Index Futures and Options and Stock Market Volatility

ANDREAS PERICLI
GREGORY KOUTMOS

INTRODUCTION

Derivative securities in general and index futures and options in particular have been blamed for excess volatility in the spot market. The popular belief is that derivatives encourage speculation, which destabilizes the spot market. The alleged destabilization takes the form of higher spot market volatility.[1] The stock market crash of 1987, the minicrash of 1989, and some recent highly publicized financial debacles have created the impression that derivatives threaten the stability of the international financial system.[2] Consequently, calls for tighter regulation and supervision of the derivatives industry are heard with higher frequency. Empirical research thus far has not produced any conclusive evidence as to the impact of derivative security trading on spot market volatility.

Schwert (1990) maintains that the growth in stock index futures and options trading has not increased volatility. Edwards (1988a, 1988b) finds that for the period 1973–1986, stock return volatility has not been higher since the advent of trading in index options and index futures. Temporary

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[1]Of course, speculation based on fundamentals is likely to be stabilizing rather than destabilizing. Destabilizing speculation may be the result of noise trading (i.e., buying and selling not on the basis of fundamentals). Feedback trading strategies also have the effect of increasing market volatility.

[2]The huge losses of Procter and Gamble, Orange County Metallgesellschaft, and Barrings, in deals involving derivatives, have created a great deal of controversy [e.g., Miller (1995) and Kuprianov (1995)].

- *Andreas Pericli is a Senior Economist with the Federal Home Loan Mortgage Corporation.*
- *Gregory Koutmos is an Associate Professor of Finance at Fairfield University.*

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increases in volatility were documented, however, during the simultaneous expiration of index futures and index options contracts, the so-called *triple witching days.* Other studies that find no significant changes in index return volatility following the introduction of futures include Kamara, Miller, and Siegel (1992), Baldauf and Santoni (1991), Becketti and Roberts (1990), Fortune (1989), and Darrat and Rahman (1995).[3]

Several studies, however, reach the exact opposite conclusion. For example, Maberly, Allen, and Gilbert (1989) conclude that volatility rose subsequent to the introduction of index futures. Brorsen (1991) finds that futures trading tends to reduce autocorrelations and increase the volatility of index stock returns. Harris (1989) reports statistically but not economically significant increases in volatility due to futures trading. Lee and Ohk (1992) find that, following the introduction of index futures, the volatility of stock returns in Australia, Hong Kong, Japan, the U.K., and the U.S. rose significantly. Antoniou and Holmes (1995) find that stock return volatility in the U.K. rose following the introduction of index futures.

From a theoretical standpoint, it is not clear why derivatives should or should not influence stock market volatility. It is possible that derivatives increase market liquidity by bringing more investors to the cash market. This should result in a less volatile cash market, unless derivatives attract mainly uninformed speculators who destabilize the market. Stein (1987) presents a model in which the introduction of futures markets improves risk sharing but can lower the informativeness of prices, resulting in destabilization and welfare reduction. Ross (1989), however, argues that in an arbitrage-free economy, the volatility of prices is directly related to the flow of information. Thus, if the derivatives market increases the flow of information, then the volatility in the cash market will rise [see also Antoniou and Holmes (1995)].

Because, theoretically, the volatility in the cash market can either rise or fall depending on the underlying assumptions, addressing the issue empirically is clearly an important task. So far most empirical studies have examined the impact of index futures and index options in a static framework, that is, by simply testing whether the unconditional variance rose subsequent to the introduction of index futures contracts [exceptions are the studies of Lee and Ohk (1992), Antoniou and Holmes (1995), and Baldauf and Santoni (1991)]. An extensive body of literature, however, has shown that individual and index stock returns are conditionally het-

[3]Studies that deal with the impact of futures trading in other markets include Figlewski (1981), Corgel and Gay (1984), Simpson and Ireland (1982) and Bhattacharya, Ramjee, and Ramjee (1986) for GNMA futures, and Powers (1970) for commodities futures.

eroskedastic; that is, the second moments are time dependent [see, for example, Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994), to mention but two]. As such, simply testing for changes in the unconditional variance is inadequate, if not misleading.

This article contributes to the ongoing debate regarding the impact of index futures and options on the volatility of the stock market. It follows closely Lee and Ohk (1992), Antoniou and Holmes (1995), and Baldauf and Santoni (1991) who model the well-known tendency of stock returns to exhibit volatility clustering (i.e., conditional heteroskedasticity) by using linear-ARCH type models, and tests for changes in both conditional and unconditional variances. Despite the similarities with the aforementioned studies, however, this article differs in several important ways. First, it examines the impact on both the conditional mean and the conditional variance of stock index returns in a unifying framework, rather than concentrating on the conditional variance alone. Second, it uses an expanded version of the nonlinear exponential GARCH model (EGARCH) to model the conditional variance. This model does not require parameter restrictions. Far from being simply a convenience, this feature is extremely important because it allows exogenous variables that enter the conditional variance to have either positive or negative influence. By contrast, linear ARCH models require nonnegativity constraints to ensure positive variances. Consequently, they cannot be used to investigate the impact of an exogenous variable whose direction of influence is not known a priori. Third, the EGARCH model accounts explicitly for the asymmetry in stock return volatility that has been documented in numerous recent studies [e.g., Nelson (1991), Koutmos and Booth (1995), Koutmos and Tucker (1995), Engle and Ng (1993), and Glosten, Jagannathan, and Runkle (1993)].[4] As pointed out by Engle and Ng, failure to model asymmetry leads to misspecification of the volatility process. For example, linear ARCH models tend to underpredict volatility associated with negative innovations. Thus, their usage in the past may have led to erroneous inferences regarding the role of derivatives on stock market volatility. Fourth, a more general probability density function which nests the normal along with several other densities is used. The reason is that the observed leptokurtosis in stock returns cannot be attributed solely to time-varying volatility. Assuming normality under these circumstances tends to produce downward-biased standard errors, thus leading to erroneous inferences [see Bollerslev, et al. (1992)]. Fifth, the sample

[4]This asymmetry has been attributed to the leverage effect, and it refers to the tendency of negative innovations (market declines) to be followed by higher volatility than positive innovations (market advances) of an equal magnitude.

size is more extensive than in any other related study. This larger sample should allow a much better assessment of the incremental impact of index futures and options on stock return volatility over and above possible structural changes that may have been induced by such factors as the change in the exchange rate regime, the introduction of currency and interest rate futures, the implementation of fully negotiated brokerage commission rates, and the introduction of individual stock options. Finally, the robustness of the empirical findings is assessed on the basis of several diagnostics, including some volatility specification tests proposed recently by Engle and Ng (1993).

The findings suggest that there have been significant structural changes in the distribution of stock returns in the period following the flexible exchange rate regime. Specifically, the sensitivity of the conditional variance to past errors (innovations) has been reduced, but the persistence has risen. It is not clear that these changes are due to the exchange-rate regime because this period coincides with the introduction of currency futures contracts and interest rate futures, the introduction of individual stock options, and the liberalization of brokerage commission rates. Consequently, the incremental impact of any of these factors cannot be assessed independently. Studies dealing with the influence of individual stock options suggest that the volatility of individual stock returns declines after options listing [e.g., Skinner (1989)]. Similarly, Conrad (1989) finds that the introduction of options on individual stocks causes a permanent increase in stock prices and a reduction in excess return volatility. Regarding index options, Chatrath, Ramchander, and Song (1995) report that index options trading has a stabilizing influence on index returns. The impact of foreign exchange volatility on stock returns is by no means apparent. Fortune (1989) argues that exchange rate volatility can impact stock returns by influencing net foreign demand for domestic equities. This can happen if foreign interest rates change relative to domestic interest rates, or if perceptions about foreign exchange risk change as a result of rising exchange rate volatility. Finally, the liberalization of brokerage commissions, according to Brorsen (1991) reduced market frictions and increased volatility.

Irrespective of the contribution of each one of these factors on the shift of the conditional variance, the evidence is unambiguous that the introduction of index futures and index options in the early 1980s caused no further shift in the volatility of index stock returns. Furthermore, the analysis of the weekly returns shows no evidence of structural shifts in volatility over the entire sample period. These findings are important because proponents of restrictions on index futures trading maintain that they increase volatility and hence the cost of capital. The evidence that conditional and unconditional volatility has not changed in the postfutures period suggests that these arguments lack merit.

The remainder of this article is organized as follows: The next section outlines an expanded exponential GARCH model (EGARCH) that is used to test whether the volatility of stock returns changed in the period following the introduction of index futures and options. Section III discusses the data and the main empirical results. Section IV concludes the article.

THE MODEL

Let R_t be the continuously compounded return on the stock index at time, t; μ_t and σ_t are the conditional mean and the conditional standard deviation, respectively; and I_{t-1} is the conditioning information set as of time $t - 1$. The expanded EGARCH model can then be described by the following set of equations:

$$R_t|I_{t-1} \sim f(\mu_t, \sigma_t, v) \tag{1}$$

$$\mu_t = \beta_0 + \beta_{0,C}\mathrm{DC}_t + \beta_{0,E}\mathrm{DE}_t + \beta_{0,F}\mathrm{DF}_t + \sum_{i=1}^{k} \beta_i R_{t-t},$$

$$\text{for i} = 1,2, \ldots, k \tag{2}$$

$$\begin{aligned}\sigma_t^2 = \exp\{&\alpha_0 + \alpha_{0,C}\mathrm{DC}_t + \alpha_{0,E}\mathrm{DE}_t + \alpha_{0,F}\mathrm{DF}_t \\ &+ (\alpha_1 + \alpha_{1,E}\mathrm{DE}_t + \alpha_{1,F}\mathrm{DF}_t)\, g(z_{t-1}) \\ &+ (\phi_1 + \phi_{1,E}\mathrm{DF}_t + \phi_{1,F}\mathrm{DF}_t)\ln(\sigma_{t-1}^2)\}\end{aligned} \tag{3}$$

$$g(z_{t-1}) = |z_{t-1}| - E(|z_{t-1}|) + \delta z_{t-1}, \tag{4}$$

where $f(\cdot)$ denotes the conditional probability density function with time-dependent conditional mean and conditional standard deviation, μ_t and σ_t, respectively; $z_t \equiv \varepsilon_t/\sigma_t$ is the standardized innovation at t, where $\varepsilon_t = R_t - \mu_t$. The variables DC_t, DE_t, and DF_t are dummies representing the October 1987 crash period, the flexible exchange rate period, and the post-index futures/index options period, respectively.[5] They are used to

[5]The variables DC_t, DE_t, and DF_t are dummies for the period surrounding the crash of 1987, the period following the flexible-exchange-rate regime and the period following the introduction of index futures and index options, respectively. They are defined as follows: (a) For the daily returns: DC_t takes the value of 1 for the period 10/5/87–10/26/87, and zero otherwise. DE_t takes the value of 1 for the period 4/26/73–4/20/82, and zero otherwise. DF_t takes the value of 1 for the period 4/21/82–9/9/94, and zero otherwise. (b) For the weekly returns: DC_t takes the value of 1 for the period 10/2/87–10/23/87, and zero otherwise. DE_t takes the value of 1 for the period 4/27/73–4/16/82, and zero otherwise. DF_t takes the value of 1 for the period 4/23/82–9/2/94, and zero otherwise.

test for structural changes in the first and second moments of the conditional distribution of returns. The conditional mean return, given by (2), is a function of the three structural dummies and past returns. The autocorrelation of index returns has been well documented in the literature. The cause has been attributed to problems associated with nonsynchronous trading of the stocks that make up the index [e.g., Scholes and Williams (1977)] or to time-varying expected returns [e.g., Fama and French (1988) and Conrad and Kaul (1988)]. The unconditional mean implied by (2) is

$$\mu = (\beta_0 + \beta_{0,C}\mathrm{DC}_t + \beta_{0,E}\mathrm{DE}_t + \beta_{0,F}\mathrm{DF}_t)\bigg/\left(1 - \sum_{i=1}^{k} \beta_i\right),$$

$$\text{for } i = 1,2,\ldots,k \tag{5}$$

The volatility of the error term in eq. (2) follows an exponential GARCH process (EGARCH) [e.g., Nelson (1991)], whereby the conditional variance at time t is a nonlinear function of its own past values as well as past standardized innovations. Modeling the natural logarithm of the variance eliminates the need to impose parameter restrictions. As mentioned earlier, this feature of the model makes it an ideal vehicle for the purpose of testing the impact of the introduction of index futures and options without imposing a priori restrictions. Another important feature of the model is the asymmetric function, $g(z_{t-1})$, of past standardized residuals. This function allows the conditional variance to respond asymmetrically to positive and negative values of z_{t-1}. The term $|z_{t-1}| - E(|z_{t-1}|)$ measures the size effect and the term δz_{t-1} measures the sign effect.[6] If the past absolute z_{t-1} is greater than its expected value, then current volatility will rise (size effect). If δ is negative, then a negative realization of z_{t-1} will increase volatility by more than a positive realization of an equal magnitude (sign effect). The degree of asymmetry can be measured by the absolute value of the ratio $(-1 + \delta)/(1 + \delta)$.[7] Several studies provide evidence of such an asymmetric response [e.g., Black (1976), Christie (1982), Nelson (1991), and Koutmos and Booth (1995), to mention but a few]. The terms $\alpha_{1,E}\mathrm{DE}_t$ and $\alpha_{1,F}\mathrm{DF}_t$, are designed to measure whether the sensitivity of the conditional variance to past in-

[6]Linear ARCH models can be modified to incorporate asymmetry [see Engle and Ng (1993)]. However, they cannot dispense with the nonnegativity constraints. Ignoring them could lead to serious problems. For example, Lee and Ohk (1992) use a linear GARCH and report convergence problems. It is likely that these problems are due to violations of the nonnegativity constraints.

[7]This measure is based on the fact that the slope of $g(z_{t-1})$ is equal to $-1 + \delta$ for negative values of z_{t-1} and $1 + \delta$ for positive values of δ [see Nelson (1991), Koutmos and Booth (1995), and Koutmos and Tucker (1995)].

novations has changed in the post-flexible-exchange-rate and post-futures periods. If $\alpha_{1,E}$ and $\alpha_{1,F}$ are statistically zero then no change has taken place. Similarly, $\phi_{1,E}\mathrm{DE}_t$ and $\phi_{1,F}\mathrm{DF}_t$ are designed to capture any changes that may have occurred in the persistence of the conditional variance in the periods following the introduction of stock options, index futures, and index options. The log of the unconditional variance implied by (3) is given by

$$\ln(\sigma^2) = (\alpha_0 + \alpha_{0,C}\mathrm{DC}_t + \alpha_{0,E}\mathrm{DE}_t + \alpha_{0,F}\mathrm{DF}_t)/ \\ (1 - \phi_1 - \phi_{1,E}\mathrm{DE}_t - \phi_{1,F}\mathrm{DF}_t). \tag{6}$$

Estimation of the expanded EGARCH-M model requires the adoption of some density function for the error, ε_t. The most commonly used density function is the normal [e.g., Engle, (1982), Kroner, Kneafsey, and Claessens (1995), and Campbell and Hentschel (1992)]. However, empirical evidence shows that accounting for second moment dependencies is not sufficient to remove the fat tails from the empirical distribution of index stock returns. Consequently, several authors use leptokurtic distributions such as the Student-*t* distribution [for example, Bollerslev (1987), Baillie and Bollerslev (1989), Akgiray and Booth (1990)], and the generalized error distribution (GED) [e.g., Nelson (1991), Booth, Hatem, Virtanen, and Ylli-Olli (1992), and Theodossiou (1994)]. This article employs the GED because of its ability to accommodate fatter tails and peakedness. The density function of the GED, also known as the power exponential distribution, is as follows:

$$f(\mu_t, \sigma_t, v) = v/2\ [\Gamma(3/v)]^{1/2}\ [\Gamma(1/v)]^{-3/2}(1/\sigma_t) \\ \exp\{-\ [\Gamma(3/v)/\Gamma(1/v)]^{v/2}\ |\varepsilon_t/\sigma_t|^v\}. \tag{7}$$

where $\Gamma(\cdot)$ is the gamma function and v is a scale parameter controlling the shape of the GED distribution, to be estimated endogenously.[8] Estimates for the parameter vector Θ are obtained by maximizing the sample log-likelihood function

$$L(\Theta) = \sum_{T=1}^{T} \ln f(\mu_t, \sigma_t, v) \tag{8}$$

[8]The GED is quite general in the sense that it nests several other density functions. For example, if $v = 2$, the GED distribution reduces to

$$f(\mu_t, \sigma_t) = (2\pi\sigma_t^2)^{-1/2} \exp(-\varepsilon_t^2/2\sigma_t^2),$$

which is the normal density. For $v = 1$ the GED yields the double exponential or Laplace distribution, and for $v \to \infty$ it yields the uniform or rectangular distribution.

which is highly nonlinear in the parameters. The maximization is based on the Berndt, Hall, Hall, and Hausman (1974) algorithm. The order, k, of the autoregressive process in (1) is decided on the basis of log-likelihood ratio tests. Also, several residual-based diagnostic tests are performed to assess the robustness of the final models.

DATA AND EMPIRICAL FINDINGS

The data used are the daily closing prices for the S&P 500 index. The sample period extends from January 2, 1953 to September 9, 1994 for a total of 10,499 observations. For the period 1/2/1953–1961/12/31 the primary source is S&P 500 Inc., and for the rest of the sample period the source is the Center for Research in Security Prices (CRSP). Daily continuously compounded returns are calculated as $R_t = 100{*}\log(P_t/P_{t-1})$, where R_t and P_t are the daily returns and daily prices, respectively.[9] Weekly returns are also calculated with the use of Friday's closing price. The number of observations for daily returns and weekly returns are 10,498 and 2,174, respectively.

Table I presents some preliminary statistics for the daily and the weekly return series for the entire sample period and the three subperiods. The preliminary evidence suggests that (a) stock returns are not normally distributed, (b) there are linear and nonlinear intertemporal dependencies, and (c) the unconditional first and second moments are unstable across subperiods.[10] The instability of the unconditional moments and the presence of intertemporal dependencies suggest that the impact of index futures and options on the volatility of the returns has to be investigated in the context of the conditional distribution so that the regularities of the first and second moments can be accounted for.

Table II reports the maximum-likelihood estimates of the model for the daily returns. During the crash of 1987 the unconditional mean fell substantially, as can be seen form the sign and size of $\beta_{0,C}$. The constant in the conditional mean equation is statistically significant at the .05 level.[11] The coefficient of the dummy for the flexible exchange rate period, DE_t, is negative and statistically significant, suggesting that the unconditional mean of the daily returns decreased. In the period following

[9]Strictly speaking, R_t is the daily capital gains yield, because the S&P 500 index does not include dividend distributions.

[10]Kamara et al. (1992) report that ". . . the distribution of daily returns could be frequently (and non-event induced) changing".

[11]All hypotheses testing is done at the .05 level of significance. Unless otherwise noted, the null hypothesis is that the true coefficient is zero and the alternative is that the true coefficient is different than zero.

TABLE I

Preliminary Statistics

	Panel A: Daily Returns			
	Subperiod 1 *1/5/53–4/25/73* *(n = 5,095)*	*Subperiod 2* *4/26/73–4/20/82* *(n = 2,270)*	*Subperiod 3* *4/21/82–9/9/94* *(n = 3,133)*	*Full Sample* *1/5/53–9/9/94* *(n = 10,498)*
μ	0.2073*	0.0014	0.0455*	0.0273*
σ	0.7008	0.9264	1.0127	0.8571
σ (w/o crash)			0.8852	0.8108
S	−0.3971*	0.1285*	−3.8558*	−1.9893*
K	8.5862*	1.3450*	89.2116*	55.0623*
D	0.0609*	0.0334*	0.0782*	0.0635*
LB(12)	115.6245*	87.3726*	29.4733*	144.8716*
$LB^2(12)$	761.2607*	605.5249*	197.2398*	707.5089*
	Panel B: Weekly Returns			
	Subperiod 1 *1/5/53–4/19/73* *(n = 1,059)*	*Subperiod 2* *4/27/73–4/16/82* *(n = 469)*	*Subperiod 3* *4/23/82–9/2/94* *(n = 646)*	*Full Sample* *1/9/53–9/2/94* *(n = 2,174)*
μ	0.1338*	0.0058	0.2214*	0.1330*
σ	1.5810	2.3234	2.0410	1.9041
σ (w/o crash)			1.9300	1.8689
S	−0.3648	0.0119	−0.5878*	−0.3271*
K	1.3489*	2.7197*	4.3660*	3.5734*
D	0.0468	0.0503	0.0635*	0.0422*
LB(12)	24.2356*	55.0679*	16.0527	26.4343*
$LB^2(12)$	198.9195*	207.9594*	130.9161*	625.3845*

Notes: μ, σ, S and K are the sample mean, standard deviation, skewness and excess kurtosis, respectively. D is the Kolmogorov–Smirnov statistic testing for normality; sample critical values are equal to $1.36/\sqrt{n}$, where n is the number of observations. LB(12) and $LB^2(12)$, the Ljung–Box statistics for the returns and the squared returns, respectively, test the hypothesis that all autocorrelations up to the twelfth lag are statistically zero; and 5% critical value is 21.026. σ(w/o crash) is the standard deviation without the crash.
*Denotes significance at the 5% level.

the introduction of index futures and index options the first moment of the distribution of returns did not change, because $\beta_{0,F}$ is statistically insignificant. Past returns, up to the second lag, are significant determinants of today's returns. Time variation in expected returns and/or nonsynchronous trading are probably responsible for the autocorrelation. The shape of the distribution of the estimated residuals is still leptokurtic, as can be seen from the estimated value of the scale parameter, v. A simple t test rejects the hypothesis that $v = 2$, the value required for normality.

The focus of this investigation is the behavior of the conditional variance and the structural changes that may have occurred in the periods following the introduction of index futures and index options. The esti-

TABLE II

Maximum-Likelihood Estimates for Daily Returns. Estimation Period 1/7/53–9/9/94 ($n = 10{,}496$)

	Conditional Mean Equation			*Conditional Variance Equation*	
	Coefficients	*Standard Error*		*Coefficient*	*Standard Error*
β_0	0.0439	0.0074*	α_0	−0.0719	0.0095*
$\beta_{0,C}$	−0.9538	0.4480*	$\alpha_{0,C}$	0.2807	0.0203*
$\beta_{0,E}$	−0.0381	0.0173*	$\alpha_{0,E}$	0.0675	0.0098*
$\beta_{0,F}$	0.0223	0.0203	$\alpha_{0,F}$	−0.0023	0.0030
β_1	0.1317	0.0095*	α_1	0.2613	0.0159*
β_2	−0.0380	0.0096*	$\alpha_{1,E}$	0.1668	0.0221*
v	1.3661	0.0163*	$\alpha_{1,F}$	−0.0116	0.0195
			ϕ_1	0.9291	0.0084*
			$\phi_{1,E}$	0.0608	0.0094*
			$\phi_{1,F}$	−0.0062	0.0051
			δ	−0.3795	0.0349*

Model-Implied Unconditional Standard Deviations

Subperiod 1 (1/5/53–4/25/73)	*Subperiod 2 (4/26/73–4/20/82)*	*Subperiod 3 (4/21/82–9/9/94)*
0.6022	0.8042	0.8141

Residual-Based Diagnostics

$E(z_t)$	$E(z_t^2)$	LB(12)	LB^2(12)	D
−0.0112	1.0074	17.0174	15.5465	0.0163

Sign Bias (t test)	*Negative Size Bias (t test)*	*Positive Sign Bias (t test)*	*Joint Test (F test; F[3,10492])*
0.1168	1.3303	0.3648	0.8558

Notes: z_t are the model standardized residuals. The unconditional standard deviations exclude the impact of the 1987 crash. *D* is Kolmogorov–Smirnov statistic testing the GED with the estimated scale parameter. The sample critical value at the 5% level is $1.36/\sqrt{n}$, where *n* is the number of observations.
*Denotes significance at the 5% level.

mated coefficients for the conditional variance show that it is clearly time dependent. Specifically, volatility at time t depends on the last period's standardized residuals and last period's conditional variance. As expected, δ is negative and statistically different from zero, indicating that market declines are associated with greater volatility than market advances. If one uses the measure of the degree of asymmetry, discussed in Section II, it can be said that a negative standardized innovation (bad news) increases volatility 2.2231 times more than a positive standardized innovation (good news) of an equal magnitude.[12] Ignoring this important property of stock return volatility can lead to erroneous conclusions regarding the impact of such exogenous factors as the introduction of index futures and options.

The degree of persistence, measured by ϕ_1, is quite high. Ignoring the impact of the dummy variables, the half-life of a shock, measured as $\log(0.5)/\log(\phi_1)$, is equal to 9.4296 days, implying that it takes approximately 4 weeks for a shock to die out. There is evidence of structural changes in the volatility process in the post-flexible-exchange-rate period. Specifically, the intercept in the conditional variance function becomes higher (-0.0044 vs. -0.0719), the sensitivity of the conditional variance to past innovations becomes lower (0.0945 vs. 0.2613), and the persistence becomes higher (0.9899 vs. 0.9291).[13] The implication of this change is that volatility is less sensitive to past news or, to put it differently, news today has a lower weight in the formation of tomorrow's volatility forecast.

Because most of the blame about spot market volatility has been placed on index futures, it is interesting to note that no structural change has occurred in the conditional variance in the period following the introduction of index futures and options. The coefficients $\alpha_{0,F}$, $\alpha_{1,F}$, and $\phi_{1,F}$, which test for changes in the intercept, the sensitivity to past innovations, and the persistence of shocks, respectively, are statistically insignificant. It can, therefore, be concluded that the introduction of index futures and options has had no incremental impact on volatility. This conclusion is in agreement with studies that deal with the U.S. stock market [e.g., Miller (1993), Baldauf and Santoni (1991) and Edwards (1988a, 1988b)], and is in contrast to the findings of Antoniou and Holmes (1995) for the U.K. market, and Lee and Ohk (1992) for an international portfolio composed of five national indices.

The unconditional standard deviations based on eq. (6) and excluding the impact of the 1987 market crash are reported for the three subperiods (fixed-exchange-rate period, flexible-exchange-rate but pre-index-futures period, and post-index-futures and options period). For the period 1/5/53–4/25/73 the unconditional standard deviation is 0.6022. For the period 4/26/73–4/20/82 the unconditional standard deviation rises to

[12]Similar degrees of asymmetry are reported by other studies dealing with the U.S. stock market, for example, Nelson (1991), Engle and Ng (1993), and Koutmos and Tucker (1995).

[13]Note that in the period following the introduction of flexible exchange rates but before the introduction of index futures, the parameters measuring the intercept, the slope with respect to z_{t-1} and the slope with respect to $\ln(\sigma^2_{t-1})$ are given by $(\alpha_0 + \alpha_{0,E})$, $(\alpha_1 + \alpha_{1,E})$ and $(\phi_1 + \phi_{1,E})$, respectively. Similarly, in the post-index futures period these coefficients become $(\alpha_0 + \alpha_{0,E} + \alpha_{0,F}\mathrm{DF}_t)$, $(\alpha_1 + \alpha_{1,E} + \alpha_{1,F})$ and $(\phi_1 + \phi_{1,E} + \phi_{1,F})$, respectively.

0.8042. As mentioned earlier, during this period several potentially important developments took place. Specifically, the Bretton Woods fixed exchange rate system was abandoned, futures contracts on currencies and interest rates and individual stock options were introduced, and, finally, broker's commission rates became fully negotiated. It is not possible, given the framework of analysis adopted here, to evaluate the impact of each one of these factors on stock return volatility.[14] Perhaps the most interesting finding is that, in the post-futures period the parameters describing the unconditional and the conditional variance remain unchanged. The implication is that index futures and options did not contribute to any incremental change in the volatility process, apart from the impact of the 1987 crash.[15] Of course there is still a possibility that the introduction of index futures and options increased volatility, but this increase was offset by other factors.[16] Existing studies, however, suggest that this is probably not the case. For example, Bessembinder and Seguin (1992) find that predictable trading activity in futures actually reduces volatility in the stock market. Kamara, Miller, and Siegel (1992) and Darrat and Rahman (1995) find that monthly macroeconomic risk factors, such as those used by Chen, Roll, and Ross (1986), do not influence the conditional variance of stock returns. Similar findings are reported by Fortune (1989). Furthermore, Ferguson (1989) argues that if futures trading were responsible for the 1987 crash, then the decline in S&P 500 stocks should have been higher than that of non–S&P 500 stocks. Because there was no difference between these two groups it must be that futures trading had no impact on the severity of the decline.

The estimates of the model with the use of weekly data are reported in Table III. The weekly returns are not autocorrelated, and the estimated value for the scale parameter, v, is closer to 2, which implies that at lower frequencies stock returns are closer to being normally distributed. The conditional variance is still a function of past standardized innovations and past variances. The weekly variance responds asymmetrically to past innovations in the sense that returns are more volatile during down markets. There is no evidence of any significant structural change in the conditional variance process over the entire sample period. All coefficients related to the structural dummy variables are statistically insignif-

[14]The impact of the 1974 oil embargo, as well as the impact of the change of the Fed's operating procedures on return volatility, are tested with the use of additional structural dummies. The results are virtually unchanged.

[15]If the October 1987 dummy is included the unconditional variance becomes extremely high. However, by most accounts, the crash of 1987 cannot be attributed to the trading of index futures and options [see Miller (1993) and references therein].

[16]This possibility was suggested by an anonymous reviewer.

TABLE III

Maximum-Likelihood Estimates for Weekly Returns. Estimation Period 1/30/53–9/9/94 ($n = 2{,}172$)

	Conditional Mean Equation			*Conditional Variance Equation*	
	Coefficients	*Standard Error*		*Coefficient*	*Standard Error*
β_0	0.1808	0.0441*	α_0	0.0913	0.0289*
$\beta_{0,C}$	−4.3791	1.1419*	$\alpha_{0,C}$	0.4778	0.2262*
$\beta_{0,E}$	−0.2179	0.1012*	$\alpha_{0,E}$	0.0068	0.0557
$\beta_{0,F}$	0.2347	0.1153*	$\alpha_{0,F}$	−0.0557	0.0512
β_1	0.0337	0.0233	α_1	0.2518	0.0523*
β_2	0.0348	0.226	$\alpha_{1,E}$	−0.0660	0.0736
v	1.7607	0.0703*	$\alpha_{1,F}$	−0.0791	0.0687
			ϕ_1	0.8741	0.0359*
			$\phi_{1,E}$	0.0614	0.0483
			$\phi_{1,F}$	0.0278	0.0360
			δ	−0.5787	0.1242*

Model-Implied Unconditional Standard Deviations

Subperiod 1 (1/5/53–4/19/73)	*Subperiod 2 (4/27/73–4/16/82)*	*Subperiod 3 (4/23/82–9/2/94)*
1.4370	2.1392	1.7818

Residual-Based Diagnostics

$E(z_t)$	$E(z_t^2)$	$LB(12)$	$LB^2(12)$	D
−0.0111	1.0025	6.4100	3.3545	0.0153

Sign Bias (t test)	*Negative Size Bias (t test)*	*Positive Sign Bias (t test)*	*Joint Test (F test; F[3,2168])*
0.4937	−0.1158	−0.5770	0.1449

Notes: z_t are the model standardized residuals. The unconditional standard deviations exclude the impact of the 1987 crash. D is the Kolmogorov–Smirnov statistic testing the GED with the estimated scale parameter. The Sample critical value at the 5% level is $1.36/\sqrt{n}$, where n is the number of observations.
*Denotes significance at the 5% level.

icant. The absence of any structural change in the weekly stock returns suggests that point estimates are sensitive to the frequency over which returns are observed. The reported unconditional variance estimates, excluding the crash of 1987, show that the unconditional variance rose in the second subperiod and fell in the third subperiod. However, these changes are not statistically significant, because the hypothesis that the structural coefficients are statistically zero cannot be rejected.

The validity of the empirical findings depends on the correct specification of the model. At a minimum, the estimated standardized residuals from the expanded EGARCH model should (a) obey the assumed distribution with the estimated scale parameter or degrees of freedom, (b) have zero mean and unit variance, and (c) exhibit neither linear nor nonlinear dependencies. The appropriateness of the density function used is tested on the basis of the Kolmogorov–Smirnov *D* statistic, where the null hypothesis now is that the estimated standardized residuals are i.i.d. and follow the generalized error distribution (GED) with the estimated degrees of freedom, v. As can be seen from both the daily and weekly returns (Tables II and III), the estimated D statistics are below their critical values, so that the assumed density function is not rejected. The means and variances of the standardized residuals fulfill the requirement of zero mean and unit variance. Linear and nonlinear independence is tested by means of the Ljung–Box statistic. The calculated LB values show that the standardized residuals, ε_t/σ_t, are uncorrelated up to 12 lags. Likewise, the squared standardized residuals, $(\varepsilon_t/\sigma_t)^2$, follow i.i.d. processes, as can be seen from the insignificant values of the LB statistics. This provides evidence that the volatility process is correctly specified. The LB statistic, however, does not provide any indication as to how well the model captures the impact of positive and negative innovations on volatility. For this purpose some diagnostics proposed recently by Engle and Ng (1993) are used. These tests are based on the news impact curve implied by the particular ARCH-type model used. The premise is that if the volatility process is correctly specified, then the squared standardized residuals should not be predictable on the basis of observed variables. These tests are (a) the sign bias test, (b) the negative size bias test, and (c) the positive size bias test.[17] For both the daily and weekly returns the estimated *t* statistics and *F* statistics are statistically insignificant, which implies that the squared standardized residuals cannot be predicted by using observed variables. On the basis of the various diagnostics performed, it can be said that the expanded EGARCH model along with the GED captures the second moment dynamics of both daily and weekly returns quite well.

[17]The sign bias test examines the impact of positive and negative innovations on volatility not predicted by the model. The squared standardized residuals are regressed against a constant and a dummy S_t^- that takes the value of unity if ε_{t-1} is negative and zero otherwise. The test is based on the *t* statistic for S_t^-. The negative size bias test examines how well the model captures the impact of large and small negative innovations. It is based on the regression of the squared standardized residuals against a constant and $S_t^- \varepsilon_{t-1}$. The calculated *t* statistic for $S_t^- \varepsilon_{t-1}$ is used in this test. The positive size bias test examines possible biases associated with large and small positive innovations. Here, the squared standardized residuals are regressed against a constant and $(1 - S_t^-)\varepsilon_{t-1}$. Again, the *t* statistic for $(1 - S_t^-)\varepsilon_{t-1}$ is used to test for possible biases. A joint *F* test can also be used, even though the individual tests are more powerful [see Engle and Ng (1993)].

SUMMARY AND CONCLUDING REMARKS

This article examines the impact of index futures and options contracts on the volatility of the spot market. In the period following the flexible-exchange-rate regime, which coincides with the deregulation of broker's commissions, the introduction of currency and interest rate futures contracts, and the introduction of individual stock options, the unconditional variance of daily index stock returns rose significantly. At the same time, the conditional variance of the daily returns became less sensitive to innovations (news) and more predictable, because the persistence rose substantially. The implication is that today's news has become less important in the formation of tomorrow's volatility forecasts. Because of the many important developments that took place over this period, their impact on stock return volatility cannot be assessed independently. There is, however, unambiguous evidence that the introduction of index futures and index options produced no further structural changes on either the conditional or the unconditional variance, apart from the impact of the October 1987 stock market crash. In fact, for the weekly returns, the unconditional variance appears to have been reduced in the post-futures period, even though the reduction is statistically insignificant. Consequently, calls for tightening regulation of index futures on the basis that they increase stock market volatility are unwarranted.

The robustness of the empirical findings is tested on the basis of an array of diagnostics performed on the estimated standardized residuals. All tests fail to produce any evidence of misspecification.

BIBLIOGRAPHY

Akgiray, V., and Booth, G. G. (1990): "Modeling the Stochastic Behavior of Canadian Foreign Exchange Rates," *Journal of Multinational Financial Management,* 1:43–71.

Antoniou, A., and Holmes, P. (1995): "Futures Trading and Spot Price Volatility: Evidence for the FTSE-100 Stock Index Futures Contract Using GARCH," *Journal of Banking and Finance,* 19:117–129.

Baillie, R. T., and Bollerslev, T. (1989): "The Message in Daily Exchange Rates: A Conditional Variance Tale," *Journal of Business and Economic Statistics,* 7:297–305.

Baldauf, B., and Santoni, G. J. (1991): "Stock Price Volatility: Some Evidence from an ARCH Model," *Journal of Futures Markets,* 11(2):191–200.

Becketti, S., and Roberts, D. J., (November/December 1990): "Will Increased Regulation of Stock Index Futures Reduce Stock Market Volatility?" Federal Reserve Bank of Kansas City, pp. 33–46.

Berndt, E. K., Hall, H. B., Hall, R. E., and Hausman, J. A. (1974): "Estimation and Inference in Nonlinear Structural Models," *Annals of Economic and Social Measurement,* 4:653–666.

Bessembinder, H., and Seguin, P. J. (1992): "Futures Trading Activity and Stock Price Volatility," *The Journal of Finance,* 47:2015–2034.

Bhattacharya, A. K., Ramjee, A., and Ramjee, B. (1986): "The Causal Relationship between Futures Price Volatility and the Cash Price Volatility of GNMA Securities," *The Journal of Futures Markets,* 6:29–39.

Black, F. (1976): "Studies of Stock Market Volatility Changes," in *Proceedings of the American Statistical Association, Business and Economics Studies Section,* pp. 77–181.

Bollerslev, T. (1987): "A Conditional Heteroskedastic Time Series Model for Speculative Prices and Rates of Return," *Review of Economics and Statistics,* 69:542–547.

Bollerslev, T., Chou, R. Y., and Kroner, K. F. (1992): "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence," *Journal of Econometrics,* 52:5–59.

Bollerslev, T., Engle, R. F., and Nelson, D. (1994): "ARCH Models," in R. F. Engle and D. L. McFadden (eds.), *Handbook of Econometrics* (Vol. IV, Chap. 49), Elsevier Science B.V.

Booth, G. G., Hatem, J. J., Virtanen, I., and Ylli-Olli, P. (1992): "Stochastic Modelling of Security Returns: Evidence from the Helsinki Stock Exchange," *European Journal of Operational Research,* 56:98–106.

Brorsen, W. B. (1991): "Futures Trading, Transactions Costs and Stock Market Volatility," *Journal of Futures Markets,* 11(2):153–163.

Campbell, J. Y., and Hentschel, L. (1992): "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns," *Journal of Financial Economics,* 31:281–318.

Chatrath, A., Ramchander, S., and Song, F. (1995): "Does Options Trading Lead to Greater Cash Market Volatility?" *The Journal of Futures Market,* 15:785–803.

Chen, N. F., Roll, R., and Ross, S. A. (1986): "Economic Forces and the Stock Market," *Journal of Business,* 59:383–403.

Christie, A. A. (1982): "The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects," *Journal of Financial Economics,* 10:407–432.

Conrad, J. (1989): "The Price Effects of Option Introduction," *Journal of Finance,* 44:487–498.

Conrad, J., and Kaul, G. (1988): "Time-Variation in Expected Returns," *Journal of Business,* 61:409–425.

Corgel, J. B., and Gay, G. D. (1984): "The Impact of GNMA Futures Trading on Cash Market Volatility." *AREUEA Journal,* 12, 176–190.

Darrat, A. F., and Rahman, S. (1995): "Has Futures Trading Activity Caused Stock Price Volatility?" *The Journal of Futures Markets,* 15:537–557.

Edwards, F. R. (January/February 1988a): "Does Futures Trading Increase Stock Market Volatility?," *Financial Analysts Journal,* 63–69.

Edwards, F. R. (1988b): "Futures Trading and Cash Market Volatility: Stock Index and Interest Rate Futures," *The Journal of Futures Markets,* 8(4):421–439.

Engle, R. F., and Ng, V. K. (1993): "Measuring and Testing the Impact of News on Volatility," *Journal of Finance,* 48:1749–1778.

Engle, R. F. (1982): "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica,* 50:987–1008.

Fama, E. F., and French, K. R. (1988): "Permanent and Transitory Components of Stock Prices," *Journal of Political Economy,* 96:246–273.

Ferguson, R. (1989): "On Crashes," *Financial Analysts Journal,* March-April 1989.

Figlewski, S. (1981): "Futures Trading and Volatility in the GNMA Market," *Journal of Finance,* 36:445–456.

Fortune, P. (November/December 1989): "An Assessment of Financial Market Volatility: Bills, Bonds, and Stocks," *New England Economic Review,* 13–27.

Glosten, L. R., Jagannathan, R., and 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.

Harris, L. (1989): "S&P 500 Cash Stock Price Volatilities," *Journal of Finance,* 44:1155–1175.

Kamara, A., Miller, T. W., and Siegel, A. F. (1992): "The Effect of Futures Trading on the Stability of Standard and Poor 500 Returns," *Journal of Futures Markets,* 12(6):645–658.

Koutmos, G., and Booth, G. G. (1995): "Asymmetric Volatility Transmission in International Stock Markets," *Journal of International Money and Finance,* 14(6):747–762.

Koutmos, G., and Tucker, M., (1995): "Temporal Dependencies and Dynamic Interactions Between Spot and Futures Stock Markets," *The Journal of Futures Markets,* 16:55–69.

Kroner, K. F., Kneafsey, K. P., and Claessens, S. (1995): "Forecasting Volatility in Commodity Markets," *Journal of Forecasting,* 14:77–95.

Kuprianov, A. (Fall 1995): "Derivatives Debacles: Case Studies of Large Losses in Derivatives Markets," *Federal Reserve Bank of Richmond: Economic Quarterly,* 81:1–39.

Lee, S. B., and Ohk, K. Y. (1992): "Stock Index Futures Listing and Structural Change in Time-Varying Volatility," *The Journal of Futures Markets,* 12:493–509.

Maberly, E., Allen, D., and Gilbert, R. (November/December 1989): "Stock Index Futures and Cash Market Volatility," *Financial Analysts Journal,* 75–77.

Miller, M. H. (1993): *Financial Innovations and Market Volatility,* Blackwell Publishers.

Miller, M. H. (1995): "Do We Really Need More Regulation of Financial Derivatives?," *Pacific-Basin Finance Journal,* 3:147–158.

Nelson, D. (1991): "Conditional Heteroskedasticity in Asset Returns: A New Approach," Econometrica, 59(2):347–370.

Powers, M. J. (1970): "Does Futures Trading Reduce Price Fluctuations in the Cash Markets?" *American Economic Review,* 55(3):460–464.

Ross, S. A. (1989): "Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy," *Journal of Finance,* 44(1):1–17.

Scholes, M., and Williams, J. (1977): "Estimating Betas from Nonsynchronous Data," *Journal of Financial Economics,* 5:309–327.

Schwert, W. G. (May/June 1990): "Stock Market Volatility," *Financial Analysts Journal*, 23–34.

Simpson, W. G., and Ireland, T. C. (1982): "The Effect of Futures Trading on the Price Volatility of GNMA Securities," *The Journal of Futures Markets,* 2:357–366.

Skinner, D. J. (1989): "Options Markets and Stock Return Volatility," *Journal of Financial Economics,* 23:61–78.

Stein, J. C. (1987): "Informational Externalities and Welfare Reducing Speculation," *Journal of Political Economy,* 96:1123–1145.

Theodossiou, P. (1994): "The Stochastic Properties of Major Canadian Exchange Rates," *The Financial Review,* 29(2):193–221.