NEXUS BETWEEN ASYMMETRIC INFORMATION AND STOCK MARKET VOLATILITY: EVIDENCE FROM SRI LANKA

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Abstract

This study examines the impact of asymmetric information behaviour and macroeconomic variability in modelling the stock market volatility. CSE market does not show the characteristics which may potentially lead to larger volatility shocks. The idiosyncratic volatility is more subjected to the irrational investment decisions with the absence of relevant market information. Therefore, the information asymmetries motivate investors to highly depend on irrational reasons which lead to irrational volatility shocks. The variance equation of the EGARCH model was applied for identifying the impact of the asymmetric information behaviour. The mean-variance equation of EGARCH has been modelled with GDP, inflation, interest rate, and money supply for recognizing macroeconomic impacts. The study finds that the CSE market was significantly experiencing asymmetric information problem. As a result, uninformed investors make their decision based on the market sentiment creating irrational price volatilities. The mean-variance equation shows that macroeconomic variability has a significant impact on explaining the future asymmetric conditional volatility. However, CSE volatility spends a few weeks to adjust the relevant macroeconomic shocks.

Keywords: *Asymmetric information, Stock volatility, Macroeconomic volatility determinants, EGARCH*

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INTRODUCTION

Stock price volatility is an essential phenomenon in equity valuation, derivatives markets, risk management, and portfolio investment decisions. The right measurement of stock volatility is a demanded task among the equity investment community. Volatility clustering and persistence are the successful assumptions on stock volatility modelling and forecasting. These assumptions are mainly driven by the impact of market news on fundamental and non-fundamental factors of equity securities. However, there are differences in the dissemination of market information between equity traders. As a result of that, equity prices may exhibit asymmetric volatility patterns. These asymmetric volatility patterns and heterogeneous information distributions are significant in frontier stock markets like Colombo Stock Exchange (CSE). There are few studies available to identify the asymmetric information distributions of the CSE market (Jaleel & Samarakoon, 2009; Kumara et al., 2014; Morawakage & Nimal, 2015; Morawakage et al., 2018). All studies are based on the volatility clustering assumption of ARCH family models which are more appropriate statistical models in stock price volatility modelling. However, no one has accommodated asymmetric volatility clustering models with explanatory stock price volatility determinants in the CSE market; whereas the variability in volatility determinants are useful for better reflection of heterogeneous shocks of market prices. This study fulfils that research gap by accommodating the asymmetric volatility cluster modelling in the CSE market with macroeconomic volatility determinants.

The stock volatility behaviour is a researchable phenomenon, because it was observed that some markets exhibit extreme volatility behaviour without any fundamental variability. This condition highly appears in less developed equity markets which have lower average daily trading volume (Kumar & Dhankar, 2009; Singhania & Prakash, 2014). The CSE market is also a less developed equity market which is suffering the problem of extreme volatility incidents. According to the empirical studies, Fernando (2017) stated that the CSE has comparatively higher volatility behaviour. Further, Perera and Ediriwickrama (2020) have identified that the idiosyncratic stock volatility in CSE is more closer to the United States (US) idiosyncratic volatility level identified by Fu (2009). However, Pukthuanthong-Le & Visaltanachoti (2009) recognized that this measurement is more than the Fu's (2009) US average stock price volatility.

This is an excellent examination of the problem since the CSE market does not show the characteristics which may potentially lead to larger stock volatility behaviour, like short-selling, exchange-traded derivatives, and cross-listing. Moreover, the idiosyncratic volatility is more subject to the irrational behaviour of investors than the systematic volatility which drives by the variability of market fundamentals. Therefore, this higher level of idiosyncratic volatility may be due to the asymmetric informational problem among the market participants. Investors behave in an irrational pattern when they do not possess a sufficient amount of information for investment decisions.

As a result of that stock prices significantly move away from their fundamental value, causing a larger volatility behaviour. Therefore, the objective of this study is to examine the relationship between asymmetric information behaviour and CSE price volatility in response of macroeconomic variability. The first part of the study covers identifying the existence of the asymmetric information behaviour in the CSE market comparing the previous study results. The EGARCH asymmetric volatility model has been modelled with CSE historical daily pricing data for the ten years from 2010 to 2019. Thereafter, the author has examined the impact of macroeconomic shocks in determining the CSE volatility and asymmetric information behaviour. The mean variation and variance equation of the EGARCH model has been undertaken with different lag intervals in order to identify the speed of volatility responses from macroeconomic shocks. Macroeconomic shocks are measured through four variables (Gross Domestic Production (GDP), Inflation, Interest Rate, Money Supply) representing goods & service market and financial market of Sri Lankan economy.

LITERATURE REVIEW

The importance of the stock price volatility modelling has been emphasized in various theoretical arguments. According to Markowitz (1952), Sharpe (1964), Ross (1976), and Fama and French (1995, 2006), a precise measure of stock volatility has a greater role in famous Portfolio Management and Asset Pricing models. Leavens (1945), Black and Scholes (1972), and Cox et al. (1979) have identified stock volatility as a basic input in their investment risk management tools and measurements. Engle's (1982) ARCH family models are more appropriate in modelling stock price volatilities because conditional volatility is a successful assumption in stock price data. The ARCH model has been further developed by different researchers for advanced statistical aims (Bollerslev, 1986; Engle et al., 1987; Engle & Ng, 1993; Nelson, 1991).

The EGARCH is one of the advanced extended ARCH models for identifying the asymmetric information problems of stock price volatility. Empirical studies have shown the better performance of the EGARCH volatility model for testing homogeneous information distributions in frontier equity markets (Epaphra, 2017; Goudarzi, 2010; Olowe, 2009).

This asymmetric information distribution is a notable issue in frontier markets which may create negative impacts to the sustainable market development (Speidell, 2009). As Glosten and Milgrom (1985) stated that the price manipulation is possible when the market is inefficient to distribute information symmetrically; whereas Wang (1993) argued that investors demand a higher risk premium for compensating unequal information distributions. Insider dealing is also a significant consequence of unequal access to market information. Therefore, identifying and measuring the information asymmetric problem helps to increase the market liquidity and quality for a better environment in capital market operations of frontier markets like CSE.

There is a fewer number of studies conducted for identifying the relationship between the stock volatility and asymmetric information behaviour in the CSE market. Jaleel and Samarakoon (2009) have initiated for recognizing the asymmetric information behaviour in determining the CSE volatility. The main focus of that study was to identify the impact of stock market volatility with respect to the trade liberalization. It was found that the volatility measures did not exhibit the asymmetric information behaviour; whereas the stock volatility level is significantly larger during the liberalization over the pre-liberalization. This is the only study which does not account the asymmetric information behaviour in CSE market. Later, Jegajeevan (2010) and Morawakage and Nimal (2015) have investigated about the asymmetric information behaviour in the CSE market by undertaking ARCH family volatility models. In addition to that Kumara et al. (2014) has compared the differences of asymmetric volatility cluster modelling during and after the Civil-War in Sri Lanka.

Furthermore, Morawakage et al. (2018) have extended the previous study by comparing the Sri Lankan asymmetric conditional volatility behaviour with another frontier market (Indonesia). However, all previous studies have pointed out the existence of asymmetric information behaviour in CSE market other than Jaleel and Samarakoon (2009). As far as the Black's (1986) leverage effect is also a significant observation in their studies. Nevertheless, earlier asymmetric volatility models failed to accommodate volatility explanatory variables. The asymmetric information problem and volatility clustering behaviour are established on exogenous and endogenous market shocks. A naked EGARCH model can significantly address the variability of endogenous impacts; whereas the exogenous variability has to be addressed with separate explanatory variables. Therefore, a combination of asymmetric volatility modelling with explanatory volatility determinants may deliver a better reflection of unequal distributions of information and its market impact. This practice can be found in the recent studies conducted with respect to the other equity markets (Butt & Taib, 2021; Hsieh, 2013; Mgbame & Ikhatua, 2013; Olugbode et al., 2014).

Macroeconomic variables significantly capture the endogenous volatility impact, because equity market price is influenced by the current and future economic fundamentals. The importance of macroeconomic variability can be found in the famous theoretical asset pricing models of the Arbitrage Pricing Model (APM) and Multifactor Model (MM) (Fama & French, 1995, 2006; Ross, 1976). This has been confirmed by different empirical studies (Butt & Taib, 2021; Chaudhuri & Smiles, 2004; Chen, 2009; Chia & Lim, 2015; Gospodinov & Jamali, 2012; Humpe & Macmillan, 2009; Konrad, 2009; Maysami et al., 2004; Mittnik et al., 2015; Rahman et al., 2009; Ratanapakorn & Sharma, 2007; Wong et al., 2006; Wongbangpo & Sharma, 2002).

However, this macroeconomic impact appears lagging responses of stock price volatilities instead of efficient market responses of publicly available information (Camilleri et al., 2019; Chaudhuri & Smiles, 2004; Maysami et al., 2004; Mittnik et al., 2015; Olugbode et al., 2014; Rahman et al., 2009; Ratanapakorn & Sharma, 2007; Wongbangpo & Sharma, 2002). Therefore, markets exhibit questionable evidence on Fama's (1965) semi-strong market efficiency in response to the macroeconomic variability.

DATA

The sample consists of daily time series data for the 10-year period between 2010 January to 2019 December. Stock pricing behaviour was measured through the All Share Price Index (ASPI) of the Colombo Stock Exchange (CSE). All available daily pricing data is considered for the study excluding the public holidays and weekends. Selected macroeconomic variables were measured by GDP growth, Colombo Consumer Price Index (CCPI), Average Weighted Deposit Rate (AWDR), and Broder Money Supply (M2).

The GDP is available only on a quarterly basis; whereas the other three macroeconomic data are available on a monthly frequency basis. Therefore, the author has accommodated a special statistical conversion process to convert relevant data frequencies to the daily data frequency. Ju et al. (2014) proposed the "Quadratic Interpolation Method" (QIM) for converting the macroeconomic data into smaller frequencies. The same QIM method has been undertaken to convert the relevant macroeconomic data frequencies to the required daily frequency. The QIM approximates smaller frequencies based on a numerical equation of given larger frequency data set. Therefore, QIM approximations have biased on the pattern of the big data set. This method is supported by the "Eviews" which is the data analysis statistical software of the study. The QIM converted daily GDP on a quarterly basis and AWDR on an annual basis; whereas the CCPI and M2 are on monthly basis.

METHODOLOGY

This study has undertaken the Engle and Ng's (1993) EGARCH statistical method for modelling asymmetric information behaviour and macroeconomic impact on stock price volatility. The existence of asymmetric information behaviour has been tested with a naked EGARCH model excluding macroeconomic explanatory variables. As suggested by Olugbode et al. (2014) the variance equation of EGARCH can identify the volatility asymmetries, clustering, and persistence. The same method has been adopted for this study for identifying and measuring the asymmetric volatility impacts. Equation 1 shows the EGARCH variance equation statistical model.

$$log(ASPI_t) = \boldsymbol{\varphi} + \sum_{i=1}^{q} \boldsymbol{\eta}_i \left| \frac{u_{t-i}}{\sqrt{Y_{t-i}}} \right| + \sum_{i=1}^{q} \boldsymbol{\lambda}_i \frac{u_{t-i}}{\sqrt{Y_{t-i}}} + \sum_{k=1}^{p} \boldsymbol{\theta}_k \, log(Y_{t-k}) \quad \text{..... (1)}$$

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad \text{............ (2)}$$

Where;

$ASPI$ = Conditional Price Volatility of ASPI

u = Error Term

φ = Constant Effect

η = ARCH Effect

λ = Asymmetric Effect

θ = GARCH Effect

P = Market Price

t = Time Period

The $\log(\mathrm{ASPI_t})$ measures the current conditional volatility based on the previous conditional volatility and error. The auto-regressive (AR) stock price variability is the input for this variance equation. Therefore, daily stock price (P) data has been converted to the daily price change ratio (R_t) by using Equation 2. Coefficient of η identifies the volatility clustering effect from the previous volatility shocks (ARCH effect). The long-term volatility persistence is measured from the θ coefficient (GARCH effect). The λ is the measurement of the asymmetric impact of the stock volatility from market information. If $\lambda \neq 0$, volatility asymmetries are present; whereas a negative coefficient of λ ($\lambda < 0$) further implies the Black's (1986) leverage effect. The φ value stands for the constant price volatility independent from the time.

The macroeconomic impact on asymmetric volatility behaviour has been tested with the mean variation function of the EGARCH model as further suggested by Olugbode et al. (2014). Equation 3 shows the extension of the mean variation EGARCH volatility model with explanatory macro variables.

$$ASPI_t = \beta_0 + \beta_{1q}GDP_{(t-q)} + \beta_{2q}INF_{(t-q)} + \beta_{3q}INT_{(t-q)} + \beta_{4q}MS_{(t-q)} + u_t \text{ ... (3)}$$

The GDP, INF, INT, and MS represent the selected macro variables of Gross Domestic Production, Inflation Rate, Interest Rate, and Money Supply respectively. It has been undertaken q number of AR lags in macro variables for identifying the lag-volatility responses of ASPI. The selection of the number of lags was based on the method followed by Chaudhuri and Smiles (2004). Here it has been used 10 different lags up to lag 90 at 10 days' intervals. β_{1q}, β_{2q}, β_{3q}, and β_{4q} measures the coefficient of volatility impact from the respective macro variables at q^{th} AR lag.

Macroeconomic variables have been selected on the previous empirical evidences of stock volatility determinants (Aslam, 2014; Chia & Lim, 2015; Hsieh, 2013; Humpe & Macmillan, 2009; Hussain et al., 2013; Khalid & Khan, 2017; Maysami et al., 2004).

Therefore, these four variables were justified to explain the overall macroeconomic impact on Sri Lankan stock market volatility.

RESULTS AND DISCUSSION

Table 01 shows the descriptive statistics of all five variables. All variables have the same number of observations leading that the data set is free from the missing values. ASPI has an average daily price deviation of 0.0263% during the sample 10-year period; whereas the GDP has a mean of 2.33%. The INF and MS have an average percentage change of 0.41% and 1.23%. The INT has a mean rate of 7.94% with a maximum value of 10.76%. However, the GDP has the highest dispersion relative to the other variables with a coefficient of variation of 3.9%. Based on the Skewness, Kurtosis, and Jarque-Bera (JB) test statistics, all five variables do not show a normal distribution pattern.

Table 1: Descriptive Statistics

	ASPI	GDP	INF	INT	MS
Mean	0.000263	2.329561	0.414247	7.940672	1.264856
Median	-0.000040	5.269082	0.329063	8.2018	1.234056
Maximum	0.104952	16.21551	3.44885	10.763	3.159563
Minimum	-0.101766	-17.8031	-2.266	5.809263	-0.34022
Std. Dev.	0.007514	9.082259	0.820512	1.379095	0.745769
Skewness	0.273022	-0.83812	0.196175	0.107929	0.274121
Kurtosis	36.31551	2.489367	3.563741	1.876141	2.812381
Jarque-Bera (JB)	111299.7	307.9454	47.31182	131.3472	33.67487
JB Prob.	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2407	2407	2407	2407	2407

Source: Author's Estimation

Diagnostic Tests

All five (05) variables were tested for stationarity by undertaking the Augmented Dickey & Fuller (ADF) test & Kwiatkowski-Philips-Schmidt-Shin (KPSS) test. As Hsieh (2013) suggested, the first difference ADF was performed for testing the unit root. The probability of ADF t-Statistics is less than 1% for all five variables which concludes to not to support the unit-root null hypothesis. This confirms that the given ASPI and other macro variables are free from the unit-root error. Furthermore, the KPSS test also confirms that the variables are stationary at a 1% and 10% significance level.

The Conditional Variance is the basic assumption for employing the ARCH family models. The Lagrange Multiplier (LM) test has been accommodated to detect the existence of Conditional Heteroscedasticity effect in the response variable (ASPI), as suggested by Olugbode et al. (2014).

According to the test results, the ASPI has Conditional Heteroscedasticity volatility effect at a 1% significance level (Refer Table 02). Moreover, the ASPI has not shown a normal distribution pattern based on the Skewness, Kurtosis, and Jarque-Bera (JB) test statistics (Refer Table 01). Therefore, the ASPI is appropriate for volatility cluster modelling, and no barrier for undertaking the proposed EGARCH model over the traditional Ordinary Least Square (OLS) method.

Table 2: Heteroscedasticity Test Result

F-Statistic	638.9057	Prob. F (1,2402)	0.0000*
Obs*R-squared	505.0894	Prob. Chi-Square (1)	0.0000

*The series has Conditional Heteroscedastic effect at 1% significance level

Source: Author's Estimation

Asymmetric Test in ASPI

The first part of the study is to test the asymmetric behaviour in ASPI daily prices. Therefore, the ASPI variable has been undertaken with EGARCH model for identifying volatility clustering and asymmetries. Table 03 shows the EGARCH test results for three (03) different error distribution assumptions i.e., Normal (Gaussian), Student's-t, and Generalized Error (GED).

Table 3: EGARCH Statistical Output in ASPI

Error Distribution	φ	η	λ	θ	AIC	MLL
Normal (Gaussian)	-0.6352*	0.3148*	-0.018***	0.960*	-7.419	8927
Student's-t	-0.7880*	0.3397*	-0.023	0.947*	-7.554	9091
Generalized Error (GED)	-0.7530*	0.3318*	-0.022	0.950*	-7.542	9076

* Coefficient is significant at 1%, ** Coefficient is significant at 5%, *** Coefficient is significant at 10%

Source: Author's Estimation

Jegajeevan (2010) and Kumara et al. (2014) have used the Akaike Information Criterion (AIC) and Maximum Log-Likelihood (MLL) measurements to select the best representative volatility clustering model. The same procedure has been followed to select the best error distribution of the asymmetric test. It can be seen that the Normal (Gaussian) error distribution has the lowest AIC and MLL statistical values than the other two error distributions (Student's-t and GED). This result is different from the other empirical studies (Alberg et al., 2008; Jegajeevan, 2010; Koima et al., 2015; Morawakage & Nimal, 2015) which have higher efficiency in student's-t distributions on financial time-series data. Nevertheless, the Normal (Gaussian) error distribution EGARCH model was selected for testing the asymmetric behaviour.

The intercept ($\boldsymbol{\varphi}$), ARCH ($\boldsymbol{\eta}$), and GARCH ($\boldsymbol{\theta}$) effects are highly significant under all three error distributions except the asymmetric effect ($\boldsymbol{\lambda}$) coefficient.

This result further confirms the conditional volatility behavior in the ASPI series. The selected Gaussian Error Distributed EGARCH model has ARCH effect ($\boldsymbol{\eta}$) of 0.3148 and GARCH effect ($\boldsymbol{\theta}$) of 0.9600. Both values are significant at a 1% level, leading to the existence of ARCH ($\boldsymbol{\eta}$) and GARCH ($\boldsymbol{\theta}$) effect in ASPI volatility. However, the GARCH effect ($\boldsymbol{\theta}$) is relatively larger than the ARCH effect ($\boldsymbol{\eta}$) by more than three (03) times. According to Dowd's (2010) explanations, higher GARCH effect ($\boldsymbol{\theta}$) and lower ARCH effect ($\boldsymbol{\eta}$) emphasize a higher volatility persistence and lower responses to the market news. Therefore, it can be seen that ASPI has poorly responded to the market news due to the lower ARCH value ($\boldsymbol{\eta}$). On the other hand, the ASPI shows a larger volatility persistence in the long term because of the higher GARCH coefficient ($\boldsymbol{\theta}$). This result complies with the conditional volatility measurement results of Jegajeevan (2010), Morawakage and Nimal (2015), and Morawakage et al. (2018). However, Jaleel and Samarakoon (2009) has a mix of GARCH ($\boldsymbol{\theta}$) and ARCH ($\boldsymbol{\eta}$) effects in CSE market for both pre and post-liberalization.

The EGACH coefficient ($\boldsymbol{\lambda}$) measures the asymmetric/ leverage impact of the ASPI. The selected model (Gaussian Error) has the EGARCH coefficient ($\boldsymbol{\lambda}$) of -0.0184 which is significant at 10%. This confirms the asymmetric information behaviour in ASPI volatility. Since the EGARCH coefficient ($\boldsymbol{\lambda}$) is less than zero, negative news (shocks) in CSE market produces a higher volatility impact than positive news. Therefore, the Black's (1976) leverage effect also can be observed in ASPI volatility. This result is in line with the previous findings of Jegajeevan (2010), Kumara et al. (2014), Morawakage and Nimal (2015), and Morawakage et al., (2018) which have been emphasized the existence of leverage effect and asymmetric effect in the CSE market. However, the magnitude of the leverage and asymmetric impact is lower than the above all the previous results.

Identifying Macroeconomic Volatility Determinants

The second part of the quantitative analysis is to identify the impact of the macroeconomic variables on conditional stock market volatility. Therefore, the ASPI volatility has been modelled further with the selected macroeconomic control variables under the same EGARCH model as stated in Equation 03. It employed the same Normal (Gaussian) error distribution assumption for this model.

The multicollinearity between macro variables has been tested from correlation statistics. It can be seen that all explanatory macro variables are free from multicollinearity problems of either 1% or 5% significance level (Refer Table 04). Therefore, the selected macro variables (GDP, INF, INT, and MS) are suitable to use as individual explanatory control variables in the proposed EGARCH model.

The study has identified the quick response as well as the short-term lagging response of selected macroeconomic variables on ASPI volatility. Quick responses were based on the results of the first autoregressive lag of explanatory macro variables; whereas the short-term lag responses have been recognized based on a division of autoregressive-lags which were suggested by Chaudhuri and Smiles (2004). Therefore, the lagging impact of four (04) macroeconomic variables has been tested from 10 different autoregressive (AR) lags with 10 days' intervals. In other words, ten different EGARCH volatility models were derived based on ten different autoregressive terms of macro variables up to 90^{th} lag at 10 days' interval. Table 05 shows the decomposition of model results of the above-specified AR lags.

Table 04: Correlation Test Result

	Correlation Coefficient			
	GDP	**INF**	**INT**	**MS**
GDP	1			
INF	0.0508**	1		
INT	-0.0836*	0.0523*	1	
MS	-0.0840*	-0.0653*	-0.1028*	1

*Variables do not have correlation relationship at 1% significance level, ** variables do not have correlation relationship at 5% significance level, *** variables do not have correlation relationship at 10% significance level

Source: Author's Estimation

The study has identified the quick response as well as the short-term lagging response of selected macroeconomic variables on ASPI volatility. Quick responses were based on the results of the first autoregressive lag of explanatory macro variables; whereas the short-term lag responses have been recognized based on a division of autoregressive-lags which were suggested by Chaudhuri and Smiles (2004). Therefore, the lagging impact of four (04) macroeconomic variables has been tested from 10 different autoregressive (AR) lags with 10 days' intervals. In other words, ten different EGARCH volatility models were derived based on ten different autoregressive terms of macro variables up to 90^{th} lag at 10 days' interval. Table 05 shows the decomposition of model results of the above-specified AR lags.

According to Table 05, the intercept ($\boldsymbol{\varphi}$), ARCH ($\boldsymbol{\eta}$), and GARCH ($\boldsymbol{\theta}$) effects are highly significant under all AR lags. The asymmetric impact ($\boldsymbol{\lambda}$) also shows a substantial significant power in the most of selected AR lag intervals. In addition to that, the coefficients of intercept ($\boldsymbol{\varphi}$), ARCH ($\boldsymbol{\eta}$), GARCH ($\boldsymbol{\theta}$), and asymmetric impact ($\boldsymbol{\lambda}$) haven't changed largely with the different AR lags in macroeconomic control variables. These coefficient values are almost similar to the naked EGARCH model of ASPI which was selected for testing the asymmetry information behaviour under Table 03. Furthermore, the AIC and MLL statistics also have similar results like volatility clustering coefficients ($\boldsymbol{\varphi}, \boldsymbol{\eta}, \boldsymbol{\theta}, \boldsymbol{\lambda}$). This emphasizes that the conditional and asymmetric volatility coefficients do not have a significant impact from the volatility explanatory variables.

Table 05: EGARCH Statistical Output in ASPI with Macroeconomic Variables

	EGARCH Coefficient				Coefficient of Macroeconomic Explanatory Variable				Efficiency Statistic	
Auto Regressive Lag (AR)	φ	η	λ	θ	GDP(-AR)	INF(-AR)	INT(-AR)	MS(-AR)	MLL	AIC
1	-0.66*	0.32*	-0.02**	0.96*	0.001	0.005	-0.003	0.000	8928	-7.42
10	-0.68*	0.33*	-0.02**	0.96*	0.000	0.017	-0.004	0.032**	8904	-7.42
20	-0.70*	0.34*	-0.02**	0.96*	0.002**	0.011	-0.004	0.046*	8876	-7.43
30	-0.71*	0.34*	-0.02	0.95*	0.002**	0.001	-0.001	0.033*	8845	-7.43
40	-0.69*	0.33*	-0.02*	0.96*	0.002**	-0.001	-0.001	-0.002	8805	-7.43
50	-0.69*	0.34*	-0.02**	0.96*	-0.005*	0.024**	0.006	-0.089*	8766	-7.43
60	-0.69*	0.33*	-0.02**	0.96*	-0.002**	0.032**	0.010	-0.049*	8733	-7.43
70	-0.67*	0.33*	-0.01	0.96*	0.001	0.029**	0.003	0.029**	8703	-7.44
80	-0.65*	0.33*	-0.01	0.96*	0.001	0.022**	0.003	0.032**	8665	-7.44
90	-0.63*	0.32*	-0.02**	0.96*	0.001	0.007	0.005	0.016	8618	-7.43

* Coefficient is significant at 1%
** Coefficient is significant at 5%
*** Coefficient is significant at 10%

Source: Author's Estimation

It can be seen that all four (04) macroeconomic variables did not exhibit quick responses to the ASPI conditional volatility since all explanatory coefficients are highly insignificant for determining daily ASPI volatility against the first AR lag. However, the MS has significant explanatory coefficients under the AR lags of 10, 20, 30, 50, 60, 70, and 80. Similarly, the GDP coefficient also shows significant AR lag terms between 20 to 60. Furthermore, the INF coefficients are significant in 50th, 60th, 70th, and 80th lags. This result reflects the short-term lagging responses of ASPI conditional volatility with respect to the GDP, INF, and MS. However, the coefficient of GDP impact is limited to the 3rd decimal; whereas the INF and MS have produced significant coefficients starting from the 2nd decimal place. Therefore, it can be seen that ASPI lagging responses are greater with respect to INF and MS variability than the GDP variability. Nevertheless, the INT is the only variable that does not show any significant impact for determining the conditional volatility of ASPI.

The overall result seems that the macroeconomic variables have significant lagging responses to the ASPI volatility on a daily basis. ASPI has consumed a few weeks to adjust its market price on macroeconomic news.

This behaviour is similar to the other study results of Wongbangpo and Sharma (2002), Chaudhuri and Smiles (2004), Maysami et al. (2004), Ratanapakorn and Sharma (2007), Rahman et al. (2009), Olugbode et al. (2014), Mittnik et al. (2015), and Camilleri et al. (2019). Therefore, this lagging volatility response is not a unique characteristic in CSE market; whereas it is a natural behaviour in a stock market. This conclusion leads to questionable evidence on Fama's (1965) semi-strong market efficient hypothesis.

CONCLUSION

Purpose of this study was to identify the impact of asymmetric information behaviour and macroeconomic variability in modelling CSE price volatility. The sample consists 10 years of daily time-series data including stock prices and four macroeconomic volatility determinants. The conditional variance of EGARCH statistical model has been undertaken to recognize the availability of asymmetric information behaviour in CSE.

The empirical results show that the CSE market was significantly experiencing the problem of information asymmetric distribution between market participants. This finding complies with similar previous studies; however, the degree of asymmetric behaviour has declined during the sample period. Further, the GARCH effect of the model is relatively higher than the ARCH model. Therefore, the majority of CSE investors do not respond well to market shocks, but the persistence of volatility shocks is higher in the long term. This is the case of asymmetric information behaviour in the market; whereas uninformed investors are unable to respond to the market news at the right time. Therefore, uninformed investors are too sensitive to market sentiment rather than fundamental news. This motivates to create higher long-term volatility persistence in response to volatility shocks. As Speidell (2009) identified, this asymmetric information problem is a common issue in thinly trading markets like CSE. However, it loses the long-term market development for a better financial system.

The EGARCH model further extended with macroeconomic stock volatility determinants. The results of the mean-variance equation show that macroeconomic variability has a significant impact on explaining the future conditional volatility. However, CSE volatility spends a few weeks to adjust the relevant macroeconomic shocks. It was observed that this lagging response is natural in stock markets since the other empirical studies also have shown similar observations at different levels of degrees. Therefore, a questionable evidence has emerged on the semi-strong market efficiency (Fama, 1965) in equity markets.

The outcome of this study is recommended for equity market participants and policymakers to improve the equity market efficiency. The study identifies the equity market dependency on the overall economic behaviour of a nation. The macro-level policymakers can closely monitor the economic performance for a successive capital market investment.

The administrators can early recognize the excessive and poor stock market volatility environment in the case of extreme economic performances. This helps to implement preliminary remedies for minimizing the negative consequences of unexpected economic conditions (Ex: COVID-19 pandemic). Identification of asymmetric information and its impact is helpful for policymakers in a wider range. The level of investor confidence, market reliability, and efficiency can be measured through the factor of asymmetric information in a market. Policymakers are able to derive better policies by considering the above constraint. Moreover, the symmetric informational distribution creates a crucial link between the stock market and economic growth, especially in developing markets. For instance, Antzoulatos et al. (2008) stated that a higher degree of asymmetric information decreases the financial development vice versa. In addition to that Easley and O'Hara (1987) identified that recognizing and measuring the asymmetric informational distribution helps to increase the market liquidity and quality for making a better environment for capital market operations.

This study is limited to one particular common price index of CSE market for explaining the overall market behaviour. However, the sector vice impact can be identified by following the method used by Butt and Taib (2021). Furthermore, the number of lags represents the short-term macroeconomic impact on CSE volatility. Therefore, the long-term impact is possible to identify with further number of lags.

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