PRICE DISCOVERY AND VOLATILITY SPILLOVERS IN THE DJIA INDEX AND FUTURES MARKETS

YIUMAN TSE

The Dow Jones Industrial Average (DJIA) is the most widely quoted stock index worldwide. This article examines the minute-by-minute price discovery process and volatility spillovers between the DJIA index and the index futures recently launched by the CBOT. The Hasbrouck (1995) cointegrating model suggests that most of the price discovery takes place at the futures market. However, by examining the volatility spillovers between the markets based on a bivariate EGARCH model, a significant bidirectional information flow is found. That is, innovations in one market can predict the future volatility in another market, but the futures market volatility-spillovers to the stock market more than vice versa. Both markets also exhibit asymmetric volatility effects, with bad news having a greater impact on volatility than good news. © 1999 John Wiley & Sons, Inc. Jrl Fut Mark 19: 911–930, 1999

I thank the CBOT and FII for providing the DJIA futures and spot data, respectively, and their staff members for helping me understand the data format. Two anonymous referees, Robert Webb (editor), Paul Grier, and Frank Samuel provide valuable comments on the article. This research is financially supported by the CBOT Educational Research Foundation. Part of this work was done while I was visiting City University of Hong Kong. All errors are my own responsibility.
Correspondence author, School of Management, Binghamton University (SUNY), Binghamton, NY 13902-6015.

■ *Yiuman Tse is an Assistant Professor of Finance in the School of Management at Binghamton University (SUNY) in Binghamton, New York.*

The Journal of Futures Markets, Vol 19, No. 8, 911–930 (1999)

CCC 0270-7314/99/080911-20

INTRODUCTION

The Dow Jones Industrial Average (DJIA) is the most widely quoted stock index in the world, as worldwide media reports continuously provide updates of the index. It is also the most recognized barometer of stock market activity. Whereas the DJIA is the easiest stock index to track, it has not been easy to trade until the Chicago Board of Trade (CBOT) introduced the DJIA futures contracts in October 1997.[1] CBOT DJIA futures allow investors to inexpensively execute trading strategies based on the DJIA. The purpose of this article is to investigate the informational role of this important futures contract. It examines the intraday price discovery process and volatility spillovers between the DJIA futures and index. A better understanding of the information transmission (specifically, which market is more efficient) may provide investors with more efficient Dow trading strategies.

In perfectly efficient financial markets, new information should be impounded simultaneously into the cash and futures markets. Real world institutional factors, however, often create an empirical lead–lag relationship between alternative securities price changes. The market that provides the greater liquidity, the lower transaction costs, and the less restrictions is likely to play a more important role in price discovery. Futures markets, accordingly, are more likely to incorporate information more efficiently than cash markets due to their inherent leverage, low transaction costs, and lack of short sell restrictions. Numerous studies have examined this relationship between the stock index and its related futures.

Ng (1987) finds that futures returns generally lead spot returns for a variety of futures contracts, including the S&P 500 Index. Herbst, McCormack, and West (1987) use tick-by-tick data to demonstrate a lead–lag relationship between the S&P 500 Index futures, the Kansas City Board of Trade Value Line Index futures, and their respective spot indices. Kawaller, Koch, and Koch (1987) show that, although S&P 500 cash returns sometimes lead futures for approximately one minute, the S&P 500 futures returns lead spot market returns by 20 to 45 minutes. Stoll and Whaley (1990) report similar results for the Major Market Index (MMI) and the S&P 500 Index. Chan (1992) and Ghosh (1992) further report the dominant role of S&P 500 futures in the price discovery process. However, using a cointegration approach like that of Ghosh, the study by Wahab and Lashgari (1993) finds that error-correcting price

[1]The futures exchanges and Dow Jones were not able to resolve certain trademark concerns. Before the introduction of DJIA futures, the Major Market Index (MMI) was designed as a proxy for the DJIA. The MMI futures contracts were traded on the CBOT but not anymore.

adjustments occur significantly in both the S&P 500 futures and cash markets in price discovery. The threshold error correction models of Dwyer, Locke, and Yu (1996) and Martens, Kofman, and Vorst (1998) (whereby the adjustment will only occur when deviations from equilibrium are larger than some threshold values) suggest that the S&P 500 futures market impounds information faster than the stock market.

Emphasizing that volatility is a proxy for information flow, Chan, Chan, and Karolyi (1991) examine the intraday volatility spillovers between the S&P 500 Index stock and futures markets by utilizing the GARCH models. They show a strong cross-market dependence in the volatility process. In particular, innovations in either market will spill over to the other, suggesting significant informational roles for both spot and futures markets. In contrast to Chan et al., Koutmos and Tucker (1996) show that volatility spillovers only run from the futures market to the stock market; that is, innovations originating in the stock market have no impact on the futures market. Koutmos and Tucker describe the asymmetric volatility effects in an EGARCH model. They find that, in both the stock and futures markets, bad news increases volatility more than does good news. Nonetheless, Koutmos and Tucker use daily data, and intraday data are more appropriate to examine the rapid dynamics between the markets.

Most of these studies and many others examine the S&P 500 Index, and, on average, support the notion that information disseminates in the futures market before the stock market. However, it is well known that differences in the frequency of trading of individual stocks within the S&P 500 Index portfolio will bias the results of the lead–lag relationship—for example, Miller, Muthuwamy, and Whaley (1994) and Fleming, Ostdiek, and Whaley (1996). Because all the 30 Dow stocks are actively traded large companies, the nonsynchronous trading problem will be mitigated.

The current article investigates the intraday price discovery process by exploring the common stochastic trend between the DJIA cash and futures prices based on the Hasbrouck (1995) cointegration model. Results show that the information share attributable to the futures market is 88.3%, implying that DJIA futures dominates the cash market in price discovery. The article also examines the volatility spillover mechanism with a bivariate EGARCH model. Innovations in both the futures and stock markets significantly affect the other market's volatility, but the spillovers are stronger in direction running from the futures to stock markets. Results of the article may provide insights on the information transmission and index arbitrage between the DJIA cash and futures markets.

DATA AND METHODOLOGY

The article uses minute-by-minute DJIA futures and cash data for the six-month period of November 1997 (a month after the introduction of the futures contracts) to April 1998. DJIA futures are very liquid with an average daily volume of 12,500 contracts for the period examined. Appendix A provides detailed contract specifications. The cash data are available from the Futures Industry Institute Data Center (FII) and the futures data of nearby contracts are obtained from the CBOT. Transaction futures prices after a change in price are recorded and stamped to the second by the CBOT. The cash index is calculated approximately every 15 seconds, as the price-weighted average of 30 blue-chip U.S. stocks. These 30 stocks represent about 20% of the market value of all U.S. stocks.

During the period examined, the floor trading hours are 8:15 AM to 3:15 PM, and the NYSE (where all the Dow 30 stocks are traded) are 8:30 AM to 3:00 PM, both in Chicago time. That is, the CBOT opens 15 minutes earlier and closes 15 minutes later than the NYSE. In the following results of price discovery and volatility spillovers, the article uses the contemporaneous trading hours of the two markets—8:35 AM to 3:00 PM To avoid the stale opening prices of the cash index, the first five minutes of the NYSE data are excluded.[2] There are 385 one-minute intervals in a trading day and the sample size is 45,415.

Cointegration, Price Discovery, and Information Shares

According to the cost-of-carry relationship, the (log) futures price, F_t, and the underlying cash price, S_t, are cointegrated (that is, move together in the long run) with a common stochastic trend. (See, for example, Koutmos & Tucker, 1996, fn. 9.) Hasbrouck (1995) describes this common stochastic trend as the common implicit efficient price in the cointegrating system. Hereafter, the futures series is arranged as the first variable (or "1") and the cash series the second variable (or "2") in the system.

The bivariate cointegrated series, $P_t = (F_t, S_t)'$, is represented by a vector error correction model (VECM):

$$\Delta F_t = a_1 + \alpha_1 z_{t-1} + \sum_{i=1}^{k} b_{1i}\Delta F_{t-i} + \sum_{i=1}^{k} c_{1i}\Delta S_{t-i} + \varepsilon_{1t} \quad (1a)$$

$$\Delta S_t = a_2 + \alpha_2 z_{t-1} + \sum_{i=1}^{k} b_{2i}\Delta F_{t-i} + \sum_{i=1}^{k} c_{2i}\Delta S_{t-i} + \varepsilon_{2t} \quad (1b)$$

[2]Excluding the first 30 minutes do not change the results qualitatively.

where $z_{t-1} = F_{t-1} - S_{t-1}$ is the error correction (EC) term. Hasbrouck (1995) shows that the VECM (1) can be written as the following common-trend model

$$P_t = P_o + \psi\left(\sum_{s=1}^{t} \varepsilon_s\right)\iota + C^*(L)\varepsilon_t \qquad (2)$$

where P_o is a constant vector, $\iota = (1\ 1)'$ is a column vector, and $C^*(L)$ is a matrix polynomial in the lag operator. [See eq. (11) in Hasbrouck.] On page 1182 of his study, Hasbrouck states that "[t]he increment $\psi\varepsilon_t$ is the component of the price change that is permanently impounded into the security price and is presumably due to new information." The variance of this permanent component is given by $\sigma_f^2 = \psi\Pi\psi'$, where Π is covariance matrix of residuals ε_t. The focus of the model is the decomposition of σ_f^2 into proportions contributed by each series. Hasbrouck defines a market's contribution to price discovery as its information share—a market's proportion of the efficient price innovation variance.

To obtain orthogonal innovations so that there is no contemporaneous correlation between the residuals, Π is transformed to a diagonal matrix by the Cholesky factorization, $\Pi = MM'$. The information share of market i is estimated as:

$$S_i = (\psi M)_i^2/\sigma_f^2 \qquad (3)$$

where $(\psi M)_i$ is the ith element of the row matrix ψM. The Hasbrouck model facilitates the quantification of the concept of price discovery.[3] Specifically, the more efficiently the market incorporates information, the higher the value of its information share.

Throughout the entire article, it is important to understand that price discovery (both in the Hasbrouck model and volatility spillovers discussed below) refers to the impounding of new information into the price. When market i is considered more informationally efficient than (or leading) the other, it means that information disseminates in market i first and subsequently in the other market. It does not necessarily imply that market i is the original source of information.

Volatility Spillovers

Substantial attention has been focused on how news from one market affects the volatility process of another market. See, for instance, Hamao,

[3]Incorporating asymmetric and/or threshold effects in the Hasbrouck model may be interesting. But this appears econometrically complicated and warrants a separate study. In addition, the current article emphasizes the volatility dynamics discussed in the next section.

Masulis, and Ng (1990), Koutmos and Booth (1995), and Lin, Engle, and Ito (1994) in the U.S., U.K., and Japanese stock markets; Booth, Martikainen, and Tse (1996) and Christofi and Pericli (1999) in other international stock markets. All these articles use the GARCH-type models to examine the volatility spillovers between markets. The theory of volatility spillovers based on the GARCH models is first introduced and named "meteor showers" by Engle, Ito, and Lin (1990). Chan, Chan, and Karolyi (1991) provide a detailed discussion on the need to focus on the volatility spillovers between the stock and futures markets. In particular, following Ross (1989), Chan, Chan, and Karolyi (p. 659) contend that "it is the volatility of an asset's price, and not the asset's simple price change, that is related to the rate of flow of information to the market."

The following bivariate EGARCH(1,1)-*t* model is used to examine the volatility spillover mechanism

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \Bigg| \Omega_{t-1} \sim \text{Student} - t(0,\ H_t,\ v),$$

$$H_t \equiv \begin{pmatrix} \sigma_{1t}^2 & \rho\sigma_{1t}\sigma_{2t} \\ \rho\sigma_{1t}\sigma_{1t} & \sigma_{2t}^2 \end{pmatrix} \tag{4}$$

$$\ln(\sigma_{1t}^2) = \omega_1 + h_1 DOPN_t + k_1 DCLS_t + \alpha_1 G_{1,t-1} + \gamma_1 G_{2,t-1} + \beta_1 \ln(\sigma_{1,t-1}^2) \tag{5a}$$

$$\ln(\sigma_{2t}^2) = \omega_2 + h_2 DOPN_t + k_2 DCLS_t + \alpha_2 G_{2,t-1} + \gamma_2 G_{1,t-1} + \beta_2 \ln(\sigma_{2,t-1}^2) \tag{5b}$$

$$G_{it} = (|u_{it}| - E|u_{it}| + \theta_i u_{it}),\ u_{it} = \varepsilon_{it}/\sigma_{it},\ i = 1,2 \tag{6}$$

$$E|u_{it}| = (2/\pi)^{1/2}[T(v - 1)/2/T(v/2) \tag{7}$$

The unautocorrelated residuals, ε_{1t} and ε_{2t}, in eq. (4) are obtained from the VECM (1), and Ω_{t-1} is the information set at $t - 1$. Eqs. (4) to (7) are then simultaneously estimated by maximizing the log- likelihood function:

$$L(\Theta) = \sum_{t=1}^{T} \ln\{l_t(\Theta)\}, \tag{8}$$

with

$$l_t(\Theta) = \frac{T[(2 + \nu)/2]}{T(\nu/2)[\pi(\nu - 2)]} |H_t|^{-1/2}\left[1 \pm \frac{1}{\nu - 2} \varepsilon_t' H_t^{-1} \varepsilon_t\right]^{-(2+\nu)/2} \quad (9)$$

where Θ is the 16×1 parameter vector of the model.

This two-step approach (the first step for the VECM and the second step for the bivariate EGARCH model) is asymptotically equivalent to a joint estimation of the VECM and EGARCH models.[4] Estimating these two models simultaneously in one step is not practical because of the large number of parameters involved. For example, if $k = 15$ (as used in the following empirical work to obtain uncorrelated residuals) in the VECM, the total number of parameters will be 80. Moreover, although the article focuses more on volatility spillovers (second moment) than cointegration(first moment), the error correction term must be included in the conditional mean equation. Otherwise, the model will be misspecified and the residuals obtained in the first step (and, consequently, the volatility spillover results) will be biased.

In the conditional variance eq. (5), *DOPN* and *DCLS* are the dummy variables for the first and last 15 minutes, respectively. The volatility spillover coefficient γ_1 indicates the volatility spillover from the stock market to the futures market, and γ_2 from futures to stock. The coefficients of α_i and β_i describe the market-specific volatility clustering/autocorrelations. The asymmetric volatility coefficient θ_i in eq. (6) should be negative, suggesting that the volatility tends to rise (fall) when it is bad (good) news or, specifically, when the previous innovation is negative (positive). This is consistent with the finding of Black (1976) in the U.S. stock market that current returns and future volatility are negatively related. Christie (1982) attributes this negative relation to the leverage effect. That is, a reduction in stock price increases the debt/equity ratio (or leverage) and therefore raises equity returns volatility. See Koutmos (1998) for other explanations.

Eq. (4) assumes constant conditional correlation ρ as in Bollerslev (1990), Baillie and Bollerslev (1990), and Chan, Chan, and Karolyi (1991), among many others.[5] In eqs. (4) and (7), ν is the degree of freedom for the Student-*t* distribution that can accommodate the excess kurtosis of the innovations (Bollerslev, 1987). Susmel and Engle (1994) point

[4]The reason is the least squares estimator used in the VECM is still unbiased and consistent in the presence of heteroskedasticity. (See econometrics textbooks, such as Fomby, Hill, and Johnson, 1984, and Greene, 1997, and Lin, Engle, and Ito, 1994, p. 514, for further information.) An anonymous referee also suggests that this two-step approach is appropriate because the system is block diagonal.
[5]The assumption of constant conditional correlation substantially simplifies the estimation process. Under this assumption, the cross products of the standardized residuals, $u_{1t} \times u_{2t}$, should be unautocorrelated.

out the importance of using *t*-distribution for more efficient estimation than normal distribution. If the model is well specified, the standardized residuals u_{it} and squares should be unautocorrelated and have no asymmetric volatility effects.

To complement the EGARCH results, the article also examines the volatility spillovers in a bivariate vector autoregression (VAR) model.

$$\xi_{1t}^2 = \nu_1 + \sum_{j=1}^{h} \alpha_{1j}\xi_{1,t-j}^2 + \sum_{j=1}^{h} \gamma_{1j}\xi_{2,t-j}^2 + \zeta_{1t} \tag{10a}$$

$$\xi_{2t}^2 = \nu_2 + \sum_{j=1}^{h} \alpha_{2j}\xi_{2,t-j}^2 + \sum_{i=1}^{h} \gamma_{2j}\xi_{1,t-j}^2 + \zeta_{2t} \tag{10b}$$

where ξ_{it} is the seasonally adjusted residual derived from the residuals of VECM (1), $\varepsilon_{it.}$ The VAR model implies a bivariate GARCH for the returns. ε_{it} is adjusted for the intraday patterns of volatility (such as the higher volatility at the market open and close) according to the Andersen and Bollerslev (1997, 1998) procedures. Andersen and Bollerslev show that intraday seasonality may distort the high-frequency volatility mechanism. See Appendix B for detailed procedures. Each market's minute-by-minute volatility is estimated by ${\xi_{it}}^2$ and is considered an endogenous variable in the VAR model.[6] Analogous to the bivariate GARCH model, the coefficient γ_1 (γ_2) describes the volatility spillover from the stock (futures) market to the futures (stock) market. α_i represents the market-specific volatility clustering.

EMPIRICAL RESULTS

Intraday Patterns in Volatility of the Futures Market

A well-known stylized fact about the intraday statistical characteristics of many financial markets is that both volume and volatility broadly follow a U-shaped pattern (see, among others, Wood, McInish, and Ord,1985, and Harris, 1986, in the NYSE). These patterns that show trade clusterings at the open and close of a market are explained in the literature by the asymmetric-information-based model of Admati and Pfleiderer (1988) and the queuing-disequilibrium model of Brock and Kleidon

[6]The VAR volatility-spillover model using daily data has been employed by, e.g., Huang, Masulis, Stoll (1996).

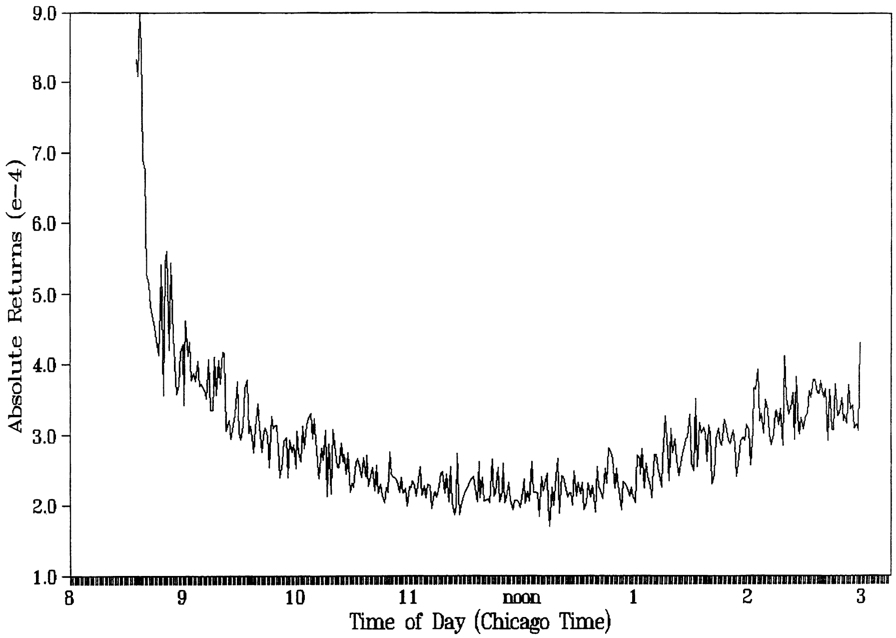

FIGURE 1
DJIA index intraday volatility November 1997–April 1998

(1992). See Harris, McInish, and Chakravarty (1995) and Tse (1999) for a summary of these two models.

Figure 1 demonstrates the intraday patterns in volatility of DJIA index. The intraday volatility is measured by the average absolute returns of one-minute intervals. The usual U-shaped patterns are observed. However, the patterns of DJIA futures (for the entire floor trading period) shown in Figure 2 are more complicated. They roughly comprise three U-shaped curves. The patterns follow a mini-U-shaped curve both at the opening and closing 15 minutes; that is, 8:15 AM to 8:30 AM and 3:00 PM to 3:15 PM The stock market is closed during these two periods. There is a U-shaped curve between 8:30 AM and 3:00 PM, the trading hours of the stock market.

These results parallel the study of Chang, Jain, and Locke (1995). In the S&P 500 futures market, they find a mini-U-shaped pattern in the closing 15-minute period. Note that the S&P 500 futures market opens at the same time as the NYSE, but closes 15 minutes later. Following the argument of Chang et al., the mini-U-shaped curves in the intraday patterns of DJIA futures and S&P 500 futures are consistent with the King and Wadhwani (1990) model. Ho and Lee (1998) also use the model to describe the observation that the close of the Stock Exchange of Hong

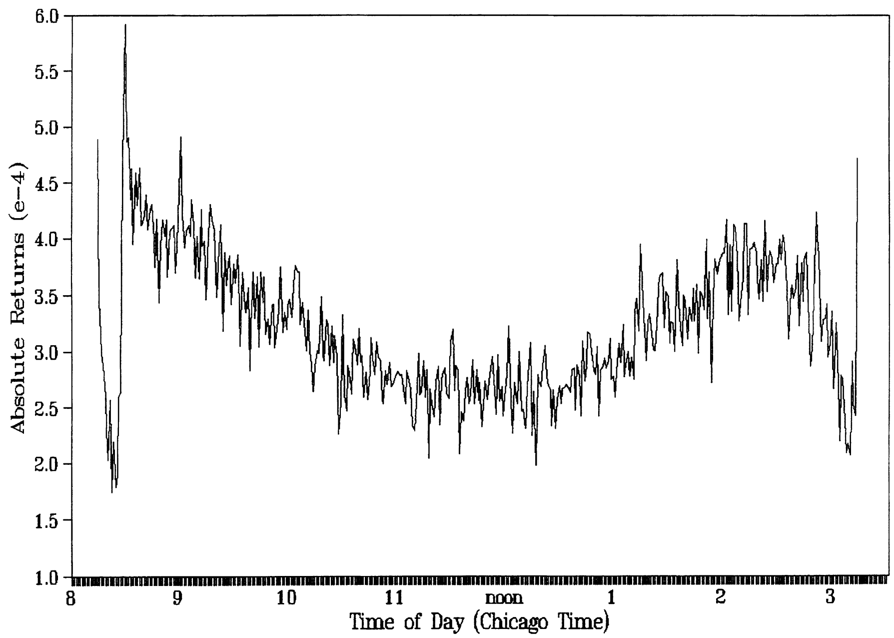

FIGURE 2
DJIA futures intraday volatility November 1997–April 1998

Kong (SEHK) leads to an immediate downturn in the trading activity of the index futures market. In this contagion model, investors react to observed price movements in other related markets; trading in one market affects the price behavior in another market. The model predicts a drop in volatility of a given market (DJIA futures in the current case) when another market (NYSE) is closed.

Price Discovery and Information Shares

The log futures F_t price and cash price S_t are cointegrated with a common stochastic trend and a cointegrating vector being equal $(1, -1)'$. These expected results shown by the Johansen (1991) cointegrating tests (which are robust to the GARCH effects as shown by Lee and Tse, 1996) are not reported but available upon request. The first panel of Table I summarizes the results of the EC terms, $z_{t-1} = F_{t-1} - S_{t-1}$. In the VECM model (1), 15 lags of F_t and S_t are used and the results are virtually the same for 10 and 20 lags. z_{t-1}'s are significant in both eqs. (1a) and (1b) with correct signs, suggesting a bidirectional error correction. However, the EC term in the cash equation (or the equation with ΔS_t being the dependent variable) is greater in magnitude than that of the futures equa-

TABLE I

Error Correction Terms and Information Shares

	Futures		*Stock*	
Error correction term[a], z_{t-1}	coef.	*t*-stat	coef.	*t*-stat
	$-2.84\text{e-}3^{c}$	-4.02	$4.67\text{e-}3^{c}$	9.41
Information share[b](%)	88.29		11.71	
	(97.98, 78.60)		(2.02, 21.40)	

[a] $z_{t-1} = F_{t-1} - S_{t-1}$ is the error correction term in the VECM (1).
[b] According to Hasbrouck (1995), information share of a market is defined as the proportion of the efficient price innovation variance that can be attributed to that market. The first (second) entry in each parenthesis is the information share when $F_t(S_t)$ is used as the first variable in the model. The figure above the parenthesis is the average of these two entries.
[c] Significant at the 1% level.

tion: 4.57e-3 (t-stat. = 9.41) versus -2.84e-3 (t-stat. = -4.02). These results indicate that when the cost-of-carry relationship is perturbed, it is the cash price that makes the greater adjustment in order to reestablish the equilibrium. In other words, the futures price leads the cash price in price discovery.

These error correction results are expanded upon by applying Hasbrouck's (1995) common-trend model. Hasbrouck points out that the information shares estimated will depend on the orderings of variables in the Cholesky factorization if the price innovations are correlated: The first (last) variable in the factorization will have a higher (lower) information share.[7] The second panel of Table I reports the averages of the information shares estimated by the two different orderings. Results of each ordering are also included in the parentheses underneath. The information share attributed to the futures price is 88.3%, whereas that attributed to the index is 11.7%. Therefore the Hasbrouck model confirms the dominant role of DJIA futures in price discovery.

Volatility Spillovers

The coefficients of importance in the bivariate EGARCH(1,1)-t model are γ_1 and γ_2. The coefficient γ_1 (γ_2) describes the volatility spillover from the stock (futures) to futures (stock) market. In Table II, both coefficients are significant at any conventional significance level: $\gamma_1 = 0.043$ (t- stat. = 10.9) and $\gamma_2 = 0.127$ (t-stat. = 27.8). Because γ_2 is about three times of γ_1, although an innovation originating in one market will influence the

[7] "Use of the Cholesky factorization in this fashion is analogous to the process of allocating the explained variance in a multiple regression by considering the incremental improvement in the R^2 associated with adding the variables in sequence" (Hasbrouck, p. 1184).

TABLE II

Volatility spillovers: Bivariate EGARCH Model

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} |Q_{t-1} \sim \textit{Student-t}(0, H_t, \nu), \; H_t \equiv \begin{pmatrix} \sigma_{1t}^2 & \rho\sigma_{1t}\sigma_{2t} \\ \rho\sigma_{1t}\sigma_{1t} & \sigma_{2t}^2 \end{pmatrix}$$

$$ln(\sigma_{1t}^2) = \omega_1 + h_1 DOPN_t + k_1 DCLS_t + \alpha_1 G_{1,t-1} + \gamma_1 G_{2,t-1} + \beta_1 ln(\sigma_{1,t-1}^2)$$

$$ln(\sigma_{2t}^2) = \omega_2 + h_2 DOPN_t + k_2 DCLS_t + \alpha_2 G_{2t-1} + \gamma_2 G_{1t-1} + \beta_2 ln(\sigma_{2,t-1}^2$$

$$G_{it} = (|U_{it}| - E|u_{it}| + \theta_i u_{it}), \; u_{it} = \varepsilon_{it}/\sigma_{it}, \; i = F \text{ or } S$$

$$E|u_{it}| = (2/\pi)^{1/2}[\Gamma(\nu - 1)/2]\Gamma(\nu/2)$$

	ΔF_t		ΔS_t	
ω_i	-0.333[a]	(-19.04)	-0.465[a]	(-20.52)
h_i	0.018[a]	(5.82)	0.012[a]	(3.15)
k_i	0.002[a]	(0.61)	0.046[a]	(16.18)
α_i	0.132[a]	(29.02)	0.096[a]	(23.26)
γ_i	0.043[a]	(10.93)	0.127[a]	(27.82)
β_i	0.983[a]	(923.9)	0.977[a]	(770.70)
θ_i	-0.088[a]	(-4.12)	-0.075[a]	(-2.85)
ρ	0.120[a]	(22.51)		
$1/\nu$	0.110[a]	(41.31)		
Log L		608940.0		
	Diagnostic checking: *P*-Values of test statistics			
Ljung-Box Q(24)-Statistics				
u_{it}	0.682		0.069	
u_{it}^2	<0.0001		<0.0001	
$u_{1t}u_{2t}$		0.037		
Engle and Ng (1993) Asymmetric Tests				
Sign Bias Test	0.938		0.212	
Negative Size Bias Test	0.044		<0.0001	
Positive Size Bias Test	0.587		<0.0001	
Joint Test	0.084		<0.0001	

t-statistics are in the parentheses.
[a]Significant at the 1% level.

volatility of the other market, the spillovers from futures to index are more significant than the other direction. These results are consistent with the above price discovery results. All indicates that DJIA futures is more informationally efficient than the underlying stock market. Moreover, the asymmetric volatility coefficient θ_i in both markets are significantly negative, supporting the notion that previous bad news (represented by negative innovations) in either market will increase volatility in both the futures and stock markets more than good news (positive innovations). As expected, the market-specific volatility clustering coefficients α_i and β_i are positively significant in both markets.

Two previous articles have employed the GARCH-type models to examine the volatility spillovers between the S&P 500 Index cash and futures markets. Chan, Chan, and Karolyi (1991) use a bivariate GARCH model with a sampling interval of five minutes. They find the extent of volatility spillover from the futures to stock market similar to that of the stock to futures market. For example in the 1988–1989 period, their corresponding volatility-spillover coefficients are $\gamma_1 = 0.145$ and $\gamma_2 = 0.107$, and both are statistically significant (see p. 673). Chan et al. conclude that both the futures and stock markets serve important and equal price discovery roles.

In another article, Koutmos and Tucker (1996) use daily closing prices from 1984 to 1993 and a bivariate EGARCH model. In contrast to the current article and Chan, Chan, and Karolyi (1991), they report an univariate directional spillover from futures to index, and conclude that "information from the futures market can be used to predict the volatility in the stock market but not vice versa" (p. 65). Their corresponding volatility-spillovers coefficients are $\gamma_1 = 0.0015$ and $\gamma_2 = 0.148$, and only γ_2 is significant.

Although it is hard to compare the current results with Chan, Chan, and Karolyi (1991) and Koutmos and Tucker (1996) because of different periods and products, it is worth noting that the current article uses higher frequency data, one-minute intervals. Ederington and Lee (1993, 1995) find that the adjustment process of interest rate and foreign exchange futures markets reacting to scheduled macroeconomic news releases completes within one minute. It is likely that higher frequency data used in the current article are more appropriate to examine the rapid dynamics between the futures and stock markets.

Nevertheless, the current results should be interpreted with caution because the diagnostic checking shows that the EGARCH model does not capture all volatility dynamics. In the last panel of Table II, the Ljing-Box Q statistics indicate significant autocorrelations in the standardized residual squares, u_{it}^2, in both markets, and the Engle and Ng (1993) asymmetric tests find significant asymmetric volatility effects in the standard residual of the stock market. Higher order EGARCH and GARCH models, for example, EGARCH(1,2) and EGARCH(1,3), have been tried. Although the spillover results are similar, these higher order models do not improve the specification diagnosis.[8]

[8]Glosten, Jagannathan, and Runkle (GJR) (1993) propose an alternative GARCH-type model that also accounts for the asymmetric volatility effects. The GJR model, however, does not converge in the current article. Besides, to the best of the author's knowledge, no published article has used the GJR model in a multivariate context, although many articles have employed the EGARCH model in this framework—for example, Koutmos and Booth (1995), Tse (1998), Tse and Booth (1996), and Christofi and Pericli (1999).

Note that although the GARCH-type models are popular in modeling the volatility process in financial series, most previous articles (including Chan, Chan, and Karolyi, 1991) using the models in high-frequency transaction data do not report satisfactory diagnostic results. A simple alternative to assess whether the model fits the data is to compare the excess kurtosis for the raw returns, Δp_{it}, and standardized residuals, u_{it}. If the model fits, the kurtosis of u_{it} should be much smaller than that of Δp_{it}. Finding such a reduction in kurtosis, Chan et al. (p. 674) conclude a reasonable fit for the GARCH model used. In the current study, the kurtosis of u_{it} for both markets (for example, 0.9 for the futures market) is also substantially smaller than the kurtosis of raw returns (2.5). These results provide evidence that the EGARCH model explains a large (though not all) portion of the volatility dynamics.

The EGARCH results are evaluated with those given by the VAR model (10) with the seasonally adjusted residual squares being the endogenous variables. The lag length h in the VAR is 15 and the results are robust for $h = 10$ and 20. Consistent with the EGARCH results, the last row of Table III shows that the sum of volatility-spillover coefficients, Σ_{ij} {from $j = 1$ to 15}, is much greater from the futures to stock markets than the other direction. The sum is 0.201 (t-stat. = 10.22) from futures to index, and 0.0257 (t-stat. = 2.85) from index to futures. The table also reports that there is only one volatility-spillover coefficient, $\Sigma_{1,11,}$ that is significant with t-stat. = 2.64 in the futures eq. (10a). But there are four Σ_{2i}'s that are significant with greater values in the cash eq. (10b). Also similar to the EGARCH results, the first five coefficients of the market-specific volatility clustering α_{ij} in each equation are highly significant.

Therefore, both the EGARCH and VAR models indicate that past innovations in DJIA futures significantly influence stock volatility, but the volatility spillovers from stock to futures are much weaker. Put another way, information disseminates in the futures market first.

CONCLUSIONS

The DJIA is the most important indicator of stock movements. This article examines minute-by-minute price discovery and volatility spillovers between the DJIA cash and futures markets. Both the VECM and the Hasbrouck (1995) common-trend model provide evidence to support the dominant role of DJIA futures in price discovery. In particular, the Hasbrouck model suggests that price discovery concentrates at the futures market, a 88.3% information share.

TABLE III

Volatility Spillover. VAR Models of Seasonally Adjusted Residual Squares

$$\xi_{1t}^2 = \omega_1 + \sum_{j=1}^{15} \alpha_{1j}\, \xi_{1,t-j}^2 + \sum_{j=1}^{15} \gamma_{1j}\, \xi_{2,t-j}^2 + \zeta_{1t}$$

$$\xi_{2t}^2 = \omega_2 + \sum_{j=1}^{15} \alpha_{2j}\xi_{2,t-j}^2 + \sum_{j=1}^{15} \gamma_{2j}\xi_{1,t-j}^2 + \zeta_{2t}$$

	ξ_{1t}^2		ξ_{2t}^2	
ω_i	0.006[a]	(25.37)	0.004[a]	(19.06)
α_{i1}	0.082[a]	(8.92)	0.052[a]	(7.64)
α_{i2}	0.054[a]	(6.22)	0.085[a]	(10.80)
α_{i3}	0.037[a]	(5.48)	0.031[a]	(4.42)
α_{i4}	0.025[a]	(3.76)	0.022[a]	(3.40)
α_{i5}	0.028[a]	(3.96)	0.022[a]	(2.77)
α_{i6}	0.013	(2.13)	0.024[a]	(3.44)
α_{i7}	0.008	(1.53)	0.010	(2.04)
α_{i8}	0.031[a]	(3.20)	0.001	(0.26)
α_{i9}	0.015	(1.61)	0.003	(−0.65)
α_{i10}	0.020[a]	(3.57)	0.003	(0.79)
α_{i11}	0.011	(1.78)	−0.004	(−0.82)
α_{i12}	(−0.003)	(−0.05)	−0.004	(−0.95)
α_{j13}	0.004	(0.76)	0.005	(1.11)
α_{i14}	0.018[a]	(2.65)	−0.004	(−0.88)
α_{i15}	0.016[a]	(3.20)	−0.003	(−0.72)
γ_{i1}	0.000	(0.05)	0.049[a]	(8.39)
γ_{i2}	0.006	(0.99)	0.046[a]	(4.26)
γ_{i3}	0.005	(0.94)	0.016[a]	(2.70)
γ_{i4}	0.008	(1.49)	0.008	(1.63)
γ_{i5}	0.002	(0.40)	0.013	(2.51)
γ_{i6}	0.005	(0.91)	0.005	(0.96)
γ_{i7}	0.000	(0.01)	0.012	(2.48)
γ_{i8}	0.002	(0.37)	0.007	(1.41)
γ_{i9}	0.000	(0.01)	0.001	(0.26)
γ_{i10}	0.007	(1.19)	0.015[a]	(3.01)
γ_{i11}	0.015[a]	(2.64)	0.001	(0.33)
γ_{i12}	−0.005	(−1.10)	0.005	(1.04)
γ_{i13}	−0.007	(−1.41)	0.003	(0.62)
γ_{i14}	0.011	(1.67)	0.015	(1.67)
γ_{i15}	0.007	(1.21)	0.009	(1.93)
P-values of hypotheses testing				
$\Sigma\alpha_{ij}$, {from j = 1 to 15}	0.360*	(14.07)	0.239*	(12.14)
$\Sigma\gamma_{ij}$ {from j = 1 to 15}	0.057*	(2.85)	0.201*	(10.22)

t-statistics derived from the White (1980) heteroskedasticity-consistent covariance matrix are in the parentheses.
[a]Significant at the 1% level.

The bivariate EGARCH model shows that although an innovation originating in one market will increase the volatility of the other market, the spillovers from futures to index are more significant than the reverse direction. Moreover, bad news (negative innovations) in either market will increase volatility in both the futures and stock markets more than good news (positive innovations).

In conclusion, DJIA futures is more informationally efficient than the underlying stock market. Because all the Dow 30 component stocks are actively traded, these results should not be induced by nonsynchronous trading. Possible reasons are the inherent leverage, low transaction costs, and the absence of short sale restrictions in the futures market. How these results can be exploited in the Dow trading strategies warrants future research.

APPENDIX A

CBOT DJIA Futures Contract Specifications

Unit of Trading:	\$10 times the DJIA.
Minimum Price Fluctuations:	One point (\$10).
Contract Months:	March, June, September, and December.
Last Trading Day:	The trading day preceding the final settlement day.
Final Settlement Day:	The third Friday of the contract month with cash settlement.
Postion limits:	50,000 contracts net long or net short in all months combined.
Daily Price Limit:	Successive price limits of 350, 550, and 700 index points below the settlement price of the previous trading session.
Ticker Symbol:	DJ

APPENDIX B

Andersen and Bollerslev Seasonal Adjustment Procedures

Consider intraday residual returns, $\varepsilon_{m,n}$, on day $m(m = 1, \ldots, M)$ and at interval $n(n = 1, \ldots, N)$ from the VECM (1) in text. Note that $\varepsilon_{m,n}$ is represented as ε_t in text, similar to $\xi_{m,n}$ (in A(5) below) and ξ_t in the VAR in text. Following Andersen and Bollerslev (1997, 1998), define

$$x_{m,n} \equiv \ln(\varepsilon_m^2/N) = \ln(s_{m,n}^2) + \zeta_{m,n} \tag{A1}$$

$x_{m,n}$ is approximated by the following Fourier functional form:

$$X_{m,n} = \sum_{j=1}^{J} \sigma_m^j \Bigg[\mu_{oj} + \mu_{1j} \frac{n}{N_1} + \mu_{2j} \frac{n^2}{N_2} + \sum_{i=1}^{I} \delta_{ij} D_{i,n} + \sum_{k=1}^{k} \left(\lambda_{kj} \cos \frac{2kn\pi}{T} + \nu_{kj} \sin \frac{2kn\pi}{T} \right) \Bigg] \tag{A2}$$

where $N_1 = (N + 1)/2$ and $N_2 = (N + 1)(N + 2)/6$ are normalizing constants, $D_{i,n}$ are intraday dummy variables accounting for the first and last thirty minutes as in Eq. (5) in text. For $J \geqslant 1$, Eq. (A2) allows for the interaction effect between the daily level of volatility σ_m and intraday volatility patterns. σ_m is estimated as the standard deviation of the one-minute returns per day m as in Kofman and Martens (1993). The Fourier form introduced by Gallant (1981, 1982) is a special case of Eq. (A2) with no interaction terms and intraday dummy variables, i.e., $J = 0$ and $I = 0$. J and the truncation lag for the Fourier expansion, K, are determined by the overall fit of the regressions and parsimony.

The estimate of $x_{m,n}$ with $J = 1$ and $K = 2$ is

$$\begin{aligned} x_{m,n} = {} & \mu_{00} + \mu_{01}\sigma_m + \mu_{10} \frac{n}{N_1} + \mu_{11}\sigma_m \frac{n}{N_1} + \mu_{20} \frac{n^2}{N_2} \\ & + \mu_{12}\sigma_m \frac{t^2}{N_2} + \sum_{i=1}^{2} \delta_{i0} D_{i,n} + \sum_{i=1}^{2} \delta_{il}\sigma_m D_{i,n} \\ & + \sum_{k=1}^{2} \left[\lambda_{k0} \cos \frac{2kn\pi}{N} + \nu_{k0} \sin \frac{2kn\pi}{N} \right] \\ & + \sum_{k=1}^{2} \left[\lambda_{k1}\sigma_m \cos \frac{2kn\pi}{N} + \nu_{k1}\sigma_m \sin \frac{2kn\pi}{N} \right] \end{aligned} \tag{A3}$$

The estimator of the intraday periodic component for interval n on day m is

$$\hat{s}_{m,n} = \frac{T \cdot \exp(\hat{x}_{m,n}/2)}{\sum_{m=1}^{M} \sum_{n=1}^{N} \exp(\hat{x}_{m,n}/2)} \tag{A4}$$

The seasonally adjusted residual is then given by

$$\hat{\xi}_{m,n} = \hat{\varepsilon}_{m,n}/(\hat{\sigma}_m \hat{s}_{m,n}) \tag{A5}$$

BIBLIOGRAPHY

Admati, A. R., & Pfleiderer, P. (1988). A theory of intraday trading patterns: Volume and price variability. Review of Financial Studies, 1, 3–40.

Andersen, T. G., & Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. Journal of Empirical Finance, 4, 115–157.
Andersen, T. G., & Bollerslev, T. (1998). Deutsche mark–dollar volatility: Intraday activity patterns, macroeconomic annoncements, and longer run dependencies. Journal of Finance, 53, 219–265.
Baillie, R. T., & Bollerslev, T. (1990). A multivariate generalized ARCH approach to modeling risk premia in the forward foreign exchange rate. Journal of International Money and Finance, 9, 309–324.
Black, F. (1976). Studies of stock price volatility changes. Proceedings from the American Statistical Association, Business and Economic Statistics Section, 177–181.
Bollerslev. T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. Review of Economics and Statistics, 69, 542–547.
Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. Review of Economics and Statistics, 72, 498–505.
Booth, G. G., Martikainen, T., & Tse, Y. (1997). Price and volatility spillovers in Scandinavian stock markets. Journal of Banking and Finance, 21, 811–823.
Brock, W. A., & Kleidon, A. W. (1992). Periodic market closure and trading volume: A model of intraday bids and asks. Journal of Economic Dynamic and Control, 16, 451–489.
Chan, K. (1992). A further analysis of the lead–lag relationship between the cash market and stock index futures market. Review of Financial Studies, 5, 123–152.
Chan, K., Chan, K. C., & Karolyi, A. G. (1991). Intraday volatility in the stock index and stock index futures markets. Review of Financial Studies, 4, 657–684.
Chang, E. C., Jain, P. C., & Locke, P. R. (1995). Standard & Poor's 500 index futures volatility and price changes around the New York Stock Exchange close. Journal of Business, 68, 61–84.
Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Financial Economics, 10, 407–432.
Christofi, A., & Pericli, A. (1999). Correlation in price changes and volatility of major Latin American stock markets. Journal of Multinational Financial Management, 9, 79–93.
Dwyer, G. P.J., Locke, P., & Yu, W. (1996). Index arbitrage and nonlinear dynamics between the S&P 500 futures and cash. Review of Financial Studies, 9, 301–332.
Ederington, L. H., & Lee, J. H. (1993). How markets process information: News releases and volatility. Journal of Finance, 48, 1161–1191.
Ederington, L. H., & Lee, J. H. (1995). The short-run dynamics of the price adjustment to new information. Journal of Financial and Quantitative Analysis, 30, 117–134.
Engle, R. F., Ito, T., & Lin, W.-L. (1990). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. Econometrica, 58, 525–542.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. Journal of Finance, 48, 1749–1778.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. The Journal of Futures Markets, 16, 353–387.

Fomby, T. B., Hill, R. C., & Johnson, S. R. (1984). Advanced econometric methods. New York: Springer-Verlag.

Gallant, A. R. (1981). On the bias inflexible functional forms and an essentially unbiased form: The Fourier flexible form. Journal of Econometrics, 15, 211–245.

Gallant, A. R. (1982). Unbiased determination of production technologies. Journal of Econometrics, 20, 285–323.

Ghosh, A. (1993). Cointegration and error correction models: Intertemporal causality between index and futures prices. The Journal of Futures Markets, 13, 193–198.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance, 48, 1779–1801.

Greene, W. H. (1997). Econometric analysis (3rd edition). Engelwood Cliffs, NJ: Prentice Hall.

Hamao, Y. R., Masulis, R. W., & Ng, V. K. (1990). Correlation in price changes and volatility across international stock markets. Review of Financial Studies, 3, 281–307.

Harris, F. H. B., McInish, T. H., & Chakravarty, R. R. (1995). Bids and asks in disequilibrium market microstructure: The case of IBM. Journal of Banking and Finance, 19, 323–345.

Harris, L. (1986). A transaction data survey of weekly and intraday patterns in stock patterns. Journal of Financial Economics, 16, 99–117.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. Journal of Finance, 50, 1175–1199.

Herbst, A., McCormack, J., & West, E. (1987). Investigation of a lead–lag relationship between spot indices and their futures contracts. The Journal of Futures Markets, 7, 373–382.

Ho, R. Y. K., & Lee, R. S. K. (1998). Market closure effects on return, volatility, and turnover patterns in the Hong Kong index futures market. Journal of International Financial Markets, Institutions and Money, 8, 433–351.

Huang, R. D., Masulis, R. W., & Stoll, H. R. (1996). Energy shocks and financial markets. The Journal of Futures Markets, 16, 1–17.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica, 59, 1551–1580.

Kawaller, I. G., Koch, P. D., & Koch, T. W. (1987). The temporal price relationship between S&P 500 futures and the S&P 500 index. Journal of Finance, 42, 1309–1329.

Kofman, P., & Martens, M. (1997). Interaction between stock markets: An analysis of the common trading hours at the London and New York stock exchange. Journal of International Money and Finance, 16, 387–414.

Koutmos, G. (1998). Asymmetries in the conditional mean and the conditional variance: Evidence from nine stock markets. Journal of Economics and Business, 50, 277–290.

Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. Journal of International Money and Finance, 14, 747–762.

Koutmos, G., & Tucker, M. (1996). Temporal relationships and dynamic interactions between spot and futures stock markets. The Journal of Futures Markets, 16, 55–69.

Lee, T.-H., & Tse, Y. (1996). Cointegration tests with conditional heteroskedasticity. Journal of Econometrics, 73, 401–410.

Lin, W.-L., Engle, R. F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. Review of Financial Studies, 7, 507–538.

Martens, M., Kofman, P., & Vorst, T. C. F. (1998). A threshold error-correction model for intraday futures and index returns. Journal of Applied Econometrics, 13, 245–263.

Miller, M. H., Muthuwamy, J., & Whaley, R. E. (1994). Mean revision of Standard and Poor's 500 index basis changes: Arbitrage-induced or statistical illusion? Journal of Finance, 49, 479–513.

Ng, N. (1987) Detecting spot forecasts in futures prices using causality tests. Review of Futures Markets, 6, 250–267.

Ross, S. (1989). Information and volatility: The no-arbitrage martingale appproach to timing and resolution irrelevancy. Journal of Finance, 44, 1–17.

Stoll, H. R., & Whaley, R. (1990). The dynamics of stock index and stock index futures returns. Journal of Financial and Quantitative Analysis, 25, 441–468.

Susmel, R., & Engle, R. F. (1994). Hourly volatility spillovers between international equity markets. Journal of International Money and Finance, 13, 3–25.

Tse, Y. (1998). International transmission of information: Evidence from the Euroyen and Eurodollar futures markets. Journal of International Money and Finance, 17, 909–929.

Tse, Y. (1999). Round-the-clock market efficiency and home bias: Evidence from the international Japanese government bonds futures markets. Journal of Banking and Finance, forthcoming.

Tse, Y., & Booth, G. G. (1996). Common volatility and volatility spillovers between U.S. and Eurodollar interest rates: Evidence from the futures market. Journal of Economics and Business, 48, 299–312.

Wahab, M., & Lashgari, M. (1993). Price dynamics and error correction in stock index and stock index futures markets: A cointegration approach. The Journal of Futures Markets, 13, 711–742.

White, H. (1980). A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. Econometrica, 48, 817–838.

Wood, R. A., McInish, T. H., & Ord, J. K. (1985). An investigation of intraday data for NYSE stocks. Journal of Finance, 40, 723–741.