The Impact of SGX MSCI Taiwan Index Futures on the Volatility of the Taiwan Stock Market: An EGARCH Approach

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ABSTRACT

This article examines the impact of SGX MSCI Taiwan Index Futures on the volatility of the Taiwan stock market. The empirical work is conducted with the use of weekly stock returns from 1995 to 1998 and by applying an expanded EGARCH model. Our findings show that there is no structural change on either the conditional or the unconditional variance after the introduction of index futures contracts. It implies that there is no significant influence of the introduction of index futures market on the volatility of the Taiwan stock market. The robustness of the empirical findings is also tested on the basis of diagnostics performed on the estimated standardized residuals. All tests fail to show any evidence of misspecification.
Keyword: Futures Market, Stock Market Volatility, EGARCH Model

INTRODUCTION

Since the introduction of index futures contracts on February 24, 1982, there has been much debate over the role of index futures trading in the volatility of the underlying stock market. In particular, the stock market crashes in October 1987 and in October 1989 led academics and regulatory authorities to focus on the possible damaging role of the index futures market in creating excess stock market volatility. A popular belief is that futures trading encourages misinformed traders and risk-loving speculators, which destabilizes the stock market and induces a higher stock market volatility.

Whether the index futures increases the volatility of the stock market is difficult to answer from either theoretical or empirical aspects. One view is that futures trading has a stabilizing influence on stock market volatility. It can reduce the stock market volatility by providing low cost state-contingent strategies, which enable investors to minimize portfolio risk, by introducing positive information externalities and by transferring speculators from stock markets to futures markets. For instance, Edwards (1988b) finds that stock return volatility of the S & P 500 has not risen after the introduction of index options and index futures trading for the period of 1973-86. In fact, he finds that the volatility in the S & P 500 was even higher in 1973-82, before futures trading began. Another view is that the higher volatility in the futures market, caused by speculators, may be the main factor in increasing the volatility of the stock market. Subrahmanyam (1996) develops a trading model that incorporates informed speculators as well as investors, who possess incorrect expectations about asset values. He shows that the introduction of an index futures market, by stimulating additional misinformed speculation, increases the volatility of stock market. Maberly, Allen, and Gilbert (1989) demonstrate that the volatility of the stock market rises with the introduction of index futures. Harris (1989) shows that the volatility of the spot market is statistically higher due to futures trading. Besides these two viewpoints, some researchers find that the introduction of index futures has no influence on the volatility of the stock market. Turnovsky (1983) presents an equilibrium model to show that the effect of futures trading on spot market volatility is ambiguous. There are also many studies that find no significant changes in the volatility of spot market after introduction of index futures, such as Fortune (1989), Becketti and Roberts (1990), Kamara, Miller, and Siegel (1992), Pericli and Koutmos (1997) and so on.

Since there is no theoretical or empirical evidence to show whether the introduction of index futures has influence on the volatility of the stock market, one wonders if the newly published index futures contracts based on stock index, which is famous for its high volatility, has any influence on the volatility of the underlying stock market.

The purpose of this article is to examine the impact of the introduction of Singapore Exchange (SGX) MSCI Taiwan Index Futures on the volatility of the underlying stock index. The model used is the expanded EGARCH model introduced by Pericli and Koutmos (1997). Despite the similarities, this article differs in the following ways: first, the object of the research is different; second, the properties of stock returns, for example the distribution, the autocorrelation, and the stationarity of the return series, are examined to ensure the fit of the model.

This article is organized as follows: The first section investigates the statistical properties of return distributions of the Taiwan stock index and tries to find out the class of return-generating stochastic processes that are consistent with these properties. In the second section, the possible processes—the ARCH families—will be introduced, and their advantages and disadvantages will be compared. The third section presents the expanded exponential generalized autoregressive conditional heteroscedastic (expanded EGARCH) model. The fourth section carries out the statistical tests of the fitness of EGARCH process that are used to verify whether the volatility of stock returns in the Taiwan stock market changes after the introduction of index futures. Finally, the fifth section concludes the article.

DATA AND METHODOLOGY

The data used in this study are weekly indices of the Taiwan stock market obtained from the AREMOS/UNIX economic and statistic database system of the Ministry of Education Taiwan. They contain 171 weekly indices covering the period from July 21, 1995, to July 20, 1998. Since the introduction of index futures both in CME and SGX is on January 9, 1997, and the local index futures contract of TAIMEX (Taiwan International Mercantile Exchange Corp.) is published on July 21, 1998, the period of weekly stock indices would be separated into pre-index futures period (from July 21, 1995, to January 8, 1997) and post-index futures period (from January 9, 1997, to July 20, 1998). The return is defined as the first difference in the natural logarithm of price indices: $R_t = \log(I_t / I_{t-1})$, where I_t is the index of time t.

Statistical Analysis

A common assumption in models of stock prices is that the stock price movements can be represented by linear white-noise processes with independent increments. Before a model for the analysis of the stock price behavior is constructed, this common assumption should first be tested. The purpose of this section is therefore to examine whether this common assumption can adequately describe the stock price movements in the Taiwan stock market and to try to discover a process that can appropriately represent the properties of the stock price movements.

To examine the properties of stock price movements in the Taiwan stock market, it is necessary to carry out some statistical tests, which are for the stationarity, for the independence and autocorrelation, and for the normality.

Traditional tests for statistical inference presume the use of stationary data. It is necessary to examine if the data used are stationary before researching further into the matter, since the regression of non-stationary variables onto each other can lead to potentially misleading inferences about the estimated parameters and the degree of association.

A common test for the stationarity is the unit root test, which provides an easy method of testing whether a series is stationary, so that rejection of the unit root hypothesis is necessary to support stationarity. The unit root tests used in this study are the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) Test, and the Bayesian Unit Root Test of Sims.

In almost all of the popular models of stock returns, it is required that returns are independent random variables. In order to test the hypothesis of independence, it must be calculated both in the frequency domain (Durbin's cumulated periodogram) and in the time domain (Ljung-Box Q test). If the hypothesis of independence is rejected, the sample autocorrelation functions must also be analyzed in order to determine the lags of autocorrelation. For the test of null hypothesis of normality, the Jarque-Bera statistic is used.

Statistical findings

Table 1 shows preliminary statistics for the weekly returns, including the following distributional parameters: mean, variance, skewness, kurtosis, median, the Jarque-Bera statistic for the null hypothesis of normality, and the statistics for unit root tests. Also included are statistics to test the null hypothesis of strict white noise both in the frequency domain (Durbin's cumulated periodogram for serial correlation) and in the time domain (Ljung-Box Q test).

Table 1: Sample Statistics on Weekly Return Series

Statistic	Period		
	95/7/21 - 97/1/8	97/1/9 - 98/7/20	95/7/21 - 98/7/20
Sample size	76	94	170
Mean	0.003473	0.002126	0.002728
SE of Mean	0.002758	0.002674	0.001920
t (mean = 0)	1.25933	0.79495	1.42064
Variance	0.000578	0.000672	0.000627
Standard Error	0.024019	0.025928	0.025038
Skewness	-0.03245	-0.13518	-0.10051
Kurtosis	1.62665*	0.00583	0.57973
Median	0.006453	0.002237	0.004741
Jarque-Bera	8.3923*	0.2864	2.6668

Cum. Periodogram	0.2072*	0.1795*	0.1902*
LB(6)	12.7643*	11.1235	18.4150*
LB(12)	19.4120	18.1458	24.5387*
LB(24)	33.2006	40.0989*	38.1920*
ADF(γ_{μ})	-6.4504*	-7.3995*	-9.9088*
Z(γ_{μ})	-54.4716*	-69.9122*	-125.3385*
γ	-43.236*	-56.175*	-98.995*

- * denotes significance at the 0.05 level.
- The critical value of the Jarque-Bera statistic is 5.99 for significance levels of 0.05.
- The critical values of the cumulated periodogram test at level 0.1, 0.05, and 0.01 are 0.1078, 0.1202, and 0.1441, respectively.
- LB(n) means the Ljung-Box statistic at lag n , which is distributed as a χ^2 variate with n degrees of freedom.
- ADF(γ_{μ}) means ADF unit root test statistics. The critical values at levels 0.10, 0.05, and 0.01 are -2.57, -2.86, and -3.47, respectively.
- Z(γ_{μ}) means PP unit root test statistics. The critical values at levels 0.10, 0.05, and 0.01 are -11.3, -14.0, and -20.7, respectively.
- γ means the Sim's statistics. If γ > 0, then the null hypothesis would not be rejected.

As can be seen, all of the three statistics for unit root tests in all three periods are statistically significant even at level 0.01. The null hypotheses of unit root are rejected in all cases. A transformation of the data for stationarity is therefore not necessary. Except the sample moments in the pre-index futures period, which indicates that the empirical distribution has a sharp peak at the center compared to the normal distribution, the sample moments in the whole period and in the post-index futures period reveal that the empirical distributions are normal distributions. Also the Jarque-Bera statistics show the same results. Only in the pre-index futures period are the null hypothesis of normality rejected.

The periodogram of each series is estimated, and the test statistics are calculated, which indicate that the hypothesis of independence is rejected in all periods. The Ljung-Box Q test statistic is calculated for lags up to 60 weeks, and those for lags 6, 12, and 24 are listed in Table 1. The null hypothesis of strict white noise is rejected in the whole period. The conclusion must be that weekly return series are not made up of independent variates.

Implication for model construction

The nonlinear dependence in weekly return series could be explained by the well-documented fact of changing variances. The changing variance is often related to the level of trading activity, the rate of information arrivals, and the corporate financial and operating leverage decisions, which then tend to affect the level of stock price. A natural way to construct a model to describe such phenomenon is to represent the return distributions as distributions of stochastic moments or a mixture of distributions. Merton (1982) and many others have proposed models of this type. Unfortunately, all of these models assume that the observations are independent random variables and the return series are strict white noise processes, which are not consistent with the empirical evidence reported here. Therefore, these models are not compatible with the nonlinear dependence structure observed here.

A possible way of solving this problem is to transform the return series to an uncorrelated residual series, which could be obtained by using ordinary least squares estimation of the following AR(1) regression:

$$R_t = \Phi_0 + \Phi_1 R_{t-1} + e_t \quad (1)$$

Table 2: The Regression Model and Residuals Statistics

		Period		
	Statistic	95/7/21 - 97/1/8	97/1/9 - 98/7/20	95/7/21 - 98/7/20
A	Estimates of the model: $R_t = \Phi_0 + \Phi_1 R_{t-1} + e_t$			
	Φ_0	0.002420	0.001474	0.002011
		(0.88)	(0.56)	(1.07)
	Φ_1	0.273711*	0.248256*	0.258352*
		(2.43)	(2.44)	(3.45)
	Durbin's h Statistic	0.399574	-0.104883	0.125897
B	Sample statistics on the residual series e_t			
	Sample size	76	94	170
	Mean	0.000000	-0.000000	-0.000000
	SE of Mean	0.002687	0.002613	0.001866
	t (mean = 0)	0.00000	-0.00000	-0.00000
	Variance	0.000542	0.000635	0.000588
	Standard Error	0.023271	0.025202	0.024257
	Skewness	-0.11970	0.05550	-0.02385
	Kurtosis	0.71658	0.20444	0.38227
	Median	0.001356	0.001456	0.001393
	Jarque-Bera	1.7838	0.2097	1.0450
	Cum. Periodogram	0.0820	0.0861	0.0795
	LB(6)	4.6974	3.5570	5.7977
	LB(12)	9.8590	9.2359	12.5448
	LB(24)	22.3434	27.2895	27.8200
	ADF(γ_μ)	-8.4240*	-9.5962*	-12.8729*
	Z(γ_μ)	-73.46810*	-92.90017*	-168.014*
	γ	-72.684*	-93.581*	-166.599*

Table 2 reports the OLS estimates of regression model (1) and a number of statistics describing the distribution of the residuals. The estimates of Φ_1 are statistically significant greater than zero, indicating the presence of first-order autocorrelation in return series. The distribution of the residuals is shown to be normally distributed. Jarque-Bera statistics are also all insignificant. The Durbin's h test statistics could not reject the null hypothesis even at 0.1 significance level. It indicates that there is no first-order autocorrelation in the residual series. This confirms that an AR(1) transformation of returns gives an uncorrelated series of residuals as desired. The unit root tests are significant in all cases, implying that the series in each period may be generated by a stationary random walk, which is consistent with the previous findings.

In order to test the hypothesis of independence for the residual series, the Durbin's cumulated periodogram and Ljung-Box test statistics are calculated. Table 2 shows that in all cases these tests fail to reject the hypothesis that the residual series is strict white noise. Therefore, the first-order autocorrelation in the return series could be modeled as a linear process of the form AR(1). The nonlinear dependence of the return series, which may be affected by the changing variance, could be represented by a nonlinear process, which includes functions of past values of e_t^2. This nonlinear process would allow the probability distribution of the return series to depend on past realizations. Unfortunately, as discussed by Priestley (1981), the statistical estimation of nonlinear processes is often intractable. An alternative way of modeling the nonlinear dependence is the model introduced by Engle (1982) under the name of the autoregressive conditional heteroscedasticity (ARCH) model, which can closely approximate the second-order nonlinear process.

The ARCH models introduced by Engle (1982) make the conditional variance of the time t prediction error a function of time, system parameters, exogenous variables, lagged endogenous variables, and past prediction errors.

$$e_t = R_t - \phi_0 - \phi_1 R_{t-1}$$
$$R_t \,|\, \Omega_{t-1} \sim N(\mu_t, \sigma_t^2)$$
$$\mu_t = \phi_0 + \phi_1 R_{t-1}$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 ,$$

where

$p > 0,$

$\alpha_0 > 0, \alpha_i \geq 0, i = 1, \cdots, p.$

Ω_t is the set of all information available at time t and p is the lag of the process. An ARCH model with p lags is called ARCH(p) model.

Empirical applications often need a relatively long lag in the conditional variance equation in the ARCH model. The estimation of a fixed lag structure is typically imposed in order to avoid the problem with negative variance parameter. In order to reduce the lags in the conditional variance equation, Bollerslev (1986) generalized the ARCH model and allowed lagged past conditional variances to enter the model and to determine the conditional variance as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 ,$$

where

$p > 0, q \geq 0,$

$\alpha_0 > 0, \alpha_i, \beta_j \geq 0, i = 1, \cdots, p, j = 1, \cdots, q.$

If $q = 0$, then the GARCH model is an ARCH(p) process. If $p = q = 0$, then R_t is a simple *white noise*.

The GARCH model is capable of capturing the three most empirical features observed in stock return data: leptokurtosis, skewness, and volatility clustering. It is found to be more appropriate than other standard statistical models because it is consistent with a return distribution, which is leptokurtic. Besides this advantage, the GARCH model also allows for a long-term memory in the variance of the conditional return distributions.

Although the GARCH model has its advantages by describing the phenomenon in the financial markets, there are still some drawbacks. Nelson (1990) pointed out three drawbacks of the ARCH families. The first one is that the (G)ARCH model assumes only the magnitude and not the positivity or the negativity of unanticipated excess returns, which determines features of conditional variance of prediction error σ_t^2 . Since the change in variance is conditionally uncorrelated with the excess returns under the assumption of symmetrical distribution of standardized residuals, it indicates that a model, which assumes the determination of

σ_t^2 through the positive and negative residuals asymmetrically, might be more appropriate for the asset pricing applications. Second, the (G)ARCH model is usually enforced to add nonnegative constraints to ensure the nonnegativity of the conditional variance of prediction error σ_t^2, (i.e., the constant term and the variance parameter of the conditional variance equation must be so defined that the nonnegativity of the conditional variance is guaranteed). These constraints rule out random oscillatory behavior in the σ_t^2 process because the σ_t^2 increase all the time when the standardized residuals increase. At the same time, these constraints make it difficult to estimate the GARCH model because in order to prevent some of the α_i coefficients from becoming negative, it is always imposed to construct a linearly declining structure on the α_i. The third drawback concerns the interpretation of persistence of shocks to conditional variance. Nelson (1990) shows that the IGARCH(1,1) model is actually a natural model of persist shocks, and therefore does not behave like a random walk. The shocks may persist in one norm and die out in another in the GARCH(1,1) model, so the conditional moments of the model may explode even when the process itself is strictly stationary and ergodic.

A model introduced by Nelson, the exponential ARCH model, can avoid these drawbacks and may be more suitable for modeling conditional variance. Nelson tried to use another device for ensuring nonnegative σ_t^2, by making $\ln(\sigma_t^2)$ linear in some function of time and lagged standardized residuals. By modeling the natural logarithm of the variance, the imposition of unduly parameter restriction can then be eliminated. The exponential ARCH model is formulated as follows:

$$R_t \left| \Omega_{t-1} \sim f(z_t, \upsilon) \right.$$

$$\mu_t = \phi_0 + \sum_{i=1}^{k} \phi_i R_{t-i}$$

$$\sigma_t^2 = \exp\left(\alpha_0 + \sum_{i=1}^{p} \alpha_i g(z_{t-i}) \right),$$

where z_t is the standardized residual and $g(z_t) \equiv \theta\, z_t + \delta\,[|z_t| - E|z_t|]$. The term $g(z_t)$ is the asymmetric function of past standardized residuals. It allows the conditional variance to respond asymmetrically to positive and negative values of the past standardized residuals. The term $\delta\,[|z_t| - E|z_t|]$ measures the size effect and represents a magnitude effect in the spirit of the GARCH models. The term $\theta\, z_t$ measures the sign effect.

Similar to the relationship between the GARCH and ARCH models, the exponential ARCH model can also be generalized and converted into an exponential GARCH (EGARCH) model as follows:

$$R_t|\Omega_{t-1} \sim f(z_t, \upsilon)$$
$$\mu_t = \phi_0 + \sum_{i=1}^{k} \phi_i R_{t-i}$$
$$\sigma_t^2 = \exp[\alpha_0 + \sum_{i=1}^{p} \alpha_i g(z_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2)].$$

The Model

The model used here is the expanded EGARCH model introduced by Pericli and Koutmos (1997).

$$R_t|\Omega_{t-1} \sim f(z_t, \upsilon),$$

$$\mu_t = \phi_0 + \phi_{0,F} DF_t + \sum_{i=1}^{k} \phi_i R_{t-i} \tag{2}$$

$$\sigma_t^2 = \exp[\alpha_0 + \alpha_{0,F} DF_t + (\alpha_{1,F} DF_t + \alpha_1) g(z_{t-1}) + (\beta_{1,F} DF_t + \beta_1) \ln(\sigma_{t-j}^2)] \tag{3}$$

$$g(z_{t-1}) \equiv \theta\, z_{t-1} + |z_{t-1}| - E|z_{t-1}|,$$

where the variable DF_t is a dummy variable representing the post-index futures period for the Taiwan stock index. The unconditional mean of equation (2) is

$$\mu = \frac{\phi_0 + \phi_{0,F}}{1 - \sum_{i=1}^{k} \phi_i}, \text{ for } i = 1, \cdots, k.$$

The logarithm of the unconditional variance of equation (3) is

$$\ln(\sigma^2) = \frac{\alpha_0 + \alpha_{0,F}}{1 - \beta_1 - \beta_{1,F}}.$$

The estimation is done by maximum likelihood. The distribution for the normalized residuals could be assumed as a student t, or a generalized error distribution (GED). The GED was originally used with the EGARCH model by Nelson (1991) and could be employed here since it can accommodate fatter tails and peakedness. The density function of the GED is as follows:

$$f(z_t, \upsilon) = \frac{\upsilon \exp\left(\frac{1}{2}\left|\frac{z_t}{\lambda}\right|^{\upsilon}\right)}{\lambda 2^{1+\frac{1}{\upsilon}} \Gamma\left(\frac{1}{\upsilon}\right)}, \text{ where } \lambda \equiv \left(\frac{2^{\frac{-2}{\upsilon}} \Gamma\left(\frac{1}{\upsilon}\right)}{\Gamma\left(\frac{3}{\upsilon}\right)}\right)^{\frac{1}{2}}.$$

υ is an endogenously estimated scale parameter, which controls the shape of the GED distribution, and $\Gamma(\cdot)$ is the gamma function.

If $\upsilon = 2$, then a GED distribution is equivalent to a normal distribution. For $\upsilon < 2$, it is a distribution with excess kurtosis, (i.e., fatter tails). For the student t, it is equivalent to a normal distribution as $\upsilon \Rightarrow \infty$, but gets very close for $\upsilon > 30$ or so.

The log-likelihood function is given by

$$L(\Theta | p, q) = \sum_{t=1}^{T} \ln f(z_t, \upsilon) .$$

The order k of the autoregressive process in equation (2) is decided on the basis of log-likelihood ratio tests.

After estimation of the coefficients of the expanded EGARCH model, the normalized residuals (i.e., the residuals divided by the square root of the conditional variance) and the squared normalized residuals will be tested for serial correlation. The linear and nonlinear independence will be tested by means of the Ljung-Box statistic.

In order to determine the answer to the question regarding how well the model captures the impact of positive and negative innovations on volatility, the diagnostics proposed by Engle and Ng (1993) will be used. The diagnostics include three tests: the sign bias test, the negative size bias test, and the positive size bias test. These tests are based on a new impact curve of the ARCH-type model and suppose if the volatility process is correctly specified, then the squared standardized residuals should not be predictable on the basis of observed variables.

RESULTS

The results of the maximum-likelihood estimates are reported in Table 3. The constant in the conditional mean equation and the coefficient of the dummy for the post-index futures sub-period $\phi_{0,F}$ are both statistically insignificant at the 0.05 level. On the basis of log-likelihood ratio tests, the order k of the autoregressive process in equation (2) is shown as unity, and the estimate of ϕ_1 is significantly greater than zero. Both of these confirm the presence of first-order autocorrelation in the time series { R_t }. Past returns, up to the second lag, are insignificant determinants of the present returns. The shape of the distribution of the estimated residuals is still normal. A simple t test could not reject the $\upsilon = 2$ hypothesis even at the 0.01 significance level.

The estimated coefficients for the conditional variance reveal that the conditional variance is time dependent. The value of θ is negative as expected, but statistically insignificant. This indicates that a negative realization has the same effect on the volatility as a positive realization with the same magnitude will do. The term $\alpha_{1,F}$, which is designed to measure whether the sensitivity of the conditional variance to past innovations in the post-index futures period has changed, is statistically insignificant. This implies that no change of the conditional variance of the weekly returns in spot market has occurred after the introduction of index futures contracts in SGX.

The term $\beta_{1,F}$ is designed to capture whether any change has occurred in the persistence of the conditional variance in the period following the introduction of index futures contracts. The insignificance of this term indicates that the introduction of index futures contracts is not related to the persistence of the conditional variance. The degree of persistence, β_1, is statistically significant, implying that it would take time for a shock to die out. If the half-life of a shock could be measured as log(0.5)/log(β_1), then it would take approximately 2.7 weeks for a shock to die out.

The insignificance of coefficients $\alpha_{0,F}$, $\alpha_{1,F}$, and $\beta_{1,F}$ implies that there is no evidence of any significant structural change in the conditional variance process over the entire sample period. As for the model-implied unconditional standard deviations based on equation (3), the values for the pre- and the post-index futures sub-period are 0.0203 and 0.0238, respectively. An F-test could not reject the null hypothesis of the equality of these two unconditional variances. The unchange of the unconditional variance in pre- and post-index futures period implies that the index futures does not contribute to any incremental change in the volatility process.

Table 3: Maximum-Likelihood Estimates for Weekly Return. Estimation Period: 1995/7/21-1998/7/20

Conditional Mean Equation			
Parameter	Coefficients	Standard Error	t -statistic
ϕ_0	0.002477	0.002830	0.87528
$\phi_{0,F}$	-0.000836	0.003780	-0.22108
ϕ_1	0.257795*	0.075104	3.43251
υ	2.148716	0.514855	4.17344
Conditional Variance Equation			
Parameter	Coefficients	Standard Error	t -statistic
α_0	-3.155147	1.014912	-3.10879
$\alpha_{0,F}$	1.866068	1.502255	1.24218
α_1	-0.053387	0.214669	-0.24869
$\alpha_{1,F}$	0.098560	0.384947	0.25604
β_1	0.594976*	0.131370	4.52902
$\beta_{1,F}$	0.232630	0.198285	1.17321
θ	-4.489157	17.474320	-0.25690

The result of the model-implied unconditional standard deviations and the residual-based diagnostics is shown in Table 4. The t statistics of the sign bias test, the positive size bias test, and the negative size bias test as well as the F statistic of the joint test are all statistically insignificant. This implies that the squared standardized residuals could not be predicted on the basis of observed variables. Therefore, it can be said that the expanded EGARCH model with GED can capture the second moment dynamics of weekly returns quite well.

Table 4: The Model-implied Unconditional Standard Deviation and the Residual-based Diagnostics

E(z_t)	-0.0079	LB(6)	6.6396
Standard Error	1.0015	LB(12)	14.5561
E(z_t^2)	0.9970	$LB^2(6)$	3.2171

Standard Error	1.3570	LB^2(12)	15.8996
Sign Bias (t test)	0.9299	Positive Size Bias (t test)	0.1583
Negative Size Bias (t test)	0.8712	Joint Test (F test; F[3,169])	0.3686

SUMMARY AND CONCLUSION

This article investigates the impact of index futures contracts published in Singapore on the volatility of weekly returns of the Taiwan stock market. The empirical work is conducted with the use of weekly stock returns from 1995 to 1998 and by applying an expanded EGARCH model. Results indicate that there is no structural change on either the conditional or the unconditional variance after the introduction of index futures contracts.

To ensure the appropriate specification of the model, the robustness of the empirical findings is also tested on the basis of diagnostics performed on the estimated standardized residuals. The results indicate that all tests fail to show any evidence of misspecification.

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