**Volatility Behavior across Short-term Investment Periods in Stock Exchange of Thailand (SET)**

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**Abstract**

The study explores volatility behavior across short-term investment periods in Stock exchange of Thailand during 2015-2019. By using GARCH and GJR-GARCH, the study has found that one-day and three-day market volatility are determined by lagged volatility and asymmetric responses to shocks. For longer investment periods, only return shock is the main factor while asymmetry is not statistically significant. This implies that traders need to take their investment periods into consideration when analyzing volatility behavior in SET index. Furthermore, the study explores volatility behavior in individual stocks to examine whether low traded volume has impacts on the model estimates. The study has found that ARCH effects are statistically significant for most individual stocks, and stocks with lower traded volumes are not associated with higher volatility persistences. Therefore, traders could expect similar volatility behaviors across stocks with different traded volumes.

**Keywords:** stock volatility, GARCH, GJR-GARCH, investment period, trade volume

**JEL Classification:** C22, G10

**1. Introduction**

Volatility in stock market simply refers to how wildly the stock market is expected to swing. This concept is concerned by most investment managers and traders because they would like to know how wildly their asset prices or returns would swing for risk management and investment strategy adjustment based on their volatility expectations. Not only do investors focus on volatility in stock market as a whole, but they also focus on volatility in individual stocks in the particular market. The study is proposed to explain overall market volatility and individual stock volatility in Stock Exchange of Thailand from 2015 to 2019. Because different investors have their own investment periods, this study investigates how the volatility behavior is different across investment periods. Only short-term investment periods are analyzed: 1-day, 3-day, 5-day, 10-day, 14-day and 20-day.

Two common behaviors usually found in financial asset volatility are volatility clustering and asymmetric response to shocks. Volatility clustering means large variances are followed by large variances, and vice versa. If volatility clustering is high, the impact of this period volatility on the next period volatility is high. Asymmetric response to shocks is referred to when the impact of positive return shocks on volatility is different from the impact of negative return shocks on volatility. Conventional financial theory attributes asymmetric responses to leverage effects. In short, leverage effects imply that the impact of negative shocks on volatility is greater than the impact of positive shocks. These two common behaviors are documented by a number of studies where the scope is Thai stock market. For example, Thammasiri and Pattarathammas (2010) found significant GARCH effects (volatility clustering) in SET50 index Futures from 2006 to 2008. Thakolsri, Sethapramote and Jiranyakul (2015) found leverage effects in SET index during 2005-2013. Thampanya and Pornpikul (2020) found volatility persistence in both bull and bear markets, and strong asymmetric response in bear markets in equity indices from ASEAN-5 countries, including Thailand from 1995 to 2013. These papers selected only one investment period to examine these two behaviors (usually one-day log return), which is insufficient for investors with different investment periods. This study extends previous studies by answering how volatility behavior differs across different investment periods in Thai stock market using recent observations from 2015 to 2019.

The framework used in this study is ARCH/GARCH model family, which is the most common framework found in literature. Its applicability to explain volatility in financial market is wide, from modelling stock index data to modelling individual stock data. For example, Ugurlu, Thalassinos and Muratoglu (2014) used GARCH to model volatility in market indices from emerging European markets. Handayani, Muharam, Mawardi and Robiyanto (2018) used ARCH and GARCH to model stock price volatility in Indonesian manufacturing sector. Brooks, Faff and Fry (2001) used GARCH to model volatility behavior across individual stocks in Australian market. To be able to explain those two common behaviors mentioned earlier, the study used both GARCH and GJR-GARCH model. By running these two models on SET index, the study found different volatility behavior across investment periods. For short investment periods (1-day, 3-day), the coefficients on lagged variance, past shocks and asymmetry are statistically significant. For longer periods (5-day, 10-day, 14-day, 20-day), only the coefficient on past shocks is statistically significant.

Investors frequently trade individual stocks. Although only a few studies address volatility behavior among individuals, understanding how volatility behaves in individual level is essential for investors. However, conducting the study from SET index to individual stocks involves one potential complication related to stocks with low traded volumes. In Australian stock market, where a number of stocks are thinly traded, lower traded volume is associated with higher volatility persistence. (Brooks, Faff and Fry, 2001) Since thin trading also occurs in a number of individual stocks in Thai stock market, it is likely that stocks with low traded volumes would have high volatility persistences. However, this study shows that stocks with lower traded volume do not exhibit higher volatility persistence. To illustrate the result, individual stocks are sorted and divided into ten deciles according to average daily traded volume, then both GARCH and GJR-GARCH are employed for each individual. The results are aggregated by taking an equal-weighted average on the coefficients found in order to summarize the results in each decile. In other words, if one stock from the decile was picked, what volatility behavior traders would expect. First, ARCH effects are 5% statistically significant for most individual stocks. Second, by comparing the magnitude of coefficients, volatility behavior is different across investment periods. Moving from short investment periods (1-day, 3-day) to longer periods (5-day, 10-day, 14-day, 20-day), the coefficients on past shocks get larger, and the coefficients on lagged variance get smaller. The differences in volatility behavior from shorter period to longer period are similar to the result found using SET index. Third, stocks with low traded volumes do not exhibit high volatility persistences. By forecasting stock volatility at individual level in Thai stock market, for each investment period, it is expected that volatility behaviors would be similar across different traded volumes.

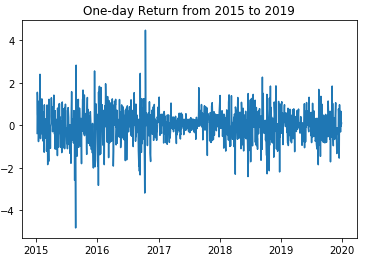
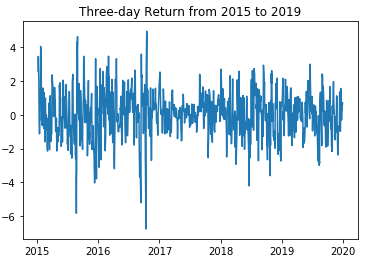
**2. Volatility Behavior in SET Index**

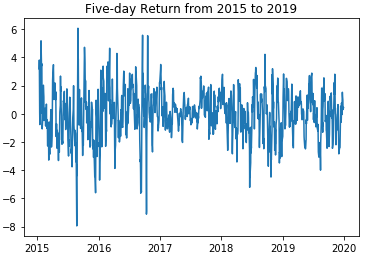
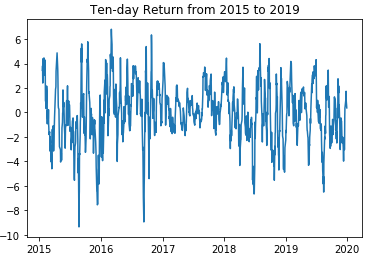
**2.1 Data Pre-processing**

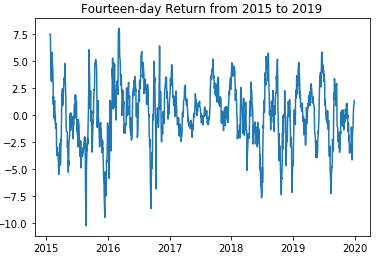
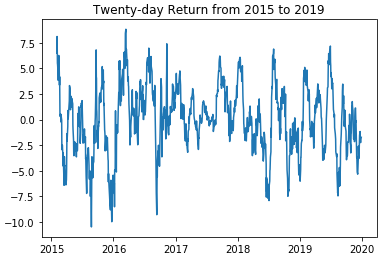
The data used in this section are daily closing SET index and daily traded volume on SET index from 2015 to 2019 collected from Thomson Reuter Datastream. First, I filtered out the rows where there were no data on volume traded (public holidays). Then, I generated log-return variables on SET index, where is the time index, and is the trading period. In this study, possible values of are 1, 3, 5, 10, 14 and 20. Therefore, denotes day log return at period in percentage term, according to the specification below. Note that the variables in percentage term are used throughout this study due to performance reasons.

**2.2 Descriptive Statistics**

Figure 1: Line plots on SET index Return During 2015 to 2019

Source: Author’s Calculations

Figure 1 shows line plots on log returns in SET index in percentage term ( during 2015-2019 in six different trading periods . Overall, most observations are close to zero with a few observations extremely positive or negative. The longer the investment horizon, the more heavily return fluctuates. By just looking at line plots, volatility clustering can be seen: high fluctuations in return are followed by similarly high fluctuations and low fluctuations are followed by similarly low fluctuations.

Table 1: Descriptive Statistics on SET Index Return During 2015-2019

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **One-day Return** | **Three-day Return** | **Five-day Return** | **Ten-day Return** | **Fourteen-day Return** | **Twenty-day Return** |
| **Number of Observations** | 1218 | 1216 | 1214 | 1209 | 1205 | 1199 |
| **Mean** | 0.005 | 0.015 | 0.02 | 0.029 | 0.033 | 0.029 |
| **Standard Deviation** | 0.73 | 1.297 | 1.662 | 2.314 | 2.738 | 3.263 |
| **Min** | -4.842 | -6.748 | -7.952 | -9.365 | -10.288 | -10.469 |
| **Max** | 4.484 | 4.937 | 6.065 | 6.814 | 8.003 | 8.826 |
| **Skewness** | -0.283 | -0.274 | -0.303 | -0.316 | -0.264 | -0.195 |
| **Kurtosis** | 3.79 | 1.511 | 1.26 | 0.532 | 0.334 | -0.135 |
| **Jarque Bera Statistics**  **(P-Values)** | 744.64  (0.000) | 130.826  (0.000) | 98.892  (0.000) | 34.456  (0.000) | 19.555  (0.000) | 8.472  (0.014) |

Source: Author’s Calculations

Table 1 shows descriptive statistics on SET index return in percentage term from 2015 to 2019 in six different trading periods. After filtering holidays, the number of observations became 1219 observations. These observations were used to generate log returns in different trading periods. The average log returns are extremely close to zero, and the average values are similar across columns. The standard deviations of log return are relatively high compared to the mean, and standard deviation increases as the trading period gets longer. The minimum and maximum are large in magnitude, consistent with outliers observed in figure 1. Returns are negatively skewed in all periods, implying longer tails in return distribution on negative side. In addition, excess positive kurtosis in returns indicates leptokurtic distribution, implying heavy tails on log returns (except for twenty-day return). Looking at Jarque Bera statistics with their associated p-values, the skewness and kurtosis of log returns are far from skewness and kurtosis in a normal distribution in all columns. In conclusion, by examining mean, standard deviation, skewness and kurtosis of log returns, these statistics are consistent with what are usually observed in financial data. Not only are these features found in Thai stock markets, other markets such as European emerging markets also have similar features (Ugurlu, Thalassinos, & Muratoglu, 2014).

**2.3 Methodology**

The models used to study volatility behavior in SET index are GARCH(1,1) and GJR-GARCH(1,1,1). GARCH(1,1) represents symmetric ARCH/GARCH model while GJR-GARCH(1,1,1) represents asymmetric ARCH/GARCH model. The difference is that asymmetric GARCH models do not assume symmetric responses of volatility to shocks. Since there are a number of variants of models in this framework such as EGARCH and Power GARCH, these two models selected are one of many possible options.

GARCH(1,1) is the standard symmetric volatility model developed by Bollerslev (1986). The variables of interest are log return on SET index (), indexed by time , and specifying the period length used in computing the return. In this study, possible values of are 1, 3, 5, 10, 14 and 20. The deviation from mean return is , where is referred to squared deviation in the previous trading day. refers to the volatility of , where is assumed to be normally distributed with mean of zero, and standard deviation of , a default assumption. In summary, this model captures volatility clustering by and . The coefficient is the response of volatility to the shocks: the higher is, the more persistently today shocks would impact next period volatility. is the coefficient on lagged variance: the higher is, the more current volatility feeds through next period volatility, indicating “high nonstop volatility” rather than “low unceasing volatility” (Khan, Khan, Mahmood and Sheeraz, 2019).

GJR-GARCH(1,1,1) from Zakoian (1994) is an extension of GARCH(1,1) as GJR-GARCH(1,0,1) is equivalent to GARCH(1,1). The only difference is that GJR-GARCH(1,1,1) does not assume symmetric response to shocks. To capture possible asymmetric response of return volatility to deviation from mean, denotes indicator random variable, which is equal to one when the deviation is negative (), and zero otherwise. According to Tsai (2013), positive indicates leverage effect as the effect of negative shocks on volatility is greater than positive ones while negative indicates anti-leverage effect where the impact of positive shocks on volatility is greater.

**2.4 Results**

Before employing GARCH and GJR-GARCH models, preliminary tests on return series should be conducted. First, Augmented Dickey Fuller (ADF) test was conducted to check whether the return series was stationary. Then, return series was examined to see if there were evidences of heteroscedasticity by using ARCH LM test. Checking heteroscedasticity is an important step before employing volatility models (Maqsood, Safdar, Shafi and Lelit, 2017). These two test results are displayed in Table 2 and Table 3 below.

Table 2: The Results of Unit Root Test on SET Index During 2015-2019 Using ADF Test

|  |  |  |
| --- | --- | --- |
| **Variables** | **Test Statistics** | **p-Value** |
| **One-day Return** | -33.588 | 0.000 |
| **Three-day Return** | -6.883 | 0.000 |
| **Five-day Return** | -6.642 | 0.000 |
| **Ten-day Return** | -5.704 | 0.000 |
| **Fourteen-day Return** | -5.754 | 0.000 |
| **Twenty-day Return** | -5.141 | 0.000 |

Source: Author’s Calculations

Table 2 shows the test statistics and associated p-values of ADF test for log returns in six different investment periods. The setting used here is constant-only ADF, which is the default one. All of these variables show large test statistics in magnitude, with extremely small p-values. Hence, the null hypothesis that there is a unit root is rejected. The log return series are stationary.

Table 3: The Results of Conditional Heteroskedasticity Test on SET Index During 2015-2019 Using LM ARCH

|  |  |  |
| --- | --- | --- |
| **Variables** | **Test Statistics** | **p-Value** |
| **One-day Return** | 116.527 | 0.000 |
| **Three-day Return** | 370.484 | 0.000 |
| **Five-day Return** | 435.875 | 0.000 |
| **Ten-day Return** | 734.716 | 0.000 |
| **Fourteen-day Return** | 809.705 | 0.000 |
| **Twenty-day Return** | 876.996 | 0.000 |

Source: Author’s Calculations

Table 3 shows the test statistics and associated p-values of ARCH LM test for log returns in six different investment periods. The setting used here is the default one. All of them show large test statistics with very small p-values. The null hypothesis that the variance is constant is rejected. In other words, the variance of returns varies, indicating ARCH effects in all six variables. After preliminary tests, GARCH and GJR-GARCH models can be used, and the results are reported in Table 4 and Table 5.

Table 4: The Results of GARCH Model on SET Index During 2015-2019

|  |  |  |  |
| --- | --- | --- | --- |
| **Dependent Variables** | **One-day Return** | **Three-day Return** | **Five-day Return** |
| **Mean Model:** |  |  |  |
|  | 0.023  (0.017) | 0.107\*\*  (0.045) | 0.1321\*\*  (0.06) |
| **Volatility Model:** |  |  |  |
|  | 0.005  (0.004) | 0.372\*\*\*  (0.101) | 0.396\*\*\*  (0.145) |
|  | 0.08\*\*\*  (0.026) | 0.5461\*\*\*  (0.065) | 0.6853\*\*\*  (0.089) |
|  | 0.914\*\*\*  (0.026) | 0.2688\*\*  (0.107) | 0.238\*  (0.133) |
| **Log-Likelihood** | -1255.27 | -1876.43 | -2098 |
| **BIC** | 2538.97 | 3781.28 | 4244.40 |

|  |  |  |  |
| --- | --- | --- | --- |
| **Dependent Variables** | **Ten-day Return** | **Fourteen-day Return** | **Twenty-day Return** |
| **Mean Model:** |  |  |  |
|  | 0.1763  (0.145) | 0.033  (0.136) | 0.043  (0.208) |
| **Volatility Model:** |  |  |  |
|  | 0.849\*\*\*  (0.129) | 0.817\*\*\*  (0.106) | 0.721\*\*\*  (0.147) |
|  | 0.828\*\*\*  (0.043) | 0.88\*\*\*  (0.036) | 0.872\*\*\*  (0.052) |
|  | 0.019  (0.031) | 0.021  (0.026) | 0.08  (0.058) |
| **Log-Likelihood** | -2399.63 | -2530.46 | -2701.21 |
| **BIC** | 4827.65 | 5089.29 | 5430.79 |

Source: Author’s Calculations

Table 4 reports the results of GARCH(1,1) in log returns across six investment periods. Considering mean model, only the means of three-day and five-day log returns are significantly greater than zero. All s in six investment periods are statistically significant, implying the shocks today actually impact the volatility in the next period. Looking at the size of coefficients, the sizes of s in short periods (1-day, 3-day, 5-day) are much smaller than the sizes in longer periods (10-day, 14-day, 20-day). In other words, the impact of the shocks is larger for longer investment periods. However, only s in short periods (1-day, 3-day) are statistically significant. Looking at the sizes, the size of is the largest for one-day, and decreases drastically for 3-day and 5-day, and becomes statistically insignificant with much smaller magnitudes on longer periods. The proportion that current volatility feeds through the next period volatility is smaller for longer investment periods. In other words, shorter period volatility exhibits “high nonstop volatility” while longer period volatility exhibits “low unceasing volatility.” From performance viewpoint, log-likelihood and BIC show that GARCH model is the best in explaining 1-day returns. In summary, the volatility clustering in shorter investment periods is much explained by volatility in previous period while in longer periods it is much explained by shocks in previous period. The result illustrates the differences in volatility behavior across investment periods by using GARCH.

Table 5: The Results of GJR-GARCH Model on SET Index During 2015-2019

|  |  |  |  |
| --- | --- | --- | --- |
| **Dependent Variables** | **One-day Return** | **Three-day Return** | **Five-day Return** |
| **Mean Model:** |  |  |  |
|  | 0.005  (0.017) | 0.111\*\*  (0.046) | 0.128\*\*  (0.061) |
| **Volatility Model:** |  |  |  |
|  | 0.01\*\*  (0.005) | 0.365\*\*\*  (0.087) | 0.386\*\*\*  (0.149) |
|  | 0.002  (0.016) | 0.407\*\*\*  (0.073) | 0.596\*\*\*  (0.123) |
|  | 0.918\*\*\*  (0.019) | 0.275\*\*\*  (0.099) | 0.251\*  (0.142) |
|  | 0.117\*\*\*  (0.034) | 0.257\*\*\*  (0.083) | 0.148\*  (0.085) |
| **Log-Likelihood** | -1235.96 | -1872.16 | -2096.67 |
| **BIC** | 2507.45 | 3779.83 | 4228.85 |

|  |  |  |  |
| --- | --- | --- | --- |
| **Dependent Variables** | **Ten-day Return** | **Fourteen-day Return** | **Twenty-day Return** |
| **Mean Model:** |  |  |  |
|  | 0.183  (0.145) | 0.034  (0.137) | 0.042  (0.209) |
| **Volatility Model:** |  |  |  |
|  | 0.844\*\*\*  (0.13) | 0.817\*\*\*  (0.106) | 0.721\*\*\*  (0.148) |
|  | 0.79\*\*\*  (0.05) | 0.8651\*\*\*  (0.043) | 0.876\*\*\*  (0.062) |
|  | 0.02  (0.031) | 0.02  (0.026) | 0.08  (0.058) |
|  | 0.074  (0.071) | 0.032  (0.061) | -0.009  (0.056) |
| **Log-Likelihood** | -2399.36 | -2530.41 | -2701.21 |
| **BIC** | 4834.21 | 5096.28 | 5437.87 |

Source: Author’s Calculations

Table 5 reports the results of GJR-GARCH(1,1,1) in log returns across six investment periods. Looking at mean model, only means of three-day and five-day log returns are significantly greater than zero, similar to GARCH(1,1) result. Most s are statistically significant, except one-day log return. The implication is similar to the result from Table 4: shocks today has an impact on the next period volatility. Looking at their sizes, the magnitudes of s in longer period are larger than s in shorter periods. The longer the investment period is, the greater the impact of today shocks will be on next period volatility. Similar to Table 4, only s in one-day and three-day log returns are statistically significant at 5%. Looking at their sizes, is the largest for one-day, and becomes smaller as the investment period changes to three days and five days. As the period increases up until 20 days, becomes much smaller. The interpretation is the same as the result from Table 4: the proportion that current volatility feeds through the next period is usually smaller for longer investment periods. Furthermore, looking at the signs of coefficients , most of them exhibit leverage effects, except for twenty-day return that shows anti-leverage effect, but still not statistically significant. In other words, the leverage effect in shorter periods is stronger than the leverage effect in longer periods. This is similar to Thampanya, Wu, Nasir and Liu (2020) where the leverage effect in one-month return from 1995 to 2018 is not significant in SET index using EGARCH(1,1) model; however, their results show positive sign on leverage effect parameter. From Table 5, the leverage effect is larger for short periods (1-day, 3-day, 5-day) than the leverage (or anti-leverage) for longer periods (10-day, 14-day and 20-day). The leverage effect () is statistically significant in one-day and three-day return only. This is similar to Thakolsri, Sethapramote and Jiranyakul (2015) where the leverage effect is statistically significant in one-day return in SET index from 2005 to 2013 by using GJR-GARCH(1,1,1)-M model and EGARCH(1,1)-M model. Also, their results show statistically significant coefficients on lagged volatility and response to shocks using one-day return. For performance viewpoint, log-likelihood and BIC show that GJR-GARCH model is the best in explaining 1-day returns, similar to the previous results. In summary, volatility in longer periods is more responsive to return shocks, and less responsive to lagged volatility than volatility in shorter periods. Asymmetry is found in shorter periods, but is not statistically significant in longer periods.

**3. Volatility Behavior in Individual Stocks**

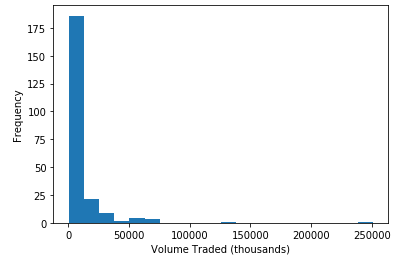
**3.1 Data Pre-processing**

The data used in this section are daily closing prices and daily traded volumes on individual stocks listed in Stock Exchange of Thailand from 2015 to 2019 collected from Thomson Reuter Datastream. Several steps of data preparation have to be done before running the model. First, I filtered out the stocks where at least one feature (either price or volume) was not available on the dataset. Then, using volume traded data on SET index, I filtered out holidays where SET index did not have trading activities. For each individual stock, I checked whether the price and volume data were available for all trading days, and whether there were any trading days where there was no volume traded. Only the stocks that passed these two criteria were allowed to proceed to calculate one-day, three-day, five-day, ten-day, fourteen-day and twenty-day log returns. Note that by excluding stocks where there was no volume traded on any trading days, the purpose is to address censoring issue. Aside from low traded volume, censoring issue is when there are a number of zero volume traded, causing zero changes in price on that trading day. This issue does not occur with index series, and addressing the censoring issue in individual stocks before running regressions is an essential task (Brooks, Faff, & Fry, 2001). Because this study focuses on the issue of low traded volume, any individual stocks with censoring issue would not be included in this analysis. Therefore, stocks that would be used for further analysis have had trading activities on every trading day as investors are usually concerned about trading stocks with trading activities exhibited in volume traded.

To investigate whether traded volume has an impact on model estimated results, stocks are divided equally into ten equal groups based on the volumes. Based on Brooks, Faff and Fry (2001), low volume traded is associated with high volatility clustering and high persistence in Australian market. By estimating the model results and grouping them into each decile, I could see whether there are any associations between traded volume and volatility behavior. Finally, I conducted LM ARCH test to see any evidences of conditional heteroscedasticity, and include only stocks with significant LM ARCH test (at 5%) in GARCH and GJR-GARCH analysis, following similar steps from Brooks, Faff and Fry (2001).

**3.2 Descriptive Statistics**

Figure 2: Histogram on Average Daily Traded Volume Among Individual Stocks During 2015-2019



Source: Author’s Calculations

Figure 2 shows histogram on average daily traded volume in individual stocks listed in SET index during 2015-2019 after data cleaning. The number of stocks included in this analysis is 227 stocks. These stocks have complete information on price and volume features, and have trading activities every day. Overall, most stocks have volume traded less than 20 million Baht per day. There are a few observations with extremely high traded volumes: the stock with maximum volume traded has more than 200 million Baht traded daily. This visualization supports why the study divides the stock based on relative ranking, rather than dividing the stocks into each bin of traded volume.

Table 6: Descriptive Statistics for Individual Stocks Listed in SET with ARRCH-LM Results

(a) One-day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 16 | -0.027 |
| **2** | 23 | 13 | -0.047 |
| **3** | 23 | 16 | -0.039 |
| **4** | 23 | 16 | -0.058 |
| **5** | 23 | 20 | -0.049 |
| **6** | 23 | 18 | -0.047 |
| **7** | 23 | 17 | -0.071 |
| **8** | 22 | 21 | -0.043 |
| **9** | 22 | 20 | -0.028 |
| **10** | 22 | 20 | -0.043 |

(b) Three-day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 23 | -0.081 |
| **2** | 23 | 23 | -0.144 |
| **3** | 23 | 23 | -0.118 |
| **4** | 23 | 23 | -0.176 |
| **5** | 23 | 23 | -0.147 |
| **6** | 23 | 23 | -0.144 |
| **7** | 23 | 23 | -0.214 |
| **8** | 22 | 22 | -0.131 |
| **9** | 22 | 22 | -0.085 |
| **10** | 22 | 22 | -0.130 |

(c) Five-day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 23 | -0.136 |
| **2** | 23 | 23 | -0.241 |
| **3** | 23 | 23 | -0.194 |
| **4** | 23 | 23 | -0.292 |
| **5** | 23 | 23 | -0.242 |
| **6** | 23 | 23 | -0.241 |
| **7** | 23 | 23 | -0.354 |
| **8** | 22 | 22 | -0.219 |
| **9** | 22 | 22 | -0.142 |
| **10** | 22 | 22 | -0.214 |

(d) Ten-day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 23 | -0.270 |
| **2** | 23 | 23 | -0.481 |
| **3** | 23 | 23 | -0.389 |
| **4** | 23 | 23 | -0.580 |
| **5** | 23 | 23 | -0.472 |
| **6** | 23 | 23 | -0.481 |
| **7** | 23 | 23 | -0.689 |
| **8** | 22 | 22 | -0.433 |
| **9** | 22 | 22 | -0.283 |
| **10** | 22 | 22 | -0.418 |

(e) Fourteen-Day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 23 | -0.373 |
| **2** | 23 | 23 | -0.664 |
| **3** | 23 | 23 | -0.542 |
| **4** | 23 | 23 | -0.796 |
| **5** | 23 | 23 | -0.649 |
| **6** | 23 | 23 | -0.663 |
| **7** | 23 | 23 | -0.950 |
| **8** | 22 | 22 | -0.592 |
| **9** | 22 | 22 | -0.390 |
| **10** | 22 | 22 | -0.579 |

(f) Twenty-Day Returns

|  |  |  |  |
| --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **Number of Firms** | **Number of Firms with 5% Significant ARCH LM** | **Average Log Return Across Decile** |
| **1** | 23 | 23 | -0.508 |
| **2** | 23 | 23 | -0.915 |
| **3** | 23 | 23 | -0.754 |
| **4** | 23 | 23 | -1.093 |
| **5** | 23 | 23 | -0.898 |
| **6** | 23 | 23 | -0.906 |
| **7** | 23 | 23 | -1.327 |
| **8** | 22 | 22 | -0.808 |
| **9** | 22 | 22 | -0.530 |
| **10** | 22 | 22 | -0.806 |

Source: Author’s Calculations

Table 6 shows descriptive statistics on 227 stocks in SET across six investment periods. Looking at average log return, log returns are negative across all deciles, and their magnitudes generally increase with longer investment periods. Note that this is an equal-weighted average, not size-weighted average used to compute SET index. This implies that if one stock was picked randomly from each decile, the average return that one should get was negative during the period 2015-2019. For one-day return, there are a number of stocks with not statistically significant LM ARCH test. A few of these stocks belong to the last three deciles while most of them belong to the other deciles. This implies that ARCH effects exist in almost all stocks with high volume traded while ARCH effects are not statistically significant in a number of stocks with relatively low volume traded. This is similar to Brooks, Faff and Fry (2001) where there is positive relationship between ARCH effects in individual stocks and trading volumes in Australian stock market. However, for three-day return onwards, all stocks included in this analysis show statistically significant LM ARCH test. In other words, not only could conditional heteroscedasticity be found in indices, it could also be found in most individual stocks. As investors are concerned about individual stocks, they should be aware of volatility behavior in individual level due to the evidence of conditional heteroscedasticity shown.

**3.3 Methodology**

The framework used to study volatility in individual stocks is GARCH and GJR-GARCH model, same as the framework used to study SET index. GARCH and GJR-GARCH are estimated for each individual stock, and the results are aggregated into each decile using average of coefficients estimated, similar to the methodology from Brooks, Faff and Fry (2001). Therefore, all variables and coefficients in the estimation have an extra index , allowing the estimates to vary across individual stocks.

Individual GARCH:

Individual GJR-GARCH:

**3.4 Results**

Table 7: The Average Coefficients from GARCH and GJR-GARCH Model on Individual Stocks Listed in Stock Exchange of Thailand across Average Daily Traded Volume During 2015-2019

(a) One-day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **GARCH** | | | **GJR-GARCH** | | |
|  |  |  |  |  |  |
| **1** | 0.134 | 0.754 | 0.888 | 0.143 | 0.769 | -0.033 |
| **2** | 0.149 | 0.806 | 0.955 | 0.157 | 0.795 | -0.018 |
| **3** | 0.122 | 0.794 | 0.916 | 0.121 | 0.815 | -0.007 |
| **4** | 0.133 | 0.780 | 0.913 | 0.118 | 0.788 | 0.019 |
| **5** | 0.156 | 0.737 | 0.893 | 0.155 | 0.726 | 0.009 |
| **6** | 0.156 | 0.771 | 0.927 | 0.114 | 0.765 | 0.099 |
| **7** | 0.095 | 0.849 | 0.944 | 0.093 | 0.824 | 0.011 |
| **8** | 0.081 | 0.859 | 0.94 | 0.051 | 0.847 | 0.063 |
| **9** | 0.124 | 0.807 | 0.931 | 0.086 | 0.811 | 0.071 |
| **10** | 0.083 | 0.868 | 0.951 | 0.063 | 0.859 | 0.049 |

(b) Three-day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average** | **GARCH** | | | **GJR-GARCH** | | |
| **Daily Volume Traded** |  |  |  |  |  |  |
| **1** | 0.528 | 0.353 | 0.881 | 0.549 | 0.326 | -0.008 |
| **2** | 0.558 | 0.300 | 0.858 | 0.574 | 0.298 | -0.024 |
| **3** | 0.578 | 0.298 | 0.876 | 0.608 | 0.301 | -0.065 |
| **4** | 0.570 | 0.290 | 0.86 | 0.561 | 0.293 | 0.014 |
| **5** | 0.563 | 0.283 | 0.846 | 0.556 | 0.285 | 0.012 |
| **6** | 0.583 | 0.314 | 0.897 | 0.583 | 0.317 | -0.003 |
| **7** | 0.608 | 0.186 | 0.794 | 0.544 | 0.182 | 0.136 |
| **8** | 0.552 | 0.272 | 0.824 | 0.572 | 0.275 | -0.042 |
| **9** | 0.505 | 0.321 | 0.826 | 0.474 | 0.325 | 0.055 |
| **10** | 0.492 | 0.304 | 0.796 | 0.487 | 0.295 | 0.029 |

(c) Five-day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **GARCH** | | | **GJR-GARCH** | | |
|  |  |  |  |  |  |
| **1** | 0.653 | 0.235 | 0.888 | 0.665 | 0.239 | -0.030 |
| **2** | 0.674 | 0.227 | 0.901 | 0.689 | 0.227 | -0.029 |
| **3** | 0.670 | 0.223 | 0.893 | 0.692 | 0.224 | -0.046 |
| **4** | 0.677 | 0.217 | 0.894 | 0.686 | 0.214 | -0.017 |
| **5** | 0.679 | 0.215 | 0.894 | 0.679 | 0.216 | -0.003 |
| **6** | 0.643 | 0.275 | 0.918 | 0.644 | 0.277 | -0.005 |
| **7** | 0.686 | 0.173 | 0.859 | 0.653 | 0.171 | 0.066 |
| **8** | 0.630 | 0.225 | 0.855 | 0.626 | 0.235 | -0.004 |
| **9** | 0.635 | 0.227 | 0.862 | 0.623 | 0.228 | 0.021 |
| **10** | 0.624 | 0.208 | 0.832 | 0.625 | 0.208 | -0.007 |

(d) Ten-day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **GARCH** | | | **GJR-GARCH** | | |
|  |  |  |  |  |  |
| **1** | 0.762 | 0.179 | 0.941 | 0.783 | 0.179 | -0.044 |
| **2** | 0.796 | 0.152 | 0.948 | 0.805 | 0.153 | -0.023 |
| **3** | 0.780 | 0.157 | 0.937 | 0.805 | 0.157 | -0.056 |
| **4** | 0.811 | 0.125 | 0.936 | 0.821 | 0.125 | -0.023 |
| **5** | 0.796 | 0.131 | 0.927 | 0.806 | 0.130 | -0.022 |
| **6** | 0.783 | 0.147 | 0.93 | 0.803 | 0.148 | -0.046 |
| **7** | 0.820 | 0.098 | 0.918 | 0.802 | 0.097 | 0.037 |
| **8** | 0.796 | 0.112 | 0.908 | 0.794 | 0.113 | -0.007 |
| **9** | 0.765 | 0.147 | 0.912 | 0.760 | 0.159 | -0.012 |
| **10** | 0.734 | 0.164 | 0.898 | 0.740 | 0.163 | -0.017 |

(e) Fourteen-Day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **GARCH** | | | **GJR-GARCH** | | |
|  |  |  |  |  |  |
| **1** | 0.800 | 0.150 | 0.95 | 0.816 | 0.150 | -0.034 |
| **2** | 0.852 | 0.099 | 0.951 | 0.857 | 0.099 | -0.015 |
| **3** | 0.798 | 0.147 | 0.945 | 0.818 | 0.146 | -0.041 |
| **4** | 0.820 | 0.120 | 0.94 | 0.833 | 0.119 | -0.026 |
| **5** | 0.830 | 0.120 | 0.95 | 0.837 | 0.120 | -0.017 |
| **6** | 0.804 | 0.148 | 0.952 | 0.817 | 0.147 | -0.028 |
| **7** | 0.839 | 0.101 | 0.94 | 0.830 | 0.101 | 0.015 |
| **8** | 0.818 | 0.114 | 0.932 | 0.825 | 0.113 | -0.017 |
| **9** | 0.797 | 0.129 | 0.926 | 0.813 | 0.129 | -0.041 |
| **10** | 0.761 | 0.165 | 0.926 | 0.772 | 0.164 | -0.025 |

(f) Twenty-Day Returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Decile on Average Daily Volume Traded** | **GARCH** | | | **GJR-GARCH** | | |
|  |  |  |  |  |  |
| **1** | 0.810 | 0.152 | 0.962 | 0.825 | 0.151 | -0.035 |
| **2** | 0.856 | 0.110 | 0.966 | 0.866 | 0.110 | -0.024 |
| **3** | 0.830 | 0.127 | 0.957 | 0.850 | 0.128 | -0.047 |
| **4** | 0.853 | 0.109 | 0.962 | 0.869 | 0.109 | -0.036 |
| **5** | 0.817 | 0.152 | 0.969 | 0.822 | 0.143 | 0.006 |
| **6** | 0.777 | 0.198 | 0.975 | 0.783 | 0.198 | -0.014 |
| **7** | 0.839 | 0.118 | 0.957 | 0.856 | 0.117 | -0.035 |
| **8** | 0.822 | 0.125 | 0.947 | 0.830 | 0.124 | -0.017 |
| **9** | 0.813 | 0.145 | 0.958 | 0.817 | 0.145 | -0.014 |
| **10** | 0.775 | 0.172 | 0.947 | 0.785 | 0.172 | -0.025 |

Source: Author’s Calculations

Table 7 reports the results of GARCH and GJR-GARCH models across six investment periods in individual stocks, where the results are aggregated into each decile. Looking at s from both models, s generally increase as the investment period is longer. In other words, the impact of the shocks is larger for longer investment periods. This observation occurs across all deciles, and this difference across investment periods is similar to the result using SET index. Looking at s from both models, the sizes of s are larger in 1-day, 3-day and 5-day returns, compared to the sizes of s from longer periods. The proportion that current volatility passes through the next period volatility is smaller in 10-day, 14-day and 20-day returns. In other words, volatility in shorter periods is “high nonstop” while volatility in longer periods is “low unceasing.” This is similar to the behavior of SET Index across investment periods, and generally holds across all volume deciles. However, s in individuals are close in magnitude along investment periods and across deciles. They are quite low in magnitude, and some of them are slightly positive while others are slightly negative. This implies that the leverage or anti-leverage effect is very weak, if exists. In summary, volatility is becoming more responsive to return shocks and less affected by lagged volatility as the period of investment increases. This result is similar to the behavior of SET index. However, one main difference here is that leverage or anti-leverage effect is weak among individuals. The implication is that investors should expect different volatility behaviors in different investment periods, similar to the implications found using SET index.

To examine whether there is the relationship between volume traded and volatility behavior, each average coefficient could be compared across different volumes traded. According to Brooks, Faff and Fry (2001), in Australian market, , and from GARCH are the largest in stocks with low volume traded, implying the relationship between lower traded volume and higher persistence (captured by ). Stocks with relatively low traded volumes had relatively high volatility persistences in Australian stock market. However, in case of Thailand, s, s and s in different traded volumes are very close to one another. Low traded volume does not affect the estimated results in GARCH and GJR-GARCH models. Stocks with lower traded volumes do not exhibit higher volatility persistences and volatility clusterings. Therefore, investors could expect similar degree of volatility clustering and persistence in Thai stock market across stocks with different traded volumes.

**4. Conclusion**

Volatility concept is essential for investment managers and traders to manage the risk and adjust their strategies. By exploring the volatility behavior across short-term investment periods, the study has found that the main determinant of market volatility varies by different investment periods. In short periods (1 day, 3 days), market volatility is determined by previous period volatility and asymmetric responses to positive shocks and negative shocks. As the trading period increases up until 20 days, the impact of previous period volatility declines, and the asymmetry between positive and negative shocks declines while the main determining factor becomes return shocks. The implication is that traders need to take their investment periods into account when analyzing volatility behavior. The main factor in explaining volatility behavior in SET index could change along investment periods. Lagged volatility is a good guess in a very short trading period while the effect of past shocks becomes main determinant of market volatility in longer periods.

As investors often trade individual stocks, they need to understand the volatility behavior in individual level. First, volatility is heteroscedastic for most individual stocks. Because the evidence of heteroscedasticity is found in individual level, investors can apply volatility models to study its behavior at individual stock in Thai stock market. Second, the behavior of individual volatility varies on different investment periods. From shorter investment periods (1-day, 3-day, 5-day) to longer ones (10-day, 14-day and 20-day), the effect of return shock on volatility increases while the impact of previous period volatility on current volatility declines. However, the asymmetry seems weak across all trading periods. This implies that traders should consider their investment periods when analyzing volatility at individual level because the impact of each factor on stock volatility changes across investment periods. Third, unlike Australian stock market, low traded volume is not associated with higher volatility persistence in Thai stock market. Volatility behaviors in individual level are similar across traded volumes but different across trading horizons. The implication is that by investigating volatility behaviors in individual stocks, traders could expect similar impacts of lagged volatility and return shocks on current period volatility across traded volumes, as long as they considered the same investment periods.

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