MEASURING MACROECONOMIC CAUSES OF STOCK MARKET VOLATILITY IN HIGH AND LOW VOLATILITY REGIMES OF AN EMERGING ECONOMY

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Abstract

An understanding of stock market volatility and its macroeconomic causes is important in assessing investment and leverage decisions of emerging economies especially where the market consists of risk–averse investors. Thus this study examines the volatility of different sectors in Colombo Stock Exchange (CSE) and how the macroeconomic factors (Narrow Money Supply, Broad Money Supply, Inflation, Interest Rate, Crude Oil Prices and Exchange Rate) influence the market volatility in high and low volatility regimes. Monthly stock returns of 20 sectors from 2007 to 2010 are used for the investigation. The Iterated Cumulative Sums of Squares (ICSS) algorithm is applied in splitting the original series into high volatile and low volatile periods. Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), Threshold GARCH (TGARCH) and GARCH Regression are the econometric models employed for the empirical analysis. Results found that 16 out of 20 sectors in CSE significantly ($p<0.05$) volatile. In the low volatility regime, all most all of the macroeconomic factors except Crude Oil Prices significantly ($p<0.05$) influence the stock market volatility. However, none of these macroeconomic factors are significant ($p>0.05$) in the high volatility regime.

Keywords: Macroeconomic Factors, Stock Market Volatility, Volatility regimes and GARCH Models.

01. Introduction

Financial markets play an important role in the process of economic growth and development by facilitating savings and mobilizing funds from savers to investors. While there have been numerous attempts to develop the financial sector, emerging economies are facing the problem of high volatility in greater extent. Stock market volatility in an emerging economy is identified as one of bone of contentions in attracting investments. Financial markets smooth down the progress of savings and channel funds from savers to investors efficiently and thus by doing so play an important role in the process of economic growth and development. Volatility basically spoils the smooth operation of the financial system and casts an unfavorable affect on economic performance. The emerging economies are facing many impediments in their financial markets, and with many other factors, high volatility in prices which also considered as high risk or uncertainty is a major factor of erosion of capital from these markets. A rise in stock market volatility can be interpreted as a rise in risk of equity investment and thus a shift of funds to less risky assets. This shift of investments form high volatile stocks to low volatile stocks is evident in markets where risk–averse investors are found. Thus, stock market volatility can be a sticking point in the way to attract investments in an emerging economy.

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Also, volatility influences the distribution of portfolio returns as this has implications for daily risk management, portfolio selection and derivative pricing. Hence, it is very much important to recognize the causes of volatility in an emerging economy. There are wide-ranging compromises on what comprises stock market volatility and, how to measure it. Engle and Ng (1993) reveal that the causes of volatility as the arrival of new, unanticipated information that alters expected returns on a stock. Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shifts in investor tolerance of risk and increased uncertainty.

Macroeconomic variables play an important role in asset pricing theories. For this reason, many policy makers and market practitioners have empirically studied the link between macroeconomic variables and stock market volatility (Hendry, 1986; Bilson, Brailsford, and Hooper, 1999; Islam, 2003; Mala & Mahendra, 2007). However, concentrations on the macroeconomic causes of volatility are still vacuum in the empirical finance literature. Thus, this study attempts to investigate the macroeconomic causes of volatility in volatile sectors of Colombo Stock Exchange (CSE) in low and high volatility regimes are to be studied.

The rest of the sections of this study are structured as follows. Section 2 outlines the theoretical background and most relevant literature. Section 3 explains the methodology adapted in this study. Section 4 outlines the analysis and discussion of results. Section 5 provides the conclusion for the study.

2. Literature Review

Macroeconomic variables play a key role in asset pricing theories. For this reason, many policy makers and market practitioners have empirically studied the link between macroeconomic variables and stock market volatility. Bilson, Brailsford, and Hooper (1999) addressed the question of whether macroeconomic variables may proxy for local risk sources. They found reasonable evidence to support this hypothesis. Further, they investigated the degree of commonality in exposures across emerging stock market returns using a principal components approach, and found little evidence of commonality when emerging markets are considered collectively. At the regional level, however, considerable commonality was shown to exist.

Hendry (1986) studied the short-run and long-run relationship between macroeconomic variables and stock market indexes of six countries. He analyzed the influence of interest rate, inflation, money supply, exchange rate and real activity, along with a dummy variable to capture the impact of the 1997 Asian financial crisis. The results confirmed that there is significant influence of macroeconomic variables on the stock market indices in each of the six countries under study. Similarly, Islam (2003) examines the short-run dynamic adjustment and the long-run equilibrium relationships between four macroeconomic variables of interest rate, inflation rate, exchange rate, and the industrial productivity and the Kuala Lumpur Stock Exchange (KLSE) Composite Index. His conclusions were similar: there existed statistically significant short-run and long-run relationships among the macroeconomic variables and the KLSE stock returns.

Fama (1965) & French (1980) investigated and concluded that; volatility caused by trades itself. It means greater the level of trade volume, greater the price movements. Bessembinder and Seguin (1993) find that an asymmetrical volatility is due to response between volume and price. French & Roll (1986) studied volatility and their results show that volatility is higher during trading hours. It is also argued that volatility is driven by trading volume followed by arrival of new information regarding new floats, or any kind of private information that incorporate into market stock prices. The stock market volatility caused by number of factors such as; credit policy, inflation rate, interest, financial leverage, corporate earnings, dividends yield policies, bonds prices and many other macroeconomic, social and political variables are involved.

Mala & Mahendra (2007) studied the impact of interest rate changes on the Fiji's stock market volatility during 2001 to 2005. Autoregressive Conditional Heteroskedasticity (ARCH) models and its extension, the Generalized ARCH model was used to find out the presence of the stock market volatility. Their results showed that the interest rates changes have a significant effect on stock market volatility. However, in their study they did consider only one macroeconomic variable to depict the causes of stock market volatility. Peiris and Peiris (2011) studied the macroeconomic causes of volatility in CSE by considering Narrow Money Supply, Broad Money Supply, Inflation and Interest Rate. They found that inflation and interest rate are the two significantly influencing macroeconomic factors on the stock market volatility.

The above previous empirical evidences revealed that the majority of researchers have studied the relationship between various macroeconomic variables and stock market indexes. Conversely, literature on examining the macroeconomic causes of stock market volatility is still unexplored, mainly in low and high volatility regimes separately.

3. Methodology

This section primarily deals with the description of data of this study. This section also gives through explanation of statistical modeling of volatility of the concerned sectors in CSE. The methodology adopted here is different to the prominent previous studies. However, some unique methodological procedures will apply when and where appropriate for the current study.

3.1 Indexes and Data

As previously mentioned, this study concerns on the macroeconomic factors which generally affect to the stock market volatility in CSE. Hence, the macro economic factors of Narrow Money Supply (M1), Broad Money Supply (M2), Inflation (I), Interest Rate (IR), Crude Oil Prices (OP) and Exchange Rate (ER) are regressed with the stock market volatility. Monthly time series data for M1, M2, I, IR, OP and ER for the period 2005 to 2010 were obtained from the Central Bank annual reports. Sector Indexes (SI) for the 20 sectors in CSE were used to determine the volatility of the market. The sectors considered; Bank Finance and Insurance (BFI), Beverage Food and Tobacco (Bft), Chemicals and Pharmaceuticals (C&P), Construction and Engineering (C&E), Diversified Holdings (Div), Footwear and Textile (F&T), Health Care (Hlt), Hotels and Travels (H&T), Information Technology (IT), Investment Trusts (Inv), Land and Property (L&P), Manufacturing (Mfg), Motors (Mtr), Oil Palms (Oil), Plantations (Plt), Power & Energy (P&E), Services (Srv), Stores Supplies (S&S), Telecommunications (Tle) and Trading (Trd). Monthly time series data for these sectors were acquired from CSE having a direct observation from its library.

3.2 Calculation of Daily Stock Returns

This study applies monthly returns of all sector indexes. Monthly stock returns are calculated by using the following equation;

$$R_{it} = \frac{I_{it} - I_{it-1}}{I_{it-1}} * 100 \qquad \textbf{(1)}$$

Where; R_{ti} is monthly rate of return on *t* day of sector index *I,* I_{ti} represents closing value on t month of sector index *I and* I_{ti-1} denotes closing value on *t-1* month of sector index *i.*

3.3 Modeling the Mean Equation.

Before starting econometric modeling it is always important to make the data series stationary. A series is said to be stationary if the mean and autocovariances of the series do not depend on time. Augmented Dickey-Fuller (ADF) test and Phillip and Perron (P-P) tests are used to measure the stationary/non-stationary behavior of the return series of all the indexes. The following unit root hypothesis is tested at 95% confidence level to determine the stationary/non-stationary pattern of the return series.

H_{i0}: *Data series has a unit root* *vs* H_{i1}: *Data series has no unit root*

H_{i0} and H_{i1} represent null hypothesis and alternative hypothesis respectively for the ith sector. In this study, the investigators used the probability value (p-value) method at 95% confidence level to measure the explanatory power of the series. Hence, the decision criterion will be; If p-value is < 0.05 then H_{i0} is rejected otherwise H_{i0} is accepted. In case, where H_{i0} is accepted, the tested data series is said to be not stationary, otherwise the series is stationary. Instances where the series is not stationary, different techniques (1st difference, 2nd difference, etc) are used to make the series stationary. These stationary data are then used to develop the mean equation. The Autoregressive Moving Average (ARMA) models are considered when developing the mean equation. The autoregressive and moving average specifications can be combined to form an ARMA(r,s) specification:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ...+ \phi_r Y_{t-r} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - .... - \theta_s \varepsilon_{t-s} \qquad \textbf{(2)}$$

Where, Y_t are the normal returns for the period t, ϕ_i represents the auto regressive coefficients, θ_j represents the moving average coefficients. In this study we considered only up to the first lag both in AR and MA components in the ARMA model. Hence, three models of ARMA(1,0), ARMA(0,1) and ARMA(1,1) were tested for the best fitted mean model. Log likelihood estimate, Akaike Info Criterion (AIC) and Schwarz Criterion (SIC) are used to select the most fitted model out of the three models considered above.

3.4 Testing for ARCH Effects

The residuals of the respective mean equations fitted for the 20 sectors are tested for the ARCH effects by using the Lagrange Multiplier test (ARCH LM) of Engle (1982). The ARCH LM test statistic is computed from an auxiliary test regression to test the null hypothesis that;

H_{0i}: *There is no ARCH up to order q in the residuals.*
H_{1i}: *There is ARCH up to order q in the residuals.*

H_{0i} and H_{1i} indicate the null hypothesis and the alternative hypothesis respectively for the ith sector. Probability value (p-value) method at 95% confidence level is used as the decision criterion. That is, if the p-value is less than the 0.05 the null hypothesis is rejected otherwise it is accepted. Hence, instances where null hypothesis is rejected ARCH effects are said to be existed in the considered sector. Sectors that depict significant ARCH effects are used to derive the composite SI as they are the significantly volatile sectors in CSE. This composite SI is then used to recognize the low and high volatility regimes.

3.5 Detection of Break Points and Volatility Regimes

Iterated Cumulative Sums of Squares (ICSS) algorithm, introduced by Inclan and Tiao (1994) is used to identify the volatility breaks in the returns of composite SI. Once the break points that cause regime changes are detected it is important to select the break points that are statistically significant. The statistically significance is tested by embedding them as dummy variables to a volatility model developed for the composite SI. Finally, the statistically significant periods will be taken as the high volatile periods and the rest are low volatile periods.

3.6 Volatility Regression.

When regressing volatility with the considered macroeconomic variables it is important to develop the volatility data series for the composite SI. Generalized ARCH (GARCH) (Bollerslev, 1986) modeling techniques are used to develop the volatility series. GARCH models have been the most commonly employed class of time series models in the recent finance literature for studying volatility. The appeal of the models is that it captures both volatility clustering and unconditional return distributions with heavy tails. The GARCH (p,q), TGARCH and EGARCH models are considered as the volatility models. Log likelihood estimate, AIC and SIC are used to select the most fitted model out of the three models considered. Finally the best fitted volatility model is regressed with the log values of macro variables (M1, M2, I, IR, OP and ER) considered to determine which variables are significantly influence the volatility of CSE. If GARCH (p,q) fits well the corresponding volatility regression model can be drawn as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \lambda_1 LnM_1 + \lambda_2 LnM_2 + \lambda_3 LnI + \lambda_4 LnIR + \lambda_5 LnOP + \lambda_6 LnER .....(3)$$

If TGARCH fits well;

$$\sigma_t^2 = \omega + \sum_{j=i}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{n} \gamma_k \varepsilon_{t-k}^2 P_{t-k} + \lambda_1 LnM_1 + \lambda_2 LnM_2 +$$
$$\lambda_3 LnI + \lambda_4 LnIR + \lambda_5 LnOP + \lambda_6 LnER .....(4)$$

If EGARCH fits well;

$$Log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j Log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{n} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \lambda_1 LnM_1 + \lambda_2 LnM_2$$
$$+ \lambda_3 LnI + \lambda_4 LnIR + \lambda_5 LnOP + \lambda_6 LnER .....(5)$$

λ_i represent the coefficients of the macroeconomic variables of M1, M2, I, IR, OP and ER respectively. Here also *p-values* at 95% confidence level are used as the decision criterion for the significance of above variables.

4. Data Analysis and Discussion

4.1 Unit Root Test

The study used two different tests, i.e. Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test to examine the unit roots in stock return series. The null hypothesis tested whether the returns under consideration have a unit root (returns are nonstationary), against the alternative that they do not. The results of these two tests are reported in Table 1.

Table 1: Unit root test for sector indexes

Stock return indexes	**Augmented Dickey-Fuller test statistic**		**Phillips-Perron Test Statistics**	
	Null Hypothesis: Returns are Nonstationary		**Null Hypothesis: Returns are Nonstationary**	
	Level	**First Difference**	**Level**	**First Difference**
BFI	-14.40139*	-13.95227*	-11.40565*	-35.99262*
Bft	-10.60279*	-11.18384*	-10.60025*	-22.12111*
C&E	-11.77371*	-8.835745*	-13.99847*	-30.71375*
C&P	-11.52249*	-9.629511*	-11.52249*	-26.91159*
Div	-13.40139*	-12.95227*	-10.40565*	-34.99262*
F&T	-10.98171*	-13.52860*	-10.98953*	-23.21845*
Hlt	-12.54598*	-10.40231*	-12.74598*	-27.61333*
H&T	-9.784211*	-13.98990*	-11.44942*	-34.27727*
IT	-12.24598*	-10.70231*	-12.24598*	-27.51333*
L&P	-9.930911*	-11.41992*	-9.930911*	-22.03544*
Inv	-11.75126*	-11.10722*	-11.75308*	-27.57938*
Mfg	-9.906091*	-15.48453*	-9.888043*	-23.04383*
Mtr	-11.17677*	-11.24283*	-11.15853*	-20.63061*
Oil	-17.84333*	-10.37120*	-18.35034*	-49.12022*
P&E	-11.930911*	-13.41992*	-10.930911*	-23.03544*
Plt	-9.984211*	-13.28990*	-11.54942*	-34.33727*
Srv	-14.58471*	-11.10476*	-14.54826*	-32.14334*
S&S	-12.24598*	-10.70231*	-12.24598*	-27.51333*
Tel	-11.54598*	-10.40231*	-10.74598*	-23.61333*
Trd	-12.19087*	-9.331454*	-11.96080*	-22.46746*

Note: * implies that the coefficient is significant at 0.05 percent probability level.

The reported results in Table 1 indicate that all the sector returns were stationary in levels and at first differences *i.e.,* the null hypothesis that each of the stock return series has a unit root (returns are nonstationary) can be rejected both under the ADF test and PP test at 5% significance level. This confirms the non existence of autocorrelations in level returns and in their first differences. Hence, according to Fama (1970) all the sectors in CSE are weakly efficient. Further, results indicate that the level returns of all the considered indexes can be used to proceed with econometric modeling since they are serially independent.

4.2 ARCH LM Test

Following Table 2 shows the reported results for the best fitted mean models and ARCH LM test for the SIs.

Table 2: Mean models and ARCH LM Test

Sector	Mean Model	F-Statistic	*P*-value	Sector	Mean Model	F-Statistic	*P*-value
BFI	ARMA(1,1)	61.66847*	0.00000	Inv	ARMA(1,0)	29.59639*	0.00000
Bft	ARMA(0,1)	13.43936*	0.00000	Mfg	ARMA(0,1)	76.65411*	0.00000
C&E	ARMA(1,1)	32.67849*	0.00000	Mtr	ARMA(0,1)	0.17101	0.67927
C&P	ARMA(0,1)	115.98260*	0.00000	Oil	ARMA(0,1)	0.86440	0.35267
Div	ARMA(1,1)	23.02382*	0.00000	P&E	ARMA(1,1)	13.88944*	0.00000
F&T	ARMA(0,1)	1.28453	0.25725	Plt	ARMA(1,0)	69.69964*	0.00000
Hlt	ARMA(0,1)	74.80935*	0.00000	Srv	ARMA(0,1)	1.50705	0.21979
H&T	ARMA(0,1)	229.20220*	0.00000	S&S	ARMA(0,1)	5.62999*	0.01779
IT	ARMA(1,1)	117.07090*	0.00000	Tel	ARMA(0,1)	30.02671*	0.00000
L&P	ARMA(0,1)	61.40053*	0.00000	Trd	ARMA(0,1)	76.16457*	0.00000

Note: * implies that the coefficient is significant at 0.05 percent probability level.

The reported results in the above Table 2 signifies that ARMA(1,1) model is best fitted for BFI, C&E, Div, IT and P&E sectors and ARMA(0,1) fits with Bft, C&P, F&T, Hlt, H&T, L&P, Mfg, Mtr, Oil, Srv, S&S, Tel and Trd sectors while ARMA(1,0) fits with Plt sector. Results for the ARCH LM test above indicate that all most all the fitted ARMA models are showing significant (P-value < 0.05) ARCH effects except models developed for F&T, Mtr, Oil and Srv sectors. That is, the ARMA models fitted for F&T, Mtr, Oil and Srv sector indexes accept the null hypothesis that there is no ARCH up to order 1 in the residuals indicating that they are not significantly volatile. Further, these results specify that the other 16 sectors are significantly volatile. Hence, those volatile 16 sectors can be used to develop the composite SI. Composite SI is developed by taking the simple average returns of those volatile sector indexes.

4.3 Volatility modeling of Composite SI and ICSS algorithm

The results of ICSS algorithm indicate that there are 3 break points ranging from return point 1 to 24, 25 to 29 and 30 to 48 in the Composite SI. The 48 average return points of the volatile sectors or the Composite SI is then used to develop the volatility model and three dummy variables drawn for three break points were then regressed with the fitted volatility model. Table 3 represents the fitted volatility model for the Composite SI with the dummy variables.

Table 3 ARMA(1,1)-GARCH(1,2) model for Composite SI

Variable	Coefficient	p-value
AR(1)	0.157555	0.0000
MA(1)	-0.35319	0.0000
C	0.002069	0.0000
RESID(-1)^2	0.037762	0.0000
RESID(-2)^2	0.442504	0.0000
GARCH(-1)	0.369747	0.0000
D_1	0.00641	0.639139
D_2	0.076883	0.036806
D_3	0.06484	0.0000

The reported results in Table 3 indicate that out of 3 dummies only 2 are statistically significant at 95% confidence level. Hence, these 2 significant periods (25 to 29 and 30 to 48) of Composite SI is taken as the high volatile regime and the rest (1 to 24) is considered as the low volatile regime.

4.4 Development of GARCH Regression models

Equation 3, 4 and 5 devoid of macroeconomic regresses are first tested separately for both low and high volatility regimes and the best fitted model is identified by using Log likelihood estimate, AIC and SIC. Results indicated that equation 5 devoid of macroeconomic regresses (EGARCH) fits well with both the regimes. Hence, the equation 5 is used to identify the macroeconomic causes of stock market volatility.

Table 4 GARCH Regression models for low and high volatility regimes

	Coefficients in Low Volatility Regime	Coefficients in High Volatility Regime
AR(1)	-0.0057	-0.5788*
MA(1)	-0.4125*	0.9975*
ω	-4.7775	-0.5883
RESID(-1)^2	-3.1261	-0.8754
GARCH(-1)	-0.2029	0.1120
γ_1	-0.1505	0.7522*
M1	1.9949*	0.8518
M2	-4.7721*	-2.2387
IR	0.8043*	-0.2709
I	2.3981*	0.9449
OP	-0.0108	0.1210
ER	2.4866*	1.4692

Note: * implies that the coefficient is significant at 0.05 percent probability level.

The reported results in Table 4 indicate that in the low volatility regime all the macroeconomic regresses except OP are statistically significant (P-value < 0.05). This indicates that the macroeconomic factors like Narrow Money Supply, Broad Money Supply, Inflation, Interest Rate, and Exchange Rate are the macroeconomic causes of volatility in the low volatility regime. However, the reported R^2 value (25%) for this regime is very low. Hence, it is apparent that the volatility in this regime is caused by many other factors (both Micro and Macro) except the considered macro factors. Interestingly, none of these macroeconomic regresses are significant (P-value > 0.05) in the high volatility regime. Also the reported R^2 value (39%) is very low. This indicates that the high volatility in the high volatile regime is mainly because of other factors which are not considered with this study.

5. Conclusions

This study examines the volatility of different sectors in CSE and how the macroeconomic factors affect on the volatility by fitting Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized ARCH (GARCH) models for the composite index of the volatile sectors.

Findings of this study indicate that 16 out of 20 sectors are significantly volatile while other four sectors (Footwear and Textile, Motors, Oil Palms and Services) are not significantly volatile.

Mala & Mahendra (2007) found that interest rate changes have a significant effect on stock market volatility of emerging economies. Peiris & Peiris (2011) found that in addition to interest rate changes, changes in inflation also affect the volatility of stock returns of emerging economies. Our empirical results go beyond the findings of most of the previous studies indicating that Narrow Money Supply, Broad Money Supply, Inflation, Interest Rate, and Exchange Rate are the most influential macroeconomic causes of volatility in the periods of low volatility. However, in the high volatile periods of emerging markets like Sri Lanka these macroeconomic factors does not cause the volatility instead other micro and macro factors may lead the high volatility in those periods.

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