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Abstract:

This study employs the daily data of the Stock Exchange of Thailand to test for the leverage and volatility feedback effects. The period of investigation is during January 4, 2005 to December 27, 2013, which includes the Subprime crisis period in the US that might affect the volatility of stock market return in emerging stock markets. The results from this study show that the US subprime crisis imposes a minimal positive impact on volatility. In addition, the estimations of the three parametric asymmetric volatility models give the results showing some evidence of the volatility feedback and leverage effects. The findings give implications for portfolio diversification and risk management.

Keywords: Asymmetric volatility, feedback effect, leverage effect, emerging stock market
JEL Classification: G10, C22

1. Introduction

The notion that stock index return is negatively correlated to its own volatility is still controversial. Furthermore, an empirical question is whether stock return shocks drive changes in volatility or volatility drives stock index return. The leverage effect posits that stock return shocks lead to changes in conditional volatilities (see details in Black, 1976, and Christie, 1982). If leverage takes effect, negative return shocks lead to higher subsequent volatilities. By contrast, the volatility feedback effect posits that changes in conditional volatility lead to changes in stock return shocks (see Bekeart and Wu, 2000, among others). For the feedback effect, anticipated increases in volatility can result in negative return and vice versa. Nelson (1991) finds a negative risk-return relationship. Campbell and Hentschel (1993) employ a simple model called a quadratic generalized autoregressive conditional heteroskedastic (QGARCH) model and conduct an application to the U. S. monthly and daily stock returns. They find that volatility feedback has little effect on return, but can be important during the period of high volatility. Harrison and Zhang (1999) examine the relation between expected stock returns and conditional volatilities over different holding periods and across different states of the economy. They find a significantly positive risk-return relation at long holding periods, but not at short holding periods. They conclude that the existing finding of a negative relation in the feedback effect may stem from misspecification. Bekeart and Wu (2000) investigate asymmetric volatility at the firm and the market levels and test for the leverage and volatility feedback effects using the data of Nikkei 225 stocks. Their evidence supports the volatility feedback effect and rejects the pure leverage effect. Xing and Howe (2003) find evidence of positive risk-return relationship in weekly data of the UK stock market when the world market return is taken into account, they posit that the UK stock market return not only depends on its own variance, but also depends on its covariance with the world market return. Their evidence disproves the negative feedback effect.[1] Brandt and Kang (2004) find that the conditional correlation between the mean return and volatility is negative, but the unconditional correlation is positive due to lead and lag correlation.

Bollerslev et al. (2006) find a negative relationship between volatility and past and future returns using high-frequency aggregate equity index data and find that high-frequency data may be used to assess volatilities asymmetries of daily return horizon. Zivot (2008) finds asymmetric effect for the S&P500 index return. Ederington and Guan (2010) also find asymmetric effect in the US stock market. Hatemi-J and Irandoust (2011) find that volatility negatively causes return. Their finding thus supports the volatility feedback effects. Mukhopdhyay and Sarkar (2013) find evidence of significant leverage effect in the Indian stock market. Tanha and Dempsey (2015) find that the impact on the Australian stock market volatility is higher following negative shocks than following positive shocks of the same magnitude. Their finding is consistent with the previous findings in the US stock market.

In the present study, we use three parametric generalized autoregressive conditional heteroskedastic-in-mean (GARCH-M) models to apply to the daily stock market return data of the Stock Exchange of Thailand during January 4, 2005 and December 27, 2013. The results reveal that the volatility feedback and leverage effects are present in the Thai stock market even though the effects are not very robust. The paper is organized as the following. Next section presents data descriptions and the estimation methods. Section 3 presents empirical results. The final section concludes.

2. Data and Methodology

2.1 Data descriptions

We employ daily data obtained from the Datastream for the sample period starting from January 4, 2005 to December 27, 2013. This sample period includes the Subprime crisis originated from the U. S. in the period from September 2008 to February 2009. The Subprime crisis can impose the impact on international stock markets especially emerging stock markets (see Dooley and Hutchison, 2009). The phase of the crisis causes the disruption of trade credits that support exporters and importers by the counter party risk and deleveraging generated by the bankruptcy of the major player in international credit markets. The phase of the crisis is hypothesized to be a recoupling of financial markets in the US and emerging markets. Therefore, we test for the impact of the US subprime crisis on conditional volatility in the Stock Exchange of Thailand. The time series dataset comprises 2,195 observations.

The descriptive statistics of stock market return is reported in Table 1. The mean of the daily returns is close to zero. The series is negatively skewed. In addition, the return series is leptokurtic compared to normal distribution. The Jarque-Bera statistic indicates that the stock market return is not normally distributed.

Since the test statistic for a unit root is greater than the critical value at the 1 percent level of significance, we can conclude that the daily market return series is stationary because the null hypothesis of unit root is rejected. Furthermore, the daily return series exhibits the presence of ARCH effect. Therefore, the parametric GARCH models should be suitable for estimating conditional volatility.

[1] Recently, Salvador et al. (2014) analyze the risk-return relationship in 11European stock markets and find a robust risk-return tradeoff in a low volatility periods. However, the tradeoff is reduced or insignificant in the high volatility periods.

Table 1 Descriptive statistics of equity sector index return

Mean	0.0003
Median	0.0007
Maximum	0.1058
Minimum	-0.1606
Standard deviation	0.0140
Skewness	-1.0097
Kurtosis	17.21
Jarque-Bera statistic	18,847.53
ADF statistic (constant only)	-10.715 (0.000)
ARCH: $Q^2(4)$	298.58 (0.000)
Number of observations	2,195

Note: The number in parenthesis is p-value.

2.2 Estimation methods

We employ the GARCH-in-mean or GARCH-M models to capture the volatility feedback effect. Since Engel and Ng (1993) have proved that the threshold GARCH (TGARCH) or GJR model of Glosten et al. (1993) and Zakoian (1994) and the exponential generalized autoregressive conditional heteroskedastic (EGARCH) model of Nelson (1991) perform better than the GARCH model of Bollerslev (1986), we thus use the GJR-M and EGARCH-M models to estimate stock market return volatility (or uncertainty) for the leverage and the feedback effects. The power GARCH or PGARCH model proposed by Ding et al. (1993) is also used. These three models are suitable because they include past variances that affect the conditional variances and exhibit asymmetric effects.[2]

We assume that each return series follows the autoregressive of order *p* (AR(*p*)) process, which is specified by the mean equation in equation (1).

$$r_t = b_0 + \sum_{i=1}^{p} b_i r_{t-i} + c\sigma_t + \varepsilon_t \tag{1}$$

and the conditional variance equations are specified in equations (2), (3) and (4).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 \varepsilon(-)_{t-1}^2 + \delta D_t \tag{2}$$

$$\log(\sigma_t^2) = \alpha + \beta \log(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \varphi \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| + \delta D_t \tag{3}$$

and

$$\sigma_t^\delta = \alpha_0 + \alpha_1 (\lfloor \varepsilon_{t-1} \rfloor - \gamma_1 \varepsilon_{t-1})^\delta + \beta_1 \sigma_{t-1}^\delta + \delta D_t \tag{4}$$

where *r* is the stock market return, which is a stationary series. The variable σ in the mean equation is the conditional volatility, which can be conditional variance or standard deviation depending on the type of the GARCH model being used. The variable $\varepsilon(-1)_{t-1} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} \geq 0$. If $\alpha_3 = 0$, the model will collapse to the GARCH(1,1) model, which is symmetric. If $\alpha_3 > 0$, negative return shocks have greater impact than positive return shocks. For the

[2] The models are specified by Engle et al. (1987). The popular GARCH model developed by Bollerslev (1986) does not allow for testing for asymmetric effects of negative and positive return shock.

EGARCH model, σ in the mean equation is $log(\sigma^2)$, which is corresponding to equation (3). In the EGARCH specification, the log of conditional variance depends on its past value. The coefficients are not restrictively non-zero. The log of GARCH variance series as a measure of equity index return volatility can be obtained from the estimate of AR(p)-EGARCH(1,1) model. If the coefficient γ is non-zero, the impact of volatility on equity index return is asymmetric. If γ is positive, positive return shocks have greater impact on conditional volatility than negative return shocks. On the contrary, the negative value of γ implies that negative return shocks have greater impact on conditional volatility than positive return shocks. If γ is zero, the model is symmetric. In the PGARCH-M model, α_1 and β_1 are the ARCH and GARCH parameters, γ_1 is the leverage parameter, and $\delta > 0$, which is the power parameter. The asymmetric effects are found when γ_1 is non-zero. We also test for the impact of the Subprime crisis on the conditional volatility. In doing so, the conditional variance equations include the dummy variable D, which is 1 during the Subprime crisis and 0 otherwise. This dummy variable is designed to capture the impact of the crisis that can affect the conditional volatility. The period of the subprime crisis is from September 2008 to February 2009.

3. Empirical Results

We first estimate equations (1) along with the corresponding GARCH specifications in equations (2), (3) and (4) of the GJR, EGARCH and PGARCH models, respectively. The results are reported in Table 2. The Ljung-Box statistics show no serial correlation and no further ARCH effects in the estimated models.

The results in Table 2 show that conditional volatility negatively causes stock market return in the GJR, EGARCH and PGARCH models with the coefficients of –0.181, –0.001, and -0.196 respectively.[3] It should be noted that the coefficient is much larger for the GJR and PGARCH models than that of the EGARCH model, but the level of significance is only 10 percent for the GJR model while the levels of significance for the PGARCH and EGARCH models are 5 and 1 percent, respectively. However, the estimated coefficient for the EGARCH model is very small even though the level of significance is high. Therefore, we conclude that the feedback effect in the Thai stock market is not strong, except for the PGARCH model. The size of the impact of the subprime crisis on conditional volatility is strong only for the EGARCH estimate. Therefore, we conclude that the subprime crisis imposes a minimal positive impact on conditional volatility in the Stock Exchange of Thailand. In addition, the null hypothesis that the relation is symmetric is strongly rejected in that $\alpha_3 = 0.251$ in the GJR model, $\gamma = -0.139$ in the EGARCH model and $\gamma_1 = -0.594$ in the PGARCH model. The estimated coefficients of $\alpha_3 > 0$ and $\gamma < 0$ indicate that large positive and negative shocks positively affect conditional volatility, but the impact of negative return shocks is much stronger. This is evidence of a reverse J-shape phenomenon. Furthermore, in the GJR estimation, $\alpha_2 = 0.057$ is small and significant. For the EGARCH estimation, $\gamma + \varphi = 0.099$, which is positive and significant at the 1 percent level. However, the impact of negative shocks is still more pronounced than that of positive shocks.

[3] In the PGARCH model, we set the power (δ) equal to one. Zivot (2008) indicates that the PGARCH model that is specified as σ_t tend to be less sensitive to outliers than the model with the power of two.

Table 2 Results of the estimate of time series models of asymmetric volatility of stock market return

Panel A: GJR-M model

(1) Mean equation: $r_t = b_0 + b_1 r_{t-1} + c(\sigma_t) + \varepsilon_t$

b_0	b_1	c
0.003	0.068	-0.181
(0.012)**	(0.009)***	(0.057)*

(2) Variance equation: $\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 \varepsilon(-)_{t-1}^2 + \varphi D_t$

α_0	α_1	α_2	α_3	φ
2.10E-05	0.701	0.057	0.251	6.45-E05
(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Log likelihood = 6,536.544

Q(4) = 0.888 (0.926), $Q^2(4)$ = 0.182 (0.996)

Panel B: EGARCH(1,1)-M model

(1) Mean equation: $r_t = b_0 + b_1 r_{t-1} + c\log(\sigma_t^2) + \varepsilon_t$

b_0	b_1	c
-0.010	0.053	-0.001
(0.060)*	(0.029)**	(0.045)**

(2) Variance equation: $\log(\sigma_t^2) = \alpha + \beta\log(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \lambda\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \varphi D_t$

α	β	γ	λ	φ
-1.141	0.891	-0.139	0.283	0.148
(0.000)***	(0.000)**	(0.000)***	(0.000)	(0.000)***

Log likelihood = 6,552.380

Q(4) = 1.203 (0.878), $Q^2(4)$ = 0.182 (0.996)

Panel C: PGARCH(1,1) model

(1) Mean equation: $r_t = b_0 + b_1 r_{t-1} + b_2 r_{t-2} + c(\sigma_t) + \varepsilon_t$

b_0	b_1	b_2	c
0.003	0.051	-0.019	-0.196
(0.003)***	(0.033)**	(0.386)	(0.021)**

(2) Variance equation: $\sigma_t = \alpha_0 + \alpha_1(\lfloor\varepsilon_{t-1}\rfloor - \gamma_1\varepsilon_{t-1}) + \beta_1\sigma_{t-1} + \varphi D_t$

α_0	α_1	γ_1	β_1	φ
0.001	0.152	-0.594	0.779	0.001
(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Log likelihood = 6,554.815

Q(4) = 2.496 (0.645), $Q^2(4)$ = 0.972 (0.914)

Note: The number in parenthesis is the p-value. ***, ** and * indicates significance at the 1, 5 and 10 percent, respectively.

The GJR, EGARCH and PGARCH models seem to be able to capture the leverage effects. The PGARCH model is superior to the other two models in terms of log likelihood. The EGARCH model performs reasonably well compared with the results of Ederington and Guan (2010). We use a simple test for asymmetric effect in the daily stock market return using Corr(r_t^2, r_{t-1}).[4] The correlation between r_t^2 and r_{t-1} is -0.172 and quite small for the series.

[4] The squared return series can be used as a proxy for the realized volatility since the actual volatility cannot be observed.

This negative and small correlation coefficient indicates that the asymmetry effect might not be strong in the case of an emerging stock market like the Thai stock market.

4. Conclusion

In this study, we examine how asymmetric volatility of the Thai stock market is. Specifically, we tests for the leverage and volatility feedback effects. The daily data of stock market return is used. The period covers January 4, 2005 to December 27, 2013 with 2,195 observations. The impact of the Subprime crisis is also tested. We use three asymmetric GARCH-M models, namely GJR, EGARCH and PGARCH models. The results show that the three models perform reasonably well in detecting asymmetric volatility in the stock market. The results show that (i) the volatility negatively causes return, which supports the volatility feedback effect, (ii) the negative return shocks cause higher volatility than the positive shocks at the same magnitude, which support the leverage effect, and (iii) the Subprime crisis imposes a positive impact on volatility, but this impact is minimal. The results from this study give implications for diversification and risk management. International investors and portfolio mangers should take into account of the feedback and leverage effects when they form portfolios that comprise emerging market stocks.

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