*Proceedings of International Conference on Economics 2017 (ICE 2017)*

**PROCEEDINGS ICE 2017 P24 – P42**
**ISBN 978-967-0521-99-2**

# FIRM LEVEL STOCK RETURNS VOLATILITY IN MALAYSIA: A SECTORAL STUDY

Saizal Bin Pinjaman*
Email: saizal.pj@gmail.com

Sarma Binti Aralas*
Email: miasarma@ums.edu.my
*Faculty of Business, Economics and Accountancy, Universiti Malaysia Sabah, Malaysia

**ABSTRACT**

This paper analyzes the level of stock returns volatility and identifies causal relationships across different economic sectors in Bursa Malaysia. We found dissimilarities of average stock returns volatility between sectors where firms in the Technology sector exhibit the highest stock returns volatility while firms in Telecommunication sector show the lowest volatility. Stock returns volatility is identified to be highly persistent, which suggests the influence of preceding shocks on current volatility level. In addition, there is evidence of leverage effects for the majority of the economic sectors, where negative news produces larger volatility when compared to positive news. Further, in the short run, the relationship of stock returns volatility between several economic sectors is found to be not statistically significant, this supports the possibility of portfolio diversification strategy to minimize risk and optimize return. However, the approach is ineffective in the long run since stock returns volatility of the economic sectors move together.

**Keywords:** Stock returns volatility, volatility persistence, leverage effects, causal relationship

## 1.0 Introduction

Analyzing stock market volatility is crucial for firms and investors in order to assess the level of risks in the stock market. Rohani (2014) argues that risk is the chance where actual return may differ from what is expected, and that investment return with higher volatility is riskier than investment with lower volatility. Volatility possesses a major threat in the stock market as an increase in volatility causes the demand of stock to fall due to its high risk. The price of stock will then decrease and a firm's failure to publish stocks at a high price will result in the inability of generating adequate capital to fund future economic activities. Financial regulators or policymakers on the other hand use volatility to estimate the performance and development of the stock market. According to Demirguc-Kunt and Levine (1996), current stock market performance reflects future economic development, and specific economic policy can be constructed based on precise stock market performance evaluation to accommodate forecasted economic situations.

In analyzing market risk based on volatility, the price or return of stock are often referred. But according to Li (2014), stock return is preferred as a measure of stock market risk instead of stock price because stock price suffers from high correlation and depends on the forces of demand and supply, which are influenced by market sentiment. Market sentiment is very difficult to assess as it depends on numerous local and international factors. On the other hand, stock returns are comparatively low in correlation and are convenient to be examined.

Kumar and Tamimi (2011) and Babatunde (2013) identify that volatility is influenced by economic innovations where the market is said to be more volatile due to discouraging economic fundamentals and is stable when economic situation becomes positive. Among the economic fundamentals that are important in influencing stock returns and volatility are inflation (Muringi, 2012), money supply (Zulkarnain & Sofian, 2012) and economic liberalization (Stiglitz, 2002; Umutlu et al., 2010)[1].

To analyze the nature of stock risks in Malaysia, the current research uses a dynamic volatility estimator to assess monthly stock returns volatility for individual firms in different economic sectors. The underlying reason why the analysis is grouped in sectors is to understand the performance of stock returns volatility of firms in each of these sectors, and to identify which sectors are more exposed to higher risks. An analysis is conducted to estimate the persistency of stock returns volatility to determine whether or not previous volatility affects current volatility levels. The existence of leverage effects will also be assessed by identifying whether similar scale of negative and positive news produce equal magnitudes of impacts towards stock returns volatility.

One of the popular approaches in managing stock risks and enhance returns is called the portfolio diversification strategy. Based on this method, risk can be decreased by investing in a diversified portfolio of securities or assets with low asset-correlation. However, investing in different classes of assets with the intention to decrease risks will be futile if risks between these assets are integrated, or highly correlated, because the risks will be transmitted from one class of assets to another class. To study the effectiveness of portfolio diversification strategy in managing stock risk in Malaysia, the current analysis also investigates the short run and long run relationships of stock returns volatility between economic sectors.

The findings of the current paper may provide useful information to the firm's decision making process in managing stock risks and contribute to the expansion of knowledge in finance and economics. The current research in this paper adds to existing research that is thus far limited in the area of stock returns volatility estimation based on firm level dynamic volatility analysis. Further, we analyze the persistency of stock returns volatility, as well as the existence of leverage effects among firms by comparing the differences in the impacts between bad news and good news on stock returns volatility. Finally, we extend scarce literature on the comparative analysis of causal relationships of dynamic stocks return volatilities in various economic sectors.

The remainder of this paper is organized as follows. Section 2 discusses previous literatures on volatility estimation in Malaysia and portfolio diversification. Section 3 describes the dynamic volatility estimation of EGARCH, the asymmetric nature of stock returns volatility, and causal relationship assessments. Section 4 shows the estimation results, and Section 5 concludes.

## 2.0 Literature Review

### 2.1 Stock Market Volatility in Malaysia

Jie (2007) analyzes the stock price and returns volatility of Malaysia based on weekly sample from January 1977 to February 2007 for both Kuala Lumpur Composite Index (KLCI) and Exchange Main All Shares index (EMAS) by utilizing the GARCH, EGARCH and TARCH models. Jie (2007) argues that

---

[1] Several researchers also found significant impacts of firm micro-characteristics on volatility. Comin and Philippon (2006), for example, argue that high research and development (R&D), CEO turnover, and competition in the goods market may affect volatility.

the volatility of stock price in Malaysia is not highly persistent and this is often observed in high frequency financial data. The estimates also found the existence of asymmetric volatility with leverage effect in KLCI where negative news produces larger magnitude of impact compared to positive news. However, this effect is not significant at any statistical level in EMAS. In terms of stock returns volatility, Jie (2007) demonstrates that volatility are highly persistent where current information is relevant in predicting future volatility. Nevertheless, both KLCI and EMAS indexes exhibit insignificant asymmetric volatility which means that negative shock on stock return will not generate more volatility than positive shock in equal magnitude.

Modeling the volatility of Malaysian stock market with regard to global financial crisis, Nor Alwani and Faridah (2015) utilize the GARCH models and involve daily stock price of KLCI from 2002 to 2011. Nor Alwani and Faridah (2015) believe that global financial crisis that occurred in 2008 has affected the KLCI with high level of fluctuation, which indicates high level of risk, as shown by high standard deviation and large difference between maximum and minimum value. Additional risk on investors is also demonstrated by the negative skewness, which indicates an asymmetric tail, and large kurtosis that implies fat-tailed distribution of the return. Based on the GARCH models, Nor Alwani and Faridah (2015) demonstrate that the KLCI showed a significant departure from normality with the existence of conditional heteroskedasticity in the residual series. Aligned with Jie (2007), Nor Alwani and Faridah (2015) also believe that volatility is persistent with the existence of leverage effect as detected by the asymmetric models, which are TARCH and EGARCH.

Focusing on the behavior of volatility on sectoral basis, Saizal and Sarma (2015) conducted an analysis to determine the stock returns volatility of 299 firms in Bursa Malaysia by utilizing data from 1995 to 2015. The firms selected are grouped into four different economic sectors, namely i). Primary, ii). Secondary, iii). Tertiary and iv). Financial sector. Based on the EGARCH model, Saizal and Sarma (2015) identify that the majority of firms in all economic sectors experience persistent volatility in the stock returns, which suggests the importance of previous volatility influence towards current stock return performance. Financial sector demonstrates the highest percentage as 100 percent of firms in the sector exhibit persistent volatility. Data analysis also shows that majority of firms in secondary, tertiary and financial sectors exhibit leverage effect. This indicates that negative news brings a larger magnitude of volatility compared to positive news with similar scale. But there is an exception in the findings as demonstrated by the primary sector, where only 33.3 percent of firms show signs of the negative asymmetry.

## 2.2 Portfolio Diversification

The Theory of Modern Portfolio initiated by Markowitz (1952) states that the returns on stocks can be maximized through investment diversification as diversification minimizes risk[2]. Statman (1987) analyzes the theory further by claiming that portfolio size plays an important role in diversification because the risk of a portfolio declines as the size or the number of diversified stocks increases. However, venturing in a large number of stocks will be ineffective if the risks between these stocks are correlated. Based on previous studies, it is found that the optimum number of stocks for portfolio diversification ranges from 10 stocks (Evans and Archer, 1968) to 30 stocks (Statman, 1987) before diversification loses its optimality to minimize risk.

There are several ways to diversify and one way that is gaining attention from investors is the sectoral or industry-specific portfolio diversification method. Based on Shamsher et al. (2006), one of the reasons for the increase in interest to diversify based on economic sectors is because of the increase in the integration

[2] Markowitz (1952) added that risk is measured by individual stock variances and the correlation between assets invested in different sectors. Correlation of risks between these sectors comes from their common dependence on market volatility while changes in correlation are caused by changes in the individual stocks volatility.

of economies across the globe due to liberalization which causes risks between these markets to be correlated. Shamsher et al. (2006) found strong relationships of stocks returns in different sectors in Malaysia, and identified the ineffectiveness of risk diversification in the short run. Nevertheless, portfolio diversification is said to be relevant in the long run because the risk correlations are unstable. This finding is contradicted by Boon and Wooi (2005) who show that firms that engage in short run portfolio diversification on a sectoral basis may gain benefits from the risk reduction, but not in the long run. They also claim that although third sectors might link these sectors indirectly, the indirect impact will exhibit lags in time.

Idwan and Mansur (2014) meanwhile looked at the role of investment diversification through global ventures and recognize the correlation between international stock markets and local sectors is low in Malaysia. By using multivariate volatility modelling to investigate the potential for portfolio diversification strategies, Idwan and Mansur (2014) add that these correlations are unstable across time and show the suitability of portfolio diversification approach to minimize risk.

Although a number of research have been conducted to analyze the nature of stock returns volatility in Malaysia, the focus has been mainly on market or index level of analysis. On the other hand, the current research uses firm level data; firm data is more pragmatic since investors are concerned about evaluating the firm's specific stock performance more than the overall market index condition. Levchenko et al. (2009) argues that information based on national or market index data level may face conceptual and econometric problems. Conceptually, the economy does not represent a firm's characteristic when the financial market is incomplete. Therefore, knowledge obtained by researchers that focus on index level is less beneficial to firms as the data are not representative data. Econometric problems may occur as the characteristic of the results based on market index data fail to measure other important variables. This is supported by Bai and Green (2010) who state the advantage of using individual firm analysis in providing additional information about risk and diversification for developing countries.

## 3. Data and Method

The current paper uses secondary data acquired from the Thomson Reuters Datastream. Individual firm stock prices listed in Bursa Malaysia, formerly known as the Kuala Lumpur Stock Exchange (KLSE), are obtained. Several other online databases are also utilized to retrieve supporting data important for the study. All firms listed in the Bursa Malaysia that have 20 years (1995 until 2015) of monthly data availability and without outliers, are included.

### 3.1 Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

Estimating stock returns volatility has been a challenge for forecasters. Figlewski (2004) believes that the problem of estimation or prediction of volatility is becoming more difficult to solve as the maturities of available instruments increase. Before the advent of the estimation of stock returns volatility by accounting for the varying nature of volatility, stock forecasters simply followed the static standard-deviation or variance method in estimating volatility. This poses a problem since it is found that variances change over time, which is contrary to a static stock returns volatility assumption of constant variance. When the dynamic measures of volatility such as Autoregressive Conditional Heteroskedasticity (ARCH) models were developed, they became the dominant methods to estimate stock returns volatility[3].

This current paper utilizes the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) to analyze stock returns volatility of Malaysia. EGARCH is constructed by Nelson (1991) as a method to analyze dynamic volatility and is extended from the Autoregressive Conditional

[3] See, for example, Sójka and Kliber (2010) on dynamic volatility estimation and how it is categorized.

Heteroskedasticity (ARCH) model introduced by Engle (1982) over the concerns of variance that changes over time. Consider a conditional distribution of individual firm excess returns $(r_{it} - r_{ft})$ as shown below[4]:

$$r_{it} - r_{ft} = \alpha_i + \beta_i X'_{it} + u_{it} \quad (1a)$$

$$u_{it}|I_{i,t-1} \sim N\,(0, \sigma_{it}^2) \quad (1b)$$

$$\sigma_{it}^2 = \omega_i + \omega_1 u_{i,t-1}^2\,, \omega_i > 0, \quad 0 \leq \omega_1 \leq 1 \quad (1c)$$

Where excess returns $(r_{it} - r_{ft})$ of individual firm $i$ at time $t$ in Equation (1a) is equal to individual firm stock returns $()r_{it}$ minus risk free rate of returns $(r_{ft})$. Excess returns is explained by a constant $(a_i)$, a set of variables or risk factors $(X'_{it})$ that is affecting stock returns and an error term $(u_{it})$. The distribution of the error term shown in Equation (1b) is conditionally normal $u_{it}|I_{i,t-1} \sim N\,(0, \sigma_{it}^2)$, where $I_{i,t-1}$ represents the information available for firm $i$ at time $t - 1$. The time varying or conditional variance, $\sigma_{it}^2$ in Equation (1c) is a case of ARCH (1) model and is a function of a constant term $(\omega_i)$ and the squared error term of previous lag 1 period $(\omega_1 u_{i,t-1}^2)$[5].

But the main problem of ARCH (p) model is that the number of parameters in the model depends on the number of lags, and the accuracy of the model tends to lose when the number of lags (p) increases. It leads to the development of Generalized ARCH (GARCH) model constructed by Bollerslev (1986) by introducing lags of conditional variance $(\sum_{j=1}^{q} \sigma_{i,t-j}^2)$ in the model with the intention to capture the long lagged effects with fewer parameters.

Based on Verbeek (2012) however, the downside of ARCH and GARCH lay in their positive and symmetry restriction where the only important aspect of innovation or change is the value, not the sign. It means that negative shock is assumed to produce similar impact towards volatility as positive shocks. In order to account on the impact of the sign of shocks or news, Nelson (1991) proposed what will be utilized in this analysis, namely the Exponential GARCH (EGARCH) model.

$$\log\left(\sigma_{it}^2\right) = \omega_i + \beta \log\left(\sigma_{i,t-1}^2\right) + \gamma \frac{u_{i,t-1}}{\sigma_{i,t-1}} + \omega_1 \frac{|u_{i,t-1}|}{\sigma_{i,t-1}} \quad (2)$$

Since the conditional variance in Equation (2) is expressed in logarithm, the model does not require the restriction of positive constraint on the estimated coefficients imposed by GARCH models.

## 3.2 Stock Returns Volatility Estimation

Stock returns volatility $(\sigma_{it}^2)$ of individual firm is estimated by using the EGARCH (1,1) model as in Equation (2) based on the conditional distribution of individual firm excess stock returns shown below:

$$r_{it} - r_{ft} = \alpha_i + \beta_i r_{i,t-1} + u_{it} \quad (3)$$

---

[4] The current analysis uses ARCH, specifically the EGARCH model, to estimate stock returns by taking advantage of its ability to capture stylized features of the real world volatility compared to static standard deviation methods of volatility estimation.

[5] Based on this model, it is shown that ARCH model analyzes the volatility or time-varying variances (heteroskedasticity) that depends (conditional) on lagged effects (autocorrelation). The ARCH (1) can be extended to ARCH (p) to capture more lags in the error terms.

Where;
$r_{it}$ = stock rate of return of firm (i) in time (t).
$r_{ft}$ = risk free rate of return at time (t).
$r_{i,t-1}$ = lag one stock returns of firm (i) at time (t).
$u_{it}$ = error terms of firm (i) at time (t).
$\beta_i$= the beta coefficient of firm (i).
$\alpha_i$ = intercept for firm (i)

Stock returns ($r_{it}$) is equal to the value of the difference between current stock price ($p_1$) to previous stock price ($p_0$) that is divided by the previous stock price ($p_0$), $r_{it} = \frac{p_1 - p_0}{p_0}$.

### 3.3 Persistency of Stock Returns Volatility and the Leverage Effects

The persistency of volatility is analyzed based on the value of $\beta$ in Equation (2) where $\beta > 0$ indicates that previous announcements or news are persistent in the time series and influences current volatility level.

The study subsequently diagnoses the asymmetric nature of volatility based on the value of $\gamma$ where $\gamma \neq 0$ indicates that negative news does not produce similar magnitude of impact on volatility with positive news. Meanwhile, $\gamma < 0$ suggests the existence of leverage effects in volatility where negative news produces greater shocks than positive news.

### 3.4 The Causal Relationship of Stock Returns Volatility between Economic Sectors

According to the Theory of Modern Portfolio, risks on stock returns can be lowered down by investing in diversified portfolio of securities that are low in correlation. In order to examine the effectiveness of this strategy in Malaysia, this research at first classifies the selected firms by following Thomson Reuters (2012) business classification approach where firms are assigned into 10 different economic sectors, namely i) Basic material; ii) Consumer cyclical; iii) Consumer non-cyclical; iv) Energy; v) Financial; vi) Healthcare; vii) Industrial; viii) Technology; ix) Telecommunication; and x) Utility sectors[6]. Stock returns volatility of each economic sector is then obtained based on the average volatility of firms that are categorized in that particular sector. The existence of long run and short run relationships of stock returns volatility between these sectors is analyzed afterward based on the ARDL and error correction modeling[7].

#### 3.4.1 Long Run Relationship using the Autoregressive Distributed Lag (ARDL) Model

Before the existence of ARDL model to analyze the causal relationship among different variables, Vector Autoregressive model (VAR) and Vector Error Correction Model (VECM) had become common tests where variables are assumed to be stationary at the same order[8]. However, in many cases, not all variables are at the same order of stationarity, specifically at I(1), and in these cases, we can use the ARDL model, a type of distributed lag model where variables can go back to infinite lags[9].

---

[6] Thomson Reuters (2012) assign firms into different economic sectors by following the Market-based approach as it is believed that financial performances of firms depend on the market that they serve.
[7] Prior to the analyses, the data are tested for unit roots using the Augmented Dickey Fuller (1979) and Phillips-Perron (1988) tests, in order to identify the non-stationary data and avoid spurious regressions.
[8] The difference between VECM and VAR is that the VECM method is the restricted version of VAR where I(1) variables are cointegrated, whereas VAR is used when I(1) variables are not cointegrated.
[9] Besides its ability to analyze causal relation for variables in different orders of cointegraton (Pesaran and Pesaran, 1997), the ARDL model also solves the problem of autocorrelated errors that the finite distributed lag model suffers

The equation for long run ARDL (p,q) model can be written as below:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \sum_{i=0}^{q} \beta_i \Delta x_{t-i} + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + u_t \tag{4}$$

$\Delta$ is the symbol of difference, $u_t$ is the error term and $\alpha, \beta$ and $\lambda$ are the coefficients that need to be estimated.

ARDL model accounts for the influence of the lagged values of both the dependent and independent variables. Optimal lags in the model will be determined by the Akaike Info Criterion (AIC) and Schwartz Criterion (SC), where the model with a certain number of lags of variables on the right hand side that produces the lowest value of AIC and SC is considered optimal.

In order to identify the existence of long run relationship, Bound Test of Pesaran, Shin and Smith (2001) is conducted to test two hypotheses:

i. $H_0: \lambda_1 = \lambda_2 = 0$, indicating the non existence of long run relationship among variables.
ii. $H_1: \lambda_1 \neq \lambda_2 \neq 0$, indicating the existence of long run relationship among variables.

The hypotheses are tested by comparing the estimated F-Statistics of Bound test with two critical Bound values for a given significance level, namely lower Bound and upper Bound critical values, obtained from Pesaran et al. (2001). Null hypothesis is rejected when the value of F-Statistics is higher than the upper critical Bound and the rejection of null hypothesis indicates there is long run relationship between the volatility of the economic sectors[10].

On the other hand, if the F-statistics is smaller than the lower critical Bound, then the null hypothesis is failed to be rejected and indicates no significant long run relationship between the economic sectors. This indicates that portfolio diversification strategy on sectoral basis is effective in the long run to manage the risk of stock returns volatility. However, when F-statistics is between the upper and lower critical Bound, then the relationship between the economic sectors is inconclusive or undetermined in the long run.

3.4.2 Short Run Relationship and Speed of Adjustment

The short run relationship is obtained from an Error Correction Model (ECM) as shown in Equation (5) with Error Correction Terms (ECT) represents the speed of adjustment for the model to reach equilibrium or long run relationship[11].

General short run ECM (p,q) model is shown below:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \sum_{i=0}^{q} \beta_i \Delta x_{t-i} + \lambda_1 ECT_{t-1} + u_t \tag{5}$$

from (Hill et al., 2008). Pesaran and Shin (1997) argue that the ARDL estimations are also consistent whether the regressors are all I(0) or I(1).

[10]If there is long run relationship between the economic sectors, then portfolio diversification strategy on sectoral basis will be ineffective as a way to lower the risk of stock returns since volatility can be transmitted or overflow from economic one sector to another.

[11] Based on Engle and Granger (1987), Error Correction Model shows the response of the dependent variable to shocks of the independent variable and also indicates the proportion of the disequilibrium from one period that is corrected in the next period.

Where $ECT_{t-1} = e_{t-1} = y_{t-1} - \alpha - \beta x_{t-1}$ is the Error Correction Terms (ECT) that represents the speed of adjustment for the model to reach long run equilibrium[12]. $\beta \neq 0$ shows that $x$ is statistically significant in influencing $y$ in the short run, while $-1<\lambda<0$ indicate a significant adjustment of the model towards long run equilibrium when shocks occur at a previous period of time[13]. The time period for the disequilibrium to be completely corrected is equal to 1 divided by the value of the ECT coefficient, $(1/\lambda)$. As this research is using a monthly data, then $(1/\lambda)$ shows the number of month(s) for the model to reach its equilibrium or long run relationship.

## 4.0 Results

### 4.1 Stock Returns Volatility Average for the Economic Sector

Table 1, see Appendix A.

As shown in Table 1, firms in Technology sector exhibits the highest stock returns volatility compared to other economic sectors, followed by firms in Basic Material and Healthcare sectors. In contrast, firms in Consumer Non-Cyclical, Energy, Telecommunication and Utilities enjoy lower risk as shown by the smaller average stock returns volatility. Interestingly, the average volatility in the Financial sector is relatively low compared to other risky sectors, although the financial market is perceived to be the most volatile when taking into account multiple economic recessions linked to the instability of financial market, such as the 1997/98 Asian financial crisis and the U.S. subprime mortgage crisis in 2008.

### 4.2 EGARCH Statistical Summary

Table 2, see Appendix B

Based on the EGARCH analysis to identify stock returns volatility for 10 economic sectors, it can be seen that a majority of firms in Bursa Malaysia suffers from persistent volatility as shown in Table 2. Among the ten economic sectors, the Energy, Technology, Telecommunication and Utility sectors exhibit the highest percentages of firms that suffer from persistent volatility, as shown by the rate of 100 percent. This is followed by the Financial and the Consumer Non-Cyclical sectors, where more than 97 percent of firms suffer from the same condition of persistent volatility.

It is demonstrated that although all of the firms in the Energy, Technology and Telecommunication sectors suffer from persistent volatility, they enjoy lower level of persistency as shown by the average value of $\beta$. The average volatility persistency for the Energy, Technology and Telecommunication sectors is 0.76, 0.68 and 0.89, respectively. On the other hand, the highest level of volatility persistency is exhibited by the Utility sector with average volatility persistency is 0.93.

Most of the firms that demonstrate an asymmetric nature of volatility experience leverage effects where negative news produce larger volatility compared to positive news. All firms in the Healthcare, Technology, Telecommunication and Utility sectors for example are found to demonstrate this effect. Conversely, the majority of firms in the Consumer Non-Cyclical share similar attribute where positive news produce larger impact on stock returns volatility compared to negative news. It is also demonstrated

---

[12] Boon and Wooi (2005) argue that the ECT measures the adjustment of the model or system from the short run deviation back to its long run equilibrium. This implies that the ECT coefficient shows the period of effectiveness for short run portfolio diversification on sectoral basis before the model enters long run relationship.

[13] Similar to Equation (4), optimal lag length for short run ECM model in Equation (5) is selected based on AIC and SC values.

that there are no firm in the Energy sector that exhibit asymmetric volatility which shows that both positive and negative news produce equal magnitude of impact towards volatility.

**4.3 The Causal Relationship of Stock Returns Volatility between Economic Sectors**

4.3.1 ARDL Model for long run relationship

The Autoregressive Distributed Lag (ARDL) model is selected due to its ability to analyze the long run relationship between variables with different orders of stationarity[14]. Based on the Akaike Info Criterion (AIC) and Schwartz Criterion (SC), lag 1 in the right hand side of the variables is considered optimal for majority of the ARDL models as it produce the lowest value of AIC and SC[15].

Table 4, see Appendix D.

Table 4 shows the important statistical result of the ARDL Models to find the long run relationship among the economic sectors where all ARDL models exhibit statistically significant F-statistic at 5 percent significance level which show joint significance of all variables. Failure to reject the null hypothesis of no serial correlation indicates that the residuals or disturbances in the models are not correlated[16]. Based on the CUSUM stability test, all models are stable against the critical Bound of 5 percent level of significance. White (1980) robust standard error is used to address the issue of heteroskedasticity[17].

Table 5, see Appendix E.

Based on Table 5, estimated F-statistics of Bound test is higher than the upper critical Bound for majority of the economic sectors and indicates the rejection of null hypothesis of no joint impact of the economic sectors. This shows that in the long run, stock returns volatility for most of the economic sectors move together. This also suggests that portfolio diversification strategy on sectoral basis will be ineffective in reducing the risk of stock returns in the long run since volatility flows from one economic sector to another sector.

But it is with the exception of the Industrial, Telecommunication and Utilities sectors where these sectors demonstrated non-significant long run relationship as shown by smaller F-statistics in comparison to the lower Bound critical value. This implies that portfolio diversification strategy is effective in managing the risk of stock returns in the Industrial, Telecommunication and Utilities sectors since volatility of these sectors did not move together with the rest of the economic sectors in the long run. Meanwhile the existence of long run relationship from the rest of the economic sectors towards the Technology sector is undetermined or inconclusive as the F-statistics is between the upper and lower critical Bound.

4.3.2 Short run relationship based on the Error Correction Model

Table 6, see Appendix F.

[14]Based on the Augmented Dickey Fuller (1979) and Phillips-Perron (1988) test of stationarity, stock returns volatility of economic sectors shows the condition of mixed stationarity, I(0) and I(1). See Table 3 Appendix C.
[15] The number of lags for several ARDL models that has serial correlation have to be adjusted by adding more lags on the independent variables until the problem of serial correlation no longer exists.
[16]The models are also free from autocorrelation where the values of Durbin-Watson statistics are around two.
[17] Based on Hill et al. (2008), White standard error is valid in large samples for both homoskedastic and heteroskedastic errors.

In the short run, it is identified that portfolio diversification on sectoral basis is effective to reduce the risk of stock returns for most of the economic sectors since the majority of the sectors are not correlated[18]. Based on Table 6, Healthcare and Telecommunication sectors have no short run relationship with the rest of the economic sectors at 5 percent significance level. It suggests that volatility from other economic sectors will not be transmitted into Healthcare and Telecommunication sectors in the short run. It also implies the effectiveness of firms to reduce the risk of stock returns volatility by diversifying their portfolio with assets from these two sectors.

At 5 percent significance level, there is no correlation of stock returns volatility from Consumer Cyclical, Consumer Non-Cyclical, Energy, Financial and Technology into other economic sectors. It suggests the effectiveness of firms in these sectors to diversify their portfolio with assets from other economic sectors since stock returns volatility from these five sectors will not overflow to the rest of the economic sectors. Unidirectional relationship meanwhile existed between the Utilities and Healthcare sectors since volatility from the Healthcare overflow to the Utilities but not vice-versa.

Table 7, see Appendix G.

The ECT coefficients on Table 7 meanwhile display the speed of adjustment process of the model towards long run equilibrium. It also indicates the effectiveness of the short run portfolio diversification strategy because when the model reaches long run equilibrium, portfolio diversification will no longer be viable since the volatilities for majority of the economic sectors move together. Except for the Industrial sector, all ECT coefficients are statistically significant and negative in value signaling the adjustment from any disequilibrium in the model.

The ECT coefficient when Basic Material sector is treated as dependent variable in the ECM model is -1.07 and this suggests that there is an unstable relationship between Basic Material with the rest of the economic sectors in the short run. Meanwhile, firms in the Consumer Cyclical, Consumer Non-Cyclical, Energy and Financial sectors find that disequilibrium occurring due to a short term deviation is corrected within 1.43 to 2.32 months.

The speed of adjustment towards long run relationship is slower in Healthcare, Technology, Telecommunication and Utilities sectors as shown by lower ECT coefficients. This suggests that firms that engaged in portfolio diversification in Technology, Telecommunication and Utilities sectors will have more time to take advantage from short run portfolio diversification before stock returns volatility of the other economic sectors jointly move in affecting these four sectors. From the ECT coefficients, it will take 4.21 to 7.65 months for the Technology, Telecommunication and Utilities sectors to enter the long run equilibrium.

## 5.0 Conclusion

Based on this study, the decision to invest in an economic sector should be considered carefully. Dynamic stock returns volatility analysis shows a significant dissimilarity of stock returns volatility level across economic sectors where firms in Technology, Basic Material and Healthcare sectors on average suffer from higher volatility compared to other sectors. Stock returns volatility is also persistent in all economic sectors where current volatility is highly impacted by previous stock returns volatility. In addition, a majority of shares in the Bursa Malaysia experience leverage effects, where negative news produce larger volatility compared to positive news. It is identified that all firms in the Healthcare and

[18] Breush-Godfrey LM test shows that the ECM model is free from serial correlation meanwhile CUSUM test shows the model is stable at 5 percent significance level. White (1980) robust standard error is utilized to address the issue of heteroskedasticity in the model.

Telecommunication sectors experience leverage effects. On the other hand, asymmetric volatility is not present in the Energy sector and implies that positive and negative news produce equal magnitude of impact towards volatility.

The relationship between stock returns volatility of economic sectors is analyzed based on a Bound test. It is shown that majority of the economic sectors exhibit long run relationship. This signifies the ineffectiveness of portfolio diversification strategy on sectoral basis in managing the risk of stock returns in the long term. However, this strategy may prove to be effective in the short run since the relationships of risks between numerous economic sectors are shown to be statistically insignificant. Based on the ECT coefficients, the time period of the effectiveness of the short run portfolio diversification strategy ranges from 1.43 months to 7.65 months before the model moves back into a long run relationship where portfolio diversification is no longer effective in reducing the risk of stock returns volatility.

**References**

Babatunde, O. A. (2013). Stock market volatility and economic growth in Nigeria (1980-2010). *International Review of Management and Business Research, 1*(2), 201-209.

Bai, Y. & Green, C. (2010). International diversification strategies: Revisited from the risk perspective. *Journal of Banking and Finance, 34*, 236–245.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327.

Boon, T.H. & Wooi, H.C. (2005). *Risk Diversification; A Sectorial Study* (Chapter in Book). In *Understanding the Behavior of the Malaysian Stock Market*. Serdang, Selangor: Universiti Putra Malaysia Press.

Comin, D & Philippon, T. (2006). The rise in firm-level volatility: Causes and consequences. *The National Bureau of Economic Research Working Paper No. 11388*. Retrieved from: http://www.nber.org/chapters/c0072.

Demirguc-Kunt, A. & Levine, R. (1996). Stock markets, corporate finance and economic growth: An overview. *World Bank Economic Review, 10*(2), 223-239.

Dickey, D. A. & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association,74*, 427-431.

Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,*50,987–1007.

Evans, J.L. & Archer, S.H. (1968). Diversification and the reduction of dispersion: An Empirical Analysis. *The Journal of Finance, 23*(5), 761-767.

Figlewski, S. (2004). *Forecasting volatility*, final draft. New York University Stern School of Business, New York.

Hill, R. C., Griffiths, W. E., Lim, G.C. (2008). *Principles of Econometrics* (Third Edition). Hoboken, New Jersey: John Wiley & Sons, Inc.

Jie, N. H. (2007). *Stock Returns and Volatility: An empirical study of Malaysian stock market.* Dissertation Submitted in Partial Fulfillment of the Requirement for the Degree of Master of Business Administration. School of Business and Economics, Universiti Malaysia Sabah, Malaysia.

Kumar, R. & Tamimi, M. (2011). Economic growth, expected stock returns and volatility: A case of Indian Stock Market. *The International Journal of Applied Economics and Finance, 5*(4), 257-268.

Levchenko, A. (2007). Growth and risk at the industry level: the real effects of financial liberalization. *Journal of Development Economics, 89*, 210-22,

Li, Y. (2014). Forecasting stock market returns volatility. Open Access Master's Theses. Paper 346.

Markowitz, H.M. (1952). Portfolio selection. *Journal of Finance,7*,77-91.

Muringi, M.C. (2012). *The impact of inflation on stock market returns and volatility: Evidence from Nairobi Securities Exchange*. Unpublished MBA report, University of Nairobi.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*, 347–370.

Nor Alwani, O. & Faridah, A, H. (2015). Modeling volatility of Malaysian stock market using GARCH models. 2015 International Symposium on Mathematical Sciences and Computing Research (iSMSC).
Retrieved from: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7594096

Pesaran, M.H., Pesaran, B. (1997). *Working with Microfit 4.0: Interactive econometric analy*sis. Oxford: Oxford University Press.

Pesaran, M.H. & Shin, Y. (1997). An autoregressive distributed-lag odeling approach to cointegration analysis. In *Econometrics and Economic Theory in the 20th Century. The Ragnar Frisch Centennial Symposium*. Cambridge: Cambridge University Press.

Phillips, P. C. B. & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*, 335-346.

Rohani A.G. (2014). *The Development of Malaysian Financial Institutions*. Shah Alam, Selangor: University Publication Center.

Saizal, B. P. & Sarma, B. A. (2015). The dynamic stock returns volatility and macroeconomic factors in Malaysia: A Sectoral Study. *South East Asia Journal of Contemporary Business, Economics and Law, 8*(3), 1-8.

Shamsher M., Taufiq H., Zulkarnain M.S. (2006). Diversification across economic sectors and implication on portfolio investment in Malaysia. *International Journal of Economics and Management, 1*(1), 155-172

Sójka, B.B., Kliber, A. (2010). Realized volatility versus GARCH and stochastic volatility models; The evidence from the WIG20 index and the EUR/PLN foreign exchange market. *Statistical Review, 57*, 105-127.

Statman, M. (1987). How many stocks make a diversified portfolio? *Journal of Financial and Quantitative Analysis, 22*(3), 353–363.

Stiglitz, J. E. (2002). Capital market liberalization and exchange rate regimes: Risk without reward. *The Annals of the American Academy of Political and Social Science, 579*, 219-248.

Thomson Reuters. (2012). Thomson Reuters Business Classification: Classification Structure 2012. Retrieved From: *http://thomsonreuters.com/content/dam/openweb/documents/pdf/financial/trbc-quick-guide.pdf.*

Umutlu, M., Akdeniz, L., Altay-Salih, A. (2010). The degree of financial liberalization and aggregated stock-return volatility in emerging markets. *Journal of Banking & Finance, 34*, 509-521.

Zulkarnain, Z. & Sofian, S. (2012). Empirical evidence on the relationship between stock market volatility and macroeconomics volatility in Malaysia. *Journal of Business Studies Quarterly, 4*(2), 61-71.

**APPENDIX**

A. AVERAGE STOCK RETURNS VOLATILITY FOR THE ECONOMIC SECTOR

**Table 1**

| Economic Sector | Average Stock Returns Volatility Level |
|---|---|
| Basic Materials | 0.031379 |
| Consumer Cyclical | 0.02604 |
| Consumer Non-Cyclical | 0.019018 |
| Energy | 0.016909 |
| Financial | 0.023319 |
| Healthcare | 0.030562 |
| Industrials | 0.025729 |
| Technology | 0.084136 |
| Telecommunication | 0.006599 |
| Utilities | 0.016296 |

Note: The average stock returns volatility is obtained from average volatility of firms in each economic sector. The average stock returns volatility are significantly different between 10 economic sectors where P-values for the standard ANOVA and the Welch adjusted ANOVA are near zero.

B. EGARCH (1,1) STATISTICAL SUMMARY FOR SELECTED FIRMS IN THE BURSA MALAYSIA FROM 1995-2015.

**Table 2**

| STATISTICS | Basic Material | Consumer Cyclical | Consumer Non-Cyclical | Energy | Financial | Health | Industrial | Tech. | Telecom | Utility |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of Firms. | 71 | 46 | 43 | 6 | 66 | 3 | 44 | 10 | 1 | 5 |
| Percentage of firms with persistent volatility at 5 percent significance level, ($\beta > 0$). | 91.54% | 95.65% | 97.67% | 100% | 98.48% | 66.67% | 95.45% | 100% | 100% | 100% |
| Average volatility persistency of firms, ($\beta$). | 0.8146 | 0.8917 | 0.8900 | 0.7637 | 0.8698 | 0.8583 | 0.7686 | 0.6868 | 0.8903 | 0.9298 |
| Percentage of firms with asymmetric volatility at 5 percent significance level, ($\gamma \neq 0$). | 42.25% | 56.52% | 48.88% | 0 % | 51.52% | 100% | 50% | 40% | 100% | 40% |
| Leverage Effects, ($\gamma < 0$). | 80% | 80.77% | 28.57% | - | 82.35% | 100% | 68.18% | 100% | 100% | 100% |

Note: The data sample for individual firm stock returns is in monthly basis from January 1995 until December 2015. Stock returns volatility of firm in each economic sector is estimated by using EGARCH (1,1). Based on Equation (6), $\beta > 0$ indicates that previous volatility is persistent in influencing the volatility in present time. $\gamma \neq 0$ indicates that stock returns volatility is asymmetric in nature where negative news does not produce similar magnitude of impact on volatility with positive news. $\gamma < 0$ indicates that stock returns volatility contains leverage effects where negative news generate greater volatility than positive news.

## C. AUGMENTED DICKEY FULLER (1979) AND PHILLIPS-PERRON (1988) UNIT ROOT TESTS

**Table 3**

| Sector | ADF without trend and intercept | | ADF with trend and intercept | | PP without trend and intercept | | PP with trend and intercept | |
|---|---|---|---|---|---|---|---|---|
| | At level | 1st difference | At level | 1st difference | At level | 1st difference | At level | 1st difference |
| Basic Materials | -2.41** | -11.66*** | -14.04*** | -11.64*** | -9.94*** | -126.87*** | -14.55*** | -128.41*** |
| Consumer Cyclical | -1.02 | -21.82*** | -2.89 | -21.74*** | -1.14 | -22.36*** | -3.25* | -22.27*** |
| Consumer Non-Cyclical | -1.08 | -14.47*** | -3.61** | -14.42*** | -1.37 | -19.61*** | -3.37* | -19.52*** |
| Energy | -2.88*** | -16.97*** | -3.96*** | -16.90*** | -4.17 | -35.54*** | -6.21*** | -35.35*** |
| Financial | -1.04 | -14.92*** | -2.44 | -14.87*** | -1.17 | -20.33*** | -3.40* | -20.25*** |
| Healthcare | -2.20** | -16.76*** | -4.43*** | -16.69*** | -1.94* | -17.35*** | -4.46*** | -17.28*** |
| Industrials | -1.17 | -17.70*** | -3.31* | -17.64*** | -1.11 | -17.70*** | -3.18* | -17.64*** |
| Technology | -1.04 | -12.85*** | -3.98** | -12.83*** | -0.90 | -15.89*** | -3.92** | -15.85*** |
| Telecommunication | -1.25 | -15.55*** | -2.88 | -15.50*** | -1.26 | -15.54*** | -2.92 | -15.50*** |
| Utilities | -1.97** | -5.69*** | -3.21* | -5.66*** | -1.64* | -18.49*** | -2.86 | -18.43*** |

Note: ADF and PP represents the Augmented Dickey Fuller (1979) and Phillips-Perron (1988) tests for stationary with and without trend and intercept at level and first difference. Firms are arranged based on their respective economic sectors by following Thomson Reuters (2012) business classification. Stock returns volatility of the economic sectors is obtained from the average stock returns volatility of firms in each sector. Stock returns volatility for individual firms are in monthly basis from January 1995 until December 2015 and estimated by using EGARCH (1,1). *, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

D. KEY REGRESSION AND DIAGNOSTIC TESTS STATISTICS OF ARDL (1,1) MODEL FOR LONG RUN RELATIONSHIP

**Table 4**

| Dependent Variable | F-Stat (Prob. F-Stat) | Adj. $R^2$ | Serial Cor. | Hetero. | Stability At 5% |
|---|---|---|---|---|---|
| Basic Materials | 13.3772 (0.0000) | 0.4985 | Prob. Chi-sq(1); 0.9695 | Prob. Chi-sq(20); 0.7862 | YES |
| Consumer Cyclical | 10.7300 (0.0000) | 0.4387 | Prob. Chi-sq(1); 0.1552 | Prob. Chi-sq(20); 0.0000 | YES |
| Consumer Non-Cyclical | 7.0374 (0.0000) | 0.3266 | Prob. Chi-sq(1); 0.4879 | Prob. Chi-sq(20); 0.0618 | YES |
| Energy | 6.6582 (0.0000) | 0.3125 | Prob. Chi-sq(1); 0.7240 | Prob. Chi-sq(20); 0.2829 | YES |
| Financial | 8.7130 (0.0000) | 0.3825 | Prob. Chi-sq(1); 0.7631 | Prob. Chi-sq(20); 0.0000 | YES |
| Healthcare | 1.8940 (0.0138) | 0.0670 | Prob. Chi-sq(1); 0.6837 | Prob. Chi-sq(20); 0.4647 | YES |
| Industrials | 2.2552 (0.0004) | 0.1318 | Prob. Chi-sq(2); 0.0930 | Prob. Chi-sq(30); 0.0000 | YES |
| Technology | 2.3285 (0.0015) | 0.0964 | Prob. Chi-sq(1); 0.5133 | Prob. Chi-sq(20); 0.9371 | YES |
| Telecommunication | 3.3713 (0.0000) | 0.3252 | Prob. Chi-sq(4); 0.0904 | Prob. Chi-sq(50); 0.0000 | YES |
| Utilities | 6.7786 (0.0000) | 0.4114 | Prob. Chi-sq(2); 0.4416 | Prob. Chi-sq(30); 0.0000 | YES |

Note: Independent variables comprise of lag(s) stock returns volatility of all economic sectors regressed based on OLS estimation. Probability value for the F-Statistics, serial correlation and heteroskedasticity test is shown in parenthesis with 0.10(10%), 0.05(5%) and 0.01(1%) significance level. Serial correlation test is based on Breusch-Godfrey serial correlation LM test statistics meanwhile Heteroskedasticity test is based on Breusch-Pagan-Godfrey LM test statistics. Standard errors of the model are based on the White (1980) heteroskedasticity-consistent standard error and covariance to address the issue of Heteroskedasticity. Optimal lag length of the model is selected based on the lowest value of Akaike Info Criterion (AIC) and Schwartz Criterion (SC). Stability test is based on CUSUM test at 5 % significance.

## E. BOUND TEST FOR LONG RUN RELATIONSHIP

**Table 5**

Note: Long run relationship is conducted based on Bound test with hypothesis null assumes no correlation between variables. Independent variables comprise of lag(s) stock returns volatility of all economic sectors. Probability value for the F-statistics is shown in parenthesis with 0.10(10%), 0.05(5%) and 0 .01(1%) significant level. Stock returns volatility of the economic sectors is obtained from the average stock returns volatility of firms in each sector. This research uses Table C(III) of Pesaran et al. (2001) with K + 1 = 10 variables (economic sectors). The Lower and Upper Critical Bounds for the F-test statistic at the 10%, 5%, and 1% significance levels are [1.88, 2.99], [2.14, 3.30], and [2.65, 3.97] respectively.

| **Statistics** | **Dependent Variable** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Basic Materials** | **Consumer Cyclical** | **Consumer Non-Cyclical** | **Energy** | **Financial** | **Healthcare** | **Industrials** | **Technology** | **Telecomm.** | **Utilities** |
| F-Statistics | 300.9763<br>(0.0000) | 6.6204<br>(0.0000) | 4.6907<br>(0.0000) | 3.3788<br>(0.0004) | 3.6753<br>(0.0001) | 4.6897<br>(0.0009) | 2.1258<br>(0.0237) | 2.8908<br>(0.0020) | 2.0350<br>(0.0317) | 2.0062<br>(0.0339) |

## F. ERROR CORRECTION MODEL FOR SHORT RUN RELATIONSHIP STATISTICAL SUMMARY

**Table 6**

| Dep. Variable | Wald Statistics | Independent Variable | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Basic Materials** | **Consumer Cyclical** | **Consumer Non-Cyclical** | **Energy** | **Financial** | **Healthcare** | **Industrials** | **Technology** | **Telecomm.** | **Utilities** |
| Basic Material | F-Stat (Prob.) | - | 0.0043 (0.9480) | 0.8819 (0.3486) | 0.6247 (0.4301) | 0.4695 (0.4939) | 0.6371 (0.4255) | 8.1663 (0.0046) | 3.8087 (0.0522) | 0.4601 (0.4982) | 1.4861 (0.2240) |
| Consumer Cyclical | F-Stat (Prob.) | 0.3705 (0.5433) | - | 2.6739 (0.1033) | 3.2377 (0.0732) | 0.0014 (0.9702) | 8.4484 (0.0040) | 4.1082 (0.0438) | 0.6594 (0.4176) | 0.2275 (0.6338) | 0.7062 (0.4016) |
| Consumer Non-Cyclical | F-Stat (Prob.) | 7.4568 (0.0068) | 0.3550 (0.5519) | - | 2.6019 (0.1081) | 0.8752 (0.3505) | 3.4444 (0.0647) | 4.3522 (0.0380) | 0.3013 (0.5836) | 0.4374 (0.5090) | 0.6753 (0.4120) |
| Energy | F-Stat (Prob.) | 0.0050 (0.9435) | 0.3528 (0.5531) | 0.0237 (0.8777) | - | 0.7882 (0.3756) | 7.0854 (0.0083) | 1.7987 (0.1811) | 0.0372 (0.8655) | 23.6240 (0.0000) | 0.3209 (0.5716) |
| Financial | F-Stat (Prob.) | 4.9986 (0.0263) | 0.1503 (0.6986) | 2.0511 (0.1534) | 0.4235 (0.5158) | - | 6.3774 (0.0122) | 2.1942 (0.1399) | 0.1718 (0.6789) | 4.5206 (0.0345) | 0.9756 (0.3243) |
| Healthcare | F-Stat (Prob.) | 0.1176 (0.7320) | 0.6961 (0.4049) | 1.8761 (0.1721) | 0.2437 (0.6220) | 0.6160 (0.4333) | - | 0.1062 (0.7448) | 0.1652 (0.6848) | 0.0260 (0.8721) | 0.0138 (0.9067) |
| Industrial | F-Stat (Prob.) | 0.8796 (0.4770) | 0.2428 (0.9138) | 0.3755 (0.8260) | 2.0662 (0.0865) | 0.8523 (0.4936) | 1.5979 (0.1762) | - | 2.3994 (0.0513) | 1.9259 (0.1074) | 2.5075 (0.0432) |
| Technology | F-Stat (Prob.) | 0.0330 (0.8559) | 0.1832 (0.6690) | 0.1577 (0.6916) | 0.1418 (0.7068) | 5.1572 (0.0240) | 1.2506 (0.2646) | 0.0194 (0.8892) | - | 4.2515 (0.0403) | 0.2528 (0.6155) |
| Telecom. | F-Stat (Prob.) | 1.4249 (0.2270) | 0.6689 (0.6143) | 0.8257 (0.5102) | 1.8463 (0.1214) | 1.9843 (0.0983) | 1.2887 (0.2757) | 0.8793 (0.4773) | 0.9656 (0.4275) | - | 1.9979 (0.0962) |
| Utilities | F-Stat (Prob.) | 1.34921 (0.2594) | 0.4342 (0.7288) | 0.4730 (0.7014) | 2.2413 (0.0844) | 2.3787 (0.2375) | 3.3959 (0.0188) | 1.6367 (0.1819) | 1.3028 (0.2744) | 1.9827 (0.1175) | - |

Note: Short run relationship between economic sectors is analyzed based on the F-Statistics obtained from Wald test with hypothesis null assumes no correlation between variables. Independent variables comprise of lag(s) stock returns volatility of all economic sectors. Probability value is shown in parenthesis with 0.10(10%), 0.05(5%) and 0 .01(1%) significant level. Stock returns volatility of the economic sectors is obtained from the average stock returns volatility of firms in each sector.

## G. SPEED OF ADJUSTMENT TOWARDS LONG RUN EQUILIBRIUM

**Table 7**

| Dependent Variable | ECT Coefficient | Correction Period[19] (Month) |
|---|---|---|
| Basic Materials | -1.0717*** (0.0458) | - |
| Consumer Cyclical | -0.6971*** (0.1407) | 1.43 |
| Consumer Non-Cyclical | -0.4761*** (0.1127) | 2.10 |
| Energy | -0.4319*** (0.1031) | 2.32 |
| Financial | -0.4669*** (0.1300) | 2.14 |
| Healthcare | -0.2063*** (0.0486) | 4.85 |
| Industrials | -0.0397 (0.1122) | - |
| Technology | -0.1307*** (0.0357) | 7.65 |
| Telecommunication | -0.1566*** (0.0092) | 6.38 |
| Utilities | -0.2375*** (0.0764) | 4.21 |

Note: Error Correction Terms (ECT) is the value of residual from OLS regression where the respective economic sector is treated as dependent variable while other economic sectors are the independent variables. The value of its coefficients is then identified by inserting lag value of the ECT as one of the independent variables in the short run ARDL model together with previous value of stock returns volatility of economic sectors. Standard errors are shown in parentheses.*, **, *** indicate statistical significance at 10%, 5% and 1% level, respectively.

[19] By referring to Eq. 5, the time period for the disequilibrium to be completely corrected is equal to 1 divided by the value of the ECT coefficient, ($1/\ \lambda$). As this research is using a monthly data, then ($1/\ \lambda$) shows the number of month(s) for the model to reach its equilibrium or long run relationship.