Short-Run Deviations and Volatility in Spot and Futures Stock Returns: Evidence from Australia, Hong Kong, and Japan

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INTRODUCTION

According to Kim and Kon (1994), security return distribution plays a vital role in financial market theory and practice. Portfolio selection models and asset pricing in equilibrium require a distribution assumption concerning financial securities [Gibbons and Ferson (1985); Harvey (1989)]. Distribution of the security return is also required in contingent claims models [Kim and Kon (1994)]. Starting with the work of Mandelbrot (1963) and Fama (1965), empirical evidence confirms unconditional distributions of security price changes to be leptokurtic, skewed, and volatility clustered. According to Fortune (1989) the quantity and quality of information about the future is also a vital factor influencing the prices and returns on financial assets. Fortune further asserts that this factor is particularly important for common stocks, which have long lives and involve no promised financial payments. Investors will accept a lower premium on equity as the quality of the information improves, and variations in both the rate of flow and the quantity of information will

My thanks to two anonymous referees and the editor of this journal for several useful comments and suggestions. All remaining errors and omissions are my responsibility alone.

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The Journal of Futures Markets, Vol. 17, No. 6, 689–705 (1997)

CCC 0270-7314/97/060689-17

alter the volatility of the equity premium. According to Fortune (1989), the introduction of stock index futures is the most important financial innovation affecting the quality of information about future common-stock prices. A stock index futures contract is an agreement between two parties in which they commit to engaging in an exchange of a bundle of stocks (in practice, the cash equivalent) for a prespecified price at a future date. Silber (1985) suggests that futures markets provide two main functions: risk transfer and price discovery. Risks are transferred to those willing to bear them and hedgers reduce their risk by paying a premium to speculators.[1] The existence of futures trading also enhances the ability of investors to form judgments about expected forward cash prices. Knowledge of the distribution of returns from the cash (spot) and stock index futures markets is important for understanding the role of futures markets in equity trading, for understanding the forecasting ability of futures prices, and for the development of optimal hedging and trading strategies.

This article provides an empirical investigation of the distribution of stock returns from the cash and futures markets and investigates the predictability of the conditional variance. Stock returns from the cash and the futures markets are modeled with the use of a bivariate generalized autoregressive conditional heteroscedastic (GARCH) model [Bollerslev (1986)]. GARCH models are capable of capturing the three most empirical features observed in stock return data; leptokurtosis, skewness, and volatility clustering. According to Bollerslev, Chou, and Kroner (1992), GARCH models can be viewed as a reduced form of a more complicated dynamic structure for the time-varying conditional second-order moments.[2] GARCH models provide a more flexible framework to capture various dynamic structures of conditional variance and allow simultaneous estimation of several parameters and hypotheses [Chou (1988)]. Compared to a single-series univariate GARCH model, a bivariate model utilizes information in two different markets' histories. Lee (1994) extends the GARCH model by linking it to the error-correction models (ECM) of co-integrated series. He calls it a GARCH-X model. Co-integration implies that a linear combination(s) of two or more non-

[1]According to Fortune (1989), risk transfer and price discovery also take place in the absence of futures markets, but these two factors are enhanced in the presence of futures markets. This happens because the costs of futures transactions are considerably less than the cost of spot transactions.

[2]Bollerslev (1987), Bollerslev, Engle, and Wooldridge (1988), French et al. (1987), and Baillie and DeGennaro (1990) apply the GARCH models in explaining the distribution of common stock prices. Chan, Chan, and Karolyi (1991) apply the bivariate GARCH model in the study of the volatility of the spot and futures stock markets in the United States. See Bollerslev et al. (1992) for an excellent survey on the application of the GARCH models in finance and economics.

stationary variables converges to an equilibrium in the long run. Individually these variables might drift apart in the short run, but in the long run they are constrained. Short-run deviations from a long-run co-integrated relationship are indicated by the error-correction term from the ECM. The GARCH-X model may be applied to investigate the predictive power of the short-run deviations between the cash and the future prices of stocks in predicting the volatility of the stock returns. According to Lee (1994), examining the behavior of the conditional variances over time as a function of short-run deviations is reasonable when one expects increased volatility due to shocks to the system that propagate on both the first and the second moments. This article also investigates the effects of the short-run deviations between the spot and the futures prices on the volatility of stock returns in the spot and futures markets.

Daily stock returns from the cash (spot) and the futures markets of Australia, Hong Kong, and Japan from 1990 to 1994 are applied in the empirical work. The choice of these markets is motivated by Bollerslev et al. (1992), who advocate the need for empirical investigation of stock market volatility in countries other than the United States. The stock cash (spot) index and stock index futures markets of Australia, Hong Kong, and Japan represent some of the larger markets in the Pacific Basin region,[3] and there are few empirical investigations of the stock index futures markets in these countries (especially Australia and Hong Kong).

This study first tests for possible co-integration of the cash and futures prices. If they are found to be co-integrated, the error-correction term from the co-integrated relationship is then applied in the bivariate GARCH model (GARCH-X). If the error-correction term is an important variable in the conditional variance (volatility), this may imply that the series may be harder to predict the further the variables deviate away from each other in the short run. This study finds significant interaction between the cash and the future prices, and evidence of significant short-run deviations on the conditional variance in all three countries.

THE DATA AND BASIC STATISTICS

As stated earlier, daily stock returns from the cash (spot) and the futures markets of Australia, Hong Kong, and Japan from January 1990 to December 1994 are used in the empirical tests. For each country, two sets (indices) of futures prices based on two different expiration dates of the

[3]The mean of the percentage of the trading volumes in number of shares in the futures markets of Australia, Hong Kong, and Japan relative to the United States futures market between 1990 and 1994 are 6.6%, 45.8%, 21.6%, respectively.

Table I

Basic Statistics

Return	Mean	S.D.	Normality	Skewness	Kurtosis
		Cash (Spot) Market			
Australia	0.00011	0.008	65.31[a]	−0.08	1.10[a]
Hong Kong	0.00080	0.014	1317.12[a]	−0.55[a]	4.83[a]
Japan	−0.0005	0.013	2679.06[a]	0.33[a]	7.03[a]
		Futures Market—First Index			
Australia	0.00012	0.011	348.57[a]	−0.13[a]	2.54[a]
Hong Kong	0.00080	0.016	719.32[a]	−0.10	3.66[a]
Japan	−0.0005	0.016	787.12[a]	0.18[a]	3.81[a]
		Futures Market—Second Index			
Australia	0.00010	0.011	3726.92[a]	−0.07	8.33[a]
Hong Kong	0.00080	0.016	7321.31[a]	−0.10	3.2[a]
Japan	−0.0005	0.016	764.53[a]	0.07	3.77[a]

Notes: Normality is checked by means of a Jarque–Bera test. S.D. = standard deviation.
[a]Significance at the 1% level.
[b]Significance at the 10% level.

futures contract are used. The Australian and the Japanese stock index futures contracts have four quarterly expiration dates in a given year—March, June, September, and December. The June contract price is used for the first index and the September contract price is used for the second index. The Australian spot stock index is based on the All Ordinary price index, and the futures prices are based on the All Ordinary futures index. The All Ordinary share index contains 307 Australian stocks. In the case of Japan, the Nikkei 500 price index prices are used for the cash price index, and Nikkei stock average futures prices are used for the futures index. The Nikkei 500 contains 500 Japanese stocks. The Hong Kong futures market operates on monthly contracts. The cash and futures prices of the Hong Kong indices are based on the Hang Seng price index and Hang Seng index futures, respectively. The first futures index is based on the May expiration contract and the second futures index is based on the June expiration contract. The Hang Seng index contains 33 stocks on the Hong Kong stock exchange.

All data are obtained from *DATASTREAM*. Stock returns are defined as the first difference in the log of price indices (both cash and futures). According to French, Schwert, and Stambaugh (1987), since the ex-dividend days are different for different stocks in a general price index, the fact that returns lack dividends should have little effect on the volatility estimates.

Table I shows some of the basic statistics of the nine stock returns under study. All nine series show excess kurtosis, implying fatter tails than a normal distribution. Due to the presence of excess kurtosis, all series are found to be nonnormal by means of the Jarque–Bera statistics (at the 1% level). Only the Japanese series are skewed to the right, but out of the nine series only four have significant skewness in them. The Australian series have the lowest standard deviations. The Japanese and the Hong Kong series have very similar standard deviations. Table II presents the cross correlation between the returns from the cash ($r_{p,t}$) and the futures markets ($r_{f,t-k}$) for up to seven leads/lags (k) for all three countries. The seven lags (1 to 7) indicate predictability from futures to cash, and the seven leads (-7 to -1) show predictability from cash to futures. The largest correlation in absolute value is found (excluding zero lags) with the use of one lag in the futures return. Otherwise, both the lead and lag cross correlations show similar results in absolute value. This is true in all six cases. The bulk of the correlations are found to be significant at the 5% level.

As indicated by Baillie and Myers (1991, p. 110), with most asset prices it is reasonable to base inference on the change in the logarithm of price. The augmented Dickey–Fuller test [Said and Dickey (1984)] is applied to check for the stochastic structure of the data.[4] All cash and futures prices reject the null hypothesis of two unit roots but fail to reject one root null.[5] In other words, the logs of all series are stationary after the first difference, but are nonstationary in levels. These results are not provided in order to save space but are available on request. Stationarity after first difference is not informative about higher moments, which usually results in higher kurtosis [Baillie and Myers (1991)].

THE BIVARIATE GARCH-X MODEL

As shown by Baillie and Myers (1991) and Bollerslev et al. (1992), weak dependence of successive asset price changes may be modeled by means of the GARCH model. According to the GARCH model, the conditional variance of a time series depends upon the squared residuals of the process [Bollerslev (1986)]. The GARCH model has the advantage of incor-

[4]The number of lags applied in the ADF test is chosen based on the evidence provided by the Akakie Information Criterion (AIC). Tests for a single unit root are conducted with the inclusion of a trend and a constant, and the two roots tests are conducted with only a constant. In this manner, the two-unit root test allows for an alternative hypothesis of stationarity with a nonzero intercept on the differenced series, and the single-unit root test allows for the alternative hypothesis of trend stationary and a nonzero intercept on the series in levels.

[5]The stochastic structure of the series are tested also with the use of the Pantula, Gonzalez-Farias, and Fuller (1994) unit root tests. Results from these tests back up the ADF tests results and are available on request.

Table II

Cross Correlations between Cash and Futures Returns

	Australia		*Hong Kong*		*Japan*	
Lag/Lead	*First Index*	*Second Index*	*First Index*	*Second Index*	*First Index*	*Second Index*
−7	−0.039*	−0.032*	−0.019*	−0.025*	−0.015*	−0.015*
−6	−0.042*	−0.033*	−0.046*	−0.045*	0.010*	0.004
−5	0.026*	0.024*	0.001*	0.011*	−0.002	0.018*
−4	0.032*	0.010*	−0.029*	−0.028*	0.017*	0.019*
−3	−0.040*	−0.054*	0.042*	0.046*	0.035*	0.006
−2	−0.046*	−0.021*	0.037*	0.047*	−0.040*	−0.042*
−1	0.053*	0.045*	0.036*	−0.033*	0.063*	0.131*
0	0.820*	0.781*	0.855*	0.843*	0.763*	0.708*
1	0.199*	0.186*	0.146*	0.148*	0.154*	0.155*
2	−0.021*	−0.019*	−0.031*	−0.031*	−0.040*	−0.053*
3	−0.051*	−0.073*	0.029*	0.025*	0.005	−0.0004
4	0.015*	0.032*	0.005	0.012*	0.025*	0.019*
5	0.010*	0.009	0.006	0.002	−0.031*	−0.020*
6	−0.033*	0.004	−0.038*	−0.045*	0.010*	0.014*
7	−0.019*	−0.026*	−0.046*	−0.047*	−0.005	−0.005

*Implies significance at the 5% level by means of Q statistics.

porating heteroscedasticity into the estimation procedure, and it also captures the tendency for volatility clustering in financial and economic data. The GARCH model may be applied both in univariate and multivariate forms. According to Wahab (1995), simplicity is the main advantage of a univariate GARCH model, but it utilizes only the information in one market's own history. As stated earlier, the multivariate GARCH model uses information from the history of more than one market. According to Conrad, Gultekin, and Kaul (1991), multivariate models provide more precise estimates of the parameters because they utilizes information in the entire variance–covariance matrix of the errors. Further, the generated regressor problem associated with univariate models is avoided in multivariate models because it estimates all parameters jointly [Pagan (1984)]. According to Engle and Kroner (1995), multivariate GARCH models are useful in multivariate finance and economic models, which require the modeling of both variance and covariance. Multivariate GARCH models allow the variance and covariance to depend on the information set in a vector ARMA manner [Engle and Kroner (1995)]. This, in turn, leads to an unbiased and more precise estimate of the parameters [Wahab (1995)].

As stated earlier, an extension of the GARCH model linked to an error-correction model of a co-integrated series has been put forward by

Lee (1994). That model is known as the GARCH-X model. Co-integration implies that in a long-run relationship between two or more nonstationary variables, it is required that these variables should not move too far apart from each other. Such nonstationary variables might drift apart in the short run or due to seasonal factors, but in the long run they are constrained.[6] Thus, co-integration means that one or more linear combinations of these variables is stationary, even though individually they are not.[7] Co-integration also implies that the transitory components of the series can be given a dynamic specification by means of the error-correction model (ECM). That is, a constrained ECM can be applied that captures the short-run dynamics adjustment of co-integrated variables toward a long-run equilibrium. According to Engle and Granger (1987) and Lee (1994), because the ECM is a conditional expectation of the first difference of the series given an information set, it may be considered as a prediction equation of the co-integrated series.

The error-correction term, which represents the short-run deviations from the long-run co-integrated relationship, has important predictive powers for the conditional mean of the co-integrated series [Engle and Yoo (1987)]. According to Lee (1994, p. 375), if short-run deviations affect the conditional mean, they may also affect conditional variance, and a significant positive effect may imply that the further the series deviate from each other in the short run, the harder they are to predict. If the error-correction term (short-run deviations) from the co-integrated relationship affects the conditional variance, then conditional heteroscedasticity may be modeled with a function of lagged error-correction term. If shocks to the system that propagate on the first and the second moments change the volatility, then it is reasonable to study the behavior of conditional variance as a function of short-run deviations [Lee (1994)].

The following bivariate GARCH(p,q)-X model may be used to represent the returns from the stock cash and futures markets:[8]

$$y_t = \mu + \varepsilon_i \tag{1}$$

[6]If the spot price (P_t) and the futures price (F_t) are integrated of the order 1, that is, nonstationary in levels, it is generally true that the linear combination, $P_t = \alpha F_t + z_t$, will also be integrated of the order 1. However, it is possible that z_t is integrated of the order zero, that is, stationary in levels, where z_t is the error-correction term (equilibrium error). When α is not zero, P_t and F_t are co-integrated and z_t is a stationary equilibrium error. In other words, if P_t and F_t are co-integrated, then z_t rarely drifts far away from zero and equilibrium will occasionally occur.

[7]Detailed analyses of co-integration are available in numerous articles and books. For examples, see Engle and Granger (1987), Dickey and Rossana (1994), and Harris (1995).

[8]Chan et al. (1991) apply the standard bivariate model in the study of the volatility of the cash and stock index futures markets of the United States. Baillie and Myers (1991) and Wahab (1995) apply the standard bivariate model in a study of the spot and futures markets of commodities and metals.

$$\varepsilon_t/\Omega_{t-1} \sim N(0, H_t) \tag{2}$$

$$\begin{aligned}\text{vech}(H_t) &= C + \sum_{j=1}^{q} A_j \,\text{vech}(\varepsilon_{t-j})^2 + \sum_{j=1}^{P} B_j \,\text{vech}(H_{t-j}) \\ &\quad + \sum_{j=1}^{K} D_j \,\text{vech}(z_{t-j})^2 \end{aligned} \tag{3a}$$

where $y_t = (r_{p,t}, r_{f,t})$ is a (2×1) vector containing stock returns from the cash (spot) and futures markets, H_t is a (2×2) conditional covariance matrix, C is a (3×1) parameter vector (constant), A_j and B_j are (3×3) parameter matrices, vech is the column stacking operator that stacks the lower triangular portion of a symmetric matrix, z_{t-j} is the lagged error-correction term (short-run deviations) from the long-run co-integration relationship, and D_j is a (3×3) matrix like A_j and B_j. The size and significance of the parameters, D_j, indicate the relationship between short-run deviations and conditional variance. According to Lee (1994), the GARCH-X model is proper for testing causality in variance through the error-correction term.

According to Engle and Kroner (1995) and Wahab (1995), various restrictions may be imposed in this parametrization to make estimation easier. A parsimonious representation can be obtained by imposing a diagonal restriction on the multivariate GARCH parameters' matrices, so that each variance and covariance element depends only on its own past values and prediction errors [Bollerslev, Engle, and Wooldridge (1988)]. In other words, this presentation is obtained by assuming that matrices, A_j and B_j, are diagonal. According to Engle and Kroner (1995) and Baillie and Myers (1991), the stated restriction seems plausible, because it implies that each variance and covariance depends only on its own past values and prediction errors. The following equations present a diagonal vech bivariate GARCH(1,1)-X conditional variance equation(s) with k equal to 1; that is, the squared error-correction term (z_t) is lagged once:

$$H_{11,t} = C_1 + A_{11}(\varepsilon_{1,t-1})^2 + B_{11}(H_{11,t-1}) + D_{11}\,(z_{t-1})^2 \tag{3b}$$

$$H_{12,t} = C_2 + A_{22}(\varepsilon_{1,t-1}\varepsilon_{2,t-1}) + B_{22}(H_{12,t-1}) + D_{22}(z_{t-1})^2 \tag{3c}$$

$$H_{22,t} = C_3 + A_{33}(\varepsilon_{2,t-1})^2 + B_{33}(H_{22,t-1}) + D_{33}(z_{t-1})^2 \tag{3d}$$

In the bivariate GARCH(1,1) system, the diagonal vech parametrization involves nine conditional variance parameters. To ensure a positive conditional variance, the values of C, A_{11}, A_{33}, B_{11}, and B_{33} are restricted to zero or greater. The ARCH process in the residuals from the cash equation is shown by the coefficient on $(\varepsilon_{1,t-1})^2$ (A_{11}), whereas the coefficient on $(\varepsilon_{2,t-1})^2$ (A_{33}) presents the ARCH process in the futures equation residuals. The parameters A_{22} and B_{22} represent the covariance GARCH parameters, which account for the conditional covariance between cash and futures prices. Significant covariance parameters imply strong interaction between the cash and futures prices.[9] As advocated by Baillie and Myers (1991, p. 116) it is vital to let the conditional covariance be time dependent, as is done in the bivariate GARCH model, rather than be a constant.

If the sum of A_{11} and B_{11} is equal to unity, this implies that current shock persists indefinitely in conditioning the future variance of the return from the cash market. Similarly, if the sum of A_{33} and B_{33} is equal to unity, the current shock persists indefinitely in conditioning the future variance of the return from the futures markets. In other words, if A_{11} + B_{11} and A_{33} + B_{33} are both less than unity, then $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are covariance stationary, respectively.[10] According to Poterba and Summers (1986), significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time. The market will not make an adjustment of the future discount rate if shocks to volatility are transitory.

As advocated by Lee (1994, p. 377) the square of the error-correction term (z) lagged once ($k = 1$) should be applied in the GARCH(1,1)-X model. The parameters, D_{11} and D_{33}, indicate the effects of the short-run deviations between the cash and the futures prices from a long-run co-integrated relationship on the conditional variance of the residuals of the cash and the futures equations, respectively. The parameter, D_{22}, shows the effect of the short-run deviations on the covariance between the two residuals. With the use of this model, the predictive power of the spread between daily stock indices from the spot and futures markets for the three countries in predicting volatility of the stock market returns may be investigated. If the squared error-correction terms are positively related to the conditional variance, this implies that the stock prices become more volatile and harder to predict as the spread between the two prices gets larger [Lee (1994, p. 376)]. A significant negative effect indicates that an increase in the spread between the spot and futures prices reduces the volatility. Thus, the presence of the short-run deviations in the conditional variance function may be exploited to obtain more precise

[9]Bera and Higgins (1993) and Engle and Kroner (1995) provide detailed analysis of multivariate GARCH models.

[10]Engle and Kroner (1995, p. 132) provide a detailed analysis of covariance stationarity in the residuals in a multivariate GARCH model.

Table III

Error-Correction Terms

Bivariate GARCH-X Test	*Error-Correction Term*
Australia first index	$P_t - 1.013^*F_t$
Australia second index	$P_t - 1.024^*F_t$
Hong Kong first index	$P_t - 0.997^*F_t$
Hong Kong second index	$P_t - 1.003^*F_t$
Japan first index	$P_t - 0.889^*F_t$
Japan second index	$P_t - 0.888^*F_t$

Notes: P_t = cash (spot) price index; F_t = futures price index

time-varying confidence intervals for point forecasts of stock price changes.

EMPIRICAL RESULTS

The test of co-integration between the indices from the cash and the futures markets is the first step in the estimation of the GARCH-X model. In this article, co-integration tests are conducted by means of the Johansen multivariate method [Johansen (1988)].[11] For all three countries, significant co-integration is found between the cash price and both the futures prices.[12] In other words, all three cash prices have a long-run stationary relationship with each of the two counterpart futures prices.[13] Table III presents the error-correction terms obtained from the co-integration tests that are applied in the bivariate GARCH(1,1)-X models.[14]

Results from the bivariate GARCH(1,1)-X models are shown in Table IV.[15,16] Significant ARCH process is found in all cash and futures tests

[11]A detailed analysis of the Johansen method is provided in Harris (1995).

[12]Ghosh (1993) finds co-integration between indices of the cash and the futures stock markets of the United States.

[13]All six cointegration tests confirm one significant vector at 5% level or above. These results are not provided but are available on request. The lag length in the co-integration tests are chosen based on the AIC evidence.

[14]The error-correction terms are also tested for unit roots by means of an augmented Dickey–Fuller test. Results show that all six error-correction terms are stationary in levels. These results are available on request.

[15]All GARCH models are estimated by means of the Berndt, Hall, Hall, and Hausman (1974) algorithm, and all computations are done by means of computer package RATS version 4.10. Given a sample of T returns, the parameters of the bivariate system are estimated by computing the conditional log-likelihood function for each time period as

$$L_t(\theta) = -\log 2\pi - 1/2 \log|H_t(\theta)| - 1/2\varepsilon_t'(\theta)H_t'(\theta)\varepsilon_t(\theta) \tag{4}$$

$$L(\theta) = \sum_{t=1}^{1} L_t(\theta) \tag{5}$$

Table IV

Bivariate GARCH(1,1)-X Results

Parameter	*Australia First Index*	*Australia Second Index*	*Hong Kong First Index*	*Hong Kong Second Index*	*Japan First Index*	*Japan Second Index*
	-0.63×10^{4}	0.26×10^{4}	-4.4×10^{4}	-2.5×10^{-4}	-1.13×10^{-4}	-1.33×10^{-4}
μ_1	(−0.29)	(0.12)	(−0.38)	(−0.18)	(−0.45)	(−0.55)
	-0.08×10^{-4}	0.85×10^{-4}	3.5×10^{-4}	13.5×10^{-4}	0.65×10^{-4}	-0.64×10^{-4}
μ_2	(−0.03)	(0.31)	(0.42)	(1.38)	(0.19)	(−0.19)
	0.07×10^{-4c}	0.05×10^{-4}	2.3×10^{-4b}	3.4×10^{-4c}	0.43×10^{-4b}	-0.44×10^{-4b}
C_1	(1.66)	(0.77)	(2.23)	(1.90)	(2.23)	(−2.35)
	0.06×10^{-4}	0.04×10^{-4}	2.6×10^{-4a}	3.2×10^{-4a}	0.08×10^{-4}	-0.2×10^{-4}
C_2	(1.56)	(0.70)	(3.11)	(2.88)	(0.37)	(−1.23)
	0.1×10^{-4b}	0.04×10^{-4}	2.9×10^{-4b}	1.8×10^{-4b}	0.37×10^{-4}	0.13×10^{-4}
C_3	(2.05)	(0.73)	(2.23)	(2.06)	(1.31)	(0.74)
	0.120^{a}	0.155^{a}	0.076^{a}	0.204	0.191^{a}	0.180^{a}
A_{11}	(8.01)	(8.57)	(2.82)	(1.49)	(14.54)	(13.10)
	0.099^{a}	0.127^{a}	0.090^{a}	0.101	0.129^{a}	0.102^{a}
A_{22}	(8.06)	(8.57)	(2.46)	(1.09)	(12.46)	(9.94)
	0.120^{a}	0.162^{a}	0.088^{c}	0.157^{c}	0.127^{a}	0.096^{a}
A_{33}	(8.03)	(11.54)	(1.79)	(1.90)	(11.84)	(10.21)
	0.727^{a}	0.6875^{a}	0.540^{a}	0.364	0.765^{a}	0.778^{a}
B_{11}	(22.56)	(18.83)	(2.81)	(1.16)	(59.58)	(53.76)
	0.753^{a}	0.722^{a}	0.172	0.087	0.809^{a}	0.847^{a}
B_{22}	(26.99)	(23.96)	(0.66)	(0.34)	(77.54)	(70.68)
	0.709^{a}	0.690^{a}	0.251	0.597^{a}	0.825^{a}	0.871^{a}
B_{33}	(21.20)	(27.04)	(0.79)	(3.55)	(85.54)	(93.14)
$A_{11} + B_{11}$	0.847	0.840	0.616	0.568	0.956	0.958
$A_{33} + B_{33}$	0.829	0.852	0.339	0.754	0.952	0.967

Table IV (continued)

Bivariate GARCH(1,1)-X Results

Parameter	Australia First Index	Australia Second Index	Hong Kong First Index	Hong Kong Second Index	Japan First Index	Japan Second Index
	0.0004	0.0002	−0.031[c]	−0.008	0.0002[a]	0.00002[a]
D_{11}	(0.98)	(1.06)	(−1.84)	(−0.25)	(2.77)	(2.87)
	0.0005	0.0002	−0.006	−0.26	0.000007	0.00001[c]
D_{22}	(1.48)	(1.51)	(−0.30)	(−0.83)	(0.90)	(1.72)
	0.0001[a]	0.0004[a]	0.034	−0.001	−0.00009	−0.000001
D_{33}	(2.75)	(2.94)	(1.18)	(−0.07)	(−0.81)	(−0.22)
L	11791.19	11745.40	9889.02	9669.86	10819.43	10627.38
Cash Equations						
Sk	−0.08	−0.08	−0.55[a]	−0.55[a]	0.33[a]	0.33[a]
Ku	1.10[a]	1.10[a]	4.88[a]	4.88[a]	7.03[a]	7.03[a]
Q(24)	14.25	16.92	25.22	25.22	30.24	30.24
Futures Equations						
Sk	−0.13[c]	−0.07	−0.10	−0.10	0.18[a]	0.07
Ku	2.54[a]	8.35[a]	3.66[a]	3.21[a]	3.81[a]	3.77[a]
Q(24)	4.97	19.68	28.16	32.65	26.93	15.36

Notes: t statistics are in parentheses. L = log-likelihood; Sk = skewness of the residuals; Ku = kurtosis of the residuals. Q(24) = Box–Ljung statistics for serial correlation in the nonnormalized residuals of order 24.

[a]Significance at the 1% level.

[b]Significance at the 5% level.

[c]Significance at the 10% level.

residuals, except for the Hong Kong cash returns equation in the test involving the futures second index. Because the size of the ARCH parameters (A_{11} and A_{33}) are less than unity, the shocks to the conditional variance are not explosive. The covariance parameters (A_{22} and B_{22}) indicate a significant and positive interaction between the two prices in most cases. The persistence measure ($A_{11} + B_{11}, A_{33} + B_{33}$) indicates a high level of persistence in some of the markets. The Japanese markets show the highest persistence of shocks to volatility and the Hong Kong data show the least amount of persistence. For example, in the case of Japanese spot market in the first test, the half-life of the initial impact is reached in 17.15 days. In the Hong Kong and Australian spot market, the half-life is reached in 2.43 and 5.17 days, respectively.[17] The residuals are found to be leptokurtic in all tests and skewed in some tests. No serial correlation in the nonnormalized residuals is indicated by the Ljung–Box Q statistics. Further diagnostic tests of the residuals are conducted to check for the presence of higher-order ARCH effect.[18] Table V presents the Ljung–Box statistics for serial correlation in the standardized (normalized) residuals ($\varepsilon_{it}/H_{ijt}^{1/2}$) and standardized squared residuals ($\varepsilon_{it}^2/H_{ijt}$). In the case of Australia in both tests, there is no serial correlation between the standardized residuals and the standardized squared residuals, which implies that there is no need to encompass a higher-order ARCH process. Results from the Hong Kong tests indicate lack of serial correlation in all

where θ is the vector of all parameters. Numerical maximization of (4) and (5) following the Berndt et al. (1974) (BHHH) algorithm, yields the maximum-likelihood estimates and associated asymptotic standard errors. The following represents the RATS procedure of maximization of function (4) by means of BHHH. The RATS procedure calculates the gradient

$$l(\theta) = \sum_{t=1}^{T} \partial L_t(\theta)/\partial\theta \tag{6}$$

Given the current estimate of θ, the procedure searches for the updated estimate in the direction

$$d = Ml(\theta) \tag{7}$$

Berndt et al. (1974) choose M as $-I^{-1}$, where

$$J = \sum_{t=1}^{T} (\partial L_t'(\theta)/\partial\theta')(\partial L_t(\theta/\partial\theta) \tag{8}$$

More detailed analyses of the BHHH method in RATS computer package is provided in Doan (1992).

[16]Tests are also conducted with the use of the standard bivariate GARCH(1,1) model. Because the results obtained are quite standard, they are not provided, but are available on request. Also, in all six tests, a comparison of the log-likelihood function value shows higher-level performance by the bivariate GARCH(1,1)-X model as compared to the standard bivariate GARCH(1,1) model.

[17]Half-life measures the period of time (number of days) over which a shock to volatility reduces to half its original size and is given by $1-[\log 2/\log(A_{ij} + B_{ij})]$. The closer to unity is the value of persistence measure ($A_{ij} + B_{ij}$), the slower is the decay rate and longer is the half-life.

[18]See Giannopoulos (1995) for a detailed analysis of the higher-order ARCH process diagnostic tests.

Table V

Test for Higher-Order ARCH Effect

Series	Ljung–Box Tests	A1	A2	H1	H2	J1	J2
		Cash Equations					
$\varepsilon_{1,t}/(H_{11,t})^{1/2}$	Q(24)	21.55	28.58	25.58	24.07	24.57	24.54
$(\varepsilon_{1,t})^2/(H_{11,t})$	Q(24)	5.17	7.81	24.95	28.06	24.97	28.85
		Futures Equations					
$\varepsilon_{2,t}/(H_{22,t})^{1/2}$	Q(24)	15.43	24.26	24.24	25.01	25.93	15.58
$(\varepsilon_{2,t})^2/(H_{22,t})$	Q(24)	0.20	7.94	28.51	86.79[a]	35.26[b]	21.99

Notes: Q(24) are the Ljung-Box statistics of order 24. $\varepsilon_{i,t}/(H_{ij,t})^{1/2}$ = standardized residuals. $(\varepsilon_{i,t})^2/(H_{ij,t})$ = standardized squared residuals. A1 = Australia First Index, A2 = Australia Second Index, H1 = Hong Kong First Index, H2 = Hong Kong Second Index. J1 = Japan First Index, J2 = Japan Second Index.
[a]Significance at the 1% level.
[b]Significance at the 5% level.
[c]Significance at the 10% level.

four standardized residuals, but do indicate serial correlation in the standardized squared residuals of the futures equations in the second index test. In the case of Japan all four standardized residuals are found to be free of serial correlation. Only the standardized squared residual from the futures first index equation shows signs of the higher-order ARCH process. Thus, some evidence is found implying a possible higher-order ARCH process.

The parameters measuring the effects of the short-run deviations on the conditional variance (D_{11} and D_{33}) are mostly found to be positive and significant, though the effects are small in size (absolute value). As stated earlier, a positive and significant effect of the short-run deviations on the conditional variance implies that as the deviation between the cash and futures prices gets larger, the volatility of stock returns increases and prediction becomes more difficult. Only in the test with the Hong Kong futures second index were both parameters, D_{11} and D_{33}, found to be negative and insignificant. This study does not find both parameters (D_{11} and D_{33}) positive and significant at the same time in any one test. The parameter indicating the effect of the deviations on the conditional variance of the cash equations residuals (D_{11}) is positive and significant at the 1% level in both tests with the Japanese data. Short-run deviations between spot and futures prices fail to affect volatility from the Japanese futures markets. Similarly, parameter D_{33}, which indicates the affect of the deviations on the conditional variance of the residuals in the futures equations, is found to be positive and significant only in both the Australian tests. Thus, only volatility from the Australian futures markets is affected by the deviations. The parameter, D_{11}, in the Hong Kong cash equation in the futures first index test is found to be negative and significant (at the 10% level). Thus, an increase in the short-run deviation between cash and stock index futures prices reduces the volatility in the spot market of Hong Kong. The covariance between the cash and futures prices does not seem to be affected by the short-run deviations. In five out of six tests, D_{22} is insignificant; it is only significant (at the 10% level) and positive in the Japanese futures second index test. The size of the effect imposed by the deviations on the covariance is small.

CONCLUSION

This article investigates the returns volatility in the stock cash and stock index futures markets. The empirical work is conducted with the use of daily stock returns from the cash (spot) and the futures markets of Australia, Hong Kong, and Japan from 1990 to 1994, and by applying bivariate generalized ARCH (GARCH) models. An altered version of the GARCH model (GARCH-X) is applied to study the effects of the short-run deviations between the cash and the futures prices on the stock return volatility. Short-run deviations between the cash prices and the futures prices are indicated by the error-correction term from the co-integration tests between the two prices. A significant and positive effect of the deviation implies that as spot and futures prices move further apart in the short run, stock returns volatility increases. Results indicate significant volatility clustering in the stated markets, and strong interaction between the cash and futures markets. Some evidence of persistence of shocks to the volatility is also provided by the results. Results indicate a significant effect imposed by the deviations on the volatility in the stock cash and futures markets of all three countries. The study finds evidence of a significant positive effect of the deviation on the spot market volatility in the case of Japan and on the futures market volatility in the case of Australia. Thus, evidence is provided that along with shocks to stock returns in the spot and futures markets, short-run deviations between the spot and futures prices also affect volatility. This result implies that more precise forecasts of changes in stock prices may be obtained by including the short-run deviations between spot and futures prices. These results also indicate the need for similar research involving other countries.

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