives, hedging, or speculation.

commercial traders are the largest group in this market. This dominance of commercial trading is typical for futures markets, including those for currencies, commodities, and other stock indices. However, unlike in non-equity contracts, the commercial traders have been net long the S&P 500 contract throughout the 1990s, while other traders have been net short. Furthermore, this imbalance in commercial trading has risen sharply since the period covered by the Chen et al. study. This changing imbalance may be an important clue in explaining differences between our results and the evidence found by Chen et al. For now, we underpin differences in the characteristics between our sample and Chen et al. by briefly noting the following statistics. The ratio (commercial long−commercial short)/(commercial long + commercial short) is 0.056 over the period 1986–1990 (Chen et al.'s sample period), but is higher, 0.092, for 1993–1996 (our sample period). Similarly, the ratio (commercial long−commercial short)/(total open interest) is 0.066 over the 1986–1990 interval, but almost double, 0.121, for 1993–1996. We later contend that the relatively high levels of long–short commercial imbalances for 1993–1996 are symptomatic of highly tilted portfolios. In the next section we provide a brief theoretical motivation for our study.[6]

THEORETICAL MOTIVATION

In this section we present a theoretical framework that draws on the work of Chen et al. The purpose of this exercise is to highlight conditions under which commercial traders will be especially predisposed to trade in the index futures market, or alternately, in the spot market. In particular, we present a framework under which a pooling equilibrium, a market where commercial traders will be divided among index futures and custom stock portfolios, will be less likely to occur.[7]

Assumptions

We make some general assumptions about the market, trader motivation, and price behavior. Because we only are interested in the index futures market and the cash market (comprising the stock index), we limit ourselves to these two markets. The futures contract and the exogenous stock index are considered perfect substitutes. There is no dichotomization of information into security specific and systematic components (e.g., Gorton & Penacci, 1993).

We introduce three types of traders into this framework to capture trading behavior. The Type I trader is institutional-based and is risk averse (commercial trader). This trader is rewarded or punished based on performance against a stock index (the benchmark). A Type I trader receives a constant endowment stream that is assigned to stocks and/or the futures contract within each interval. Of particular importance is the propensity for Type I traders to hold customized stock portfolios. Because the commercial trader is predisposed to keeping the makeup of the underlying stock portfolio constant, rebalancing can be

[6]A careful reading of Figure 1 also will highlight the differences in the long positions across the trader groups. For example, in 04/91 the long positions of commercial traders were almost double the long position of small traders. Gould (1988) noted that it is common for fund managers to use index futures as a stepping stone into equity markets in order to profit from futures mispricing. Some of the long commercial positions may reflect this mispricing. However, the pattern of sustained imbalances that may be noted in Figure 1 suggest that factors other than the stepping-stone argument are also in play.

[7]The term "pooling equilibrium" is employed loosely here. In prior research, the term has been employed to mean that traders employ different markets (e.g., stock, options, etc.) to transact in the *identical* underlying asset.

accomplished by engaging in two actions. Let θ_F, θ_S, and θ_L denote weights pertaining to the holdings of the futures index, custom portfolio, and cash, respectively. The trader can increase customization by raising θ_S (reducing $\theta_F + \theta_L$) via the purchase of stock, the sale of futures, or a mix of these two trades. Similarly, the commercial trader can reduce customization by lowering θ_S, by selling stock, or by buying futures.

The Type II trader is assumed to trade for reasons that are exogenous to the model. Each trader in this category trades in only one market, either in the futures index or in the stock market. A Type II trader has no discretion over order size, and Type II trades contain no information. The aggregate stock holdings of Type I and Type II traders mimic the stock index on which the futures contract is written.

We also introduce a Type III trader simply to maintain arbitrage-free conditions. The Type III trader is the arbitrageur, trading on the relative valuation of the stock index and futures contracts. Arbitrageurs continually force the difference in a unit price in the futures market (P_F) and the cash market (P_S) to be within the bounds $-A \leq [P_{F,t} - P_{S,t}e^{\overline{\omega}(T-t)}] \leq B$ at time t, where $\overline{\omega}$ represents the annualized borrowing rate minus the dividend yield rate, $T - t$ represents years to contract maturity, A represents transaction costs associated with buying futures and shorting stock, and B represents transaction costs associated with buying stock and selling futures. Following Chen et al. (see their Appendix B), we assume that the no-arbitrage bounds are reasonably large so that the theoretical results on basis behavior and market leadership can occur in the presence of arbitrageurs.

A Multimarket Trading Model for the Commercial Trader

Let the kth security ($k = 1, 2, \ldots, K$) in the custom portfolio of the ith informed trader have a value at $t = 0$ given by $S_k(0)$. Assuming, like many others, that prices in the next interval can be represented by a linear pricing rule, the price of the kth security at $t = 1$ is:

$$S_k(1) = S_k(0) + \lambda_k \omega_k \tag{1}$$

where ω_k is the rate at which the net trade is absorbed by the market maker, and λ_k is a pricing parameter that is an inverse measure of market depth (see Kyle, 1985).

The theoretical construct we adopt is similar to the model presented by Chen et al. in many ways. There is a single trading period, two risky securities (stocks and index futures), and a continuum of $i = 1, 2, \ldots, N$ traders. Futures and the stocks underlying the index have an uncertain final payoff that is normally distributed as $N(\mu\tau, \sigma^2\tau)$, where σ is the underlying volatility and τ is the investment horizon. An investor's stock portfolio can be tailored to generate a customization value (CV). Therefore, the CV for the ith trader is distributed normally as $(\alpha^i\tau, \gamma^i\beta^2\tau)$, where α^i represents the ith trader's preference for customization, γ^i represents the trader's risk aversion, and $\beta^2\tau$ represents the risk incurred from holding a portfolio unlike the benchmark. Chen et al. used their model to examine the effects of volatility on basis and open interest. Our focus is different. We use this model to examine market leadership between the futures market and the underlying cash market.

Given the above assumptions, the question of the greatest interest is: Upon the arrival of new information, in which market will the commercial trader transact? To answer this question, we solve for the commercial trader's optimization problem in certainty equivalent form, much like in Chen et al. The Type I traders (on aggregate) face the optimization problem

$$\mathrm{Max}_{\theta_S^i, \theta_F^i}\left[\mu\tau(\theta_S^i + \theta_F^i) - \frac{\gamma^i\,\sigma^2\tau}{2}(\theta_S^i + \theta_F^i)^2\right] + \left[\alpha^i\tau\theta_S^i - \frac{\gamma^i\beta^{i^2}\tau}{2}\theta_S^{i^2}\right]$$

$$- [P_S(\theta_S^i - \overline{\theta_S^i}) + P_F(\theta_F^i - \overline{\theta_F^i})] + r\theta_L^i - k\tau \qquad (2)$$

subject to,

$$\theta_S^i + \theta_F^i + \theta_L^i = 1 \qquad (3)$$

where $k\tau$ represents the cost of entry (or the opportunity cost of active trading), $\overline{\theta_S^i}$ and $\overline{\theta_F^i}$ represent trader i's initial weights in the stock portfolio and futures contract, and P_S and P_F represent the aggregate price for the custom stock portfolio and the futures index value, and r is the return on cash holdings. The second term represents the net benefits from customization, so that trader i's marginal customization value is given by $(\alpha^i\tau - \gamma^i\beta^{i^2}\tau\theta_S^i)$. This value is decreasing in the weight θ_S^i and can be negative or positive. Solving for the first order conditions, it is fairly straightforward to show that:

$$P_F = \mu\tau + \psi - \gamma^i\sigma^2\tau(\theta_L^i - 1) \qquad (4)$$

and

$$P_S = \mu\tau - \gamma^i\sigma^2\tau + \alpha^i\tau - \gamma^i\beta^2\tau\theta_S^i + \psi \qquad (5)$$

Subtracting (5) from (4) yields the relationship for the basis,

$$P_F - P_S = \tau(\gamma^i \beta^2 \theta_S^i - \alpha^i) \tag{6}$$

Note that the right hand side of (6) is equal to -1^*(marginal CV). Thus, the basis is related negatively to the marginal customization value, positively related to the risk aversion of the trader, and negatively related to the preference for customization. The marginal customization value (MCV) and eq (6) can be used to interpret market leadership outcomes and basis behavior.

Implications for Market Leadership and Basis Behavior

The commercial trader faces two competing preferences. First, the trader has a predisposition to maintain portfolio customization. Second, the trader suffers the risk that the custom portfolio will underperform the benchmark index. These competing preferences determine the choice of trades following bad news and good news.

Consider the commercial trader's MCV. Importantly, changes in MCV are not symmetric for bad news and good news, given the commercial trader's risk aversion. We expect rates of decrease in MCV following bad news to be larger than rates of increase in MCV following good news. In the face of bad news, γ^i (the trader's risk aversion) will rise. Moreover, as β^2 (the risk of holding a portfolio unlike the benchmark index) is an increasing function of portfolio tilt, the holder of a highly customized portfolio may find that changes in $\gamma^i\beta^2$ will overwhelm the preference for maintaining customization (α^i). The need for the trader to mimic more closely the benchmark index will result in the sale of the custom portfolio, thus lowering θ_S. On the other hand, if the information event is positive, the trader who derives utility from portfolio customization will prefer to transact in the futures market, raising θ_F. In the face of good news, it is possible that the commercial trader also might desire an increase in the loadings of *favorite* stocks. However, this may be the less likely outcome, given diminishing MCV with factor loadings. In summary, our model suggests that the highly customized commercial trader will prefer to trade in equity markets when the news is unfavorable, but primarily in the futures market when the news is favorable. Thus, we expect informed equity market (futures market) trading to be relatively more pronounced in falling (rising) markets. Our framework suggests that in an environment of highly customized portfolios index futures prices will lead the underlying market in rising markets, but that this leadership will be less evident in falling markets. In the above framework, it is trader selectivity, rather than information disparities, that is the source of leadership. Both markets have access to the same information because markets share the same potential participants.[8]

These arguments also predict a role for portfolio tilt in the relationship between basis and volatility in the face of bad news and good news. Equation (6) suggests that the basis is positively related to the level of risk aversion and to the risk inherent in holding a customized portfolio, a factor that also arises in portfolio tilt. In other words, the basis–volatility relationship is expected to be more positive when there is a higher level of customization. This relationship also follows from our discussion on leadership. We expect a positive basis–volatility relationship in an environment of highly customized portfolios because we expect futures prices to move *first* on market upturns, and cash prices to move *first* on market downturns. Thus, the basis will be related positively to the volatility in the *active market* if the *active market* is defined as the market that draws a rise in commercial trading.[9]

Commercial Imbalances and Portfolio Customization

Our framework suggests that portfolio customization (tilt) could play an important role in market leadership and basis behavior. It is noteworthy that our arguments also predict imbalances in the long–short futures positions of commercial traders when their stock portfolios are tilted highly. Here, we argue that in the absence of portfolio tilt, such commercial imbalances will be unlikely. In essence, one can argue that the long-lasting commercial imbalances of 1993–1996 are symptomatic of highly customized or tilted portfolios.

[8]Obviously, futures markets may lead cash markets for reasons exogenous to our model. For instance, futures leadership may arise from differences in transaction costs, liquidity constraints, or some other factor not considered here. In any event, our model will predict that futures leadership will be relatively stronger in rising markets as long as traders hold customized portfolios.

[9]The implied positive relationship between volatility and basis differs from the arguments in Chen et al. In Chen et al., θ_S^i and θ_F^i denote the stock and futures positions rather than weights (as in our paper), and the mean over entering traders is taken as $X/N = \theta_S^i + \theta_F^i$, where X is the supply of stock, which is always positive. The authors substituted this equality in the optimal position to yield a basis that is decreasing in volatility. Here, θ_S^i and θ_F^i represent the weights in the custom stock portfolio and the futures index, respectively, so that the basis in eq (6) is different from the one derived in Chen et al.

In the absence of tilt, the commercial trader will take on a long futures position only for liquidity reasons (traders may be liquidity constrained when new information arrives), and not to maintain overall customization.[10] Once this trader purchases the underlying stock (when liquidity improves), one can expect the trader to unwind the futures position fairly quickly. Not doing so will leverage the trader's position, resulting in the loss of *commercial* status. Preservation of commercial status is important, as these traders have certain privileges such as reduced margin requirements. Holding a long position in futures while fully invested in the underlying asset will push the sum of θ_F and θ_S over 1, so that the futures position can no longer be considered hedging. Thus, it can be argued that, in the absence of tilt, any long-over-short commercial imbalances are likely to be transitory.

On the other hand, when tilt is present, long futures positions are employed for more than just liquidity reasons. As discussed above, some commercial traders will be motivated to maintain $\theta_F > 0$ in the face of positive information. Given that offsetting short positions may be entered into only after a relatively long period of time when there is no longer a need for reduced customization, long-over-short commercial imbalances will be more likely. Moreover, these long-lived futures positions will continue to remain *commercial* as the futures positions represent near substitutes for futures long positions in the spot market.

DATA AND PRELIMINARY DIAGNOSTICS

We examine intraday price data for the S&P 500 futures and cash index over the interval January 1993 through December 1996. The data span an interval that offers an extension to the Chen et al. study on basis behavior. Moreover, the sample selection allows us to raise and address some interesting questions pertaining to the role of commercial trading in the relative price behavior in futures and spot markets. The period under study witnessed some of the largest commercial imbalances in the S&P 500 contract (as may be noted from Fig. 1). In contrast, the commercial imbalances during the Chen et al. interval were relatively small.

The data consist of opening and closing prices for 15-min intervals between 8:30 am and 3:00 pm CST.[11] Following common practice, the nearby futures contract is followed until the last day of the expiration

[10]The advantages of employing futures as an intermediary to the final transaction in stocks is discussed in Gould (1988).

[11]The data for the S&P 500 series are obtained from Tick Data Incorporated (TDI). The data are prescreened by TDI for gaps and miss ticks.

month, at which point the series switches to the next nearby contract. Alternate returns definitions for market j are given by the difference in log of 15-min *closing* prices, $R^c_{j,t} = \ln P^c_{j,t} - \ln P^c_{j,t-1}$, and the difference in the log of 15-min *closing* and *open* prices, $R^o_{j,t} = \ln P^c_{j,t} - \ln P^o_{j,t}$. The latter formulation allows us to exclude overnight returns without losing the 8:30 am CST price information (also see Ederington & Lee, 1993). The basis is computed as the difference in the futures and cash index values employing interval-closing prices, and alternately, interval-opening prices. Similarly, the adjusted basis is computed employing interval-closing values, $D^c_t = P^c_{F,t} - P^c_{S,t}e^{q(T-t)}$, and interval-opening values, $D^o_t = P^o_{F,t} - P^o_{S,t}e^{q(T-t)}$, where $T - t$ represents the contract's time to expiration in years, and q is the difference in the Treasury bill rate with maturity closest to the expiration and the dividend yield on the S&P 500.[12]

Table I presents summary statistics for the intraday S&P 500 futures and cash returns. The spot and futures returns exhibit significant nonlinear dependence, as indicated by the Ljung-Box Q statistics of squared returns [$Q^2(24)$] and the Brock, Dechert, and Scheinkman (1987) (BDS) statistic for the OLS (AR = 3) errors. We also find autoregressive conditional heteroskedasticity (ARCH) from the ARCH test statistics (Engle, 1982). However, it is noteworthy that a relatively simple Generalized ARCH (1,1) model captures most of the nonlinear dependence in the data. This is evidenced by the relative size of the $Q^2(24)$ and BDS statistics of the generalized autoregressive conditional heteroskedasticity (GARCH) (1,1) standardized errors; these statistics are substantially reduced relative to their OLS counterparts. Finally, the cross-serial correlations for the standard residuals provide preliminary indications of futures leadership, with no feedback from the cash market.

EMPIRICAL RESULTS

Lead–Lag Dynamic and the Burden of Convergence: VAR Estimates

We first evaluate leadership patterns and the burden of convergence between these two markets employing a VAR framework. While leadership issues brought out via standard VAR methodology are interesting in their own rights, the approach employed here also addresses the potential

[12]The Treasury bill rate for securities that mature closest to the expiration of the nearby futures contract is gathered from various issues of the *Wall Street Journal*. The weekly dividend yield on the S&P 500 is obtained from the Pinnacle Data Company. Dividends are assumed to be paid out continuously.

TABLE I
Summary Statistics

	Futures	*Spot*
Observations	26,804	26,804
Mean	9.71×10^{-4}	1.89×10^{-3}
SD	0.116	0.115
Skewness	−0.372[a]	−0.837[a]
Kurtosis	10.971[a]	21.890[a]
ARCH(6), χ^2	2883.111[a]	548.070[a]
$Q^2(24)$ (OLS errors)	9684.510[a]	1205.670[a]
BDS (OLS errors)	18.728[a]	15.991[a]
$Q^2(24)$ (GARCH standard errors)	34.510[c]	15.710
BDS (GARCH standard errors)	1.391	0.889
Cross serial-correlations of standard residuals		
Lag		
0	0.670	0.670
1	-3.15×10^{-3}	0.127
2	−0.005	0.021
3	0.016	0.004
4	0.003	−0.002
5	0.013	0.003
6	0.006	0.003

Note. This table reports statistics for 15-min intraday returns and standardized residuals of returns for the S&P 500 index and S&P 500 index futures over the interval January 1993–December 1996. Returns for each 15-min interval are given by ($\ln P_t^c - \ln P_t^o$), where P_t^c represents the closing (last transacted) price in interval t, and P_t^o represents the opening (first transacted) price in interval t. Overnight returns are excluded from the sample. ARCH (6) is the Lagrange Multiplier test statistic (χ^2 with 6 degrees of freedom) for ARCH errors (Engle, 1982). $Q^2(24)$ is the Ljung-Box statistic for the squared errors, where the errors are obtained from an OLS autoregressive model with three lags. Standard residuals are from the GARCH (1,1) model. BDS represents the Brock et al. (1987) statistic for nonlinearity. The BDS statistic ($\varepsilon = 2$ standard deviations of the data, and dimension $m = 3$) is standard normal for the OLS error series. For GARCH standard errors, the BDS statistic is evaluated against critical values provided in Brock et al. (1993). The OLS and GARCH errors were obtained by regressing returns on a constant, past returns (3 lags), and four day-of-week dummies (Monday–Thursday). a, b, and c represent significance levels of .01, .05, and .10, respectively.

asymmetry in burden of convergence between the two markets. We employ a model of the form

$$y_t = v + B_1 y_{t-1} + \cdots + B_p y_{t-p} + \xi z_{t-1} + \xi^- z_{t-1}\eta_{t-1}^- + \varepsilon_t \qquad (7)$$

where y_t denotes the 2×1 vector of returns included in the VAR, z_{t-1} is a vector of error-correction terms, ε_t is a vector of error terms, and η_{t-1}^- is a dummy variable taking the value of 1 when market returns at $t - 1$ are negative, and 0 otherwise. In the specification where returns are measured by the log difference in closing and opening prices for each 15-min interval, z_{t-1} is the adjusted basis, D_t^o. When returns are measured by the log difference in closing prices for each interval, z_{t-1} is given by D^c_{t-1}. With the exception of the treatments of the error-correction term, the above specification is similar to those widely employed in the investigation of causal relationships in financial markets.[13] For instance, significant coefficients on lagged cash returns in the futures return equation would be interpreted as information flowing from the cash market to the futures market. Furthermore, the ξ coefficients, $-1 \leq \xi_F \leq 0$ and $1 \geq \xi_S \geq 0$, with strict inequality for at least one coefficient, indicate the burden of convergence among the two markets. For instance, if $\xi_F < 0$ and $\xi_S = 0$, then, as the spread widens, the futures price falls in the process of convergence; that is, the futures market is said to bear the burden of convergence. The decomposition of the error-correction term allows us to test for asymmetry in convergence across non-negative and negative market periods. For example, if the ξ_t^- coefficient is negative and significant in the futures return equation, the result would imply that the futures contract bears a greater burden of convergence to the spread when markets are falling than when they are rising.[14]

Table II reports the ξ and ξ^- coefficients from the decomposed error-correction model. In the interest of brevity, the coefficients and statistics for the lagged returns are not provided. The results for lagged returns indicate bi-causality, although the sums of coefficients suggest that the influence flowing from the cash market to futures market is weaker than that from the futures market.[15] The reported results indicate a greater degree of convergence of the futures market to the cash market when prices are falling. Specifically, ξ^- is significant and negative in the futures equation for both return specifications (Models I and II) and across the three criteria for establishing market direction, change in futures price (Panel A), change in spot price (Panel B), and change in futures and spot prices (Panel C). Moreover, ξ^- is significant and negative in the spot equation, but indicates weaker convergence pressures for the cash market when markets are falling. Thus, the evidence suggests

[13]Prior studies that employed VAR models to examine futures–spot leadership employed the lagged unadjusted basis (the difference between futures and spot prices) as the error correction term. Theoretically, however, the true attractor between futures and cash prices is the deviation from fair futures value, which is the adjusted basis, D_t. It follows that this is appropriate error correction in the VAR model involving futures and underlying spot prices. Nonetheless, our findings on leadership and convergence are unchanged when the unadjusted basis is the error correction.

[14]An alternate model with no decomposition of the error correction also was estimated, with findings of leadership and convergence similar to that in eq (7).

[15]These results are available from the authors.

TABLE II

Convergence Coefficients: The Role of Market Direction

	Model I: $R_{j,t} = \ln P^c_{j,t} - \ln P^o_{j,t}$			Model II: $R_{j,t} = \ln P^c_{j,t} - \ln P^c_{j,t-1}$	
	Futures	*Spot*		*Futures*	*Spot*
Panel A: Market Direction Given by ΔP_F					
z^o_{t-1}	1.80×10^{-4a} (3.51)	1.13×10^{-3a} (23.42)	z^c_{t-1}	-7.49×10^{-6} (−0.83)	4.68×10^{-5a} (6.04)
$z^o_{t-1}\eta^-$	-4.85×10^{-4a} (−19.41)	-3.40×10^{-4a} (−14.82)	$z^c_{t-1}\eta^-$	-2.90×10^{-5a} (−2.79)	-2.24×10^{-5b} (−2.12)
Panel B: Market Direction Given by ΔP_S					
z^o_{t-1}	7.77×10^{-5} (1.34)	1.11×10^{-3a} (22.52)	z^c_{t-1}	4.65×10^{-6} (0.51)	6.88×10^{-5a} (8.73)
$z^o_{t-1}\eta^-$	-3.96×10^{-4a} (−14.17)	-3.51×10^{-4a} (−15.26)	$z^c_{t-1}\eta^-$	-5.35×10^{-5a} (−4.42)	-6.91×10^{-5a} (−6.64)
Panel C: Market Direction Given by ΔP_F, ΔP_S					
z^o_{t-1}	1.25×10^{-4b} (2.26)	1.10×10^{-3a} (23.49)	z^c_{t-1}	-2.66×10^{-6} (0.32)	5.40×10^{-5a} (7.42)
$z^o_{t-1}\eta^-$	-4.57×10^{-4a} (−16.72)	-3.70×10^{-4a} (−15.99)	$z^c_{t-1}\eta^-$	-5.27×10^{-5a} (−4.07)	-5.09×10^{-5a} (−4.58)

Note. This table reports the decomposed error correction coefficients from the extended VAR model (see Eq (7)). For Model I, returns are given by ($\ln P^c_t - \ln P^o_t$), where P^c_t represents the closing price in interval t, and P^o_t represents the opening price in interval t. The error correction is decomposed into two components, $z^o_{t-1} = (P^o_{F,t} - P^o_{S,t}e^{q(T-t)})$ and $z^o_t\eta^-$, where η^- is set equal to 1 if the "market" is falling and 0 otherwise. To establish η^-, we alternately employ futures price changes (Panel A), spot price changes (Panel B), and both futures and spot price changes (Panel C). The time series for Model I excludes overnight returns. In Model II, returns are given by ($\ln P^c_t - \ln P^c_{t-1}$), and the error correction is decomposed into $z^c_{t-1} = (P^c_{F,t-1} - P^c_{S,t-1}e^{q(T-t)})$ and $z^c_{t-1}\eta^-$. The time series for Model II includes overnight returns. Figures in ( ) are t-statistics, and a and b represent significance levels of .01 and .05, respectively.

that, in falling markets, the burden of convergence is relatively stronger for the futures market.

It is possible that leadership is most apparent when trading is relatively thin, and that the asymmetry in the patterns of convergence is related to market liquidity. In response, we examine whether the patterns in Table II are found throughout the trading day, only around the market's open or close (when markets are the most liquid), or only for intervals away from the market's open or close (when markets are relatively thin). To do this, we estimate two sets of variations of eq (7) with additional controls on the error-correction terms. Specifically, we estimate the VAR model with the error-correction variables decomposed into z_{t-1} and $z_{t-1}\eta_1\eta_2$ where $\eta_1 = 1$ if the return of a particular market is negative, and 0 otherwise, and $\eta_2 = 1$ if the time of day is the market's opening or the market's closing, and 0 otherwise. An alternate set of estimations is conducted where $\eta_2 = 0$ if the time of day is the market's opening or the market's closing, and 1 otherwise. The results from these alternate estimations, not reported in the interests of brevity, show that the results in Table II are robust to controls for time of day. That is, the burden of convergence of futures market to the cash market is significantly greater in declining markets, no matter the time of day.

The Temporal Relationship Between Cash and Futures: Bivariate GARCH Results

The statistics in Table I show that the price changes in both markets exhibit time-varying volatility. Moreover, it is highly likely that the time-varying volatility is correlated across the two markets. It is well known that the failure to incorporate these effects can lead to invalid statistical inferences. Thus, in this and subsequent sections, we turn our attention to the results from models that allow for persistence and co-persistence of volatility in the data. The results, intended to be more than just tests of robustness, provide additional insight into the futures–cash-market relationship.

Consistent with Ross (1989), we employ volatility as a measure of information flow. If information arrives first in the cash market, one should see a volatility spillover from that market to the futures contract. Chan et al. (1991), among others, employed extensions of Bollerslev's (1986) GARCH model to document spillovers between the S&P 500 futures and the S&P 500 index. Furthermore, a bivariate (rather than univariate) representation of the model is preferred when volatility co-persistence is suspected (see Baillie & Bollerslev, 1990; Bollerslev, Engle, & Wooldridge, 1988). The following bivariate GARCH model is used:

$$h_{F,t} = \phi_{F,0} + \phi_{F,1}\varepsilon^2_{F,t-1} + \phi_{F,2}\varepsilon^2_{F,t-1}\eta^-_{F,t-1} + \nu_{F,1}h_{F,t-1} + \pi_{F,1}\varepsilon^2_{S,t-1} + \pi_{F,2}\varepsilon^2_{S,t-1}\eta^-_{F,t-1} + \varphi_F O_t + u_{F,t}$$

$$h_{S,t} = \phi_{S,0} + \phi_{S,1}\varepsilon^2_{S,t-1} + \phi_{S,2}\varepsilon^2_{S,t-1}\eta^-_{S,t-1} + \nu_{S,1}h_{S,t-1} + \pi_{S,1}\varepsilon^2_{F,t-1} + \pi_{S,2}\varepsilon^2_{F,t-1}\eta^-_{S,t-1} + \varphi_S O_t + u_{S,t}$$

$$h_{FS,t} = \phi_{FS,0} + \phi_{FS,1}\varepsilon_{F,t-1}\varepsilon_{S,t-1} + \phi_{FS,2}\varepsilon_{F,t-1}\varepsilon_{S,t-1}\eta^-_{FS,t-1} + \nu_{FS,1}h_{FS,t-1} + \varphi_{FS}O_t + u_{FS,t} \tag{8}$$

The return shocks (ε^2_F, ε^2_S) are from a standard VAR representation with error correction;[16] $h_{F,t}$ and $h_{S,t}$ are the variance functions, and $h_{FS,t}$ is the covariance function conditional on information at $t - 1$; $\eta^-_{i,t-1}$ is a dummy variable taking on the value of 1 if ε_{t-1} for the ith market is negative, and 0 otherwise; and O_t is a dummy variable taking on the value of 1 if the interval represents the market's open, and 0 otherwise. The allowance for asymmetry in the intramarket shock components (pertaining to the $\phi_{S,2}$ and $\phi_{F,2}$ coefficients) is motivated in Glosten, Jagannathan, and Runkle (1993) (GJR). There is prior evidence of a strong negative relationship between the mean and volatility for individual stocks and stock indexes (e.g., Black, 1976; Christie, 1982; French, Schwert, & Stambaugh, 1987).[17] The π parameters capture intermarket volatility and indicate whether market leadership is related to market direction. If, for instance, both $\pi_{F,1}$ and $\pi_{F,2}$ are positive, the indication would be that there is information flowing from spot markets, and that this flow is asymmetric: stronger during market downturns than during upturns.

In Table III we report the bivariate GARCH-GJR results for the variance and covariance functions. The diagnostics indicate that our bivariate parameterization with time-dependent covariance matrix provides a good representation of the conditional second-moment properties of the data. GARCH effects are suggested by the significant coefficients on the equations own lagged shocks ($\varepsilon^2_{j,t-1}$) and own lagged variances ($h_{j,t-1}$). The $\phi_{F,2}$ coefficient (-0.024 and significant) indicates an asymmetry in the relationship between the futures variance and prior return shocks.

[16]The model is estimated while allowing for the variance–covariance matrix to be time-dependent. The bivariate GARCH results are not substantially changed when, in the right-hand side of the mean equation, we employ a univariate autoregressive formulation ($p = 6$), or the lagged adjusted basis.

[17]A long-standing explanation for this asymmetry in the return–volatility relationship is that negative shocks in returns drive up volatility (Black, 1976) so that the asymmetry will exhibit itself in the variance equations rather than in the return equations. No matter what the origins of the asymmetry, such an allowance should provide further improvements in our model's ability to capture the (nonlinear) serial dependencies. Moreover, as noted by Glosten et al. (1993), not controlling for the possible asymmetry in the return–variance relationship may bias the parameter estimates (also see Engle & Ng, 1993).

TABLE III

The Temporal Relationship Between Cash and Futures: Bivariate GARCH-GJR Model

Conditional Variance Equations	*Futures*	*Spot*
Constant	0.005[a] (87.44)	0.003[a] (90.86)
Own Lagged Shock	0.109[a] (38.88)	0.117[a] (33.71)
Own Lagged Shock $\cdot \eta_{t-1}^{-}$	−0.024[a] (−4.99)	0.001 (0.20)
Lagged Conditional Variance	0.413[a] (80.54)	0.335[a] (79.34)
Intermarket Lagged Shock	0.026[a] (13.85)	0.065[a] (27.14)
Intermarket Lagged Shock $\cdot \eta_{t-1}^{-}$	0.061[a] (16.97)	0.007 (1.16)
Market-Open Dummy	0.003[a] (27.45)	0.008[a] (70.11)
Conditional Covariance Equation		
Constant	0.003[a] (95.53)	
Product of Lagged Residuals	0.156[a] (62.17)	
Product of Lagged Residuals $\cdot \eta_{t-1}^{S-}$	0.008[a] (2.57)	
Lagged Conditional Covariance	0.373[a] (103.48)	
Market-Open Dummy	0.001[a] (7.56)	
Log Likelihood		107513.50
Diagnostics		
$Q(24)$	11.74	10.44
$Q^2(24)$	30.72	14.95
Sign Bias (t)	−0.03	−0.15
Positive Sign Bias (t)	−0.45	−0.17
Negative Sign Bias (t)	−0.75	−0.42
Joint Test (F)	1.97	2.02

Note. The table reports the results for the variance and covariance equations from the Bivariate GARCH-GJR model fitted to 15-min (open to close) return data for the S&P 500 index and S&P 500 index futures. The dummy η_{it-1}^{-} takes on the value of 1 if the respective lagged residual is negative and 0 otherwise. To obtain the t statistic in the Sign Bias test, the square of the standardized residuals, $(\varepsilon_{it}/\sqrt{h_{it}})^2$, are regressed on η_{it}^{-}. The Negative Sign Bias and Positive Sign Bias test statistics are obtained from the regressions of $(\varepsilon_{it}/\sqrt{h_{it}})^2$ on $\eta_{it}^{-} \times \varepsilon_{it}$ and $\eta_{ti}^{+} \times \varepsilon_{it}$, respectively. The joint test statistic is the F value from the regression of $(\varepsilon_{it}/\sqrt{h_{it}})^2$ on η_{it}^{-}, $\eta_{ti}^{-} \times \varepsilon_{it}$, and $\eta_{ti}^{+} \times \varepsilon_{it}$ (see Engle and Ng, 1993). Q statistics (Q^2) are the Ljung-Box statistics for autocorrelation in standard errors (square of standard errors), a, b, and c represent significance levels of .01, .05, and .10, respectively.

The variance in the futures market is lower following negative shocks. There is no asymmetry noted for the spot market.

The results are consistent with a stronger leadership role for the futures contract. The intermarket volatility spillover from the futures market to the cash market is greater; the χ^2 test rejects the null for equality of the two intermarket spillover coefficients (.026 vs .065). However, there is evidence that the spillover from the cash market to the futures market is greater when the price movements are negative than when they are positive. The $\varepsilon_{S,t-1}^2 \eta_{F,t-1}^{-}$coefficient (0.061 in the futures variance equation) is positive and significant while the coefficient for $\varepsilon_{F,t-1}^2 \eta_{S,t-1}^{-}$ (0.007 in the spot variance equation) is not statistically different from zero. These results are consistent with the notion that feedback from the cash market is strongest during market declines. It also is notable that $(\pi_{F,2}/\pi_{F,1}) > (\pi_{S,2}/\pi_{S,1})$, suggesting that the relative volatility spillover during market downturns is greater from the cash to the futures market. The conditional covariance results in Table III suggest that comovements are relatively stronger during market declines, which further supports the evidence that leadership is weaker when prices are falling. Further, the positive coefficient on the O_t (market-open dummy) suggests that the comovements are higher at the market's open. Similar results are obtained when the dummy is altered to represent the market's open as well as its close.

Leadership, Market Returns, and Time-of-Day Effects

The role of the market's opening and closing and the effects of thin trading were noted briefly with respect to our preceding investigation of the burden of convergence between the two markets. In this section, we examine the role that market returns and time of day might play in leadership and leadership asymmetry.

To motivate our tests, let $x_{F,t}$ and $x_{S,t}$ represent, respectively, the standardized residuals for the futures and cash returns from the above GARCH model. Futures market leadership would imply

$$\delta_t = x_{S,t}x_{F,t-1} - x_{F,t}x_{S,t-1} > 0 \tag{9}$$

where δ can be thought of as a leadership statistic.[18] Asymmetry in the lead–lag relationship can be evaluated by testing whether this relationship is consistent across rising and declining markets, that is, whether $(x_{S,t}\, x_{F,t-1})^- > (x_{S,t}\, x_{F,t-1})^+$, or $(x_{F,t}\, x_{S,t-1})^- > (x_{F,t}\, x_{S,t-1})^+$, where the superscripts $-$ and $+$ represent declining and rising markets, respectively.

Leadership and Market Returns

In Table IV we present evidence on leadership across samples sorted by return percentiles. For comparative purposes, we report results from the above technique employing both residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})$ and GARCH standard residuals $(x_{F,t}, x_{S,t})$. The theoretical constructs presented in ear-

[18]The term is a simple extension of the serial cross-covariance measures employed in Lo and McKinlay (1990) and Mech (1993). If futures price changes lead cash price changes, perhaps due to more timely information flows, we have $\mathrm{Cov}(\Delta P_{S,t}\Delta P_{F,t-1}) > \mathrm{Cov}(\Delta P_{F,t}\Delta P_{S,t-1})$. If we assume conditional means of ΔP_S and ΔP_F to be time invariant, this can be simplified to $\Delta P_{S,t}\Delta P_{F,t-1} - \Delta P_{F,t}\Delta P_{S,t-1} > 0$. Without loss of generality, the relationship can be captured as $\varepsilon_{S,t}\varepsilon_{F,t-1} - \varepsilon_{F,t}\varepsilon_{S,t-1} > 0$, which is the nonstandardized version of eq (9).

TABLE IV
Leadership and Market Returns

	Residuals-Based Tests			*Standard Residuals-Based Tests*		
RetsPercentile	$\varepsilon_{F,t} \times \varepsilon_{S,t-1}$	$\varepsilon_{S,t} \times \varepsilon_{F,t-1}$	F	$x_{F,t} \times x_{S,t-1}$	$x_{S,t} \times x_{F,t-1}$	F
95–100	-4.77×10^{-7c}	3.82×10^{-6a}	21.40	−0.011	0.704[a]	92.70
90–95	-1.67×10^{-8}	4.84×10^{-7b}	16.30	−0.009	0.321[a]	51.86
85–90	1.36×10^{-8}	-9.69×10^{-8}	3.43	−0.044	0.126[a]	24.99
80–85	2.75×10^{-8}	8.56×10^{-8}	2.72	−0.022	0.096[a]	16.71
75–80	-2.94×10^{-8}	-7.26×10^{-8b}	2.05	−0.032	0.047	5.69
70–75	-8.07×10^{-9}	-1.03×10^{-7a}	7.09	−0.016	0.028	4.42
65–70	-1.54×10^{-8}	-1.28×10^{-7a}	6.73	−0.028[c]	−0.039[a]	0.64
60–65	-1.79×10^{-8}	-1.13×10^{-7a}	8.70	−0.045[a]	−0.053[a]	0.36
55–60	-1.97×10^{-8}	-6.33×10^{-8a}	4.96	−0.047[a]	−0.076[a]	3.65
50–55	-2.22×10^{-8c}	-1.17×10^{-7a}	7.59	−0.027[c]	−0.082[a]	9.76
45–50	-2.89×10^{-7b}	-1.72×10^{-7a}	7.94	−0.032[b]	−0.070[a]	7.79
40–45	1.95×10^{-8}	-7.21×10^{-8}	2.83	−0.027[c]	−0.033[b]	0.85
35–40	3.76×10^{-8}	-1.18×10^{-7a}	11.32	−0.024[c]	−0.072[a]	5.18
30–35	-1.19×10^{-8}	-1.14×10^{-7a}	13.25	−0.037[b]	−0.039[a]	0.02
25–30	-3.95×10^{-8}	-1.36×10^{-7a}	8.71	−0.020	−0.022[c]	0.10
20–25	1.71×10^{-8}	-1.07×10^{-7b}	11.46	−0.010	0.038[c]	3.21
15–20	4.02×10^{-8}	-8.56×10^{-8}	9.24	0.008	0.075[b]	5.76
10–15	2.16×10^{-8}	-1.09×10^{-8}	1.05	0.018[c]	0.203[a]	17.02
5–10	6.98×10^{-8b}	1.72×10^{-7a}	6.51	0.076[a]	0.362[a]	23.89
0–5	4.86×10^{-6a}	1.20×10^{-5a}	21.26	0.357[a]	0.988[a]	38.81
Full Sample	2.08×10^{-7}	7.53×10^{-6a}	6.45	0.001	0.125[a]	325.13
Positive Rets	-5.64×10^{-8c}	3.69×10^{-7a}	22.12	−0.028[a]	0.107[a]	227.78
Negative Rets	4.73×10^{-7a}	1.14×10^{-6a}	19.26	0.031[a]	0.143[a]	117.09

Note. The table reports the products of nonsynchronous residuals, $(\varepsilon_{I,t} \times \varepsilon_{J,t-1})$, and products of standard residuals, $x_{I,t}x_{J,t-1} = (\varepsilon_{I,t}/\sqrt{h_{I,t}})(\varepsilon_{J,t-1}/\sqrt{h_{J,t-1}})$, for percentile-based samples of 15-min S&P 500 index returns (open to close intervals). The residuals and standard residuals are from a bivariate GARCH (1,1) model with VAR mean equations. The F value tests the null of equality of the two variables, and a, b, and c represent significance levels of .01, .05, and .10, respectively.

lier sections imply that futures leadership should be stronger in rising markets. The results show that when returns are very positive (i.e., for returns in the highest percentiles), futures leadership is strong and the feedback from the spot market is weak. For instance, $x_{S,t}$, $x_{F,t-1}$ is significant and positive for returns above the 80th percentile, and $\varepsilon_{S,t}\varepsilon_{F,t-1}$ is positive for returns above the 90th percentile. The corresponding spot leadership statistics, $x_{F,t}x_{S,t-1}$ and $\varepsilon_{F,t}\varepsilon_{S,t-1}$, are consistently non-positive and mostly insignificant during these periods.

On the other hand, there is much stronger evidence of feedback from the spot market in periods of very negative returns. The spot leadership statistics, $x_{F,t}$, $x_{S,t-1}$ and $\varepsilon_{F,t}$, $\varepsilon_{S,t-1}$, are positive below the 15th and 10th percentiles of returns, respectively. The lead–lag relationship between the futures contract and spot market is less clear for the intermediate returns, with negative cross-serial correlation suggested when employing residuals or standard residuals. The F value for the significance of δ also suggests a relative absence of leadership during periods of intermediate returns. In other words, the majority of the leadership (and feedback) in futures and spot markets seems is concentrated in the top and bottom return percentiles. This finding is consistent with the notion that the leadership is associated with information arrival. Finally, the statistics at the bottom of Table IV further highlight the importance of considering market direction when studying leadership. For the full sample, the statistic $x_{F,t}x_{S,t-1}$ is not significantly different from zero (0.001), but is significantly positive in falling markets (0.031), and is significantly negative in rising markets (-0.028).

Leadership and Time of Day

In Table V we report statistics for $x_{S,t}x_{F,t-1}$ and $x_{F,t}x_{S,t-1}$ for rising and falling markets across the 15-min intervals in the trading day. There is an absence of leadership near the open and close of trading. The statistics are non-positive at 9:00 am and not statistically different at 3:00 pm. For the remainder of the day, the evidence of leadership (or feedback) is very different across rising and falling markets. During rising markets, futures leadership is indicated for most of the time intervals ($x_{S,t}x_{F,t-1}$ is typically positive) but there is a lack of positive feedback from the spot market ($x_{F,t}x_{S,t-1}$ is typically non-positive, and those coefficients that are positive are not significant). On the other hand, during falling markets, there is significant positive feedback from the spot to futures market during 12 of the 25 intraday intervals.

In summary, the results in Table V continue to suggest that the lead–lag relationship between spot and futures is asymmetric. The evidence indicates that while the S&P 500 futures contract leads the cash index, the feedback from cash markets is relatively weaker in rising markets. We also find a diminished role for futures in falling markets when there is a stronger feedback from the cash market. Finally, the absence of leadership at the market's open and close is consistent with the notion that infrequent trading plays an important role in leadership. This evidence also suggests that the leadership patterns are unlikely to be the result of bid–ask spreads because leadership is weakest during the times of day that are associated with the highest bid–ask spreads.

TABLE V

Leadership and Time-of-Day

Time (CST)	Rising Markets N	Rising Markets $x_{F,t}x_{S,t-1}$	Rising Markets $x_{S,t}x_{F,t-1}$	Rising Markets F	Falling Markets N	Falling Markets $x_{F,t}x_{S,t-1}$	Falling Markets $x_{S,t}x_{F,t-1}$	Falling Markets F
9:00	443	−0.496[a] (−3.41)	−0.089[b] (−2.13)	4.91	551	−0.432[a] (−3.51)	−0.038 (−1.38)	8.20
9:15	465	−0.113[c] (−1.89)	0.022 (0.19)	6.42	529	0.053 (1.18)	0.164[a] (3.68)	5.74
9:30	521	−0.011 (−0.07)	0.064[c] (1.70)	4.00	473	0.002 (0.01)	0.158[a] (3.16)	10.87
9:45	528	0.001 (0.00)	0.100[a] (3.29)	9.80	466	0.021 (0.28)	0.122[a] (3.22)	7.81
10:00	513	0.019 (0.39)	0.108[a] (3.89)	9.20	481	−0.015 (−0.15)	0.116[a] (2.81)	6.37
10:15	522	−0.001 (−0.05)	0.134[a] (4.02)	12.75	472	0.063[b] (2.13)	0.182[a] (5.24)	9.17
10:30	519	0.006 (0.09)	0.094[a] (3.73)	9.36	475	−0.004 (−0.03)	0.154[a] (3.61)	13.36
10:45	505	0.001 (0.24)	0.067[a] (3.15)	9.91	489	0.043[b] (2.16)	0.081[b] (2.28)	1.71
11:00	512	−0.016 (−0.37)	0.079[a] (4.19)	16.10	482	0.064[a] (3.37)	0.172[a] (6.12)	11.06
11:15	519	−0.048[c] (−1.69)	0.078[a] (3.24)	18.14	475	0.063[a] (3.23)	0.099[a] (3.81)	1.98
11:30	531	−0.029 (−1.04)	0.063[a] (2.90)	13.70	463	0.062[a] (2.95)	0.127[a] (5.40)	4.89
11:45	534	−0.051[b] (−2.26)	0.054[b] (2.51)	18.76	460	0.059[b] (1.93)	0.127[a] (4.60)	4.78
12:00	537	−0.025 (1.04)	0.062[a] (3.10)	13.80	457	0.073[a] (3.17)	0.119[a] (3.78)	1.77
12:15	545	−0.057[b] (−2.50)	0.050[b] (2.16)	15.77	449	0.026 (0.7[illegible])	0.140[a] (4.77)	13.22
12:30	548	−0.045[c] (−1.70)	0.082[a] (2.84)	19.56	446	0.002 (0.1[illegible])	0.080[b] (2.39)	5.01
12:45	524	−0.012 (−0.14)	0.106[a] (4.01)	17.15	470	0.046 (0.[illegible])	0.139[a] (3.97)	5.95
13:00	517	−0.053[b] (−2.11)	0.029 (1.07)	6.29	477	0.026 (0.61)	0.126[a] (3.90)	7.28
13:15	487	−0.046 (−0.93)	0.106[a] (3.44)	17.67	507	0.032 (1.02)	0.211[a] (7.46)	15.86
13:30	536	−0.034 (−0.62)	0.056 (1.61)	4.35	458	0.031 (1.07)	0.195[a] (5.78)	14.38
13:45	528	0.063 (1.07)	0.215[a] (5.46)	8.81	466	0.052[c] (1.67)	0.155[a] (3.70)	3.79
14:00	555	0.007 (0.02)	0.172[a] (3.52)	14.93	439	0.025 (0.23)	0.166[a] (3.60)	7.22
14:15	493	0.071 (1.14)	0.272[a] (7.08)	14.10	501	0.134[a] (3.07)	0.234[a] (4.32)	2.31
14:30	523	−0.091[c] (−1.90)	0.036 (0.79)	7.15	471	0.067[c] (1.72)	0.082 (1.51)	0.75
14:45	507	−0.046 (−1.13)	0.113[a] (3.15)	15.23	487	0.159[a] (3.21)	0.197[a] (4.23)	0.56
15:00	607	−0.010 (−0.06)	0.043 (1.60)	2.25	386	0.273[a] (4.72)	0.310[a] (5.10)	0.42

Note. The table reports the product of nonsynchronous standard residuals, $x_{F,t}x_{S,t-1} = (\varepsilon_{F,t}/\sqrt{h_{F,t}})(\varepsilon_{S,t-1}/\sqrt{h_{S,t-1}})$, and $x_{S,t}x_{F,t-1} = (\varepsilon_{S,t}/\sqrt{h_{S,t}})(\varepsilon_{F,t-1}/\sqrt{h_{F,t-1}})$, sampled over 15-min intervals (open to close). The product of the standard residuals is aggregated by market direction, determined by the spot price change. The standard residuals are from a bivariate GARCH (1,1) model with VAR mean equations. *N* is the number of observations. The *F* value tests the null of equality of the two coefficients, and a, b, and c represent significance levels of .01, .05, and .10, respectively.

Basis Behavior and Market Volatility

We conclude our empirical investigation by examining the relationship between basis and volatility. The arguments in Theoretical Motivation section point to a positive relationship between market volatility and the basis and suggest that the basis will be related positively to the volatility in the market that draws the commercial trader. To examine the evidence on this relationship employing intraday data, we first obtain pre-whitened measures of basis by regressing the basis ($P^c_{F,t} - P^c_{S,t}$) on past levels (12 lags), time-to-maturity, and dummy variables representing the market's open and close. Alternately, the adjusted basis ($P^c_{F,t} - P^c_{S,t}e^{q(T-t)}$) is regressed on past levels. The pre-whitened basis and adjusted basis then are regressed on past and contemporaneous levels of volatility. Furthermore, to examine whether the relationship is asymmetric, the pre-whitened basis is regressed against the conditional variance, and on the product of the conditional variance and a market direction dummy.

Table VI presents the regression results, where Model I and II differ by the variable that tests for asymmetry. The results show a positive relationship between the autocorrelation-corrected basis (adjusted basis) and volatility. The coefficient on the contemporaneous and/or lagged conditional variance is positive across the regressions involving cash market volatility (Panel A) and those involving futures market volatility (Panel B). We also find the expected asymmetry in the volatility–basis relationship. The basis and adjusted basis react relatively more to spot volatility when spot markets are falling (the $h_{S,t}\eta^-_{S,t}$ coefficient is positive for the basis and adjusted basis). In contrast, the basis reacts to futures market volatility more when this market is rising than when it is falling (the $h_{F,t}\eta^-_{F,t}$ coefficient is negative for the basis and adjusted basis). This evidence reinforces prior evidence on futures leadership, that is, that futures leadership is perverse in rising markets.

We argued earlier that the observed positive basis–volatility relationship is not necessarily evidence against the results in the Chen et al. study. We ascribe differences between our results and theirs primarily to pronounced portfolio tilt evident in our sample compared with CCH's sample (inferred from Fig. 1). We also note that we consider, unlike Chen et al., the effects of changing market dynamics (rising and falling markets). If our explanations on the differing results between Chen et al.'s study and ours are robust, then we should detect a change in basis–volatility relationship when we compare Chen et al.'s sample with our sample.

We present in Table VII evidence of a changing basis–volatility relationship between our sample and Chen et al.'s sample. The results in Table VII report the correlation coefficient between the basis and alternate

TABLE VI

Basis and Volatility: Regression Results

	Basis		*Adjusted Basis*	
	I	*II*	*I*	*II*
Panel A: Volatility Defined by Conditional Variance of Cash Returns				
Constant	−0.007[b]	−0.006[b]	−0.005[c]	−0.004
	(−2.45)	(−2.16)	(−1.89)	(−1.57)
$h_{S,t}$	0.303[c]	0.243[c]	0.157	0.123
	(1.93)	(1.79)	(1.61)	(0.94)
$h_{S,t-1}$	0.191	—	0.206[b]	—
	(1.21)		(2.11)	
$h_{S,t}\eta_{\bar{S},t}$	—	0.389[b]	—	0.364[b]
		(2.19)		(2.16)
R^2	0.001	0.001	0.001	0.001
DW	2.001	2.001	2.000	2.000
Panel B: Volatility Defined by Conditional Variance of Futures Returns				
Constant	−0.011[a]	−0.003	−0.005[c]	0.005[c]
	(−3.19)	(−1.17)	(−1.79)	(1.74)
$h_{F,t}$	0.279[c]	5.652[a]	0.286[c]	5.380[a]
	(1.78)	(37.80)	(1.94)	(37.27)
$h_{F,t-1}$	0.441[a]	—	0.424[a]	—
	(2.82)		(2.88)	
$h_{F,t}\eta_{\bar{F},t}$	—	−11.763[a]	—	−11.206[a]
		(−58.96)		(−59.58)
R^2	0.001	0.116	0.001	0.117
DW	1.999	2.001	2.000	1.988

Note. The table reports the results from regressions of the prewhitened basis and the adjusted basis on GARCH conditional variance and the product of the conditional variance and a market-direction dummy. To obtain the dependent variable in the unadjusted basis equation, the basis, $P^c_{F,t} - P^c_{S,t}$, is regressed on past lags (12), time to maturity, and dummies for the market's open and close. The dependent variable in the adjusted-basis equation is obtained by regressing the adjusted basis, $P^c_{F,t} - P^c_{S,t}e^{q(T-t)}$, on past lags (12), and dummies for the market's open and close. $\eta_{\bar{i},t}$ represents a dummy variable equal to 1 if the ith market's price change is negative, 0 otherwise. DW is the Durbin Watson statistic. Values in ( ) are t statistics, and the a, b, and c designations represent significance levels of .10, .05, and .01, respectively.

measures of market volatility for daily data across the Chen et al. sample (1/1986–5/1990) and our sample (1/1993–5/1996).[19] The evidence clearly shows that the basis is related negatively to volatility in Chen et al.'s sample, but not in ours. Collectively, the results related to basis and volatility points to a changing relationship across the samples. As indicated earlier, a

[19]Chen et al. examined the relationship between the adjusted basis and the implied and realized volatility in the cash index. In their study, the realized volatility at time t is given by the return variance measured over a 10-day window around t. We employ multiple measures of volatility for both the futures and the cash market. The volatility measures, σ_F, σ_S are the absolute values of returns of the futures and cash index, where returns (t) is computed as $(\ln P_{j,t} - \ln P_{j,t-1}) \times 100$; h_F, h_S are the GARCH (1,1) conditional variance of the futures and cash returns; and σ_I is the intraday volatility measure given by the difference between the daily high and low values of the futures index standardized by the average of the high and low values.

TABLE VII

The Changing S&P 500 Volatility-Basis Relationship: Daily Correlations

1/1986–5/1990			*1/1993–5/1996*	
Volatility Measure	*Adjusted Basis*	*Basis*	*Adjusted Basis*	*Basis*
$\sigma_{F,t}$	−.53	−.53	.02	.03
$\sigma_{F,t-1}$	−.44	−.43	.08	.07
$\sigma_{S,t}$	−.51	−.50	.01	.01
$\sigma_{S,t-1}$	−.43	−.42	.06	.03
h_F	−.42	−.42	.05	.07
$h_{F,t-1}$	−.16	−.15	.05	.08
$h_{S,t}$	−.36	−.37	.07	.08
$h_{S,t-1}$	−.23	−.24	.07	.08
σ_I	−.67	−.67	.07	.07
$\sigma_{I,t-1}$	−.47	−.46	.15	.13

Note. This table reports the correlation coefficient between the basis and alternate measures of market volatility across the Chen et al. sample (1/1986–5/1990) and this article's sample (1/1993–5/1996). Two measures of basis are used. The adjusted basis is given by $P^c_{F,t} - P^c_{S,t}e^{q(T-t)}$, where $P^c_{F,t}$ and $P^c_{S,t}$ represent futures and cash prices at the close of day t, q represents the difference between the Treasury bill rate and the dividend yield on the S&P 500, and $T - t$ represents the contract's time to expiration in years. The unadjusted basis is given by $P^c_{F,t} - P^c_{S,t}$. Our measures of volatility are σ_F, σ_S and are the absolute values of returns of the futures and cash index, where return $s_t = (\ln P_{j,t} - \ln P_{j,t-1}) \times 100$; h_F, h_S are the GARCH (1,1) conditional variance of the futures and cash returns, and σ_I is the intraday volatility measure given by the difference between the daily high and low values of the futures index standardized by the average of the high and low values.

major difference across the two intervals is that there were relatively large long-over-short imbalances in the commercial positions over our sampling period.[20]

To incorporate more directly the data in Figure 1 into the testing structure, we examine the relationship between commercial trading and the adjusted basis. First we conduct a regression of the adjusted basis, averaged over bimonthly periods, on the past and future ($t+1$) adjusted basis, and on the past, contemporaneous, and future commercial imbalances.[21] Second, we conduct a similar regression of the close-to-close daily return on the past and future close-to-close return and on the past, contemporaneous, and future commercial imbalances. The results from these tests generally indicate some causality from the imbalances to the basis and returns. These results hold for the Chen et al. sample period, the sample period of the present study, and for the period 1/1986 to

[20]Since we use daily data over both samples in Table VII, any concern regarding the role that data frequency might exert on the evidence of a changing basis–volatility relationship is unfounded.

[21]These results are not reported in the interests of brevity but are available from the authors on request. Commercial imbalances were computed as (commercial long − commercial short)/(commercial long + commercial short).

12/1996. Thus, the evidence supports our hypothesis that commercial imbalances (and portfolio tilt) play a role in explaining the differences in basis–volatility relationship across the sampling intervals.

SUMMARY AND CONCLUSION

This study provides evidence that tilt in portfolios (i.e., holdings in portfolios unlike the components of the benchmark index) plays an important role in index futures leadership over the underlying cash market. We also find that tilt plays a role in the cash–futures basis–volatility relationship.

Our tests employ intraday data on the S&P 500 futures contract and underlying cash index from January 1993 through December 1996, a period that witnessed a great deal of imbalances (tilt) in commercial trading in the S&P 500 contract. We find evidence of undisputed futures leadership when markets are rising with no feedback from the spot market. In contrast, when markets are falling, futures leadership is less evident, but considerable feedback from the spot market is detected. We also note that most of the leadership asymmetry is evidenced during periods of high volatility, and that there is a relative absence of leadership at the market's open or close. A positive relationship between basis and volatility also is detected.

We offer the following explanations and conclusions. We suggest that the nature of index futures–spot leadership and the basis–volatility relationship depend, at least partly, on the predisposition of commercial traders to select index trading over trading in stock portfolios when markets are rising. Our theoretical framework specifically models the role of this commercial trader who derives utility from holding a custom stock portfolio. This trader systematically selects between index futures and spot markets when this trader's portfolio is tilted. We also propose that portfolio tilt had important effects on the basis–volatility dynamic. These hypotheses generally are supported by the data.

While the evidence from the study will be of interest to market participants and academics, the findings also should be of some import to regulators. We believe our findings provide further insights into the ongoing debate on whether or not futures on narrow-stock portfolios should be reintroduced. Futures trading on stocks and narrow-based stock indexes were banned in 1982 (via the Shad-Johnson Accord) when the SEC and CFTC failed to agree on how these contracts should regulated. The options and stock exchanges have contended that the listing of futures on stocks or narrow-stock indexes would disrupt the stock and options markets, implying that futures trading on stocks or stock indexes cause avoidable volatility, especially when the markets are vulnerable. The evidence in this study is not consistent with the contention that such disruptive trading would ensue following the introduction of narrower futures contracts, especially in an environment where portfolio customization is popular. In our framework, large customized portfolio traders are seen to avoid index futures in vulnerable markets. It also is important to note that the demand for futures contracts on narrower indexes could lead to some custom portfolios being better able to mimic their benchmark index via any of several futures contracts, dispersing trading activity across several futures contracts.

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