Measuring Asymmetric Volatility And Stock Returns In The Philippine Stock Market

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Abstract: This paper aims to study the relationship between expected stock market returns and conditional volatility in the Philippine stock market index (PSEi). It also aims to investigate the presence of asymmetric effects of good and bad news on conditional volatility. The paper also aims to put to the test the significance of the risk-return trade-off prescribed by traditional finance theory. In contrast to past literature, there are an increasing number of empirical evidence on developed markets claiming a negative relationship between stock market returns and volatility. However, only a few studies were made on emerging markets such as the Philippines. By applying an asymmetric volatility model such as the Exponential GARCH-In-Mean (EGARCH-M) and GJR GARCH (Threshold GARCH) models to the weekly Wednesday returns of the Philippine Stock Exchange Composite Index over the period of January 5, 1994 to December 26, 2012, we found the existence of a negative relationship, although insignificant, between stock market returns and conditional volatility. Our results also showed that conditional volatility reacts to good and bad news asymmetrically. That is, the arrival of bad news was found to have a greater impact on conditional volatility than the arrival of good news. Since the study was conducted on a market-wide level, the researchers surmised that asymmetric volatility may be the result of a down-market effect. We recommend that given the presence of asymmetric volatility, policy makers should continue regulating the financial market to ensure a smooth integration of the Philippine stock market to the world economy.

Key Words: Asymmetric volatility, Risk-returns trade-off, EGARCH-M model, Threshold-GARCH model, the Philippines

This paper is an abridged version. The full version is planned by the authors to submit to other journals for publication.

1. INTRODUCTION

It is well-known in financial research that stock return volatility is highly persistent. At the same time, existing literature cannot find a definite relationship between asset returns and its variance, which is used as a proxy for risk. Theoretically, asset pricing models (Sharpe, 1964; Linter, 1965; Mossin, 1966; Merton, 1973, 1980) link returns of an asset to its own variance or to the covariance between the returns of other stocks and the market portfolio.

Yet, there are also many empirical studies that implicates a negative relationship between returns and volatility such as Black (1976), Cox and Ross (1976), Bekaert and Wu (2000), Whitelaw (2000), Li et al. (2005) and Dimitrios and Theodore (2011). Bekaert and Wu (2000) explain that it appears that returns and conditional volatility are negatively correlated in the equity markets.

There is an increasing number of empirical evidences saying that negative (positive) returns are generally associated with upward (downward) revisions of conditional volatility, this phenomenon is often referred to as asymmetric volatility. (Goudarzi, 2011) As Wu (2001) was quoted saying, "the presence of asymmetric volatility is most apparent during stock market crashes when a large decline in stock price is associated with a significance increase in market volatility." The theory that considers the relationship between volatility and equity price is called the "down market effect" which states variation in market volatility is driven by variation in market conditions.

If asymmetric volatility is present during a crisis then it should also be noted that this event does not only impact developed markets but emerging markets as well. Thus, this study aims to investigate the asymmetric relation between stock returns and its volatility in the Philippines. To model the asymmetry in stock market volatility and allow the possibility to measure the different impact on the conditional variance of bad and good news, the Exponential GARCH-In-Mean (EGARCH-M) model proposed by Nelson (1991) and Engle et. al (1987) and the Threshold GARCH (TGARCH) model by Glosten, Jagannathan, & Runkle (1993) were used.

2. METHODOLOGY

Method of Data Analysis

A. Measuring asymmetric volatility

For the following models, the innovations are assumed to be Gaussian distributed.

A.1 EGARCH Model

To answer such a problem of not capturing signs, Nelson (1991) modified the GARCH which led to the EGARCH model. By modifying ϵ_t or the residuals of the mean equation such that

$$\frac{\epsilon_t}{\sqrt{\mathrm{h_t}}} = z_t \mathbf{(1)}$$

$$where\ z_t \sim iid\ (0,1)$$

and is called the standardized residuals

Furthermore, the EGARCH model is given by:

$$\ln(\mathrm{h_t}) = \alpha_\mathrm{i} + \sum_{k=1}^{\infty} \beta_k\, g(z_{t-k}), \beta \leq 1\ (\mathbf{2})$$

$$where\ g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$$

Thus upon simplification, the EGARCH variance equation becomes

$$\ln(\sigma_\mathrm{t}^2|\Omega_{\mathrm{t}-1}) = \alpha_\mathrm{i} + \sum_{\mathrm{j}=1}^{\mathrm{q}} \gamma_j\left[\left|z_{t-j}\right| - E\left|z_{t-j}\right|\right] + \sum_{\mathrm{j}=1}^{\mathrm{q}} \theta_j z_{t-j} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \Delta_\mathrm{i} \ln(\sigma_{\mathrm{t-i}}^2|\Omega_{\mathrm{t-i-1}}) \quad (\mathbf{3})$$

Equation (2) employs the natural logarithm of the conditional variance in order to ensure that the conditional variance remains non-negative. Given this freedom, $g(z_t)$will now be able to accommodate asymmetric volatility.

The parameter denoted by $'\theta'$ capture the effect of the sign of the innovation. While $'\gamma'$measures the impact of the current innovation with its long run average, we can say that it captures the magnitude (size) of the innovation. By incorporating lags of the conditional variance, to allow for a longer memory, we arrive at Equation (3).

Overall, the EGARCH model, unlike the linear GARCH models, uses the natural logarithm of the conditional variance to relax the non-negativity constraint of the model's coefficients and to allow for the persistence of shocks to the conditional variance.

A.2 Threshold-GARCH Model

In order to verify the presence of asymmetric volatility in stock returns, we employ another model first proposed by Glosten, Jagannathan, & Runkle (1993). By assigning a dummy variable to negative returns, they were able to allow asymmetric effects of good and bad news on conditional volatility. It is also known as Threshold GARCH (TGARCH)

since we consider $\epsilon_{t-1} = 0$ as a point of separation of the impacts of negative and positive shocks. (Enders, 2004)
Considering the TGARCH process:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \vartheta D_{t-1} \epsilon_{t-1}^2 + \beta h_{t-1} \quad (4)$$

Where: $h_t -$ *the conditional variance at time t* $\alpha_1 -$ *the coefficient for the ARCH(1)process*
$\beta -$ *the coefficent for the GARCH(1) process*
$D_{t-1} = 1$ *whenever* $\epsilon_{t-1} < 0$

When $\epsilon_{t-1} < 0$, the effect of ϵ_{t-1}on h_t is $(\alpha_1 + \vartheta)\epsilon_{t-1}^2$ and when $\epsilon_{t-1} \geq 0$ the effect of ϵ_{t-1} is $\alpha_1 \epsilon_{t-1}^2$.It can be clearly seen here, if that the coefficient ϑ is positive and statistically significant, past lagged negative innovations (bad news) have a greater impact on volatility than lagged positive innovations (good news).

However, Stata presents another variation of the TGARCH process wherein it modifies the dummy variable D_{t-1} on Equation (4) so that it will represent positive shocks rather than negative shocks. (Stata,2009)

Therefore, in our paper, to be able to determine asymmetric volatility, we will look at the coefficient 'ϑ'. If 'ϑ' is positive and statistically significant, we can conclude that positive innovations create more volatility than negative innovations. However, if 'ϑ' is negative and statistically significant then we can conclude that negative innovations indeed produce higher volatility than good news.

B. Measuring asymmetric volatility and expected stock returns

The EGARCH-M model developed by Nelson (1991) incorporates volatility in the mean equation. That is, modifying the original GARCH conditional variance equation, hence

$$R_t = \alpha_0 + \sum_{i=1}^{k} \beta_i X_i + \delta h_t + \sum_{j=1}^{h} \psi_j R_{t-j} + \epsilon_t \quad (5)$$

Equation (5) postulates that aside from the explanatory variables and the auto-regressive terms, the return of the asset at time t is also affected by its conditional variance. The study will estimate and interpret the parameter 'δ' for this will determine both the nature and significance of the impact of conditional volatility on stock returns.

C. *Determination of the ARMA component of the Mean Equation and 'Best Fitting' volatility model*

In determining the right model that best fits the mean equation, by employing the methodology of Box and Jenkins (1976) In order to determine the most appropriate EGARCH model, we employ the following techniques:

C.1. Akaike Information (AIC) and Schwartz Bayesian (SBC/ BIC/ SBIC) Criterion

We look at the two information criterion in our search for a more parsimonious model. The AIC and SBC are defined respectively as

$$AIC = Tln(RSS) + 2n \quad (6)$$

And

$$SBC = Tln(RSS) + nln(T) \quad (7)$$

where:
$T -$ *number of observations*
$RSS -$ *Residual sum of squares of the model*
$n -$ *number of parameters being estimated*

As it can be seen in the equations, the criterions test whether adding more lags is worth its weight in reducing the RSS. A model is said to be superior than the other if it yields a lower AIC or SBC. (Enders, 2004)

C2. Ad-Hoc estimation method

In our post estimation, we use the various tests proposed by Engle and Ng (1993). The tests indicate whether the squared normalized residuals can be predicted by variables in the past that are not included in the volatility model. If these variables can predict our z_t^2, then the model is not correctly specified.

$$z_t^2 = \alpha + \psi_1 S_{t-1}^{-} + \psi_2 S_{t-1}^{-}\epsilon_{t-1} + \psi_3 S_{t-1}^{+}\epsilon_{t-1} + \beta' X_i + \varepsilon_t \quad (8)$$

where:

$z_t^2 -$ *squared normalized residuals*
$\beta' -$ *coefficients of other explanatory variables in the model*

(a) The sign bias test
(b) The negative size bias test
(c) The positive size bias test

Sampling Design and Data Collection Method

The raw data comprised of the Philippine Stock Exchange Composite Index (PSEi)'s weekly closing prices from January 5, 1994 and December 26, 2012. The weekly closing prices were taken on Wednesdays. If a particular date falls on a holiday, the closing price of the previous day was taken. All data in the study were obtained from the Philippine Stock Exchange (PSE) and had a total of 989 observations. As such, the weekly return series is generated from the following equation:

$$R_t = (100)*(ln(P_t)-ln(P_{t-1})) \quad (9)$$

where *ln* is the natural logarithm operator; *t* represents time in weeks; R_t is the return for period *t*,; P_t is the index closing price for period *t*.

3. RESULTS AND DISCUSSION

Pre-testing

The kurtosis coefficient was positive, having a relatively high value for the return series (Kurt = 4.975861) this points out, that the distribution of returns is leptokurtic. The weekly return series being negatively skewed implies that the distribution is not symmetric. The Augmented Dicky-Fuller (ADF) statistic indicates that the stock return series is stationary. The ADF test statistics rejected the hypothesis of the existence of a unit root in the returns series at 1% level of significance.

The Breusch-Godfrey LM Test included 24 lags of the return series. It did not reject the null hypothesis of no serial correlation, the test statistics confirmed the absence of autocorrelation in the first and the higher orders but showed autocorrelation in the 2nd, 3rd and 8th lag. Overall, the PSEi returns exhibit little correlation. Lastly, before the estimation of ARCH models, the ARCH-LM test was done to indicate the presence of ARCH effect on a .001 level of significance on the residuals of the 1st lag, .01 level of significance on the residuals of the 2nd lag and .05 level of significance on the residuals of the 3rd, 7th and 19th lag.

Diagnostic Tests

The coefficients of both the positive size bias test and the negative size bias testare statistically insignificant at a 5% level. Therefore it can be said that the underlying volatility model used, EGARCH(1,2), captures the effects of both large and small negative(positive) returns. Testing for the joint significance of $'\psi_1', '\psi_2', \&' \psi_3'$ concludes that jointly, all three coefficients are equal to zero (p-value of .5910). We apply the post-estimation tests to the different GARCH type models. Only the EGARCH(1,2) and TGARCH(1,1) model pass the test against the failure of GARCH models with different orders.

Empirical Findings and Analysis

A. EGARCH (1,2)-M Model Results

Findings indicate that the PSEi returns can be reasonably modelled with an AR(3) component for the mean equation and an EGARCH(1,2) for the variance equation . From our post-estimation testing, we conclude that EGARCH-M (1, 2) is adequate and is indicative of asymmetric volatility in the PSEi.

The modified model based on the results of the EGARCH-M (1, 2) are presented:

$$R_t = .181 + .0230R_{t-1} + .0592R_{t-2} + .0450R_{t-3} - .0104\mathrm{h_t} + \epsilon_t \ \mathbf{(10)}$$

$$\ln(\mathrm{h_t}) = .0907 + .129[|z_{t-1}| - E|z_{t-1}|] - .115(z_{t-1}) + .260\ln(\mathrm{h_{t-1}}) + .703\ln(\mathrm{h_{t-2}})\mathbf{(11)}$$

In order to verify the traditional notion of the risk-return trade-off, it is imperative to examine the coefficient (δ) of the conditional variance (h_t) in the mean equation (Equation 10). As our results show, the parameter of the conditional variance in Equation (10) is -.0104. This implies that there is a negative, yet statistically insignificant relationship between conditional volatility and returns on the PSEi. This result is consistent with the findings of Fama and Schwert (1977), Campbell (1987), Nelson (1991), Glosten Jagannathan and Runkle (1993) whose studies showed a negative relationship between stock returns and its variance.

The coefficient of $[|z_{t-1}| - E|z_{t-1}|]$ with a value of 0.129 is significant at a 0.001 level. The positive coefficient implies that large unpredictable innovations (whether positive or negative) have destabilizing effects on the conditional variance of stock returns.

To analyze asymmetric volatility, we take a look at the coefficient of z_{t-1}. Based on our results, the coefficient takes on a value of -.115 and is statistically significant at the 0.001 level. This means that whenever the innovation ϵ_{t-1} is negative, which implies that z_{t-1} is negative, conditional volatility will tend to rise. Conversely, when the innovation ϵ_{t-1} is positive, which means there was an inflow of good news, conditional volatility will tend to fall. This confirms our hypothesis that there is asymmetric volatility in the returns of the PSEi. In other words, there is an existence of the 'down market effect' or the 'leverage effect'. Extending on this outcome, it might indicate that bad news creates speculative bubbles, particularly when the socioeconomic and political circumstances are very unpredictable. (Ogum et. al., 2008).

We also look at whether shocks in the conditional volatility persist over time. Our findings show that the GARCH (Δ) parameters of .260 and .703 are statistically significant at .05 and .001 level of significance. This confirms our notion that shocks in the conditional volatility persist, although it dies down quickly. This finding is not surprising and has already been documented (Campbell, 1998). This suggests that once volatility increases, it is likely to remain high for over two weeks based on the models used and their results. Again, this supports the spirit of the ARCH models, which acknowledges the presence of volatility clustering.

B. TGARCH-M (1,1) Model Results

Furthermore, in order to verify the asymmetry of the impacts of good and bad news on conditional volatility, we also present the results of the TGARCH model. Based on previous literature, it can be concluded that TGARCH-M (1,1) is adequate in detecting asymmetric volatility in the returns of the PSEi.

The following coefficients for the mean and variance equation were estimated using the TGARCH (1, 1):

$$R_t = -.304531 + .0541989R_{t-1} + .0715812R_{t-2} + .064076R_{t-3} + .0333968h_t + \epsilon_t \quad (\mathbf{12})$$

$$h_t = .3352319 + .0728316\epsilon_{t-1}^2 - .0982595D_{t-1}\epsilon_{t-1}^2 + .9444847h_{t-1} (\mathbf{13})$$

We notice that the coefficient $'\vartheta'$ which represents asymmetry is negative with a value of -.0982595. It is important to highlight that Stata presents another variation of the TGARCH process wherein it modifies the dummy variable D_{t-1} on Equation (4) so that it will represent positive shocks rather than negative shocks. (Stata, 2009).
Therefore, the sign of $'\vartheta'$ supports our finding that the arrival of bad news (negative innovations) induce greater volatility than the arrival of good news (positive innovations).

Looking at the intercept of the mean equation Equation (12) and the coefficients of the AR(3) component, it implies that the distribution of the returns of the PSEi are skewed to the left. This means that there is a greater probability of incurring negative returns on the index.

C. *EGARCH-M (1,2) Results with another variable specification*

One flaw of the EGARCH-M model is the specification of the functional form of the risk parameter in the mean equation. As it was pointed out, a reason why we may have anomalous results was that the coefficient 'δ' in Equation (5) represents the impact of the conditional variance on the returns, wherein the standard deviation is the actual measure of risk. Hence, we modify our in-mean equation such that we substitute the conditional variance with the conditional standard deviation.

Based on the results and comparing it with the original EGARCH-M(1, 2) results (the one with conditional variance as part of our in-mean equation), it is clear that the risk parameter is still negative and statistically insignificant. We also find a statistically significant presence of asymmetric volatility and size effect.

Theory Meets Reality

In order to determine whether our econometric model is in accordance to the news (whether good or bad) are happening in the Philippines, we plotted the predicted conditional variance along with the residuals of the EGARCH-M model. To narrow down the time period, we took the top 20 largest and lowest returns of the PSEi from 1994 to 2012 and compared it with the top 20 positive and negative residuals. Surprisingly, 60-70% of the results have dates belonging to two volatile periods in our study which are the 2008 Global Financial Crisis and the 1997 Asian Financial Crisis.

After listing down the highest and lowest residuals, we have matched the dates of those residuals with news coming from the Business World Online Archives (CODEX) to explain the anomalous returns during that period.

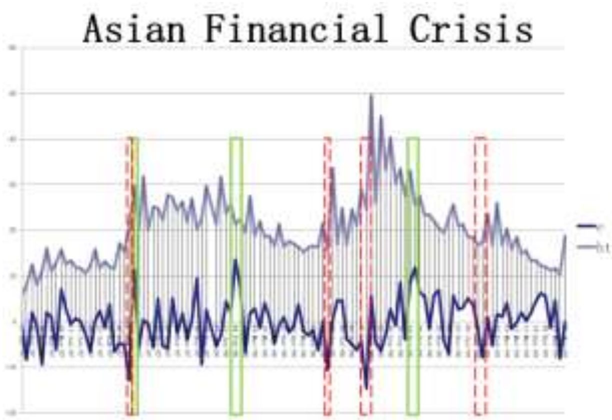

Figure 5: Positive and Negative Residual and Conditional Variance during the AFC

For easier analysis, we graphed the two specified time periods, residuals (ϵ) and conditional variance (h_t). In Figure 5, we aimed to capture the volatility during the Asian financial crisis. The dashed red boxes represent the top negative residuals while the solid green boxes represent the top positive residuals during that time period. As presented, it shows the top 7 spikes during the Asian Financial Crisis (which also belongs in the top 10 highest and lowest returns of the PSEi from 1994-2012) in terms of volatility with their corresponding events occurring during the specified week.

Figure 6 represents the Global Financial Crisis. It shows the top 6 positive and negative residuals during the Global Financial Crisis (which also belongs in the top 10 highest and lowest returns of the PSEi from 1994-2012) with their corresponding events that occurred during that specified week.

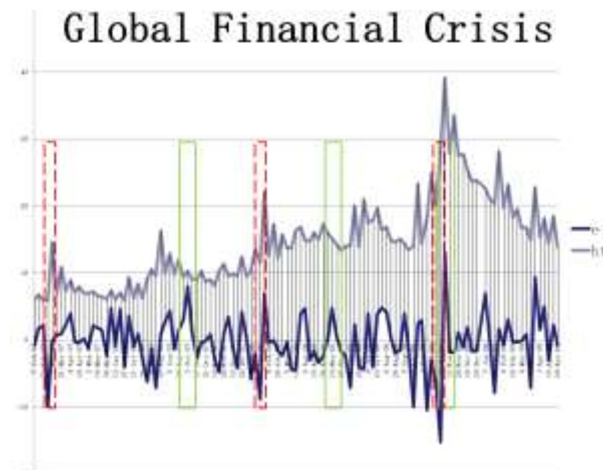

Figure 6: Positive and Negative Residual and Conditional Variance during the GFC

Upon closer examination of Figures 5 and 6, it can be seen that a negative residual increases conditional volatility and continues to do so until it reaches its peak after two weeks. The opposite can be said with a positive residual wherein it decreases conditional volatility until it reaches its through two weeks later, these findings are consistent with our EGARCH (1,2) model. Furthermore, we discovered that the top positive residuals (green solid boxes) and top negative residuals (red dashed boxes) correspond to an inflow of good and bad news during that week.

In fine, we conclude that our model is attuned to real-life scenarios for it is clear that good news in effect produces positive residuals and in turn dampens conditional volatility. On the contrary, bad news produces negative residuals, which then increases conditional volatility.

4. CONCLUSION

The volatility of PSEi stock returns from January 1994 to December 2012 have been investigated and modeled using two asymmetric conditional volatility models, the EGARCH-M (1,2) and the TGARCH-M (1,1). We found that PSEi returns series exhibit leverage effects and showed persistence of shocks in the conditional volatility for at least 2 weeks. These are in line with findings done on developed stock markets. Our results also showed a negative yet insignificant relationship between risk and return like many recent studies.

The presence of asymmetric volatility in the returns of the PSEi, gives light to the presence of the down market effect as modeling the index does not necessarily capture the changes in the leverage of each firm. However, as we have shown, persistence in volatility changes die down after at least 2 weeks.

The down market effect states that conditional volatility is more related to falling stock prices rather than changes in the financial leverage of firms. It may explain why the market was highly volatile during the periods covering the two crises in the last two decades: Asian Financial Crisis and Global Financial Crisis. Given the sensitivity of the PSEi to the inflow of information, we recommend that policy makers maintain a well-regulated financial market in order to facilitate a smooth integration of the Philippine market with the global economy. By taking immediate action to neutralize the effects brought about by economic reverses and social or political upheavals, we can promote the Philippines as a haven for safe investments.

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