CHAPTER 2

Theory and Literature Review

2.1 Theory

2.1.2 Ordinary Least Square Method (OLS)

OLS is a method for estimating the parameters in a linear regression model. The goal of OLS is to closely fit a function with the data. It does so by minimizing the sum of squared errors from the data. The use of this methodology, however, has two drawbacks. First, errors in the model may be auto correlated resulting in misleading inferences. The other drawback is that error variances may not be constant over time. Especially to solve the second drawback the variance of the errors terms are allowed to be time dependent so as to include conditional heteroskedasticity. To address the autocorrelation problem, the study can include lagged values of the return variable in the equation (H. Kiyamaz, H. Beaumont, 2003).

OLS Regression is the common approach employed by the previous research to investigate the day of the week effect in stock returns. But their shortcoming lies in utilizing only one regression equation to find the day of the week effect for trading days of the week. This approach is possible only if the study holds a prior belief that an effect exists on one specific day, such as Wednesday. However, this specification is not appropriate if the study has no previous expectation as to on which day the said effect might exist. The study overcomes this shortcoming by estimating a different model for finding the day of the week effect for each trading day of the week by omitting the dummy variable for the day under scrutiny in each case (Borges 2009).

To comply with the conditions. (Berument H.&Halil Kiyamaz.H.,2001)

$$R_{j(t)} = \alpha_0 + \alpha_1 R_j (D_{Mt}) + \alpha_2 R_j (D_{Tt}) + \alpha_3 R_j (D_{Ht}) + \alpha_4 R_j (D_{Ft}) + \sum_{i=1}^{p} \beta_j R_{j(t-i)} + \varepsilon_t \quad (2.1)$$

Where D_{Mt}, D_{Tt}, D_{Ht} and D_{Ft} are the dummy variables for Monday, Tuesday, Thursday and Friday

D_{Mt} = 1 if there is the dummy variable of Monday and 0 if there is other days.

D_{Tt} = 1 if there is the dummy variable of Tuesday and 0 if there is other days.

D_{Ht} = 1 if there is the dummy variable of Thursday and 0 if there is other days.

D_{Ft} = 1 if there is the dummy variable of Friday and 0 if there is other days.

$\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4$	=	coefficient
β_j	=	coefficient of $R_{j(t-i)}$
R_j	=	return on ICT stock index of country j on day t
$R_{j(t-i)}$	=	return on ICT stock index of country j on day t
t	=	Time
p	=	Lead and Lag
ε_t	=	error of time that h_t ($\varepsilon_t \sim N(0,h_t)$)
j	=	(Singapore, Thailand, Indonesia, Malaysia, the Philippines)

We exclude Wednesday's dummy variable from the equation to avoid the dummy variable trap.

The dummy variable trap is a scenario in which the independent variables are multicollinear. There are two or more variables that are highly correlated, which means in simple terms, one variable can be predicted from the others (Halil Kiymaz and Hakan Berument, 2003).

The solution to the dummy variable trap is to drop one of the categorical variables, or drop the intercept constant terms. If there are m numbers of categories, use m-1 in the model. The value left out can be thought of as the reference value, and the fit values of the remaining categories represent the change from this reference. The dummy variable is an assigned value of "one" if return for that day is there. A value of "zero" is assigned for returns on the remaining days.

The study drops Wednesday because in the aforementioned research about the day of the week patterns, for example, Berument (2003), Mansorech (2012) and Karolyi (1995), etc., also droped Wednesday. Moreover, my own investigation of ASEAN stock markets also shows that Wednesday has the lowest volume.

2.1.2 Time Series Analysis

The time series analysis is a method used to evaluate data or observations that change over a period of time. There might be either stationary or non-stationary changes regarding the time series. If the time series analysis is able to explain or interpret the changes in the past, then those finding can be engaged as a tool to predict or estimate the future(RueyS.Tsay,1951).

The time series adapted should be stationary. There are two ways to test whether time series are stationary or non-stationary. The first is the Box- Jerkins method of time series analysis (Autocorrelation Coefficient Fuction: ACF). The other one is the Dickey-Fuller's method called 'unit root'(Pimolmas Sawatmongkhonkul, 2011).

Stationary and Unit Root Test

Stationary Stochastic Process: " A stochastic process is said to be a stationary one if its mean and variance value are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods, and not the actual time at which the covariance is computed" (Gujarati, 2004 p. 797).

Mean: $E(X_t) = \mu$ (2.2)

Variance: $V(X_t) = E(X_t - \mu) = \sigma$ (2.3)

Covariance: $COV(X_t, X_{t-k}) = E(X_t - \mu)(X_{t-k} - \mu) = \sigma_k - \mu$ (2.4)

Where X_t is the time series in random process

The Unit Root Test employs an autoregressive model to establish whether the time series is stationary. The study uses the Dickey-Fuller test (DF) and the Augmented Dickey-Fuller Test (ADF) (1979).

DF Test

Parameters are not constant: $X_t = \rho X_{t-1} + \varepsilon_t$ (2.5)

Assumption: $H_0 : \rho = 1$

$H_1 : |\rho| < 1$

If accept $H_0 : \rho = 1$, the data is not stationary

If reject $H_0 : \rho = 1$ or accept $H_1 : |\rho| < 1$, the data is stationary

Test Equation

Non constant and trend: $\Delta X_t = \theta X_{t-1} + \varepsilon_t$ (2.6)

Constant without trend: $\Delta X_t = \alpha + \theta X_{t-1} + \varepsilon_t$ (2.7)

Constant and trend: $\Delta X_t = \alpha + \beta t + \theta X_{t-1} + \varepsilon_t$ (2.8)

Assumption: $H_0 : \theta = 0$

$H_1 : \theta < 0$

ADF Test: The difference from DF Test is lagged change [$\sum_{i=1}^{\rho} \lambda_i \Delta X_{t-1}$]

Non Constant and Trend: $\Delta X_t = \theta X_{t-1} + \sum_{i=1}^{\rho} \emptyset \Delta X_{t-1} + \varepsilon_t$ (2.9)

Constant without Trend: $\Delta X_t = \alpha + \theta X_{t-1} + \sum_{i=1}^{\rho} \emptyset \Delta X_{t-1} + \varepsilon_t$ (2.10)

Constant and Trend: $\Delta X_t = \alpha + \beta t + \theta X_{t-1} + \sum_{i=1}^{\rho} \emptyset \Delta X_{t-1}$ + If (2.11)

lag length has t-statistic that is not significant at 10%, from this study reduces lag length for 1 range

2.1.3 Autoregressive Integrated Moving Average (ARIMA)

In the statistical analysis of time series, ARMA models provide a parsimonious description of a stationary stochastic process in terms of two polynomials: one for the auto-regression (AR), and the second for the moving average (MA). It is a tool for understanding and predicting future values in time series.

The AR model outlines the relationship between the current value and history value. The MA model describes the error accumulation of the autoregressive part (Yin Lanwenjing, 2012).

$$X_t = C + \mathcal{E}_t + \sum_{i=1}^{p} \varphi x_{t-i} + \sum_{i=1}^{q} \theta \varepsilon_{t-I} \quad (2.12)$$

2.1.4 Generalized Autoregressive Condition Heteroscedasticity (GARCH)

In econometrics, Autoregressive Conditional Heteroskedastic (ARCH) models are used to characterize and model observed time series. The models are designed to capture the volatility of financial returns. They were proposed by Eagle (1982) and put to use whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular, ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods'error terms. They are employed commonly in modeling, regression analysis and forecasting of financial time series that exhibit time-varying volatility clustering (Shaen Corbat and Cian Tomey, 2015).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \quad (2.13)$$

If an autoregressive moving average model (ARMA model) is assumed for the error variance, the model is a generalized autoregressive condition heteroscedasticity (GARCH, Bollerslev 1986) model. The GARCH model embodies a specialized build regression model for financial data. In addition to the same parts of ordinary regression models, the GARCH model carries out further arithmetic on error variance. It is particularly suitable for the analysis and forecasting of volatility which can play a very important guiding role for investors' decisions. Its significance often exceeds the value itself for analysis and forecasting. The GARCH (p, q) model (where p is the order of the GARCH term σ^2 and q is the order of the ARCH terms ε^2) is given by

$$\sigma^2_t = a_0 + \sum_{i=1}^{q} a_1 \varepsilon^2_{t-1} + \sum_{i=1}^{q} B_i \sigma^2_{t+} \quad (2.14)$$

2.2 Literature Review

Literature review about the day of the week patterns

Choudhry (2000) examined the day of the week effect on return and volatility in seven emerging Asian stock markets. The researcher used daily returns from Thailand, Taiwan, South Korea, the Philippines, Malaysia, Indonesia, and India over the period from January 1990 to June 1995. The result showed that there is significant day of the week effect on Mondays for both stock returns and variance. The cause for this finding might derive from the Japanese market. However, there remains need for more investigation of the day of the week effect in different countries and for different time periods.

Brock and Persand (2001) studied the day of the week effect for five Southeast Asian countries i.e. Malaysia, South Korea, the Philippines, Taiwan and Thailand. The data came from daily stock indices over the period from 31 December 1989 to 19 January 1996. There were significant results in three of the five markets. The researchers suggested that market risk alone could not characterize this situation.

Hakan Berument and Halil Kiyamaz (2001) studied the day of the week effect on stock market volatility. They looked at data from the S&P market index during the period of January 1975 to October 1997. Three different models were used. The First model applied the OLS model method. The findings based on this model imply that day of the week effect is present in the return equation. Result showed that Wednesday had the highest return and the lowest return was on Monday. The Second model allowed volatility to change over time. The result of the second model was similar to the first model, in as much as the highest return was on Wednesday and the lowest on Monday. Finally, the third model used the Modified-GARCH model. The finding showed that day of the week effect was present in both volatility and the return equation. The results suggested that the highest return was on Wednesday and the lowest return was on Monday. All of these findings were statistically significant.

Berument and kiyamaz (2003) investigated daily seasonality in five international markets, namely Canada, Germany, Japan, United Kingdom, and the United States, over the period of January 1, 1988 through June 28, 2002. The results show that Canada has the highest volatility on Friday which is consistent with the day of the week effect in returns. The highest returns on Fridays relate with the volatilities on Friday. Germany and Japan have the highest volatility on Mondays. The United States has the highest volatility on Fridays. The United Kingdom has the highest volatility on Thursdays. The lowest volatility for Canada is on Mondays, whereas for Germany, Japan, the United Kingdom and the United States is on Tuesdays.

Hakan Berument and Halil Kimaz (2003) investigated the day of the week effect on return and volatility for the Istanbul stock Exchange (ISE) from 1986 to 2003 by using the generalized autoregressive conditional heteroscedasticity (GARCH) model. This study used the daily observations. The research found that the highest effect on return was on Friday with 0.015 and the lowest return was on Monday with 0.003. In terms of volatility of return, the highest volatility occurred on Mondays with 0.933 and the lowest one on Tuesdays with 0.716.

Aly, Mehdian and Pery (2004) used the GARCH model to estimate the volatility of stock returns in the Egyptian stock market. The research used daily closing values from the Egyptian stock market index from April 26 1998 to June 6 2001. Their results concluded that there was no significant difference between daily mean returns. Moreover, Monday returns had a significantly more volatile character than returns from the rest of the week. The outcome of this probe remains inconclusive since the Egyptian stock market merely had a limited number of about 100 stocks that are traded among the 1,071 listed stocks.

Hui (2005) compared the day of the week effect for 4 Asian pacific markets with the US and Japan. The Asian countries in question were Hong Kong, Korea, Singapore and Taiwan. The researcher focused on the presence of day of the week effects during and after the Asian financial crisis in 1997 and the collapse of the blue chip stocks in the US. The non -parametric tests revealed that only Singapore had significant day of the week effects, whereas the other countries displayed no notable evidence thereof. For Singapore, high returns were on Wednesday through Friday and low returns were on Monday and Tuesday.

Basher and Sadorsky (2006) studied day of the week effects in 21 emerging stock markets. The researcher used the daily closing price in 21 emerging stock markets and MSCI world index over the period from December 31, 1992 to October 31, 2003, for a total of 2827 observations. The results demonstrated that day of the week effects existed in the Philippines, Pakistan and Taiwan. In contrast, day of the week effects did not occur in a majority of emerging stock markets.

Phukubje and Moholwa (2006) tested the week form efficiency in the South African futures market for wheat and sunflower seeds. This research investigated the daily futures price changes for wheat and sunflower seeds over the period from 2000 to 2003. There was no clear evidence for the weak form inefficiency in the South African future market for wheat and sunflower seeds. This study had certain limitations as spot price data on wheat and sunflower seeds were unavailable, and due to the assumption that the investors were risk neutral. The researchers suggested further testing of market efficiency, allowing for a non-zero risk premium.

Rosa Maria Caceres Apolinario, Octavio Maroto Santana and Lourdes Jordan Sales (2006) analyzed the day of the week effect on European stock Markets from July 1977 to March 2004. This research revolved around investment opportunities, specifically on the analysis of the day of the week effect on the major European stock markets. The means of GARCH and T-ARCH models were used to estimate the data. The results showed that abnormal behavior was not present in the returns of these stock markets. The French and Swedish markets had a seasonal effect on Mondays. The Swedish markets also reflected a significantly higher return on Friday. Day of the week effect existed in all of these financial markets except for Portugal and the Czech Republic. In conclusion, Mondays and Thursdays were more uncertain than Wednesdays, while the Wednesday measure was lower than Tuesdays and Fridays measures.

Kenourgios and Samitas (2008) examined the day of the week effect in the Athens stock Exchange General Index. They separated into 2 periods which were 1995-2000 and 2001-2004. The first period considered banking, Insurance and Miscellaneous and the second period considered FTSE-20 and FTSE-40. The results showed that there is the day of the week in mean return of the period 1995-2000 and the day of the week effect anomaly was not present strongly in return and volatility of the period 2001-2004 except the general and FTSE-40 indices. This came in the wake of Greece's entry into the Euro-Zone and the ensuing promotion to a developed market.

Charles (2010) studied the day of the week effect for five major international stock markets consisting of France, Germany, the United States, the United Kingdom and Japan. This research applied a GARCH framework to estimate seasonal effects and the volatility. Charles founded that outcomes differed, depending on the model used, hence the volatility model played an important role in the day of the week effect on volatility. Besides, such asymmetry does not influence the seasonal effect. It is not worth including day of the week effects in trading strategies.

Hussain, Hamid, Akash and Khan (2011) became aware of a stock market anomaly on the equity market practices in Pakistan. They used the daily stock prices of the KSE-100 index over the period from January 2006 to December 2010. It was discovered that the returns on Tuesday were significantly positive. So, the Karachi stock exchange distinctly manifests a day of the week effect. The returns on Tuesday were higher than on other days.

Mansocreh Kozemi Lari,Abbac Mariano and Mchsen Aghaeibocrk (2012) analyzed the annual returns, returns volatility and day of the week effect on 15 stock markets in Southeast Asia, Indonesia, the Philippines, Thailand, Malaysia and Singapore were the selected countries. The study spanned from December 2007 to December 2011. It used non-parametric and parametric test methods to extrapolate equality of variance returns and equality of mean returns on daily returns of the week. The effort found out that the day of the week effects were present only in Indonesia. Other stock returns, including Malaysia, the Philippines, Singapore, and Thailand didn't provide any evidence of existence of the daily effect. The results showed that the indexes were highly negative, but from 2008 onwards market growth, especially in Malaysia and Thailand had the highest returns on Monday. Indonesia had the highest returns on Wednesday. The Philippines and Singapore had highest returns on Tuesday. Indonesia, Malaysia and Thailand had the lowest returns on Monday. The Philippines and Singapore had the lowest return on Friday.

Muhammad Arshad Haroon and Nida Shah (2013) studied the day of the week effect in stock returns in the primary equity market of the Karachi Stock Exchange (KSE) of Pakistan. They used the OLS regression strategy to investigate the daily closing prices of the KSE 100 index from January 01, 2004 to December 30, 2011. The results were separated into two periods because of political instability. The first period lasted from 2004 to 2007. The second period, after the general election, extended from 2008 to 2011. The conclusion was a negative on Monday and a positive on Friday. Accordingly, investors can reap the benefits of this research by investing on Monday and withdrawing on Friday.

Umar Bida Ndako (2013) studied the day of the week effect for the Nigerian and South African equity market over pre-liberalization and post-liberalization periods. This study used the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model. For Nigerian, the study covered only the post-liberalization period since there were no available data for the pre-liberalization period. The Nigerian equity market exhibited the mean equation on Fridays and the variance equation on Tuesdays and Thursdays. The South Africa of the pre-liberalization period displayed significant evidence on Mondays and Fridays. During the post-liberalization, the study of South Africa revealed a day of the week effect on Thursdays with regard to the mean equation and on Fridays in the
variance equation.

Literature review about ICT sector

Kuanla Jantapan (2006) analyzed risk and return of stock in the ICT sector of the Stock Exchange of Thailand. The goal of this study was to estimate the price of ICT stock and to compare those prices with a view towards investment decisions by using four securities out of 12 popular securities including SATTEL, ADVANC, TA and UCOM. The data consisted of five years of recorded weekly closing prices from January 4, 1998 to December 4, 2002, comprising a total of 261 weeks. The data from the SET index delineated the returns of the market, and the three month fixed interest rate illustrated the returns of the no risk assets. The model was CAPM. The results found that at year 2000 generated the lowest returns. Furthermore, a comparison of the returns in the ICT market and the no risk assets showed the returns for the years 1998 to 2002 to be higher in the ICT market than no risk assets. SATTEL topped with highest returns and TA had the lowest ones. In addition, aggressive stocks TA and UCOM were deemed which meant their prices changed faster than market prices. So, this would imply that TA and UCOM faced high risk. ADVANC and SATTEL were defensive stocks which meant their prices changed slower than market prices. Therefore, ADVANC and SATTEL were considered low risk. In conclusion, all of the 4 stocks were undervalue, so investors were well advised to invest before the prices rose.

Atcharaporn Jaiboon (2012) analyzed, with the help of ARDL, the factors that influenced the returns of the ICT stocks at the stock exchange of Thailand. The objective was to study the aspects that had an effect on returns in the ICT stock sector and to approximate the prices of oil, gold, interest rate and exchange rate. The data of monthly closing prices of the ICT sector for 5 securities, SAMART, ADVANC, DTAC, THCOM and TRUE, was used from 2007 to 2012, stretching over 54 weeks in total. The results showed all of the 5 securities had a stationary at level 0 and 1. Furthermore, the price and volume of ADVANC had a relationship in short term and long term.

Sandusit Tikan (2013) investigated estimating risk of securities in the Information and Communication Technology Sector of the Stock Exchange of Thailand using the state space model. This research estimated the time varying coefficient and used 261 weekly closing prices from 2008 to 2012. In this study THCOM, JAS, TRUE and SAMTEL were established as aggressive stocks, whereas ADVANC, INTUCH, SAMART, DTAC, SVOA and IEC. Furthermore, MFEC and AIT counted as negative risk stocks. In terms of expected returns on securities with the Securities Market Line (SML), securities that were declared under value were SAMART, ADVANC, DTAC, INTUCH, SAMTEL, JAS and THCOM. This implied that investors should judiciously buy them before a price increase. On the other hand, the securities with over value were AIT, MFEC, IEC, SVOA and TRUE, and were meant to be invested in before prices dropped.

Siriporn Kannitade (2013) studied the factors affecting the rate of returns on securities in the telecommunication sectors using the ARDL approach to cointegration in ASEAN exchanges. The aims of this study were to understand the characteristics of structure and performance of the telecommunications sector and to investigate the short term and long term relationships between macroeconomic factors and the rate of return security in the telecommunications sector in ASEAN exchanges. The secondary data of the daily closing price of the ICT sector in ASEAN was used on May 30, 2012 from 5 stock exchanges, namely the Stock Exchange of Thailand Index, the Kuala Lumpur Stock Exchange, the Philippines Stock Exchange, the Jakarta Stock Exchange and the Straits Times. The results of long run through ARDL indicated that the relationship between the rate of return on telecommunication securities and the total GDP had a negative effect with respect to ADVANC, JAS, EXCLT, ISM and TBGI. It showed a positive effect for DTAC, ISAT, STH, NERT and I2I. Besides, in terms of the relation between the exchange rate and the return on stocks, a positive effect was detected for DTAC and EXCL. Furthermore, the returns on 12 ICT stocks that we selected in this study had an adjustment from short run to long run equilibrium.

Suchanat Chaiyen (2013) analyzed the volatility of stock returns in the Information and Communication Technology (ICT) sector in 5 ASEAN countries including Thailand, Malaysia, the Philippines, Indonesia and Singapore. The various models used in this study were Multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model, Baba Engle Kraft Kroner (BEKK), Diagonal Vectorization (DVEC), Constant Conditional Correlation (CCC), and Vector Autoregressive Moving Average GARCH (VARMA-GARCH). Utilizing the DVEC model, it was pointed out that the current volatility of ICT stock returns was influenced by their volatility in the past. The BEKK model confirmed that the volatility of stock returns in the past can determine the present volatility of other stock returns. After running the CCC model, the researcher contended that the stock returns in the ICT sector had correlations between each other. And, last not least, the VARMA-GARCH model pointed out the volatility spillover between ICT stock returns. To sum it up, each stock return is convergent to the long run equilibrium after unpredicted stocks at different rates.

Worathep Chakritthipong (2013) scrutinized the effects of the broadband internet on Production efficiency of small and medium sized enterprises in terms of cost reduction, the speed of production and the benefits of more useble resources. This research took advantage of a questionnaire to collect a total of 600 data samples. The aspirations of this study were to extrapolate and understand which factors of production affect the production activities of small and medium sized enterprises and to assist the making decision process of entrepreneurs as to which segments of the production activities should use the broadband internet. The researcher contended that the consequences of making the right decisions assist the small and medium sized enterprises to increase production efficiency, reduce costs and gain profit from transitioning to broad bandinternetuse.

The study uses the GARCH model to investigate which day has an effect on ICT stocks in the ASEAN market. It solely focuses on the ICT sector and not as a whole market. This fact renders it informative to readers interested only in results of the day in the ICT sector rather than the entire market.