Philippine Management Review
2005, Vol. 12, pp. 1-8.

A NOTE ON THE ASYMMETRIC EFFECT OF SHOCKS ON MARKET RETURN VOLATILITY: THE PHILIPPINE CASE

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This paper extends the research on stock return volatility in the Philippines. It presents evidence on the asymmetric effects of positive and negative shocks on the volatility of market returns in the Philippines. The empirical findings of the study provide additional support to the so-called leverage effect at the aggregate level. A drop in security returns lowers market value of equity and increases the leverage of firms. The change in financial leverage raises the risk and is reflected in increased volatility.

I. INTRODUCTION

As a measure of risk, volatility of security returns is among the central themes in finance. Together with expected returns, volatility estimates are used as inputs in asset pricing, estimation of capital costs, and asset allocation decisions.

Traditional models assume that volatility, as measured by the variance of stock returns, is constant (i.e., homoskedasticity assumption). But empirical evidence shows otherwise. It has been noted that security returns exhibit volatility clustering: Periods of large security price movements alternate with periods of small price changes. This phenomenon results in fat-tailed distribution of stock returns, suggesting that large returns occurs more often than what can be expected from a normally distributed variable.

Another notable pattern in the volatility of stock returns is the asymmetry in the effect of positive and negative shocks. It has been observed that periods of large volatility are ushered by a significant negative shock. Black (1976) explains that such phenomenon is due to the way firms are financed. A drop in the stock price of a firm raises the debt-to-equity ratio and, as a consequence, increases the volatility of returns to equity. More popularly known as the leverage effect, this explanation has found more support in subsequent studies that empirically established volatility as an increasing function of financial leverage (e.g., Christie, 1982 and Schwert, 1989).

Volatility clustering in aggregate returns in the Philippines has been established by earlier studies. Aragon (1993) and Bautista (1996) established evidence on time-varying pattern of aggregate stock return volatility in the Philippines. They noted high transitory volatilities in the market returns in the Philippines and associated this pattern to political events and fluctuations in economic activity.

This paper extends the research on stock return volatility in the Philippines. It presents evidence on the asymmetric effects of positive and negative shocks on the volatility of market returns in the Philippines. In addition, this study compares volatility patterns of different data frequency, i.e., daily, weekly, and monthly.

This paper is organized as follows: Section II describes the empirical approach of the study: the threshold generalized autoregressive conditional heteroskedastic (T-GARCH) model. Section III describes the data used in the study and provides some

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statistical properties of aggregate stock returns in the Philippines. The section also presents the empirical results. Section IV concludes the paper.

II. EMPIRICAL APPROACH

Like any time series, security returns, $r_{i,t}$, can be expressed as the sum of two components: a predictable and an unpredictable component. Thus,

$$r_{i,t} = E[r_{it} | \Omega_{t-1}] + \varepsilon_t \qquad (1)$$

where $E[r_{i,t} | \Omega_{t-1}]$ is the predictable component[1] given the information set, Ω_{t-1}, available at time t-1 and ε_t is the unpredictable component[2]. Traditional econometric models generally assume homoskedasticity, i.e., the variance of the unpredictable component, ε_t, is constant. Thus, $E[\varepsilon_t^2] = E[\varepsilon_t^2 | \Omega_{t-1}] = \sigma_i^2$, at any time period t.

In the past two decades, the advances in quantitative modeling relax the assumption of homoskedasticity and specify a conditional variance function $E[\varepsilon_t^2 | \Omega_{t-1}] = h_{i,t}$ for some non-negative function $h_{i,t} = h_{i,t}(\Omega_{t-1})$. Most of the advances in modeling the conditional variance function are concentrated on the family of GARCH models. Introduced by Engle (1982) and subsequently generalized by Bollerslev (1986), a GARCH(p,q) model considers a time-varying conditional variance as a linear function of the square of errors (or shocks) in the past p periods and the conditional variance of the past q periods.

$$h_{i,t} = c + \sum_{j=1}^{p} a_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} b_j h_{t-j} \qquad (2)$$

With non-negative parameter estimates, this model specification ensures a non-negative estimate of the conditional variance and predicts large (small) shocks ensuing after a large (small) shock, of either sign.

Since its development, the GARCH model has evolved into a number of variants. Among them is Threshold-GARCH (T-GARCH) which was developed by Glosten, Jagannathan, and Runkel (1993). Sometimes referred to as GJR-GARCH to acknowledge the authors, the model incorporates not only volatility clustering but also the asymmetric effect of the positive and negative shocks on conditional variance. A dummy variable is introduced in the basic GARCH model to alter the effect on volatility of a positive shock from a negative shock[3]. A parsimonious T-GARCH(1,1) model of conditional variance of security i can be expressed as:

$$h_{i,t} = c + a\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + bh_{i,t-1} \qquad (3)$$

where $d_{t-1} = 1$ if $\varepsilon_t < 0$, and zero otherwise. Thus, a positive news ($\varepsilon_t > 0$) will increase the conditional variance by a; In contrast, a negative news ($\varepsilon_t < 0$) will increase the conditional variance by $a + \gamma$. If $\gamma = 0$, then positive and negative news have no asymmetric effect on volatility. To ensure non-negativeness in the conditional variance, the following conditions must hold: $c > 0$, $(a + \gamma)/2 \geq 0$, and $b > 0$. The condition for covariance stationarity is $(a + \gamma)/2 + b \geq 0$.

III. DATA AND EMPIRICAL RESULTS

Data and Descriptive Statistics

The data series for market return, $r_{m,t}$, is computed as follows:

$$r_{m,t} = 100 * \ln(Phisix_t / Phisix_{t-1}) \quad (4)$$

where Phisix is the value weighted portfolio of 30 companies that represent the different traded sectors in the Philippine equity market. While the computation of the daily market return is straight forward, the weekly return is based on the Wednesday level of the Phisix to avoid the possible abnormal returns at the start or end of the week. Meanwhile, the monthly return is based on the end-of-the month level of Phisix following the convention in computing for monthly holding period returns.

Descriptive statistics of the daily, weekly, and monthly market return for the period 3 July 1997 to 5 December 2005 is summarized in Table 1. Note that different measures of central tendency (i.e., mean and median) vary with the frequency of the data. This is due to the difference in the underlying assumption on the investor's holding period. The daily returns are premised on the assumption that, at the start of the day, the investor invests on a portfolio of stocks that reflect the composition of the Phisix and divests from this investment at the end of the day. Meanwhile, the weekly and monthly returns assume that the investor will hold on to the portfolio of securities for one week and one month, respectively. The difference in the assumption on the investor's holding period also affects the range of returns (i.e., maximum and minimum) and standard deviation, a measure of dispersion of the returns.

The skewness of the market returns series across the different frequencies is fairly close to zero. This suggests that the returns are relatively symmetric around the mean. However, the kurtosis of the market return series of the different frequencies is greater than three, the kurtosis of the normal distribution. This means that the market returns series is peaked: The prevalence of returns around the mean is much more than that of a normally distributed series (refer to Charts 1-3.) Consequently, the Jarque-Bera test statistics and corresponding probability value reject the null hypothesis that the data series is normally distributed.

Table 1
Descriptive Statistics

	Daily	Weekly	Monthly
Mean (%)	-0.01216	-0.06269	-0.21999
Median (%)	0.00000	-0.09340	-0.22617
Maximum (%)	16.1776	13.79998	33.16657
Minimum (%)	-9.74416	-15.3867	-29.8906
Std. Dev.	1.570496	3.774805	8.674958
Skewness	0.896083	0.107668	0.015797
Kurtosis	15.82955	4.750245	5.701245
Jarque-Bera	15368.52	56.88211	30.40718
Probability	0.000000	0.000000	0.000000
Sum	-26.7332	-27.5187	-21.9986
Sum Sq. Dev.	5418.808	6241.128	7450.234
Observations	2198	439	100

Empirical Results

The mean equation of the market return is specified as an AR(1) process while the variance equation is specified as a parsimonious T-GARCH(1,1) model. Results are summarized in Table 2. Panel A presents the estimates for the daily model; Panels B and C present the estimates of the weekly and monthly models, respectively.

A review of the parameter estimates of the variance equation for c, a, γ, and b show that the model fulfills conditions for non-negativity (i.e., $c > 0$, $(a+\gamma)/2 \geq 0$, and $b > 0$) and covariance stationarity $(a+\gamma)/2 + b \geq 0$.

The parameter estimates for γ are all positive and statistically significant, suggesting that a drop in market returns in the previous period results in an increased volatility. This empirical finding provides additional support to the so-called leverage effect at the aggregate level. A drop in security returns lowers market value of equity and increases the leverage of firms. The change in financial leverage raises the risk and is reflected in increased volatility.

It is also worth noting that the statistical significance of the parameter γ diminishes with the decrease in the frequency of the observation. It can be conjectured that the market returns for longer holding period have incorporated market corrections for over reaction of investors to drops in market returns. The increased volatility in daily return caused by a drop in return may reflect not only the leverage effect but also other phenomenon such as over reaction of investors.

Table 2
Parameter Estimates of T-GARCH Model of Market Return Volatility:
Daily, Weekly, and Monthly Return on the Phisix
July 2, 1997 to December 5, 2005

Panel A. Daily Return on Phisix

	Coefficient	Std. Error	z-Statistic	Prob.
B	-0.034636	0.036993	-0.936287	0.3491
AR(1)	0.163254	0.020739	7.871968	0.0000
	Variance Equation			
b	0.080224	0.011234	7.141234	0.0000
a	0.023268	0.004358	5.339698	0.0000
γ	0.094180	0.008488	11.09609	0.0000
b	0.897796	0.007658	117.2411	0.0000

Panel B. Weekly Return on Phisix

	Coefficient	Std. Error	z-Statistic	Prob.
b	-0.033209	0.174695	-0.190096	0.8492
AR(1)	0.050433	0.044271	1.139206	0.2546
	Variance Equation			
b	0.192783	0.074203	2.598056	0.0094
a	-0.028778	0.012004	-2.397395	0.0165
γ	0.077585	0.022063	3.516493	0.0004
b	0.974594	0.010307	94.55700	0.0000

Panel C. Monthly Return on Phisix

	Coefficient	Std. Error	z-Statistic	Prob.
b	-0.580996	0.839526	-0.692052	0.4889
AR(1)	0.044728	0.055459	0.806498	0.4200
	Variance Equation			
c	15.12081	9.593401	1.576168	0.1150
a	-0.121948	0.098639	-1.236301	0.2163
γ	0.542063	0.218506	2.480766	0.0131
b	0.652972	0.236350	2.762737	0.0057

IV. SUMMARY AND CONCLUSION

This study extends the empirical investigation on aggregate stock return volatility. It presents evidence on the asymmetric effects of positive and negative shocks on the volatility of market returns in the Philippines. Statistical results confirm the asymmetric effects of shocks on aggregate stock return volatility and provide additional evidence in support of so-called leverage effect at the aggregate level. It also noted that the asymmetric effect of shocks on volatility diminishes with the decrease in the frequency of the observation. It conjectured that longer period market returns have already incorporated corrections that could have induced increased volatility after a negative shock.

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APPENDIX

Chart 1
Daily Market Return
3 Jul 1997 to 5 Dec 2005

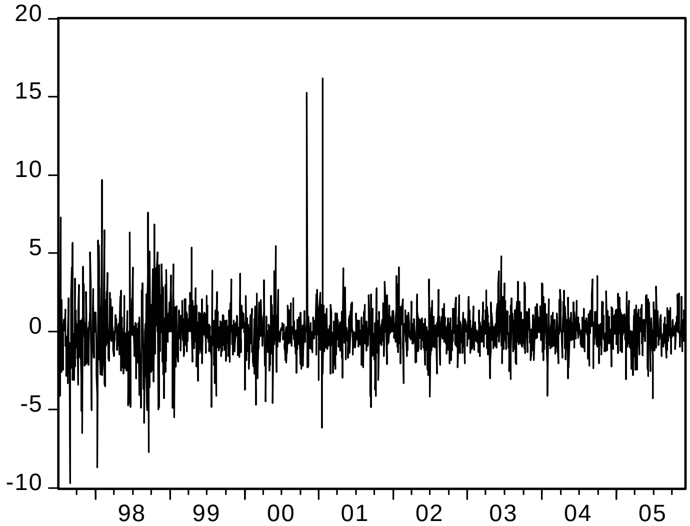


Chart 2
Weekly Market Return
Jul 1997 to 5 Dec 2005

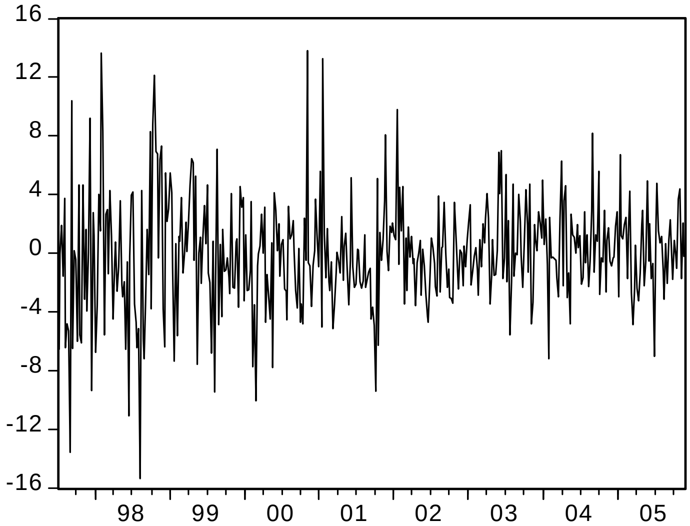
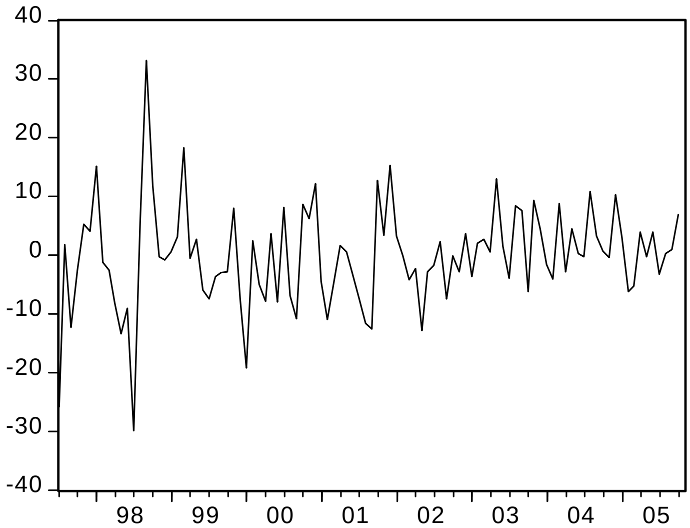


Chart 3
Monthly Market Return
3 Jul 1997 to 5 Dec 2005



NOTES

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[1] Also referred to as the conditional mean.

[2] Also referred to as shock, error, residual, or news.

[3] Although this modification is often cited in the literature on GARCH model, Glosten, et al., also modified the GARCH-M model to consider seasonal patterns in volatility as well as the effect of interest rates in determining conditional variance.