Cross-Sectional Volatility Index Analysis In Asian Markets With No Derivatives Market.

by:

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Declaration

I, Futeri Jazeilya Binti Md Fadzil, hereby certify that this thesis, which is approximately 46000 words in length, has been written by me, that it is the record of work carried out by me and it has not been submitted in any previous application for a higher degree.

I was admitted as a research student in October 2013 and as a candidate for the degree of Ph.D in March 2015; the higher study for which this is a record was carried out in the University of Essex between 2013 and 2018.

The work and results in Chapter 3 were published in collaboration with John G.O'hara and Ng Wing Long, in a paper published at Md Fadzil, F.J, O'Hara, J.G, and Ng, W. L (2017). Cross-sectional volatility index as a proxy for the VIX in an asian market. *Cogent Economics & Finance,* (just-accepted):13644011. 57,95

The result in Chapter 4 was presented and published in collaboration with John G.O'hara, in a proceedings at Md Fadzil, F.J., and O'Hara,J.G. (2016). The Volatility Index Performance in Non-derivatives Southeastern Asian Market: Cross-Sectional Volatility Index Approach. *Proceedings of ISF*, Program ISSN 1997-4124.

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Abstract

In recent years, a growing literature has emerged that focuses on the performance of volatility indices in the derivatives market. The VIX has been very popular in the US market. Since its introduction in 1993, the VIX is a barometer of investor sentiment and market volatility. However, the VIX is mostly applied to markets that have derivative options price, and it turns out that less or no derivatives market would not be able to utilize the VIX as a benchmark of volatility.

Chapters 1 and 2 provide an overview of the thesis and recent developments in volatility literature. Chapter 3 presents the construction of Cross-sectional Volatility Index (CSV) which is applied to an Asian market as an alternative to the VIX. One problem with the construction of a VIX-styled index is that it depends on the price of calls and puts. However, the CSV Index may be applied to measure the volatility when no derivatives market exists. Chapter 4 uses the CSV Index model to approach the no derivatives market in Southeast Asian countries. As to validate the CSV Index model, we use the GARCH family and Realized volatility models to explore the predictive power of CSV Index in a non-derivatives market. The results capture symmetric and asymmetric effects on the volatility and yields for better predictive performance.

Chapter 5 provides a new empirical methodology for computing a Cross-mixed Volatility (CMV) index that characterizes the country risk understood here as the financial market risk measurement. It encapsulates all the sources of risk stemming from the financial markets for any given country. The Factor-DCC model has been adopted to construct the CMV Index and to build the composite aggregation of the CMV Index. The results exhibited that the commodities were the most prominent contribution of the composition index. Chapter 6 is the conclusion of the thesis.

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Chapter 1

Introduction

Over recent decades, international markets have become increasingly volatile mainly after the financial liberalization and the opening of economies. This phenomenon has generated an increasing interest in the analysis of market volatility. In each country, the country risk varies from one country to the other. Some countries may have a high risk to discourage much foreign investment where country risk is defined as the collection of risks associated with investing in a foreign country. Country risk is a combination of risk related to investing in a foreign country which includes exchange risk, economic risk, political risk, sovereign risk and transfer risk[1]. These risks are controlled by government operations. Also, these risks are dependent on changes in the macroeconomics and business environments affecting any of its financial markets and will influence the volatility of a financial market. Recent globalization has increased and substantially adds the exposure of investors to risks related to an event in other countries. In a similar context, risk analysis and risk hedging have had less attention compared to international investment, for example, see discussions in Saini and Bates (1984), Cosset et al. (1992), Oetzel et al. (2001), Hassan et al. (2003), Andrade (2009) and more recently Agliardi et al. (2012). So, it is quite crucial that investors construct an aggregate volatility index to improve volatility risk hedging strategies. The mentioned risk refers to the risk that arises from all the markets, namely, interest rates, equities, commodities and foreign exchange. Modeling the volatility dynamics between the assets and volatility index is an important and timely argument to analyze because of recent developments in increased integration between the financial

[1] Transfer risk or so-called the conversion risk, is where a local currency is not able to convert into foreign currency due to restrictions imposed by a foreign government that makes it impossible to transfer money out from the country.

markets and the financialization[2] of commodity markets. It is securing the investors with alternative ways to diversify, hedge and risk manage their investment portfolios, see for example Silvennoinen and Thorp (2013), Tang and Xiong (2012) and Vivian and Wohar (2012).

After the Global financial crisis in 2008, many institutional investors and pension funds came under pressure from their stakeholders to find better ways of limiting the risks that occur. With a market consensus expectation of increased volatility, even those investors free of such stakeholder pressure are considering ways of locking gains of the equity in a bull run. The financial crisis has led the market volatility to conditions of instability and an increase of risk protection in investment portfolios. Investors are increasingly considering how best to manage tail risk and reduce drawdowns. The US has introduced the VIX indicator to capture the impact of global financial conditions and hence perceived risks of exposure in a developing market. The Chicago Board Options Exchange Volatility Index or VIX is used by stock and options traders to gauge the market's anxiety level. The VIX is based on options prices specifically on the S&P 500 Index. The VIX estimates the next 30 days of volatility implied by at-the-money S&P 500 Index. The components of the VIX calculation are near-and next-term put and call options with more than 37 days to expiration. The daily percentage moves of the VIX tend to be faster moving compared to the S&P 500, and unlike the stock market, the VIX stays within a relatively limited range, see the following illustration in Figure 1.1;

According to the statistic recorded by the World Federation of Exchanges, there was 2.2 percent increase in volumes traded in 2015, which reached a total number of 24.9 billion derivatives contracts. Compared to 2011, total volumes traded were up to 9.4 percent representing an average annualized growth rate of 2.2 percent over the last 5 years.

Figure 1.2 exhibit the total volumes of exchange traded derivative contracts over time. Regionally, there was an increase in the volume of traded in Americas and the EMEA region, which reported up to 6.7 percent and 7.8 percent in 2015 by the World Federation of Exchange. The Asia Pacific region is down 5.5 percent for a decrease in the volume traded.

These leads to market diversification as a solution for the Asia Pacific region. Most of the countries in Asia Pacific,m particularly the developing countries such as Malaysia, Philippines, India, Thailand, Indonesia and others. In Figure 1.3, the percentages of re-

[2]Financialization refers to capturing impact of financial markets, institutions, actors, motives and institutions in the operation of the domestic and international economies.

Figure 1.1: The Relationship of the S&P and the VIX index
Source: Bloomberg

gional volume traded is presented in a histogram bar chart. Asia Pacific equities derivatives volume are low compared to the other two regions, the Americas and the EMEA.

From Figure 1.2, Asia Pacific volumes of trading are much lower than Americas but higher than Eastern Europe. It shows that developing market in Southeast Asian using the derivatives are increasing. This could lead to market diversification when derivatives are used. However, from the trading volumes of contract indicated in Figure 1.2, there are countries that are unable to trade derivatives as much as developed countries in Asia. This refers to markets in Malaysia, Philippines, India, Thailand, Indonesia, and others. Looking at As in Figure 1.3, specifically in the Asia Pacific market, the equities trading volumes are low in derivatives which is about 38 percent compared to equity derivatives trading in Americas which is 44 percent. However, in Asia Pacific commodity derivatives trading is much higher which is 27 percent higher than in Americas. It indicates that more commodity trading occurs in Asia Pacific countries.

One of the purposes of this research study is to focus on the construction of a volatility index, and finding an alternative to the VIX, that may be used in the non-derivatives market. So, there may be ways to outperform benchmark[3] indexes and volatility benchmark indexes such as the S&P 500 or Russell 1000 and the VIX. According to Gorman et al. (2010), cross-sectional dispersion of returns is more relevant as a measure of risk than time series volatility. This is because the return dispersion is positively related to all key

[3]All benchmark are indexes but not all indexes are benchmark.

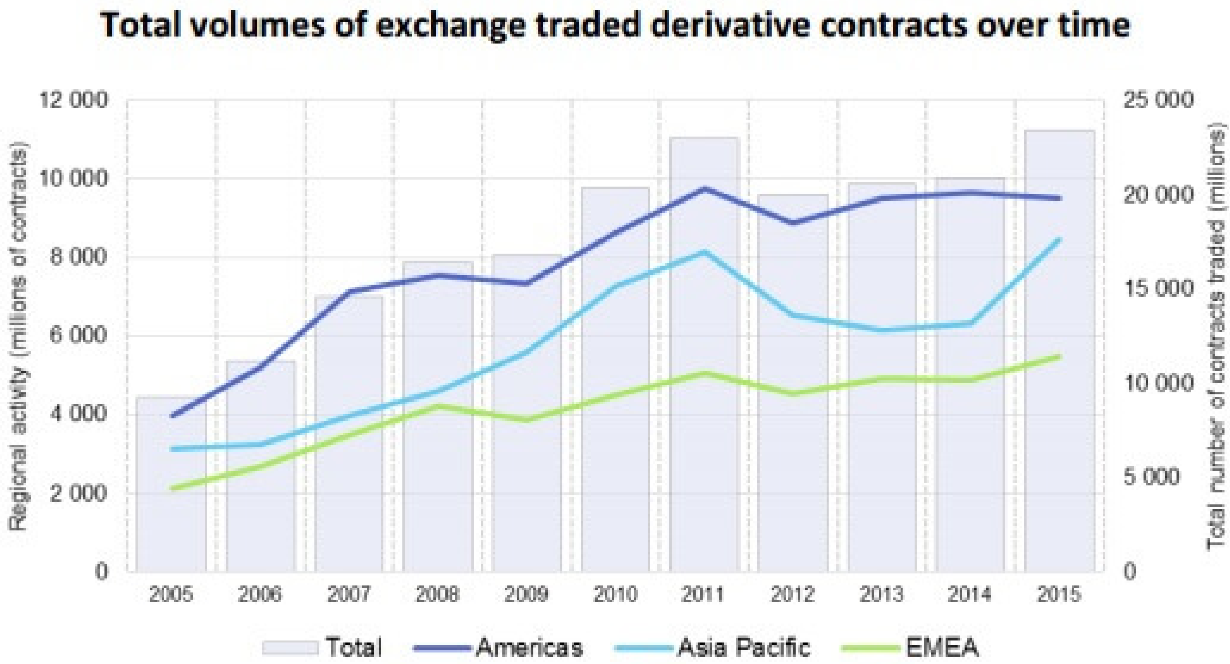


Figure 1.2: Derivatives trend, 2005-2015
Source: https://financefeeds.com,2016

measures give of portfolio risk. Besides that, most investors aim to reduce active weights in a portfolio, so cross-sectional dispersion will able to hold the risk aversion constant to reduce it. For instance, Cross-sectional dispersion reduces active weights in the stock market when the cross-sectional dispersion of returns increases. So, this study introduces the cross-sectional volatility index as an indicator to assess risk in a longer term, specifically in the Southeast Asian market. The BRIC countries have established the VIX for the investors to monitor risk and uncertainty, namely; Brazil and China. These countries are fortunate to have dedicated volatility indices based on the VIX methodology established by the CBOE compared to the other Southeast Asian countries. An article by Chan (2013) found that the cross-sectional volatility of returns helps active fund managers to determine the change of trends in market relationships. The study shows that the active funds outperform the benchmark index when the cross-sectional variance is at a low and moderate period.

A volatility index is not only useful to the stock market but also to the commodities such as oil, gold, silver, corn, soybeans and wheat. For instance, the CBOE has established the VIX in commodities based on ETFs such as CBOE Gold ETF Volatility Index (GVZ), CBOE Crude Oil ETF Volatility Index (OVX) and others. By establishing the volatility index in the commodity market, shows that the volatility index does not limit to the financial markets but also encapsulates both financial markets and the real economy. The

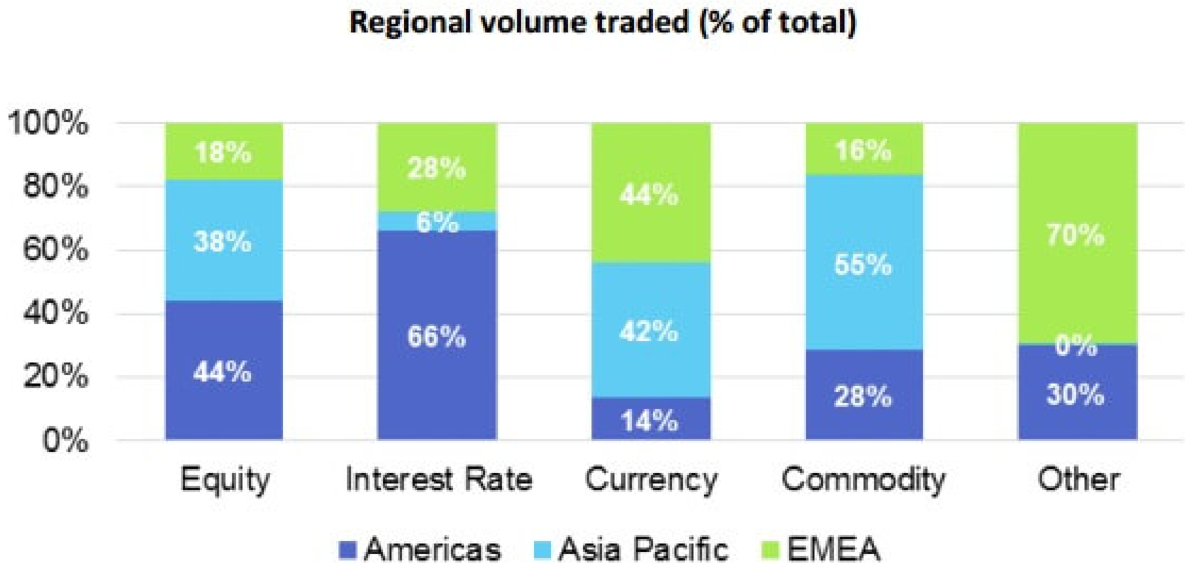


Figure 1.3: Regional Volume traded, 2005-2015
Source:WFE

commodities highlight the current trends and market implications. The commodity price trends and volatility continue to be driven far more by market fundamentals. Several studies are integrating the volatility of commodities and equities into econometric specifications. Baur and Lucey (2010) applies the GARCH asymmetric model to determine that both gold and equities in bear markets have a negative and significant relationship. Besides that, Sari et al. (2011) examine the relation between the VIX, metals, and oil using the VAR model. The CBOE has constructed the VIX which measures the implied volatility of the S&P 500 (SPX) to the commodities as it allows investors to measure the market's expectation for the volatility of the specific commodity prices. It replicates the CBOE VIX methodology new indexes extended to commodity producing sectors such as Oil VIX, Gold VIX, Silver VIX based on 30 a day period. The investors can hedge volatility exposure in other classes. Aboura and Chevallier (2015a) proposed an empirical methodology to construct a cross-volatility index that describes the country risk known as the financial market risk measurement. The methodology explained by these authors provide an investor with a unique hedging instrument to reduce the fluctuation of the volatility index. Commodity and equity markets have linkages between them. There may be several reasons that may contribute to these linkages. According to Büyükşahin and Robe (2014), both of commodity and equities linkages fluctuate more than the equities and other assets. There exist correlations between the returns on investable commodities and equity indices increase amid greater partipation by speculators generally and hedge funds especially.

The purpose of this study is to propose appropriate volatility indices and a volatility-based derivative on less liquid markets in Asia based on a methodology that is crucially well-known. The Cross-sectional Volatility Index methodology is a method that will be constructed in this study. One of the reasons for choosing the Cross-Sectional Volatility (CSV) Index method is because the volatility measurement is a model-free nature as we do not need to specify a particular factor model to compute it. Besides that, it is flexible enough to apply to any region, sector, and style of the world equity markets in any frequencies. Another advantage of this method is that the model will not need to resort to any auxiliary option market. This model predicts the volatility index using CSV Index in the Asian market with no derivatives option prices to gauge in an implied volatility model as with other prediction models. The method will be written in more detailed later in the thesis. This study continues by introducing the Cross-Mixed Volatility Index with Factor-DCC (CMV)Index that describes the country risk which reflects on the major causes of risks for any given country. Our aim is to set up an empirical methodology that combines all the commodity volatilities with other traditional financial asset volatilities using the CMV Index approach. This method has never been implemented by mixing volatilities stemming from commodity markets with the traditional asset volatilities in foreign exchange, bonds, and equities. This cross-sectional commodity volatility index might be far more representative of the country risk than the classical financial indexes. The classical financial indexes here means the statistical aggregate that measures change which usually refers to stock market performance or economic performance. The general purpose of this study is to expand the alternative way of monitoring financial assets in emerging and developing markets around Asia.

The contribution of this thesis to the literature is threefold. First, we introduce and examine the cross-sectional volatility index approach as a new form of volatility index in the US market. The US market has its well-known VIX but however as to implement the new form of volatility index in the non-derivatives market, especially in developing countries, we need to validate the new form of volatility index with the VIX. This is to achieve at least the same measurement performance level as the VIX index. The CSV Index allows us to obtain consistent estimates of parameters of the financial market model using a single cross-section of return data for the Japanese market. This CSV Index approach is a measure that is observable and has a model-free nature that is available for every region, sector, and style of the world equity markets. We show that the cross-sectional measure provides a good approximation of average idiosyncratic variance. Secondly, we show that the proposed form of volatility index in the Japanese market is an alternative benchmark index to the VXJ index providing the cross-sectional variance returns is the average idiosyncratic variance of stocks within the Asian countries. Additionally, the measure is different from the historical volatility and implied volatility as it is available for every region, sector and style of world equity markets. Thirdly, we test the forecast capabilities of the cross-sectional volatility index in the market. It is to predict the future volatility and to be compared with the VIX and the CSV Index. The results of the volatility prediction for both methods will conclude the CSV Index may be a proxy to the VIX.

This dissertation is structured in the following way; Chapter 2 deals with a literature review and methodology of each model and sketches the appropriate method associated with the specified models.

Chapter 3 discusses the construction of a volatility index for an Asian market as an alternative to the VIX and highlights the advantages of applying the volatility index in a non-derivatives market. The chapter present a Cross-Sectional Volatility (CSV) Index applied to an Asian market as an alternative to the VIX. One problem with the construction of a VIX-styled index is that it depends on the price of calls and puts, however, the CSV Index may be applied to measure the volatility when no derivatives market exists. The CSV Index formulates this volatility index based on observable and model-free volatility measures. We provide a statistical argument to support that an equally-weighted measure of average idiosyncratic variance would forecast market return and show that this measure displays a sizable correlation with economic uncertainty.

In chapter 4 the CSV Index is applied to the Southeast Asian market and, in particular, the examining of its performance using GARCH-family model. Looking at the past few years, Southeast Asia faced a global economic environment that presents further uncertainty and challenges similar to the 1997 Southeast financial crisis. During the financial stress, the VIX rises and becomes popular among investors and they become complacent. The market requires a better prediction, hence the VIX increases in popularity in most derivatives market to measure and predict the magnitude of market moves over the next 30 days period. In Southeast Asian, most of the area is a non-derivatives market which also applies to Malaysia, Indonesia, Philippines, and Thailand. Therefore, Cross-sectional Volatility (CSV) Index is proposed as an alternative to the VIX. This approach is particularly appropriate when a country's financial market does not trade local options. The CSV

Index approach must at least be intimately related to option-based implied volatility measures in order to proxy the VIX as close as possible. As to strengthen the performance of CSV Index, this paper utilizes the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Heterogeneous Autoregressive Realized Volatility (HAR-RV) model to explore the predictive power of CSV Index of Southeast Asian market. This study adopts the GARCH, E-GARCH, GJR-GARCH and HAR-RV models to the CSV Index. The performance of the prediction is measured by Root Mean Square Error (RMSE), Mean Square Error (MSE) and Mean Absolute Error (MAE). The results capture symmetric and asymmetric effects on the volatility and yields for better predictive performance.

Chapter 5 shows a composition of a mixed commodity volatility model, namely Cross-mixed Volatility Index (CMV)Index, that characterizes the country risk which is a part of a financial risk measurement. It is based on the idiosyncratic cross-sectional volatility index approach and requires encapsulating all the sources of risk stemming from the financial markets for any given country. This volatility index construction will capture the unpredicted risk. Then, filter the factors using the Zhang et al. (2010) methodology which is based on the Factor-DCC framework. The Factor-DCC refers to the extension of a factor GARCH model which allows one to overcome the factors that are weak in conditional correlation. Daily price returns of 10 assets in 10 years period between January 2005 until March 2015 are extracted from DataStream and examined in the newly construct volatility model. The assets include the equity market, CSV index, foreign exchange market and commodity market. The Principal Component Analysis (PCA) is used in the study to extract the loading factors before applying the Factor-DCC. The Factor-DCC was used to reduce number of factors by implementing an appropriate criterion that will be discussed in the next chapters. Then, the CMV Index is constructed based on factor loadings. We created a composition from the factor loadings of the CMV Index for any researchers to reproduce their own volatility index following on few steps that will be explained in Chapter 5. It will show the contribution by percentages of all assets that are used in this aggregate form of volatility index. From the results of composing the new volatility, the percentage expressed that the proportion of commodity market is the largest compared to other asset markets. The contribution seen from the composition that is created, at investor's point of view, the CMV Index will be an exposure to their domestic market and overweight of their assets allocation will allow them to forecast the future cross-market index.

Finally, Chapter 6 summarizes the main findings: the flexibility of the CSV Index model in volatility exercises over the VIX and the 'simpler' time series models, models preferred by finance practitioners. This chapter also provides concluding remarks as well as propositions for future research on the issues addressed in this thesis.

Chapter 2

Literature Review

2.1 Financial Issues in Non-Derivatives Market

Recently, the Asian market is mostly focused on bank financing and unregulated Over-the-Counter (OTC) derivatives market. This is partly due to the absence of hedging instruments for corporations to diversify risk. The diversification of risk is more demanding towards investors after the Asian financial crisis arose in 1997 where currency devaluations spread rapidly. Five leading derivatives products that are traded in Asian markets are the foreign exchange derivatives, credit derivatives, equity derivatives, commodity derivatives and credit interest rate derivatives. According to Fratzscher (2006), in the Asian market, equity derivatives are rapidly increasing every two to three years which refers to mostly exchange-traded (ETD) with Korea, India, and Hong Kong. In these countries, the most widely traded products are the Index futures with massive participation of institutional investors and significant foreign participation. However, in other Asian market that has low derivatives trading, they are unable to produce an index to set up as a benchmark. This leads to develop an instrument to hedge against risk.

Concerning stock volatility, after the 1980s, some researchers found that growth of financial volatility is limited in the developing countries. It linkages with the global economy that existed a decades ago. The financial wave in the mid-1980s has been marked by a surge in capital flows among industrial countries between industries and developing markets. Over the same period, some developing countries have faced a periodic collapse in growth rates and significant financial crisis. So, showing that the capital flows has been related with the growth rates. Lin (2018) and Jiang et al. (2017) stressed out the reason to study financial market and the precaution concerning the risk. There were two reasons that might allow investors and policymakers to study financial market concerning the risk in it. One of the reason was investors find difficulty to believe that the prime volatility in short-term assets changes were due to economic fundamentals. Another reason is that the investors are concerned about the funds that invested in the companies especially the probability of default company. The next reason is that the risk premium is important to be determined as it is a volatility and normally, the greater the risk is due to greater volatility. Apart from these reasons, hedging financial instruments like insurance, the price of them is generally positively correlated with their volatilities.

Kharroubi (2006) indicates that some developing countries have a weak financial system. He mentioned that liquidity in a firm's asset is important to allow the investors to monitor their portfolio performance. Without liquidity in assets and liabilities, it would lead to liquidity crisis. Bankruptcy of large corporations in developing countries need to hedge against changes in the level of volatility in the financial market. Sudden fluctuations of volatility created the opportunity for volatility trading, see Carr and Madan (1998), Guo (2000) and Poon and Pope (2000). Gonzalez-Perez and Novales (2011) examine the current and future market conditions by analyzing the information content in volatility indices. This is because to volatility indices reflect better current markets sentiment than any sensible expectation about future market conditions. The study applied Deutche Board(2005) methodology to construct VIBEX volatility index because the method does not use any option pricing model and was a widely range of implied volatility smile. It is mainly applicable for illiquid markets such as the Spanish option market on IBEX-35. The results support the alternative interpretation where volatility index plays a good role in capturing current perception of risk. Developing economies are more likely to experience more frequent and more severe aggregate shocks from macroeconomic policy, see Koren and Tenreyro (2007), and domestic shocks, generated by intrinsic instability of the development process, volatile fiscal policy, see Fatás and Mihov (2006), social conflict, economic mismanagement and political instability, see Raddatz (2007).

The recent financial crisis has caused highly volatile shocks across all asset classes globally, including foreign exchange markets, see Fratzscher (2009) and Melvin and Taylor (2009). Many researchers have categorized this crisis as more severe than the Great Depression of the 1930s, regarding its longevity and the extent of severity in economic and social costs, and in policy interventions by governments around the globe Fratzscher (2012) and Fratzscher (2009). In many ways, this led to the reason why a volatility index could be used as a way of hedging. The volatility index is a way for investors possibly monitor their profits or protection of their portfolios. An effective investing is an accurate measurement of historical stock market volatility. Volatility is an important factor in the comparison of risk and reward between stocks and other asset classes. The comparison helps to determine the appropriate strategic asset allocation for an investor, given objectives and tolerance. As the existing literature in this area provides very little evidence in this context, this research aims to make a significant contribution in this hedging alternative. Bollerslev et al. (1992) mentioned that speculative activity, noise trading and feedback trading has increased and been an undesirable consequence of destabilizing market. However, the author suggests that the increased volatility could be an innovation instead of unwanted. In fact, monetary policy has its roles to face financial market volatility. According to Mishkin (1988), the monetary policymakers deal with volatility by reducing the volatility intervening in markets or to become a lender of last resort in the event of a financial crisis. A volatility change affects investors and policymakers. There are some ways that the investors strategized their investment. When volatility increased, they could shift their portfolios towards less risky short-term assets, or hedging strategies, for their portfolios.

Volatility indicates the amount of uncertainty or risk by depending on the size of changes in a security's value. A greater volatility means a security's value can potentially be spread out over a larger range of values. However, lower volatility means a security's value does not fluctuate dramatically, but changes in value over a period. Over the last few years, modeling volatility of a financial time series has become an important area and has gained lots of attention from academics, researchers and others. The time series analysis accounts for the fact that data points taken over time may have an internal structure that should be considered for. For instance, the internal structure meant in this context are autocorrelation, trend or seasonal variation. It can be used to test how the changes associated with the chosen data point compared to shifts in other variables over the same time. The stock market volatility changes with time and exhibits volatility clustering. It occurs when large changes tend to be followed by significant changes, of either sign, and small changes tend to be followed by minor modifications noted by Mandelbrot (1997). This phenomenon of volatility clustering can be observed using GARCH and its extension volatility model and stochastic volatility model. The extension of GARCH model can be Exponential GARCH (E-GARCH), Glosten GARCH model (GJR), Asymmetric Power ARCH (APARCH) model or many more. Stock market volatility is often discussed among investors which is referring to standard deviation of a stock market index returns. Standard deviation reflects on the index's historical volatility. Assumption has to be made in order to find information of future volatility by looking at the distribution of historical volatility results.

Variance or standard deviation is often used as the risk measure in risk management. Engle (1982) introduced Autoregressive Conditional Heteroskedasticity (ARCH) model to the world to model financial time series that exhibit time-varying conditional variance. A generalized ARCH (GARCH) model extended by Bollerslev (1986) is another traditional model for estimating stochastic volatility. These models are widely applicable in the various subsidiary of econometrics, especially in financial time series analysis.

Volatility modeling and forecasting developments in international stock market have increased the interest for regulators, reseachers and practitioners towards the volatility of such returns. The researchers moving their attention on developing and improving the econometric models so it is able to generate accurate forecasts of such swings in returns' volatility. An improvement in volatility modeling is needed to allow more accurate internal forecast and efficient parameter estimation. Volatility is significantly important to anyone who is involved in financial markets. It is because the volatility has been associated with risk, and high volatility is an assumption of market disruption. Figlewski (1997) discovered that volatility forecasting is vital to managing the exposure of investment portfolios is crucial. Walsh and Tsou (1998) found that there are many reasons why forecasting volatility is important. They conducted a research on forecasting techniques comparing the naive approach or the so called historical approach, an improved extreme-value method (IEV), the ARCH and GARCH class models and an exponential weighted moving average (EWMA) of volatility. They found that larger number of stocks from indices makes the forecasting more accurate in volatility of larger indices. Another reason of studying the volatility forecasting is to minimize ex ante risk by controlling the estimation of the portfolios error.

Researchers are carrying out an empirical analysis by comparing models from the current volatility model used by most financial instituition and policymaker and proposing the adoption of further key parameters in improving the accuracy of volatility modeling and forecasting. The primary purposes of forecasting volatility are for risk management, for risk asset allocation and for taking bets on future volatility. Some studies propose a few models of volatility to improve volatility forecast. Almost all the large stock markets are now accompanied by a volatility index. For example, the large stock markets are the Dow Jones Industrial Average, Russel 2000, DAX 30, FTSE 100, CAC 40 and Nasdaq 100. Besides, there are volatility indices calculated for commodity prices and individual stocks. Virtually all the economic uses of volatility models entail forecasting aspects of future returns. Estimation of forecast volatility is best when it is highly accurate and must be made of future volatilities and correlations. Typically, a volatility model is used to predict the absolute magnitude of returns, but it may also be used to predict quantiles or, in fact, the entire density of the returns. Such forecasts are used in risk management, derivative pricing and hedging, market making, market timing, portfolio selection and many other financial activities. In each, it is the predictability of volatility that is required, and this is mentioned by Engle and Patton (2001).

A good volatility model must be able to capture and reflect stylized facts. Understanding the ability of the volatility model is essential for the banking system, institutional and individual investors which are trying to protect themselves from increased risk and increased volatility. The developed financial market has already taking precaution by monitoring the implied volatility index. However, in the developing financial market, there is insufficient information of derivatives and options prices, leading to a restriction of a volatility index model. In a developing market, sometimes the volatility of the stock market tends to be high. This might be due to greater crises exposure of exogenous shocks and augmenting factors, and those related to faulty policies and structural issues. As to overcome exogenous shocks and increasing factors, researchers constructed a few different models and are widely used in modern practice. The different models involved in these practices are called "moving average" averages autoregressive, conditional heteroscedastic models, and implied volatility concept. Besides that, there will be a "blending" procedure model that will be introduced in this thesis which potentially can improve individual "classic" methods. Volatility modeling and forecasting have been the centre of attraction for researchers and policymakers. Readers may have different ways of perspective in defining the stock market volatility. Volatility from the aspect of the investor is one of the most intimidating characteristics of the stock market but also presents an opportunity for advantageous investing for those who understand and have the diligence and fortitude to take advantage of it. Daly (1999) argues that investors may find it difficult to agree that the changes lie in information about fundamental economic factors when asset prices fluctuate sharply over a time differential as short as one, or less. These might lead to an erosion confidence in the capital market and reduced flow of capital into equity markets. He also mentions volatility can provide shrewd investors the chance to buy stocks at price swings when the price falls below the value of the company's intrinsic value and sell when the prices increase well above the company's [1]intrinsic value. There are many reasons that

[1]Intrinsic value is the actual value of a company based on an underlying perception of its true value including all aspects of the business, in terms of both tangible and intangible factors.

contribute to the increase and decrease of the stock market especially it can be seen during the economic crises or changes in national economic policy. For instance, individual companies can freely detect the possibility of bankruptcy by determining the significant factor of the volatility model. The higher the volatility of a stock, the larger the spread between the bid and asked prices of the market marker. The stock market volatility influences the liquidity of the market. So, monitoring the volatility of stock market helps to increase the exploration of hedging techniques. Daly (1999) argued that volatility does affect the liquidity of the market. The volatility of stock markets around the world has become more integrated and volatile in general. An indicator is needed to allow policymakers to rely on financial volatility estimation when the economy and financial market is vulnerable.

In addition to stock market volatility, aggregate idiosyncratic volatility may be important to determine the equity premium. Equity premium is an equity risk premium which is the excess return that investing in the stock market provides over a risk-free rate. Idiosyncratic volatility is an idiosyncratic risk that is endemic to a particular asset such as a stock and not a whole investment portfolio, and [2]idiosyncratic risk affects an asset on its underlying company at the microeconomic level. Idiosyncratic volatility has capture the interest of the researcher as some studies have discovered the significant relationships between returns and idiosyncratic volatility. For instance, Malkiel and Xu (2002), Goyal and Santa-Clara (2003) and Fu (2009) find that stock returns in the US market is significantly and positively related. Idiosyncratic volatility has been taken into the subject because it is a way to diversify a portfolio in the world of investors. A study by Fazil and İpek (2013) suggest that idiosyncratic volatility is the largest component of total volatility and shows no trend in the period of his study. Malkiel and Xu (2002) determine a significant positive relation exists between idiosyncratic risk and cross-section of expected returns at the firm level. In contrast, research by Ang et al. (2006) which measure the idiosyncratic volatility and the results of the study proved a strong negative relation between the idiosyncratic volatility and expected stock returns, Bali and Cakici (2008).

2.2 Daily Returns Stylized Facts

Stylized facts of daily returns depend on the data attributes of financial studies. The data attribution is based on empirical observations. Different characteristics are not necessary to generalize the financial market. So, this section is to introduce the concept of stylized

[2]By definition, idiosyncratic risk is independent of the common movement of the market, see Fu (2009).

facts in the non-derivatives market. The daily return series for the non-derivatives market is used to demonstrate in the following section.

2.2.1 Distribution and Moments

There are four moments regarding the characteristics and distribution abilities which are expected returns, variance, skewness, and kurtosis.

2.2.1.1 Expected Returns

Under full market efficiency, the expected returns,$E(r_t)$ are written in a simple form as;

$$E(r_t) = a_0 + \epsilon_t \tag{2.1}$$

where a_0 is the mean value and ϵ_t, is a random shock. Normally, the mean of daily returns is close to zero and statistically insignificant. If $a_0 = 0$, then the equation becomes

$$E(r_t) = \epsilon_t \tag{2.2}$$

The returns are justified by risk in common notion in finance. So, when daily mean values are close to zero, in both directions, the deviation ϵ_t are driven entirely by variance.

There are several ways to estimate the average of series of returns. When the portfolio is re-balanced by each period, the arithmetic mean reflects the average return when the total amount is fixed. At the same time, the geometric average shows the return of a buy-and-hold strategy in which gains are passively reinvested. The magnitude of the difference between approaches depends on the sample variance.

2.2.1.2 Variance

Variance or a standard deviation is defined as a financial risk in time series. It is quantified through price variation. The standard deviation, σ of daily return can be written as;

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{2.3}$$

where x_i is denoted as the observed outcome for each day, N shows the number of daily observations and μ is the mean value of x_i.

In econometric analysis, usually, a phenomenon known as homoskedasticity is an assumption showing the volatility or variance of the data set is constant in time. According to Gujarati (2008), in order to estimate the best linear unbiased estimator (BLUE), the ordinary least squares (OLS) is necessary to be applied in regression analysis. However, the researcher mentioned that without the presence of heteroskedasticity, it may lead to an overestimation of a goodness of fit[3].

Even though that volatility can be shown easily when it is seldom on time, Enders (2004) found true for many kinds of financial and economic time series. So, meaning that the consequences of volatility clustering indicate that the squared or absolute deviations are serially dependent.

2.2.1.3 Skewness

Skewness or the third moment is a measure of symmetry, and the distributional form of daily returns is regularly assumed to follow normality of symmetry. In a huge sample of stock portfolio returns, we can see that the distributional form is negatively skewed. Skewness $\hat{s}(x)$, is written as follows

$$\hat{s}(x) = \frac{1}{\sigma^3}\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3\right) \tag{2.4}$$

and,

$$t = \frac{\hat{s}(x)}{\sqrt{6/N}} \tag{2.5}$$

where t shows the test statistic for which $H_0 : \hat{s}(x) = 0$.

2.2.1.4 Kurtosis

Daily stock returns entail extreme observations putting more weight on the tails than expected under normality. This phenomenon is referred to as excess or leptokurtosis and is often found in monthly returns. Tsay (2005) found leptokurtosis is more often in stock indices than for individual stocks. The normal distribution of x produces $\hat{k}(x)$, and the measure $\hat{k}(x) - 3$ defines excess kurtosis and can be estimated as;

$$\hat{k}(x) = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \mu)^4}{\sigma} - 3 \tag{2.6}$$

where N defines the number of observations, σ is the standard deviation, μ is the mean value of x_i which is also the observed outcome.

[3]Even though the estimator may still be linear unbiased, it is not efficient or 'Best' and has not had minimum variance in the class of unbiased estimators, Gujarati (2008).

and

$$t = \frac{\hat{k}(x) - 3}{\sqrt{24/N}} \tag{2.7}$$

where t is the test statistic for which $H_0 : \hat{k}(x) - 3 = 0$.

2.3 Modelling Volatility

One of the motivations of finance researchers is identifying and improving the volatility model that is currently being applied in the markets. The early volatility model is calculated based on the continuously compounded return of a given period, using the standard deviation. Liu et al. (1999) mentioned that when stocks are underpriced or overpriced, volatility is a way of quantifying the risk to the traders. Das (2004) discussed the Asian emerging market crisis, market disequilibrium and volatility has continuously embedded in the functioning of the global financial market. So, volatility can be reduced by financial integration which creates opportunities for lending and borrowing to the world market. Two measurements that are widely approached by financial and risk management practitioners to determine levels of volatility risk which are the historical volatility and the implied volatility. Numerous studies in finance sector, the historical volatility and implied volatility have got a lot of attention as to measure stock market volatility. Poon and Granger (2003) examine the standard deviations, stochastic volatility and ARCH and GARCH model can be used to predict volatility in financial markets. Financial market volatility is clearly forecastable. The paper discussed on the accuracy of volatility forecast using different type of model as to what extent could volatility changes be predicted. The most information about future volatility can be measured using the option implied volatility. However, the historical time series models depend on the type of asset being modeled.

2.3.1 Historical Volatility Measures

The historical volatility measure is widely used in research as it formulates the conditional variance directly as a function of observables. The historical volatility measures the past return of equity by estimating the standard deviation of the returns. The advantage of this test that it can be measured directly on the time-series of individual stock and stock index returns. It is also to measure the amount of asset return fluctuation and predict future volatility. It is one of the simpler models compared to other volatility models. Based on

Poon (2005), the simplest model of all historical price model is the random walk model where it is modeled as a random noise. In financial market volatility, volatility model in the form of cluster is popular and representable. Another attractive approach to these types of models are the ARCH and GARCH models. The ARCH model is also one of the simplest form of volatility model. ARCH, Autoregressive Conditional Heteroscedasticity, was mainly to find the persistency of volatility in stock return when the inflation period occurs. The error terms will be assumed constant overtime. So, the conditional variance of stock return will be a reasonable one. The ARCH model calculate conditional variance of stocks return using the maximum likelihood method, when past standard deviations were not used. See, Reider (2009). So, lets begin with the basic structure denoting r_t as the daily log return;

$$r_t = log(p_t) - log(p_{t-1}) = log(\frac{p_t}{p_t - 1}) \tag{2.8}$$

where r_t is defined as the interdaily difference of natural logarithm of daily asset prices, p_t. The GARCH model needs the r_t as it is serially uncorrelated, so, consider the conditional mean μ_t and the conditional variance h_t^2 defined as;

$$\mu_t = E(r_t|F_{t-1}), h_t^2 = Var(r_t|F_{t-1}) = E[(r_t - \mu_t)^2|F_{t-1}] \tag{2.9}$$

where F_{t-1} denotes the information set available at time $t-1$. Since this thesis will concentrate on the conditional variance, but however, conditional mean will be briefly explained in this chapter. This is to work on the conditional variance in proper. The zero mean model supported by Figlewski (1997) where the conditional mean is written as $\mu_t = 0$, and the constant mean model with the conditional mean given by $\mu = \phi_0$ where ϕ_0 is the unconditional mean of the in-sample period and the AR(1) mean model is defined by ;

$$\mu_t = \phi_0 + \phi_1 r_{t-1}, \tag{2.10}$$

where the conditional means are computed and substracted from the series to get the mean adjusted return series Z_t.

The conditional variance, h_t, is using the same notation as in Equation 2.9, written as;

$$h_t^2 = var(r_t|F_{t-1}) = var(Z_t|F_{t-1}), \tag{2.11}$$

where Z_t is

$$Z_t = r_t - \mu_t. \tag{2.12}$$

So, this thesis focuses on examining the forecasting performance of three models that use the GARCH model and its extension which are GARCH, E-GARCH and GJR-GARCH. Each model will be discussed further in the thesis.

2.3.2 The ARCH Model

The ARCH model in Z_t is assumed to be written in the below equation;

$$Z_t = h_t e_t, \{e_t\} \sim IID(0, 1) \tag{2.13}$$

where h_t^2 denotes the conditional variance and $Z_s, s < t$ is a function defined by

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i Z_{t-1}^2 \tag{2.14}$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0$, $i = 1, 2, ..., p$ as to allow the conditional variance is positive. p is the parameter has to be specified before fitting the model to take in-sample data. All parameters α_0, α_i are non-negative parameters. It indicates the short-run persistency of shocks. ARCH has a weakness that normally requires high order to accurately be able to model the conditional variance. The ARCH model needs many parameters to describe the volatility process. The ARCH model is only able to model the conditional variance with square shocks as a variable and this model is unable to model asymmetric effects of positive and negative shocks. The ARCH model is more likely to over predict volatility because the responds slowly to large, isolated shocks.

Since then, Bollerslev (1986) proposed the extension of ARCH model to the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) which is similar to the ARCH in properties but requires less parameters to model the volatility process.

2.3.3 The GARCH Model

GARCH models were among the first models to consider the volatility clustering phenomenon. Financial time series such as exchange rates or stock returns exhibit so-called volatility clustering. It means that large changes in these series tend to be followed by large changes and small changes by small changes. This GARCH model synchronized both lagged squared residuals and lagged variances. With past shocks, the GARCH can stand by its own on both recent variances of itself. Similar to the representation of the ARCH model, the GARCH model Z_t is assumed as;

$$Z_t = h_t e_t, \{e_t\} \sim IID(0,1) \tag{2.15}$$

however in a different model of h_t which is written as;

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i Z_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{2.16}$$

where $\alpha_0 > 0$, $\alpha_i \geq 0$,$\beta_j \geq 0$ and $\sum_{i=1}^{max(p,q)} (\alpha_i + \beta_j) < 1$. Denoted $\alpha_i \equiv 0$ for $i > p$ and $\beta_j \equiv 0$ for $j > q$. All parameters α_0, α_i and β_1 are non-negative parameters. α_i indicates the short-run persistency of shocks and β implies the long-run persistency. This GARCH model is normally use to estimate the volatility clustering. It imposes restrictions on the parameters to have a finite fourth moment as in the ARCH model. Additional lagged conditional variances, h_{t-1}^2, and the lagged squared returns shows the difference between the ARCH and the GARCH. By considering the GARCH(1,1) the conditional variance can be written as;

$$h_t^2 = \alpha_0 + \alpha_1 Z_{t-1}^2 + \beta_1 \left(\alpha_0 + \alpha_1 Z_{t-2}^2 + \beta_1 h_{t-2}^2\right) \tag{2.17}$$

or continuing the recursive substitution, as

$$h_t^2 = \frac{\alpha_0}{1-\beta_i} + \alpha_1 \sum_{i=0}^{\infty} Z_{t-1-i}^2 \beta_1^i \tag{2.18}$$

which shows the GARCH(1,1) model corresponds to an ARCH(∞) model with a certain structure for the value of the parameters of the lagged returns Z_{t-i}^2. The GARCH model only resulted best on symmetric in modeling volatility. The GARCH model improves the ARCH model by including the asymmetric feature of stock market volatility. We consider the future prediction of the study by forecasting the volatility using the GARCH model.

Forecasting GARCH model can be obtained recursively as the autoregressive-moving-average (ARMA) models that provide a parsimonious description of a stationary stochastic process in terms of two polynomials, one for the autoregression and the second one for the moving average. If the conditional mean is assumed to follow stationary ARMA(p,q) model, the model framework is described as

$$r_t = \mu_t + Z_t, \quad \mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i Z_{t-i} \tag{2.19}$$

for r_t and where p and q are the nonnegative parameters of the ARMA(p,q) model.

So, if we consider the GARCH(1,1) model which is one of the GARCH models under study at the forecast origin k, the 1-step ahead forecast of h^2_{k+1} is;

$$h^2_k(1) = \alpha_0 + \alpha_1 Z^2_k + \beta_1 h^2_k \tag{2.20}$$

When to calculate the multistep ahead forecast, volatility of equation $Z_t = h_t e_t \; IID(0, 1)$ can be written as $Z^2_t = h^2_t e^2_t$, which will provide

$$h^2_{k+1} = \alpha_0 + (\alpha_1 + \beta_1)h^2_t + \alpha_1 h^2_t (e^2_t - 1). \tag{2.21}$$

So, let us say $t = k + 1$ the equation yields at

$$h^2_{k+2} = \alpha_0 + (\alpha_1 + \beta_1)h^2_{k+1} + \alpha_1 h^2_{k+1}(e^2_{k+1} - 1) \tag{2.22}$$

with $E(e^2_{k+1} - 1|F_h) = 0$, the 2-step volatility forecast is

$$h^2_k = \alpha_0 + (\alpha - 1 + \beta_1)h^2_k(1). \tag{2.23}$$

So, if the general step of j-step ahead forecast for h^2_{k+j}, at the forecast origin k, is

$$h^2_k(j) = \alpha_0 + (\alpha_1 + \beta_1)h^2_k(j - 1), \quad j > 1 \tag{2.24}$$

By repeating the substitution for $h^2_k(j - 1)$ until the j-step forecast can be written as a function of $h^2_k(1)$ gives the explicit expression for the j-step ahead forecast

$$h^2_k(j) = \frac{\alpha_0[1 - (\alpha - 1 + \beta_1)^{j-1}]}{1 - \alpha_1 - \beta_1} + (\alpha_1 + \beta_1)^{j-1} h^2_k(1). \tag{2.25}$$

Nonsymmetrical dependencies are used to incorporate asymmetries in the modeling of volatility. The model that depends on non-symmetric dependencies is called the Exponential GARCH or E-GARCH model and was carried out by Nelson (1991).

2.3.4 The E-GARCH Model

The ARCH and GARCH model is to examine the persistence of volatility, so they are called volatility clustering. However, both of these models assume that positive and negative shocks have similar impact on volatility. So, introducing the E-GARCH model provides the additional function to capture the skewness and allows the ARCH process to be asymmetrical. E-GARCH is able to allow for asymmetric effects of positive and negative asset returns. E-GARCH model can also forecast future volatility model depending on the nature of the data that we are determining later in the future chapters. Brandt and Jones (2006) stated that predicting the next level is unseen and unpredictable. They proved that E-GARCH models capture the most important stylized features of return volatility, namely time-series clustering, negative correlation with returns, lognormality, and under certain specifications, long memory. In the E-GARCH(p,q)model, representing again on the Z_t as the same representation as in Equation (2.15), with the h_t^2 conditional variance given as;

$$\log(h_t^2) = \alpha_0 + \sum_{i=1}^{p}[\alpha_i Z_{t-i} + \gamma_i(|Z_{t-i}| - E(|Z_{t-i}|))] + \sum_{j=1}^{q}\beta_j \log(h_{t-j}^2). \tag{2.26}$$

where γ_i is the leverage effect, α_0, α_i and β_j are the non-negative parameters. The presence of γ_i indicates an asymmetric effect of shocks on volatility and the positive value of this parameter implies the presence of leverage effect. See, Ahmed and Suliman (2011). There are no restrictions to make sure of a non-negative conditional variance on the parameters. So, E-GARCH(1,1) is written as;

$$\log(h_t^2) = \alpha_0 + \alpha_1 Z_{t-1} + \gamma_1(|Z_{t-1}| - E(|Z_{t-1}|) + \beta_1 \log(h_{t-1}^2). \tag{2.27}$$

where the coefficient γ_1 captures the asymmetric impact of news with negative shocks having a greater impact than positive shocks of equal magnitude if $\gamma_1 < 0$, while the volatility clustering effect is captured by a significant α_0, α_1 and β_1. The logarithm form is used to allow the parameters to be negative without the conditional variance becoming negative. There is no guarantee that a nonnegative conditional variance are imposed on the parameters. So, here no restrictions on E-GARCH(1,1) given as;

In order to illustrate the ability to model for asymmetrical effects of positive and negative asset returns consider the function g defined by

$$g(Z_t) = \alpha_1 Z_{t-1} + \gamma_1(|Z_{t-1}| - E(|Z_{t-1}|)). \tag{2.28}$$

Assuming the properties of Z_t, function $g(Z_t)$ has zero mean and is uncorrelated, the function can be rewritten as;

$$g(Z_t) = (\alpha_1 + \gamma_1)Z_t I(Z_t > 0) + (\alpha_1 - \gamma_1)Z_t I(Z_t < 0) - \gamma_1 E(|Z_t|) \tag{2.29}$$

where the asymmetrical effect of positive and negative asset returns is evident. Positive shocks have an impact $(\alpha_1 + \gamma_1)$ on the logarithm of the conditional variance while negative shocks have an impact $(\alpha_1 - \gamma_1)$. Typically $\alpha_1 < 0$, $0 \leq \gamma_1 < 0$ and $\beta_1 + \gamma_1 < 1$. This configuration negative shocks have a larger impact than positive shocks which is in line with empirical evidence by the so called leverage effect.

In order to investigate the impact of the CSV index on the volatility of return, the E-GARCH(1,1) forecast model that will be used in this study, will be at the forecast origin k, the 1-step ahead forecast of h^2_{k+1} which is;

$$log(h^2_k(1)) = \alpha_0 + \alpha_1 Z_k + \gamma_1(|Z_k| - E(|Z_k|)) + \beta_1 log(h^2_k). \tag{2.30}$$

Since all of the parameters at the right hand side are known at time k,the one-day ahead volatility forecast is written as $h^2_k(1) = h^2_{k+1}$. The forecast evaluation will be based only on the 1 day ahead forecast the general expression for the multi day ahead volatility forecast of the E-GARCH(1,1) model is omitted.

However, there is another way to model the asymmetric effects of positive and negative asset returns, we employed the Glosten et al. (1993) model called the GJR-GARCH model.

2.3.5 The GJR-GARCH Model

The GJR-GARCH model was introduced by Glosten, Jagannathan and Runkle (1993) to model the asymmetric of positive and negative asset returns. The representation for the GJR-GARCH(p,q) model is the Z_t which is the same as in Equation 2.15 where the conditional variance is denoted as;

$$h^2_t = \alpha_0 + \sum_{i=1}^{p}(\alpha_i Z^2_{t-1}(1 - I[Z_{t-i} > 0]) + \gamma_i Z^2_{t-1} I[Z_{t-i} > 0]) + \sum_{j=1}^{q} \beta_j h^2_{t-j} \tag{2.31}$$

where $\alpha_0 > 0$, $\alpha_i \geqslant 0$,$\beta_j \geqslant 0$ and $\gamma_i \geqslant 0$ are parameters to ensure the conditional variance is nonnegative.The GJR-GARCH(1,1) is given by

$$h^2_t = \alpha_0 + \alpha_1 Z^2_{t-1}(1 - I[Z_{t-1} > 0]) + \gamma_1 Z^2_{t-1} I[Z_{t-1} > 0] + \beta_1 h^2_{t-1}. \tag{2.32}$$

Positive shocks thus have an impact γ_1 on the logarithm of the conditional variance while negative shocks have an impact α_1. The $\alpha_1 > \gamma_1$ imposes a larger weight for adverse shocks than for positive shocks in line with the leverage effect. The properties of the GJR-GARCH model are very similar to the E-GARCH model which both are able to capture the asymmetric effect of positive and negative shocks. The GJR-GARCH and the E-GARCH may both be considered for the same series and it is hard to distinguish a criterion for choosing either one of the two models.

This function below at equation (2.33) can be considered when the case of asymmetrical E-GARCH shocks effect can be seen.

$$g(Z_t) = \alpha_1 Z_{t-1}^2 (1 - I[Z_{t-1} > 0]) + \gamma_1 Z_{t-1}^2 I[Z_{t-1} > 0]) + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{2.33}$$

As to forecast the GJR-GARCH(1,1) model, we considered at the forecast origin k, the 1-step ahead forecast of h_{k+1}^2 written as;

$$h_k^2(1) = \alpha_0 + \alpha_1 Z_k^2 (1 - I[Z_k > 0]) + \gamma_1 Z_k^2 I[Z_k > 0] + \beta_1 h_k^2. \tag{2.34}$$

The volatility equation $Z_t = h_t e_t$, e_t $IID(0,1)$ can be written using $Z_t^2 = h_2^t e_t^2$ which gives

$$h_k^2(2) = E[\alpha_0 + \alpha_1 Z_{k+1}^2 (1 - I[Z_{k+1} > 0]) + \gamma_1 Z_{k+1}^2 I[Z_{k+1} > 0] + \beta_1 h_{k+1}^2 | F_k] \tag{2.35}$$

with $E(e_{k+1}^2 - 1 | F_h) = 0$, the 2-step volatility forecast is

$$h_k^2(2) = \alpha_0 + \left(\frac{\alpha_1 + \gamma_1}{2} + \beta_1 \right) h_k^2(1) \tag{2.36}$$

The basic common step of j-step ahead forecast can be written as;

$$h_k^2(j) = \alpha_0 + \left(\frac{\alpha_1 + \gamma_1}{2} + \beta_1 \right) h_k^2(j-1). \tag{2.37}$$

Substitutions of $h_k^2(j-1)$ until the j-step forecast after repetition can be written as a function of $h_k^2(1)$ that gives explicit expression for the j-step ahead forecast

$$h_k^2 = \alpha_0 \sum_{i=0}^{j-2} \left(\frac{\alpha_1 + \gamma_1}{2} + \beta_1 \right)^i + \left(\frac{\alpha_1 + \gamma_1}{2} + \beta_1 \right)^{j-i} h_k^2(1). \tag{2.38}$$

2.3.6 The HAR-RV model

Corsi (2009) proposes the heterogeneous autoregressive (HAR) model as an alternative. This is a simple autoregressive-type model, specified as an additive cascade of volatility components defined over different time periods. Economically, these components represent the actions of different types of market participants and capture the heterogeneity in their trading frequency, which arises from their differences in endowments, temporal horizons, and geographical locations, among other factors. Corsi (2009) shows that the additive structure of the model leads to a simple restricted linear autoregressive model of volatilities realized over different time horizons.The HAR-RV takes realized over several horizons into accounts. This study is aiming to model and forecast volatility in a easy implementation that holds promise for high-dimensional return volatility modeling, see Andersen et al. (2003). At day t, the model's forecast of the Realized Volatility(RV) over day $t+1$ is given by;

$$RV_{t+1}^{(d)} = c + \beta^{(d)} RV_t^{(d)} RV_t^d + \beta^{(w)} RV_t^w + \beta^{(m)} RV_t^m + w_{t+1}, \tag{2.39}$$

where $RV_{t+1}^{(d)}$ is the RV over day t and RV_t^w and RV_t^m are the average daily realized volatilities over the past week and month, respectively.

2.3.7 Implied Volatility Model

Implied volatility (IV) is one of the most important concepts for options traders to understand for two reasons. First, it shows how volatile the market might be in the future. Second, implied volatility can help to calculate volatility. Implied volatility is a critical component of options trading which may be helpful when trying to determine the likelihood of a stock reaching a specific price by a certain time. Implied volatility indices are based on equity index options.

An option is a financial contract which gives the right but not the obligation to buy (call) or to sell (put) a specific quantity of a specific underlying, at a particular price, on (European) or up to (American), a specified date. Such an option is called a plain vanilla option. An underlying of an option could be stocks, interest rate instruments, foreign currencies, futures or indices. Option buyers (long positions) usually pay an option premium (option price) to the option seller (short positions) when entering into the option contract. In return, the seller of the option agrees to meet any obligations that may occur as a result of entering the contract.

Usually, financial institution uses them as an expectation of future volatility, a gauge of sentiment, and as an alternative way to buy and sell volatility itself. Black-Scholes option pricing formula is the basic theory to calculate implied volatility model. It states that the option price is a function of the price of the underlying asset, the strike price, the risk-free rate, the time to option maturity and the quoted option price. Implied volatility is also a market derived a σ as an input using the backward induction techniques as it is used in the Black-Scholes model when given the market price of options and four other variales. Examples of the basic Black-Scholes option pricing model can be found in Day and Lewis (1992), Canina and Figlewski (1993) and Lamoureux and Lastrapes (1993). Research found in the US and western countries on the superiority of implied volatility over other volatility methods, as for instance the historical volatility measure and the GARCH model. Then, Whaley (1993) extended the idea of implied volatility by introducing the new concept of volatility which is the VIX model. The VIX model is a type of model that measures the implied volatility of S&P 500 index options. It is calculated by the Chicago Board Options Exchange (CBOE). It has quickly became the benchmark for stock volatility. The VIX measures market expectations of near term volatility conveyed by stock index option prices.

2.4 Volatility Index Model

Numerous econometric models including the GARCH-family models and stochastic volatility models have been developed to measure and predict volatilities. One of the model is the implied volatility that construct volatility dynamics which is based on current market prices of tradable financial assets. It contains most available information and reflects the sentiment and expectations of market participants, see Poteshman (2000), Blair et al. (2001), Giot and Laurent (2007) and Ryu (2012). VIX is the popular benchmark measure for stock market volatility. The VIX is also refer as the fear index or the fear gauge that represents a measure of the market's expectation of equity market volatility over next period of 30-day period. The VIX is a well-known index of the US market which is a model-free method based on implied volatility. The VIX model calculation is based on information content of implied market volatility meaning looking into prices of a portfolio of 30-calendar-day S&P 500 calls and puts with weights being inversely proportional to the squared strike price. The VIX gathered the information from option prices over the whole volatility skew, not just at-the-money strikes as in the original index. This was an improvement when the VIX is introduced after the VXO[4]. The VIX is motivated by the S&P 500 index and plays a significant role in derivative products. The volatility index, sometimes called by financial professionals and academics as "the investor gauge of fear" has developed over time to become one of the highlights of modern-day financial markets.

The VIX index is calculated by the Chicago Board Options Exchange (CBOE). It is introduced in 1993 which is derived from the bid or ask quotes of options on the S&P 500 index. It reflects the investor sentiment and risk aversion and is the market expectation of the volatility in the S&P 500 index over the next month. According to Blair et al. (2001) and Mayhew and Stivers (2003), the VIX is an indicator of market implied volatility that improves the problems of measurement errors and model misspecification. For instance,

[4]The older version of VIX constructed by Whaley (1993) in 1993 based on S&P 100(OEX) options.

when less frequent trading occurs among the component stocks of the index, the index level can be misjudged under the underlying asset of an option pricing model. Besides, there is no right measure for the volatility required as an input in a pricing such as the traditional Black-Scholes model, see Ahoniemi et al. (2009). To allow the VIX method closer to the actual finance industry, the VIX was changed and the S&P 500 is the base of VIX rather than the S&P 100 options. Jiang and Tian (2005) stated that the S&P 500 is most commonly used as a benchmark of the US equity market, and the most popular underlying for the US equity derivatives. The model-free estimator of the implied volatility that CBOE employs to calculate the VIX index reads

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \tag{2.40}$$

where T is the time expiration, T=$\frac{M_{current \quad day} + M_{settlement \quad day} + M_{other \quad days}}{Minutes \quad in \quad a \quad year}$,

$M_{current \quad day}$= minutes remaining until midnight of the current day,

$M_{settlement \quad day}$=minutes from midnight until 8.30AM on S&P index (SPX) settlement day,

$M_{other \quad days}$=total minutes in the days between current day and settlement day,

F= Forward index level derived from index option price which is determined as Strike Price + $e^{RT} * (CallPrice - Putprice)$,

K_0= First strike below the forward index level F,

K_i= Strike price of the i^{th} out-of-the-money option; a call if $K_i > K_0$ and a put if $K_i < K_0$; both put and call if $K_i = K_0$.

ΔK_i=Interval between strike price-half the difference between the strike on either side of K_i: $\quad \Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$,

R = Risk - free interest rate to expiration,

$Q(K_i)$=The midpoint of the bid and ask spread for each option with strike K_i.

After estimating the variance σ_1^2 and σ_2^2 of the near and next term-option using Equation 2.40, then the 30-days weighed average can be calculated. In order to calculate the 30-days weighed average, implied with the Equation (2.40) variances to Equation (2.41).

$$VIX = 100 * \sqrt{T_1\sigma_1^2\left(\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}}\right) - T_2\sigma_2^2\left(\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}}\right)\frac{N_{365}}{N_{30}}} \tag{2.41}$$

The parameters in the equation are as follows:

σ_1^2= Variance for near-term, less than 30 days left

σ_2^2= Variance for next-term, more than 30 days left

N_{T_1}= number of minutes to settlement of the near-term options

N_{T_2} =number of minutes to settlement of the next-term options

N_{30}= number 0f minutes in 30 days (43,200)

N_{365}= number of minutes in 365 days (525,600)

T_1=Time to expiration for near-term

T_2=Time to expiration for next-term

When liquidity of the options of calls and puts are available, then VIX would take place as the "fear gauge" in the particular market index. This fear occurs when the fear of variance is higher than expected. However, not all markets in the world can measure the market expectations by using the VIX index because of lack of derivative information. There are some limitations in the world market to measure volatility using the VIX-styled model. This is because the particular market does not have enough information on derivatives to apply the VIX-styled model. So, investors find other alternative way to measure the volatility of stock market index. For instance, in some developing markets or emerging markets, see Goltz et al. (2011). The researcher mentioned although in developed markets, the volatility indices appear at the broad aggregate level because of the non-existence of volatility index available in small-cap stocks, growth, the value of stocks, sectors and other more. So when the volatility indices exist, the implied volatility estimates are affected by option-market problems that have less to do with underlying equity markets. By introducing an alternative to the VIX is the best proposal to encounter this problem.

2.5 Cross-Sectional Volatility Index (CSV)

The Cross-sectional Volatility index is a collection of volatility indices that is model-free, and it is based on the equity market data. It is available for all markets and sectors at all frequencies. The CSV index is constructed using the content in the cross-sectional distribution of stock returns; for instance, the distribution of stock returns on a given date. That is, it measures the distribution of a set of asset performance at given period. The level of distribution of the assets performance shows an adequate indication for active managers to exploit. It is an indication of market potential outperformance. So, the root of this indication process is the variation of time series. Any significant trend that occurs, the CSV index method is the model to monitor in the long term. For instance, active managers have views on shares they are interested in, so they show the skill by overweighting or underweighting shares against a benchmark. The active managers regularly predict their performance shares by forecasting the cross-sectional dispersion of returns. When CSV index increases, the likelihood of outperforming and underperforming the index also increase. Garcia et al. (2011) show the conceptual and technical foundations by illustrating a summary to motivate the use of cross-sectional dispersion as a measure of volatility is written in a short overview of formal arguments.

It is assumed the excess stock returns $r_{it} = \beta_{it} F_t + \varepsilon_{it}$ where F_t is the factor excess return at time t, β_{it} is the beta of stock i at time t, and ε_{it} is the residual or specific return on stock i at date t, with $E(\varepsilon_{it}) = 0$ and $cov(F_t, \varepsilon_{it}) = 0$. The factor model that is under consideration is a strict factor model is assumed as $cov(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for $i \neq j$.

The assumptions that is has been made by Goltz et al. (2011) is as follows;

- homogeneous beta assumption:$\beta_{it} = \beta_t$ for all i;
- homogeneous residual variance assumption: $E(\varepsilon_{it}^2) = \sigma_\varepsilon^2(t)$ for all i.

  These assumptions illustrate in detailed by Garcia et al. (2011) where the cross-sectional variance converges towards specific variance with an increasingly large number of constituents as its limit. The equation is written as;

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}(r_{it} - r_t{}^{(w_t)})^2 \xrightarrow[N_t \to \infty]{} \sigma_\epsilon^2(t) \tag{2.42}$$

  where N_t is the number of increasing constituents of the stock index market for a given date t, $r_t^{(w_t)}$ is the weighted return with weights w_{it} at time t and $CSV_t^{(w_t)}$ is the cross-sectional variance. The expansion of Equation 2.42 will be described further in Chapter 3.

2.6 Factor-DCC

Estimating high-dimension matrices of assets are different among the asset managers. They seem to incorporate two problems at a time. In this study, there are two problems that arised during the analysis. The first problem is determining the correct correlation function when the nature market data is precisely captured and secondly, is choosing the correct methodology in order to evaluate the market data factors. So, the approach of Factor-DCC is applied in this study. Factor-DCC or so Factor Dynamic Conditional Correlation is a methodology that has been established by Zhang et al. (2010) to simplify a multivariate framework estimation process. It estimates the correlation function on a small number of factors instead of multiple pairwise DCCs. Since the extracted factors in the paper still have weak conditional correlations, factor-DCC model is proposed as an extension to the multivariate generalized orthogonal GARCH(GO-GARCH) models with dynamic condition correlation(DCC). Aboura and Chevallier (2015a) mentioned that there are hundreds of time-series variables as proxies for the state of an economy so that factor methods would be in need for macroeconomists and central bankers. This factor models can extract information from datasets with a lot of variables by keeping the model parsimonious at the same time. It can be similar to the current working research due to many variables in a dataset. Gathering much information is necessary for the research thesis due to high volumes of variables. Antonakakis and Kizys (2015) has extended the work of Aboura and Chevallier (2015a) evaluating the volatility spillover effects using the econometric framework by Zhang et al. (2010). In their article, they try to accommodate the factor modeling techniques in financial econometrics sector, comprising that the time-varying conditional correlations are essential. By performing the factor modeling method, a standard static Principal Component (PCs) method is used to extract the indicating factors. Most of the research that applies the Generalized Orthogonal approach adopt the Factor-DCC model, see (Ghalanos (2015),Basher and Sadorsky (2016),Aboura and Chevallier (2015b)). To compute the Factor-DCC model, Zhang et al. (2010), allows an arbitrary choice of factors. An optimal criterion that minimizes the number of factors is implemented. There are two steps to imply the Factor-DCC model's which are in the first step, common factors will be extracted from the datasets of the study using the PCA approach. According to the statistical criterion, the number of factors is restricted to two first factors of PCA. Then, the second step has been identified thoroughly by Zhang et al. (2010) approach is representing the estimation of time-varying conditional correlation equation. Further discussion will be explained in Chapter 5.

2.6.1 Principal Component Analysis

In this study, the Principal Component Analysis (PCA) is used to perform the Factor-DCC econometric model. The PCA model able to determine a parametric or semiparametric factor model to become a natural choice to represent the data applicable. PCA is a dimension-reduction tool that can be used to reduce a high dimension data and reduces a large set of variables that most of the information in the large set is still contained. It is one model of factor analysis. Aït-Sahalia and Xiu (2017) stated that when factors are latent, PCA shall become the main tool at their study disposal. An extension of PCA by Aït-Sahalia and Xiu (2015) has used PCA to construct estimators for the number of common factors and exploiting the factor structure to build estimators of the covariance matrix in an increasing dimension setting, without requiring that a set of observable common factors be pre-specified. To perform Factor-DCC model, Principal Component Analysis or namely (PCA) approach is adopted first to analyze data table which the observations are characterized by a clear inter-correlated quantitative dependent variables. The extraction of the data consists only the relevant variables to perform it as a set of new orthogonal variables called the principal component. This important information displays the pattern of connection of the observations and the variables as points in the design. This method is widely known among many researchers that need to extract many data set. Aboura and Chevallier (2015a) extract two factors using PCA before computing the dynamic conditional correlation among the principal explanatory factors that are similar to the implied volatility series representing the G20 countries. Yang and Copeland (2014) and Brown and Cliff (2004) composed investor sentiment of UK stock market applying the procedure of PCA to capture the standard component in the underlying economic variables. Refining the number of factors has been an important issue in large data sets. Many pieces of literature on factor models have been proliferating in the recent years, and it has been expanding the interest of criteria which can consistently estimate the number of common factors driving the data.

Large data sets need to be reduced, and dimension also needs to be curtailed in both the time and cross-section size. This study extracted a high dimension data and the data may need to apply the PCA model to comply with another approach which is called the Factor-DCC method. Bai and Ng (2012) and Alessi et al. (2008) provides a tool to determine the number of factors and address the theoretical properties. Six criterions are introduced by Bai and Ng (2012), which customize the Akaike information criteria (AIC) and Bayesian information criteria (BIC) to take into account both dimensions of the dataset as arguments of the function penalizing overparameterization. PCA explain the variance which factor analysis explains the covariance between the variables. PCA is a method to extract element to reduce the number of variables which retaining variance as much as possible. Then after determining the number of factors, Bai and Ng (2012) and Alessi et al. (2010) propose a panel of criteria to allow these factors are consistent. PCA is one of the famous ways of dealing with large systems of non-stationary macroeconomics variables. It distinguishes the variables in a univariate fashion; see, for instance Su and Wang (2017);Stock and Watson (2012);Barhoumi et al. (2013);Buch et al. (2014) and

Poncela et al. (2014) for recent references. An adjusted matrix, X, that consist n observations(rows) and p variables(columns). The adjustment is composed by subtracting the variable's mean from each value. This is due to PCA handles with the covariances among the original variables, so the means are irrelevant. New variables then are constructed as weighted averages of the original variables. The new variables are called the factors, latent variables, or principal components. The basic PCA equation is written in a matrix notation;

$$Y = W'Y \tag{2.43}$$

where W is representing the matrix of coefficients that is determined by PCA. It may also be written as a set of p linear equations that form the factors out of the original variables;

$$y_{ij} = w_{1i}x_{1j} + w_{2i}x_{2j} + ... + w_{pi}x_{pj} \tag{2.44}$$

The factors are a weighted average of the original variables. The weights, W, are constructed so that the variance of y_1, $Var(y_1)$, is maximized. Also, so that $Var(y_2)$ is maximized and that the correlation between y_1 and y_2 is zero. The remaining y_i's are calculated so that their variances are maximized, subject to the constraint that the covariance between y_i and y_j, for all i and j (i not equal to j), is zero. The matrix of weights, W, is calculated from the variance-covariance matrix, S. This matrix is calculation using the formula:

$$s_{i,j} = \frac{\sum_{k=1}^{n}(x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j)}{n-1} \tag{2.45}$$

The singular value decomposition of S provides to solve the PCA problem. It is defined as U'SU=L, where L is a diagonal matrix of the eigenvalues of S, and U is the matrix of eigenvectors of S. W is calculated from L and U, using the relationship:

$$W = \frac{U}{\sqrt{L}} \tag{2.46}$$

where W is the eigenvector matrix U, scaled so that the variance of each factor, y_i, is one. The correlation between an i^{th} factor and the j^{th} original variable may be computed using the formula:

$$r_{ij} = \frac{u_{ji}\sqrt{l_i}}{s_{jj}} \tag{2.47}$$

where u_{ij} is an element of U, l_i is a diagonal element of L, and s_{jj} is a diagonal element of S. The correlations are called the factor loadings. When the correlation matrix of R is used, instead of the diagonal elements of S, then the equation for Y is modified to:

$$Y = W'D^{-1/2}X \tag{2.48}$$

where D is a diagonal matrix made up of the diagonal elements of S. In this case, the correlation formula may be simplified when s_{jj} are equal to one.

2.6.2 Dynamic Conditional Correlation (DCC)

A flexible of univariate GARCH can be proposed using the Dynamic Conditional Correlation(DCC) estimators. The conditional correlations can be directly parametized using the DCC model in two steps. The first step is the estimation univariate GARCH series and the second step is the correlation estimation. Potentially, estimation of the very large correlation matrices can be calculated. Engle (2002) suggests this new class of multivariate GARCH estimators which can be viewed as a generalized of Bollerslev (1990) constant conditional correlation estimator. In his setting, multivariate series r_t is denoted as;

$$r_t|\omega_{t-1}\ N(0, H_t) \tag{2.49}$$

where $H_t = D_tR_tD_t$, and $D_t = diag\{\sqrt{h_{i,t}}\}$ and

$$h_{it} = w_i + \sum_{p=1}^{P_i} \propto_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq}h_{it-q} \tag{2.50}$$

where R_t is the time varying correlation matrix containing the conditional correlations, D_t is the diagonal matrix obtained with the univariate GARCH models. The structure of the DCC can be defined with positive matrix Q_t and

$$R_t = diag\{Q_t\}^{-1/2}Q_t diag\{Q_t\}^{1/2} \tag{2.51}$$

According to (Aboura and Chevallier, 2015a), from the two GARCH variance equations, the DCC certain the conditional correlation function. It is one of the simple and practical models that uses a sequential estimation scheme and a very parsimonious parameterization to enable it to estimate models with fifty or more assets rather easily. Basically, Bollerslev (1990) has introduced the Constant Correlation Coefficient model (CCC), but Engle (2002) eased the estimation by allowing the relationships to change over time using the DCC model. With this model, it provides more flexible parameterization of correlation dynamics in the factors generated from the PCA model with the approached criteria proposed by Bai and Ng (2012) and Alessi et al. (2010), by maintaining at the same time the parameter number at a possible level. This approach has much introduced by Bautista (2003), Cappiello et al. (2006), Kim et al. (2006), Lee (2006) and Ledoit et al. (2003).

2.6.3 Determining number of factors in Factor-DCC model.

Large datasets have more information when analyzing factor to reduce dimension of the datasets. Determining the number of common factors in large dataset are particularly difficult as traditional information criteria as BIC and AIC cannot be applied anymore. Bai and Ng (2012) proposed an information criterion aimed at minimizing the variance of the idiosyncratic components. Bai and Ng (2012) specified in six different forms of criterion which modifies AIC and BIC to consider both dimensions of the dataset as arguments of the penalizing overparametrization. However, a refinement of dynamic factors criterion was revised by Hallin and Liška (2007). After evaluating the criterion for a whole range of values for this constant, an estimation of static factors are determined. Alessi et al. (2008) has improved the criterion to a more robust than it would be the constant being fixed. The criterion is similar to the original Bai and Ng (2012), and the only difference is that the criterion being a multiplicative constant.Alessi et al. (2010) determined the number of factors by proposing Bai and Ng (2012) information criterion to determine the number of static factors. The static factor model $x_t = AF_t + \epsilon_t$ which is a static representation, with r factors for an N-dimensional vector process of finite time length T. Common factors $F_t^{(k)}$ and their loading $A^{(k)}$ are estimated using the static principal components. Superscript k is used when k static factors are chosen. The information criterion is aimed at minimizing the residual variance of the idiosyncratic components which is computed as a function of k. Namely the static factors and their loading must minimize computed for all the possible numbers of static factors $k\epsilon[0, r_{max}]$ up to $r_{max} = min\{N, T\}$. The minimization is subject to the normalization $A^{(k)'}A^k/N = I_k$ or $F^{(k)'}F^{(k)}/T = I_k$. Indeed all estimators satisfying such theorem span the same space $V(k, \hat{F}_t^{(k)})$ is a quantity that cannot increase as k approaches r_{max}. Overparametrizing is avoided by introducing a penalty function $p(N, T)$ which counterbalances the fit improvement due to the inclusion of additional common factors. Bai and Ng (2012) propose two classes of criteria which refers to Equations 2.53 and 2.54:

$$V(k) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \lambda_i^{(k)'}F_t^{(k)})^2 \tag{2.52}$$

$$PC_N^T(k) = V(k, \hat{F}_t^{(k)}) + k\sigma^2 p(N,T), \tag{2.53}$$

$$IC_N^T(k) = log\left[Vk, \hat{F}_t^{(k)}\right] + kp(N,T) \tag{2.54}$$

The number of static factors is consistently estimated if the penalty function satisfies the two conditions $\lim_{\substack{N\to\infty \\ T\to\infty}} p(N,T) = 0$ and $\lim_{\substack{N\to\infty \\ T\to\infty}} p(N,T)\left[min(\sqrt{N}, \sqrt{T})\right]^2 = \infty$

Depending on the chosen criterion, the estimated factors is written as $\hat{r}_n^T = \underset{0\leq k\leq r_{max}}{argmin}\, PC_N^T(k)$ or $\hat{r}_n^T = \underset{0\leq k\leq r_{max}}{argmin}\, IC_N^T(k)$. The P C specifications depend explicitly on it while the IC specifications depend on it only when implementing them in practice. There are six different criteria analogous to the study of Bai and Ng (2012) when dynamic factors of multiplying the penalty function by a positive constant c. There are as follows;

1. $PC_1^*(k) = V(k, \hat{F}_t^{(k)}) + ck\left(\frac{N+T}{NT}\right) log\left(\frac{NT}{N+T}\right)$;
2. $PC_2^*(k) = V(k, \hat{F}_t^{(k)}) + ck\left(\frac{N+T}{NT}\right) log(min\{\sqrt{N}, \sqrt{T}\})^2$
3. $PC_3^*(k) = V(k, \hat{F}_t^{(k)}) + ck\frac{log(min\{\sqrt{N},\sqrt{T}\})^2}{min\{\sqrt{N},\sqrt{T}\})^2}$
4. $IC_1^*(k) = log\left[Vk, \hat{F}_t^{(k)}\right] + ck\left(\frac{N+T}{NT}\right) log\left(\frac{NT}{N+T}\right)$;
5. $IC_2^*(k) = log\left[Vk, \hat{F}_t^{(k)}\right] + ck\left(\frac{N+T}{NT}\right) log(min\{\sqrt{N}, \sqrt{T}\})^2$;
6. $IC_3^*(k) = log\left[Vk, \hat{F}_t^{(k)}\right] + ck\frac{log(min\{\sqrt{N},\sqrt{T}\})^2}{min\{\sqrt{N},\sqrt{T}\})^2}$

The estimated number of factors are depend on either these two chosen criterion,

$$\hat{r}_{c,N}^T = \underset{0\leq k\leq r_{max}}{argmin}\; PC_{a,N}^{T*}(k)$$

$$\hat{r}_{c,N}^T = \underset{0\leq k\leq r_{max}}{argmin}\; IC_{a,N}^{T*}(k)$$

The degree of freedom represented by c can be exploited when implementing the criterion in practice. The only information we have about the asymptotic behavior of $\hat{r}_{c,N}^T$ comes from considering subsamples of sizes $n_j \leq N$ and $T_j \leq T$ with $j = 0, ..., J$.

2.7 Performance Measure

In the existing literature, there are three primary classes of asset return volatility models, which are called stochastic volatility models, the Generalized Autoregressive Conditional

Heteroskedasticity (GARCH) class models and realized models volatility. However, most of the studies focus on short horizon volatility modeling and forecasting. It is a one- month maximum period but mostly one day ahead. Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model with a normal innovation capturing stylized characteristics of financial assets. Then the ARCH has extended to become GARCH which is introduced by Bollerslev (1986) proposing better parameters performance to evaluate the conditional variance. As to estimate each of the models, there are a few measurements that need to be considered while executing the model. This thesis examines the forecasting of the volatility index. Recently, asset returns are available at on a tick-by-tick basis. The predictable model of volatility being examined in this thesis is the GARCH and its extended-GARCH model followed by the Heterogenous Realized Volatility (HAR) model. The extended GARCH models are the E-GARCH and GJR-GARCH. The performance is generated after forecasting the GARCH and its extension model. The forecast of the GARCH model is attained recursively as the ARMA[5] model. Further explanation, see Choi (2012).

Poon and Granger (2003) have extended their review of forecast performance criteria and the popular measure of forecasting accuracy of each model is estimated with the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (TIC). Gabriel (2012) implies the forecast accuracy measurement using the RMSE, MAE, TIC and MAPE model and conclude that the asymmetric models are better than symmetric models. Accuracy measure has also been mentioned in the forecasting literature. For instance, Schwartz (1999) used Mean Absolute Percentage Error (MAPE),Yüksel (2007) and recent project Lim and Chan (2011) used Root Mean Square Error (RMSE). Lim and Sek (2013) evaluated the GARCH-type models using the MSE, RMSE and MAPE.

[5]ARMA model provides a parsimonious description of stationary stochastic process regarding two polynomials, one for the autoregression and secondly for the moving average.

Chapter 3

Cross-Sectional Volatility Index as a Proxy for the VIX in an Asian Market

3.1 Introduction

The VIX is a widely accepted measure of the level of volatility in the developed markets. However, this index does have a number of limitations especially in relation to Asian markets which are under review. The calculation of a VIX-styled index depends on a vibrant derivative market. In less developed markets, where the derivative market is illiquid or non-existent, it becomes inappropriate to use this approach. In such cases, we propose to use a Cross-sectional Volatility index methodology as a measure of volatility level. The Cross-sectional Volatility Index is a recent form of measure associated with volatility, see Goltz et al. (2011) for details. Cross-sectional Volatility (CSV) is another way to attain the stock markets' co-movement and global risk measurement. The construction of the CSV is quite distinction from the VIX. Ahoniemi et al. (2009) demonstrate the VIX calculation to forecast the future by directional accuracy and etimating the profitablity of the trades. Few Asian markets have a vibrant derivatives sector to supply the necessary inputs to calculate a VIX-styled index. The CSV index approached is based on observable and model-free volatility measures of all data and frequencies. This new form of index provides a good approximation of average idiosyncratic variance. The technical foundations of the new form indices have been defined by Garcia et al. (2011). The results of the new form of volatility index can be used as a reliable proxy when other measures of volatility are not available.

The idiosyncratic volatility has also been of interest among researchers. Nartea et al. (2011) and Campbell et al. (2001) show how idiosyncratic volatility benefited diversification. In this thesis, we test the validity of the CSV index by showing the measure is strongly correlated to the performance of the VIX. This is important as we wish to show that the CSV index can be used as a reliable proxy in a VIX-styled market without a local derivatives market. So, in this study, we will develop a volatility index based on model-free implied volatility. As an illustration, we shall apply the method to the Japanese market. In subsequent work, we expand the method into developing countries. The purpose of this study is to propose appropriate volatility indices and volatility-based derivative with its foundation focusing on crucial methodology in less liquid markets in Asia. One of the reasons for choosing this method is because the volatility measurement has a model-free nature and is flexible enough to apply to any region, sector and style of the world equity markets in any frequencies. Another advantage of this method is that with the model, there is no need to resort to any auxiliary option market.

A volatility measure has been the focus among researchers and policy makers. Less attention has been given to cross-sectional volatility of the dispersion of stock returns. There are two forms of volatility measures: systematic and unsystematic. For instance, Ang et al. (2006) discuss systematic volatility as a measure on the sensitivity of the variation in stock returns. However, unsystematic volatility is measured by residual variance of stocks in a specific period of time by the use of error terms. A study of the systematic volatility can be found in Cutler et al. (1989). Previous studies have focused on the GARCH model as a volatility model. Due to information content, the bias, the efficiency forecast of the predictor, a GARCH model can be employed to examine and compare with other volatility models, see Bentes (2015) for more details. Besides that, Bagchi (2016) suggests that the dynamic relationship between the stock price volatility and exchange rate volatility in India exist by the extension of GARCH namely, asymmetric power ARCH (APARCH) model is applied.

When using implied volatility to construct the VIX index, the standard deviation is estimated on its volatility of security prices. For example, as experienced by the South African market, only recently has the market had access to the information content in SAVI implied volatility, see Kenmoe S and Tafou (2014). They also mentioned that once all information contents are retrieved, essentially the options price, then one can compute stock's market volatility equation option price and the pricing model. The information on option prices are available in more developed countries. This is the reason that researchers intend to carry out further studies on volatility in more liquid markets of the developed world, see Ang et al. (2006); Goltz et al. (2011); Garcia et al. (2011). Apart from this, as mentioned in Siriopoulos and Fassas (2012), less emergent countries have established derivative markets, but many are without this dimension.

Many Asian derivative markets are still in the early stages of development compared to the western market, as surveyed by Hohensee and Lee (2006). The transparency and liquidity of the underlying markets are the fundamental success factors for derivatives markets. However, the derivative market in many Asian countries is either non-existent or in the early stages of development; and so unsuitable for a VIX-like index.

The contribution of this chapter to the literature is threefold. Firstly, we introduce and examine the Cross-sectional Volatility index approach as a new form of volatility index in the US market. This, in turn, allows us to obtain consistent estimates of parameters of the financial market model using a single cross-section of return data for the Japanese market. This CSV Index approach is a measure that is observable and has a model-free nature that is available for every region, sector, and style of the world equity markets. We show that a cross-sectional measure provides a good approximation of average idiosyncratic variance. Secondly, we show that the new form of volatility index in the Japanese market is an efficient benchmark index providing the cross-sectional variance returns are the average idiosyncratic variance of stocks within the Asian countries. Additionally, the measure is different from the historical volatility and implied volatility as it is available for every region, sector and style of world equity markets. Thirdly, we test the forecast capabilities of the Cross-sectional Volatility index in the market that has a lack of derivatives options. This is to measure its performance against the VIX.

3.1.1 Outline

The remainder of this chapter is organised as follows; Section 3.1 gives an account of previous works. Section 3.2 describes the methodology and research model, the GARCH models, the Volatility measures and forecasting measurements used to construct the Cross-sectional Volatility Index. Section 3.3 describes the data used in this paper. Our new results are described in Section 3.4. Finally, Section 3.5 gives the conclusions.

3.2 GARCH Model with Cross-Sectional Market Volatility

The Cross-sectional Volatility index indirectly describes the changes in the environment driven by country[1], pressures, stock behaviour, and financial sector selection. In Ankrim and Ding (2002), it is shown that the model depends largely on inter-temporal measures. This relates to variability of daily, monthly, or quarterly returns for a market of a long horizon. There are also three factors that are combined to generate an expected change of cross-sectional volatility. The factors are the change in the average volatility in the sectors making up the market, the change in overall market volatility and the change in the sector mean dispersion. The Cross-sectional Volatility method is based on a statistically robust estimation and outlier detection. To detect outlier, Principal Component Analysis is adopted and the method will able to remove stocks with negative weight.

Assumptions by Garcia et al. (2011) state that the cross-sectional measure of variance provides a good approximation for average idiosyncratic variance of a given universe of stock. The stock returns r_{it} are modeled as follows:

$$r_{it} = \beta_{it} F_t + \varepsilon_{it} \tag{3.1}$$

where F_t is the factor at time t, β_{it} is the beta of stock i at time t, and ε_{it} is the residual or specific return on stock i at time t, with $E(\varepsilon_{it}) = 0$ and $cov(F_t, \varepsilon_{it}) = 0$. A strict factor model is assumed as $cov(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for $i \neq j$. In a strict factor model, the idiosyncratic returns are assumed to be uncorrelated with one another. This is where the covariance matrix of idiosyncratic risks is a diagonal matrix. The idiosyncratic variance measurement over asset i is obtained by computing the residuals of the regression of $\sigma_i^2 = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}^2$. So, there are two main advantages of CSV idiosyncratic measurement. Firstly, the observed return can be computed directly and secondly, within any universe of stocks it is readily available at any frequency. When it can be computed directly, it means that no other parameters, such as betas, need to be estimated first. As to see this, let $(w_t)_{t \geq 0}$ be given weight vector process and then the return, $r_t^{(w_t)}$, will be written as:

$$r_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it} r_{it}, \qquad 0 < w_{it} < 1 \quad \forall i, t, \tag{3.2}$$

where N_t represents the total number of stocks at day t, and assume no loss of generality a conditional single factor model for excess stock returns. So, for all $i = 1, ..., N_t$, the stocks

[1] The fluctuation of asset prices may change at times along with the globalisation of the world economy. If the equity market is unstable, it will give a negative impact on economic growth, financial resources and income distribution. It may also lead to increased poverty.

are written in terms of the excess of the risk-free rate. Based on the assumptions outlined in the study of Garcia et al. (2011), the cross-sectional variance measure is defined as :

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}(r_{it} - r_t^{(w_t)})^2. \tag{3.3}$$

An equally-weighted CSV is denoted as follows:

$$CSV_t^{EW} = \frac{1}{N_t}\sum_{i=1}^{N_t}(r_{it} - r_t^{EW})^2, \tag{3.4}$$

where r_t^{EW} denotes the return of an equally-weighted portfolio and the corresponding to the weighting scheme $w_{it} = 1/N_t \quad \forall i, t$.

This assumption is important as it draws a formal relationship between the dynamics of cross-sectional dispersion of realised returns and the dynamics of idiosyncratic variance. The assumption in equation (3.3) is that the variance of the equally weighted cross-sectional volatility for a specific variance will disappear in the limit of an increasingly large number of stocks[2].

The CSV Index has a model-free nature, so there is no need to specify a particular factor model to compute it. For instance, the study by Garcia et al. (2014) explains the feature model is model-free and there is no need to obtain residuals from other models to compute this model. Also, the corresponding cross-sectional measure is readily computable at any frequency from observed returns.

Xu and Malkiel (2004) and Merton (1987) have assumed that idiosyncratic risk is positively correlated with expected stock returns in the cross-section. Idiosyncratic risk has little or no correlation with the market risk which may be eliminated from a portfolio by using sufficient diversification. As in Garcia et al. (2011), we simplify the situation by introducing into the two following assumptions:

1. Homogeneous beta assumption: $\beta_{it} = \beta_t, \forall i$.

2. Homogeneous residual variance assumption: $E(\epsilon_{it}^2) = \sigma_\epsilon^2(t), \forall i$.

The $E(\epsilon_{it}^2) = \sigma_\epsilon^2(t)$ represents the residual variances across stocks. In accordance with Garcia et al. (2011), as the number of constituents increases, the cross-sectional variance convergences to a specific limit. The results established a formal link between the CSV

[2]The third proposition of the equally-weighted CSV in idiosyncratic variance context, is proved to appear a consistent and asymptotically efficient estimator based on the study of Garcia et al. (2011).

Index and idiosyncratic variance and it will show the assumptions of homogeneous beta and residual variance across stocks. In other words, by assumptions, we have

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}(r_{it} - {r_t}^{(w_t)})^2 \xrightarrow[N_t \to \infty]{} \sigma_\epsilon^2(t) \tag{3.5}$$

where N_t is the number of increasing constituents of the stock index market for a given date t, $r_t^{(w_t)}$ is the weighted return with weights w_{it} at time t and $CSV_t^{(w_t)}$ is the cross-sectional variance. For readers attention, the asymptotic result holds for any weighting scheme that satisfies $0 < w_{it} < 1 \ \forall i, t$.

Consequently, this gives a formal relationship between the cross-sectional dispersion and the idiosyncratic variance. Garcia et al. (2011) conclude that the equally-weighted CSV resulted the best among all-positively-weighted estimators. To analyze the variance of the CSV estimator, without allowing negative weight scheme, the assumption of homogeneous beta, $\beta_{it} = \beta = 1$ for all i, t needs to be maintained. The following equation shows the equally-weighted $CSV_t^{(EW)}$ as the best estimator for idiosyncratic variance within the class of CSV estimators under a positive-weighting scheme:

$$E[CSV_t^{(w_t)}] = \sigma_\epsilon^2(t)\left(1 - \sum_{i=1}^{N_t} w_{it}^2\right) \tag{3.6}$$

$$Var[CSV_t^{(w_t)}] = 2\sigma_\epsilon^2(t)\left(\left(\sum_{i=1}^{N_t} w_{it}^2\right)^2 + \sum_{i=1}^{N_t} w_{it}^2 - 2\sum_{i=1}^{N_t} w_{it}^3\right). \tag{3.7}$$

The CSV is a biased estimator of the idiosyncratic variance. The bias estimator is given by the multiplicative factor $\left(1 - \sum_{i=1}^{N_t} w_{it}^2\right)$ which can be corrected since it is available in explicit form. This equally-weighted $CSV_t^{(w_t)}$ is among the best estimators when it is composed of positively-weighting estimators. It has been shown that the bias and variance of $CSV_t^{(w_t)}$ is minimal for an equally-weighted (EW), corresponding to $w_{it} = \frac{1}{N_t}$ of every date t. So, when the number of stocks grow large, this bias disappears and the variance tends to be zero for the EW scheme. However, the asymptotic result that holds for any weighting scheme has improved to a finite number of constituents N_t. It is explained in the following proposition. The equally-weighted scheme are written as

$$E[CSV_t^{EW}] = \sigma_\epsilon^2(t)\left(1 - \frac{1}{N_t}\right) \xrightarrow[N_t \to \infty]{} \sigma_\epsilon^2(t) \tag{3.8}$$

$$Var[CSV_t^{EW}] = 2\sigma_{\epsilon_t}^2\left(\frac{N_t - 1}{N_t^2}\right) \xrightarrow[N_t \to \infty]{} 0. \tag{3.9}$$

Normally average idiosyncratic variance will be used to calculate the beta of each stock portfolio where beta is the co-movement of an asset within the market[3]. Hence, we can evaluate the market risk of a portfolio and the market variance. However, by adopting the CSV, it gives two advantages. The first advantage is that we can directly compute from the observed returns excluding beta as the parameters at any frequency. The second advantage is that the model is a nature-free model as we do not need to specify a particular model in order to compute it.

Even when larger number of stocks are computed, the bias may still be small as CSV appears to be a biased estimator for average specific variance especially when the homogenous beta does not apply. Empirically, it was shown by Garcia et al. (2011) that the value of the median from a sample period between July 1963 and December 2006 is small. As discussed in Goltz et al. (2011), the assumption of homogeneous residual variances and homogeneous beta is as follows:

$$E[CSV_t^{EW}] = \left(\frac{1}{N_t} \sum_{i=1}^{N_t} \sigma^2_{\epsilon i}(t) \right) \left(1 - \frac{1}{N_t} \right). \tag{3.10}$$

After a straightforward simplification of the homogeneous beta assumption, for $\beta_{it} = \beta_t$, we may write equation (3.10) as:

$$E[CSV_t^{EW}] = \left(\frac{1}{N_t} \sum_{i=1}^{N_t} \sigma^2_{\epsilon i}(t) \right) \left(1 - \frac{1}{N_t} \right) + F_t^2 CSV_t^{\beta} \tag{3.11}$$

where

$$CSV_t^{\beta} = \frac{1}{N_t} \sum_{i=1}^{N_t} \left(\beta_{it} - \frac{1}{N_t} \sum_{i=1}^{N_t} \beta_{it} \right)^2 \tag{3.12}$$

So the expected return is computed as an unbiased estimator which is the Cross-sectional Volatility index as follows:

$$CSV_t^{EW} = \sqrt{\frac{\sum_{i=1}^{N_t} (r_{it} - \bar{r}_t^{EW})^2}{N_t - 1}} \tag{3.13}$$

where $\bar{r}_t^{EW}$ represents the return of equally-weighted stocks at date t and N_t is the number of constituents in each of the stock markets.

3.2.1 GARCH Volatility Measures

The GARCH model in its simplest form, proves that conditional variances can be estimated easily while giving parsimonious models than the ARCH model. The feature of GARCH

[3] Average idiosyncratic variance is an average measure as observed, which can be obtained by averaging across assets such as individual idiosyncratic variance estimates.

explains a great predictive power with minimum number of parameters. It is widely employed by many researchers to predict variance using GARCH specification asserts in the next period. A study by Su (2010) estimates financial volatility of daily returns extracted in the Chinese stock market. GARCH and E-GARCH have been employed to fit the sample of the data and it is suggested that E-GARCH fits better than the GARCH model. GARCH has also been a model used to forecast the volatility of the Shanghai and Shenzen composite stock indices. The study examined how specifications of return distribution influence the forecast performance, see Liu et al. (2009). When forecasting the volatility performance of the VIX and Cross-sectional Volatility index, we use the GARCH (p,q) by computing;

$$Z_t = h_t e_t, \{e_t\} \sim IID(0,1) \tag{3.14}$$

where Z_t is the mean adjusted return series and h_t is the conditional variance. However in a different model of h_t which is written as of in equation (2.16) and we shall consider the GARCH(1,1) as written in Chapter 2 at equation (2.17).

The GARCH model only resulted best on symmetric in modeling volatility. The GARCH model improves the ARCH model by including the asymmetric feature of stock market volatility. We consider the future prediction of the study by forecasting the volatility using the GARCH model.

We have chosen the E-GARCH because it is an extension to the GARCH model which allows us to observe the a symmetric effects of positive and negative asset returns, see Brandt and Jones (2006) for further illustration. Since GARCH is the most popular measure of volatility among the researchers, we shall examine our data using the GARCH model. However, there are two limitations that makes the GARCH and E-GARCH different. The limitation of the model assumes that only the magnitude of unanticipated excess returns that determines $log(h_t^2)$. Another limitation is the persistence of volatility shock. The E-GARCH model is specified as:

$$\log(h_t^2) = \alpha_0 + \sum_{i=1}^{p} [\alpha_i Z_{t-i} + \gamma_i(|Z_{t-i}| - E(|Z_{t-i}|))] + \sum_{j=1}^{q} \beta_j \log(h_{t-j}^2). \tag{3.15}$$

where γ_i is the leverage effect,α_0 and β_j are the non-negative parameters. The presence of γ_i indicates an asymmetric effect of shocks on volatility and the positive value of this parameter implies the presence of leverage effect. Using this model, we can expect a better estimate of the volatility for asset returns due to how the E-GARCH counteracts the limitations on the classic GARCH model, see Engle and Patton (2001).

3.2.2 Forecasting Volatility Measures

Both forecasting GARCH and E-GARCH model has been discussed in Chapter 2. The reason to forecast is to predict the CSV index and the VIX as well as to measure the errors occurs. To determine the efficiency of the Cross-sectional Volatility index (CSV) approach, a forecast of both VIX and the CSV indexes have been generated to estimate the volatility errors. We have used the finite sample scale-sensitive performance criteria which is the root mean square error (RMSE), the mean absolute error (MAE) and the Theil Inequality Coefficient (U_2). The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2} \tag{3.16}$$

where $\hat{\sigma}_t^2$ is the forecasted volatility of the CSV index and the VIX at time t, and σ_t is the actual volatility of the CSV index and the VIX at time t and T is the sample size. The MAE is dependent on the scale of the dependent variable but is less sensitive to large deviations than the usual squared loss defined as

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2 - {\sigma_t}^2\right|. \tag{3.17}$$

The benchmark forecast value of the last observations appears to be the Theil Inequality Coefficient, U_2 which is the earliest relative forecast accuracy measure. It is scale invariant and lies between zero and one. However, if the Theil Inequality Coefficient is equal to zero, then it is a perfect fit. We have

$$U_2 = \frac{\sum_{t=1}^{T}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2}{\sum_{t=1}^{T}\left(\sigma_{t-1}^2 - \sigma_t^2\right)^2} \tag{3.18}$$

where $\hat{\sigma}_t^2$ is the forecasted volatility of the CSV Index and the VIX at time t, σ_t is the actual volatility of of the CSV index and the VIX at time t and T is the sample size.

3.3 Data and the Construction of Volatility and Control Variables

We employ all stocks included in the S&P 500 and Nikkei-225 index during the period from October 2004 to September 2014 [4]. This period of this data can only retrieved at this range due to limited index data from the VXJ. The VXJ is a new model based on

[4]Daily stock return, stock price and shares outstanding data through this period are obtained from DataStream.

the new VIX methodology developed by Fukasawa et al. (2011) as a model-free index of market volatility implicit in the bid and ask prices of Nikkei-225 options traded at the Osaka Securities Exchange. So, we obtain the daily time series of the CBOE VIX and Japanese VXJ obtained from Bloomberg database for the same period as the stock index. We use the daily returns to estimate the idiosyncratic volatility following the approach of Cross-sectional Volatility index as a proxy for the classic VIX index. Table 3.1 shows the descriptive statistics on the volatility index measures.

Table 3.1: Descriptive Statistics On Volatility Return Index Measures Sample Period (2004-2014)

Measure	CBOE VIX	S&P 500 CSV	VXJ	Nikkei-225 CSV
Mean	0.0023	0.0258	0.0021	0.0209
Median	-0.0052	-0.0015	-0.0038	-0.0063
Maximum	0.6421	1.6997	0.7826	4.3323
Minimum	-0.2957	-0.5779	-0.3089	-0.5502
Std.Deviation	0.0705	0.2412	0.0670	0.2257
Skewness	0.6862	0.1750	1.5262	0.3392
Kurtosis	7.2681	3.7917	14.8883	5.7385
Jarque-Bera	5584.2981	2208.9521	58242.1700	323686.1000
Observation	2429	2429	2519	2519

Table 3.1 presents the sample size, unconditional mean, unconditional variance, skewness, excess kurtosis and the Jarque-Bera test-statistic. The CBOE VIX and the CSV Index have a small mean value. It reflects on the average of the volatility return for both models. From the standard deviation, it shows that the daily volatility is more volatile in Cross-Sectional Volatility Index compared to the CBOE VIX. The returns have a small skewness and a high kurtosis. The highest kurtosis is the return index of Nikkei-225 using CSV Index model which is 14.88. High peak often shows that the distribution has fatter tails where Nikkei-225 return index may have probability of extreme outcomes compared to other return index.

Table 3.2 reports the descriptive statistics of the volatility index for both US and Japanese markets. Firstly, the oft-noted tendency of implied volatility to over-estimate actual volatility is reflected in that the mean implied volatility is 19.97% while the annualised standard deviation of the CSV S&P 500 index is 13.1% as calculated from the daily returns. Secondly, the volatility index for both implied volatility and the cross-sectional volatility are positively serially correlated and the level of the index in the best of range (less than 30% per annual). Thirdly, the VXJ is more volatile than the CSV Nikkei-225 with an annualised standard deviation of daily log percentage changes of 10.91%. Both of the implied and cross-sectional volatility index are highly positively correlated with correlations of 0.63 and 0.77.

Table 3.2: Descriptive Statistics of Implied Volatility Index and Cross-Sectional Volatility Index

Series	Mean	Standard Deviation	Correlation between CSV and VIX	Daily Returns (annualized)
CSV NIKKEI 225 index-levels	26.72	9.79	0.6293	2429
VXJ levels	25.28	10.91	0.6293	2429
CSV S&P 500 index-levels	26.25	13.01	0.7693	2519
VIX levels	19.97	9.99	0.7693	2519

Table 3.3: Correlation Matrix Analysis of Volatility Return Index

Correlation	CBOE VIX	S&P 500 CSV	VXJ	NIKKEI-225 CSV
CBOE VIX	1	0.7662	0.5203	0.3607
S&P 500 CSV		1	0.53	0.4016
VXJ			1	0.6294
NIKKEI-225 CSV				1

Table 3.3 indicates that the CBOE VIX index approach model has a strong positive correlation with the Cross-sectional Volatility index model of S&P 500. This is also the same for Nikkei-225 which has high correlations between the VXJ and NIKKEI-225 CSV Index approaches. Here, it indicates that the CSV Index may have a potential proxy for VIX index essentially on non-derivatives market. This is because it shows a high correlation between the CBOE VIX and the new form of volatility index approach, the CSV Index.

We extract daily components of S&P 500 and Nikkei-225 price returns to construct a Cross-sectional Volatility Index to measure the idiosyncratic risk. The sample period is from October 2004 to September 2014. The number of firms from each components varies between 300 to 500. Illiquid stocks have been filtered out from the data using the

Principle Component Analysis (PCA). There are a few constituent stock returns from S&P 500 and Nikkei-225 that have been removed. The outliers of the removed stocks are the stocks that have extreme return movements throughout the time period. Iliquid stocks that are identified as stocks with stale prices[5], for instance indicating zero returns over a given day, high first-order autocorrelation as well as abnormal values for other common liquidity measures including trading volume. The new construction of volatility index will perform a greater robustness of the constructed risk measure. We have generated a sample from the period ranging from October 2004 to September 2014 in Table 3.3 and the results generated are quite consistent and the volatility returns index are highly correlated.

There are formal tests to examine whether the CSV Index approach produces significant results to proxy the CBOE VIX. This is achieved by using the GARCH-type model to determine first whether the CSV Index is indeed a good predictor of volatility. Also, we can see whether the CSV Index is a better predictor than the alternative measures of volatility. It predicts the period's variance by looking at the weighted average of the long term historical variance. It gives parsimonious models that are easy to estimate, even in its simplest form; this has proven surprisingly successful when predicting conditional variances. The data employed for the forecast performance measure is the CSV and the VIX daily index for the US and Japanese markets. The data is divided into two subsets. The first subset is called the in-sample data set and is built up model for the underlying data and the second subset is called the out-sample data set used to investigate the performance of volatility forecasting. The in-sample data set analysis starts from 2004 to 2013 and out-sample data set is from 2013 to 2014. Here we evaluate the forecast performance with 2430 US data observations and 2519 Japanese data observations. We forecast the performance of volatility using a GARCH and E-GARCH model.

3.4 Empirical Analysis

3.4.1 The Behaviour of the Market Volatility Index

We examine the daily CBOE VIX index for sample periods running from 4th October 2004 to 3rd October 2014. The total daily observations are 2519. Figure 3.1 plots the time series of the VIX during the particular sample period. It seems that the VIX tends to oscillate in long swings between a quite volatile regime with high index values and a more stable regime with low index values. According to Figure 3.1, high volatility characterises

[5] An old price of the asset that does not reflect the most recent information.

the periods ranging from September 2008 to May 2009. This is the year of the massive financial crash in the market and the inevitable financial chaos is consequently reflected in the VIX. The collapse of Lehman would also be the main reason for the high volatility in the VIX in 2008 and the subsequent credit crunch and global financial crisis. In contrast, low volatility seems dominant from October 2004 to August 2008 and from June 2009 to October 2014. It is consistent with the claim in Whaley (2000), that one may interpret the VIX as the investors' fear gauge.

Figure 3.1 shows a high correlation of 0.77 between the CBOE VIX and the S&P 500 CSV index based on the correlation test in Table 3.3. The sample period runs between 4th October 2004 to 3rd October 2014. It suggests the average idiosyncratic volatility counterpart is close to the option implied volatility because the two models exhibit close gap between them and it shows strong relationship. The closer the gap of the volatility of each model, the closer the relationship. It seems that a high correlation exists in the return index due to the condition of market changes, with a correlation that tends to be higher in down markets. The pattern of the volatility using the VIX approach is almost the same where the spikes move together.

Figure 3.1 also demonstrates the volatility of S&P 500 using the second approach; the Cross-Sectional Volatility Index (CSV). The volatility fluctuates decidedly when it reaches the same period with the CBOE VIX and the trend of the volatility seems to move together. The CSV Index value reaches the peak at 123.1017 in November 2008 whereas the CBOE VIX has an index value of 64.7. Then both measures simultaneously continue to display high volatility. When these readings are high in the VIX or CSV index, the mark periods on higher stock market volatility tend to move in same direction with the stock market bottom[6]. Figure 3.2 shows the VXJ and the CSV of Nikkei-225 volatility movement and the correlation is also high and positive with the value of 0.62. Both models exhibit the movement of volatility and it results that they coordinately move together with the average dispersion at 15.80. The volatility index of cross-sectional method has a lower index compared to the Japanese VXJ. We confirm this intuition by reporting the high correlation between the VIX index and the corresponding CSV index based on the S&P 500 and Nikkei-225 universe. The correlation test is an important measure of unsystematic risk based option prices and the CSV index which is a model-free, efficient and unbiased proxy for specific risk. Cross-sectional Volatility Index in Japan is an alternative to measure risk in an Asian markets, the volatility of the index is more

[6]Stock market bottom is when at early stages of an upward trend, stock falls to its lower point. It has always been an opportunity for investors to purchase a stock when the security is underpriced.

certain and stable compared to the Japanese VIX initiated by the CBOE VIX in the United States. We could see that there is a sharp increase of the index value in the CBOE VXJ between July 2008 to October 2008 in the figure. Although low volatility is still consistent through out the time period after a slight period of high spikes averaging an index value of 25.28, albeit still under the value index 30. According to the white paper of CBOE, generally, a VIX value above 30 is an indication of high uncertainty and fear in the market. Figure 3.2 illustrates the volatility of Nikkei-225 using CSV approach. It shows a stable index value and the index value runs along together smoothly with the Japanese VXJ approach. It seems that both figures show a sharp drastic correlation downwards and an upward trend in the years 2007, 2008 and 2010. It shows the significant relationship between the CBOE VIX and the CSV Index approach.

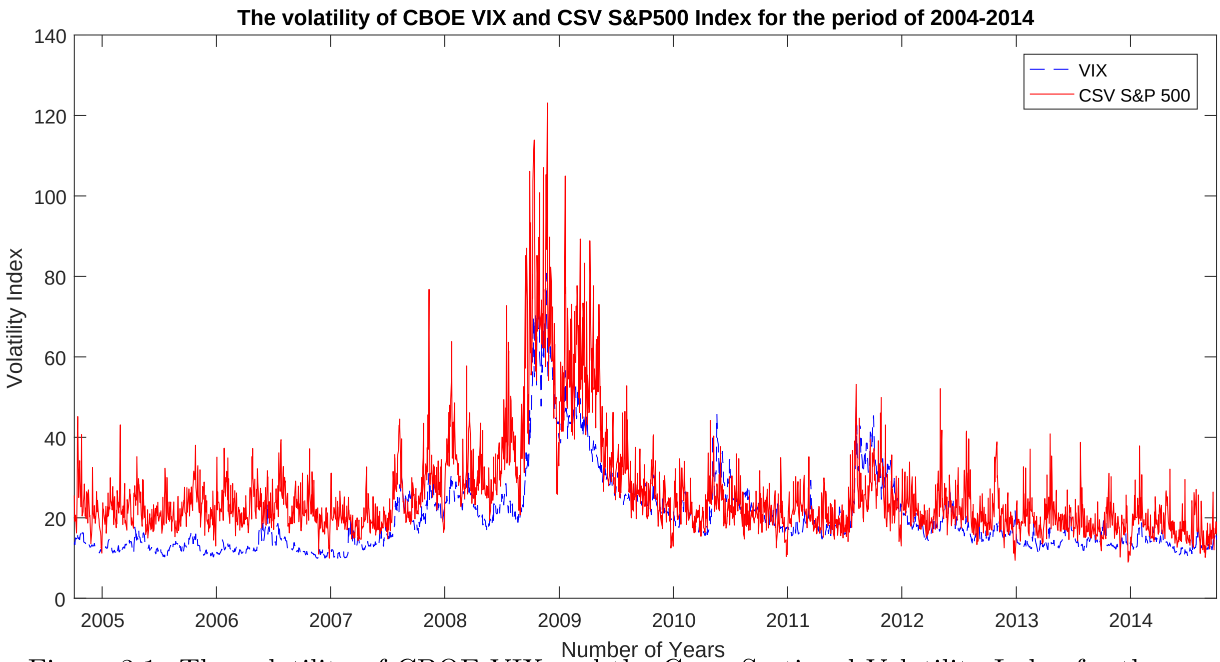


Figure 3.1: The volatility of CBOE VIX and the Cross-Sectional Volatility Index for the sample period of 2004-2014

We have also run an analysis of a 252-day rolling window correlation from 2004 to 2014 to provide a further co-movement check between the the VIX and the Cross-sectional Volatility Index for both markets in the US and Japan. The results suggest that the correlation of the two returns series fluctuates and are inconsistent within the sample period. Figure 3.3 and Figure 3.4 show the 252-day rolling window correlation. The bigger the size of the window, the more certain and stable the correlation will be. However, Figure 3.3 illustrates the rolling window correlation between the CBOE VIX and CSV Index. The volatile correlation surged during the financial crisis. There is a similar trend between

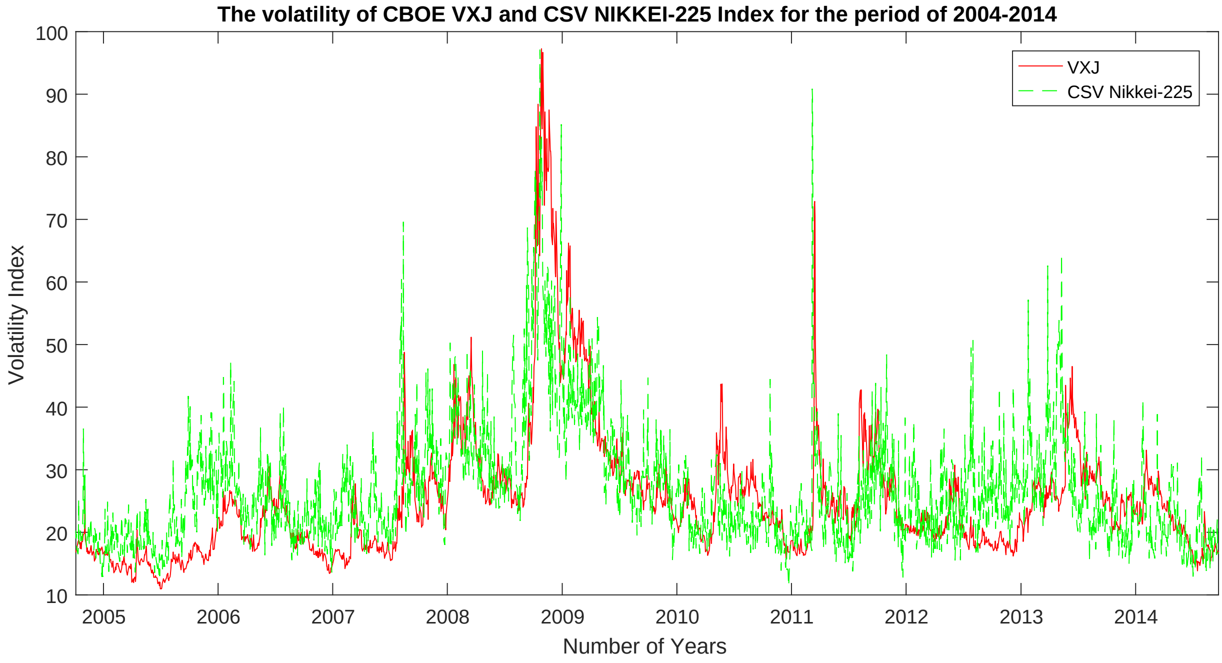


Figure 3.2: The volatility between the Japan CBOE VIX and the Nikkei 225 Cross-Sectional Volatility Index for the sample period of 2004-2014

Figure 3.3 and Figure 3.4 when comparing the rolling correlation's standard deviation amongst each other.

Table 3.4 describes the estimate of conditional volatility measures for the GARCH and E-GARCH of the CBOE VIX and CSV index approaches for both markets namely in the US and Japanese. We model the conditional volatility as a GARCH(1,1) process. The specification would show a parsimonious representation of conditional variance that adequately fits many high-frequency time series. The GARCH and E-GARCH models represent the estimation for the return series of 500 stocks in the US and 225 stocks in Japan. From the observations, the size of the parameters α and β determine the short-run dynamics of the resulting volatility time series. Most of the parameter estimates in Table 3.3 are statistically significant at a 5% level. The GARCH results indicate the persistence in volatility with α and β ranging from 0.72 to 0.93 which is closer to 1.00. This suggests a stronger presence of ARCH and GARCH effects towards the CSV S&P 500, Japanese VXJ and CSV Nikkei-225. The E-GARCH is applied to examine the asymmetric effects of volatility and coefficients of the asymmetric effect. The parameter γ shows the leverage effects and from the observation, the effects are mostly positive at a significance level of 5%.

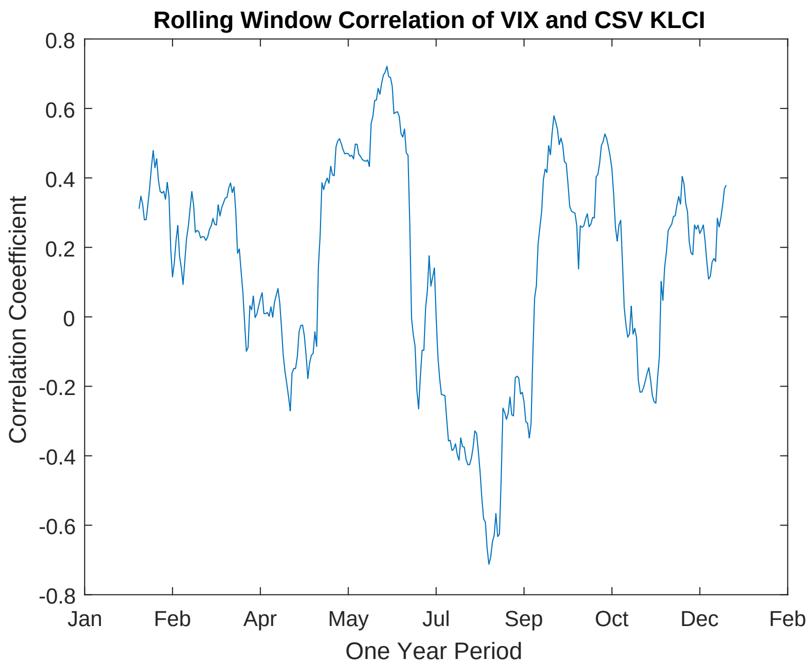


Figure 3.3: 252-Days Rolling Window Correlation of VIX and CSV S&P 500 between 2014 to 2015.

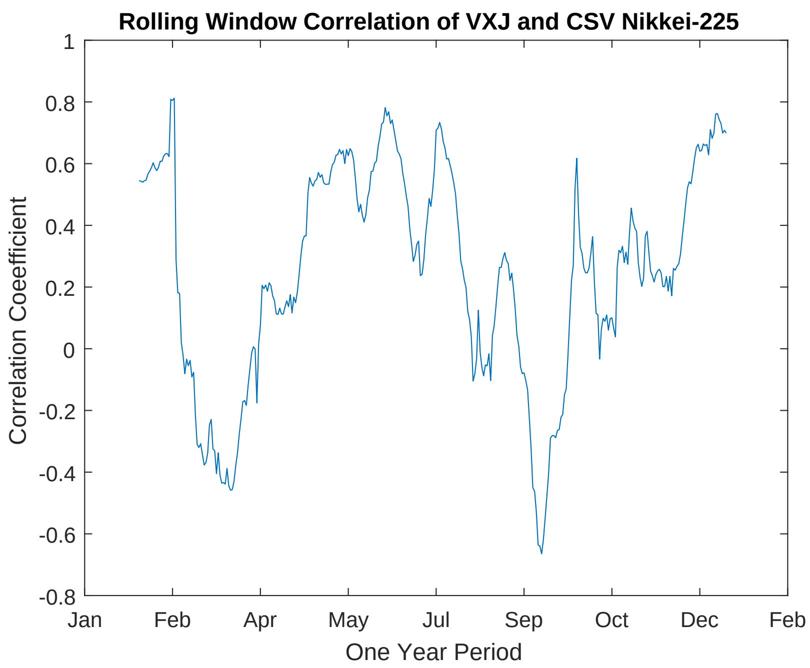


Figure 3.4: 252-Days Rolling Window Correlation of VXJ and CSV Nikkei-225 between 2014 to 2015.

Table 3.5 provides results of forecast error statistics for each model according to symmetric error measures of the two stock markets: S&P 500 and Nikkei-225. Results of the RMSE and MAE criteria suggest that GARCH is the best performing and prediction

Table 3.4: The Estimation of Conditional Volatility Meaures of GARCH/E-GARCH

	GARCH(1,1)				E-GARCH(1,1)			
	CBOE VIX	CSV S&P500	Japan VXJ	CSV Nikkei-225	CBOE VIX	CSV S&P500	Japan VXJ	CSV Nikkei-225
Constant	0.0060**	0.0083**	0.0003**	0.0095**	-0.3334**	-0.6771**	-0.4964**	-1.0700**
α	-0.4710	0.06501**	0.1465**	0.0920**	0.0625**	0.1330**	0.1258**	0.1829**
β	0.7293**	0.7432**	0.7870**	0.6298**	0.1784**	0.03060	0.2031**	0.03312
γ	-	-	-	-	0.9467**	0.8181**	0.9281**	0.7259**
** is statistically significant level of 0.05								

Table 3.5: The Volatility Forecast Error with Different Approach of GARCH Model

	GARCH(1,1)				E-GARCH(1,1)			
	CBOE VIX	CSV S&P500	Japan VXJ	CSV Nikkei-225	CBOE VIX	CSV S&P500	Japan VXJ	CSV Nikkei-225
Root Mean Square Error(RMSE)	0.0872	0.1693	0.0714	0.1600	0.1005	0.1689	0.0714	0.1602
Mean Absolute Error	0.0723	0.1410	0.0409	0.1322	0.0780	0.1406	0.0415	0.1323
Theil Inequality Coefficient	0.5958	0.6553	0.9178	0.6621	0.9676	0.6551	0.9296	0.6613
Bias Proportion	0.0000	0.0425	0.0006	0.0038	0.0313	0.0374	0.0008	0.0056
Variance Proportion	0.4563	0.4611	0.8522	0.3722	0.9586	0.4655	0.8822	0.3689
Covariance Proportion	0.5437	0.4694	0.1472	0.6241	0.0101	0.4970	0.1170	0.6255

model compared to E-GARCH for the CBOE VIX and VXJ. On the other hand, the E-GARCH provides the worst forecast for the Nikkei-225 and S&P 500 CSV index. However, considering the Theil Inequality Coefficient criteria, it seems that the CSV index for both S&P 500 and Nikkei-225 perform better in E-GARCH. The forecast error statistics are employed to compare the performance of VIX and the CSV index approaches. The use of RMSE is to help provide a complete picture of the error distribution when forecasting the volatility of the VIX and CSV index. The RMSE and the Mean Absolute Error(MAE) are very small when using the CSV Index and the VIX approach methods, see 3.5. The smaller the values of MAE and RMSE , the more accurate, on average, the forecast of the model. The smaller the value of the U-Theil, the better the model performs compared to a naive forecast with no change. Therefore, the most accurate forecast is based on the Mean Absolute Error criteria for the two models which are the GARCH and E-GARCH. This reflects on whether the CSV index approach could possibly a proxy of the CBOE VIX approach.

Figures 3.5 to 3.8 show the performance of volatility forecasts of the VIX and CSV for both the US and Japanese markets based on the GARCH and E-GARCH volatility model. The red legend shows the actual CSV volatility whereas the blue legend describes the

GARCH or E-GARCH prediction volatility. The observations from the figures are made using the sample prediction from 3rd September 2014 until 3rd October 2014. The actuals and predictions for each of the VIX and CSV volatility approaches are quite persistent and may have a significant influence on volatility. As to compare the two methods of GARCH and E-GARCH volatility model, it appears that the GARCH has a better forecast for a volatility model for both the CSV and VIX models as these may be seen from the size of the gap.

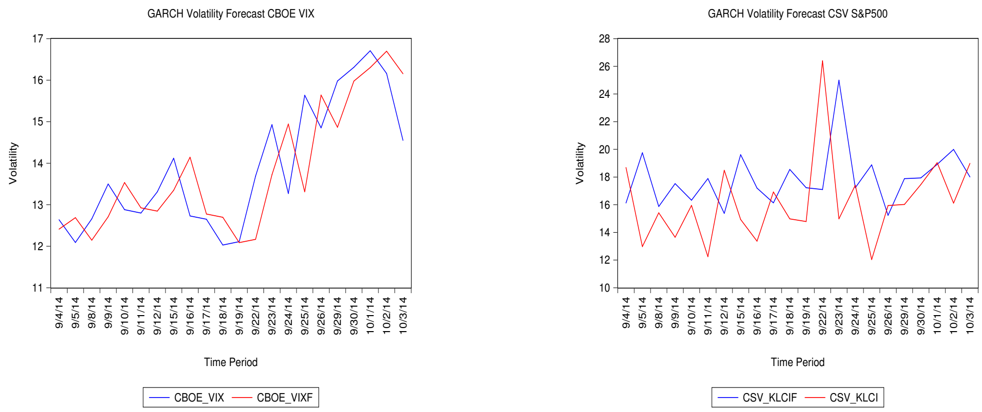


Figure 3.5: Volatility forecast of VIX and Cross-Sectional Volatility Index(CSV) using GARCH in US market

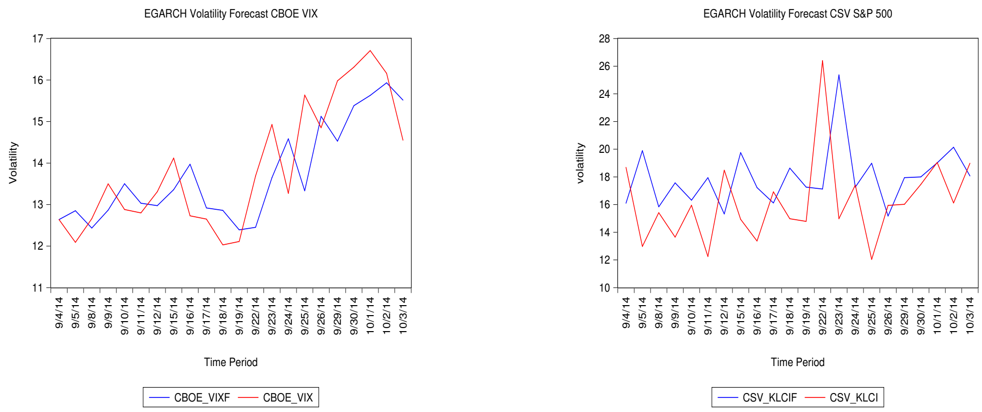


Figure 3.6: Volatility forecast of VIX and Cross-Sectional Volatility Index(CSV) using EGARCH in the US market

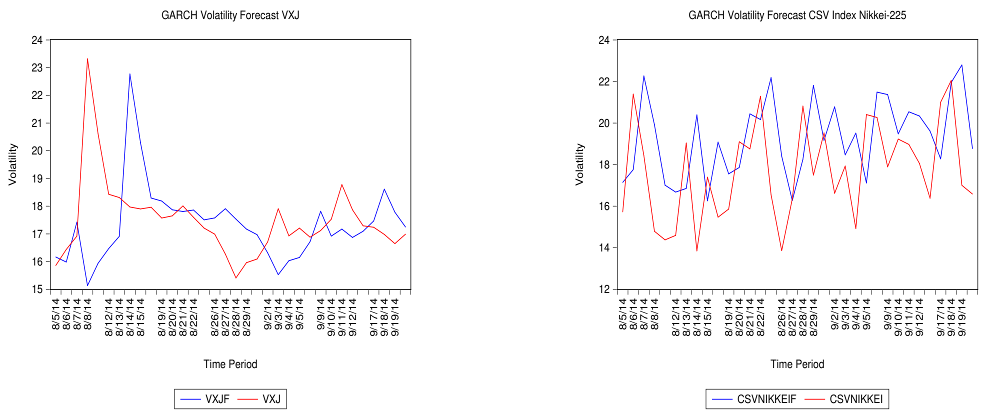


Figure 3.7: Volatility forecast of VXJ and Cross-Sectional Volatility Index(CSV) using GARCH in the Japanese market

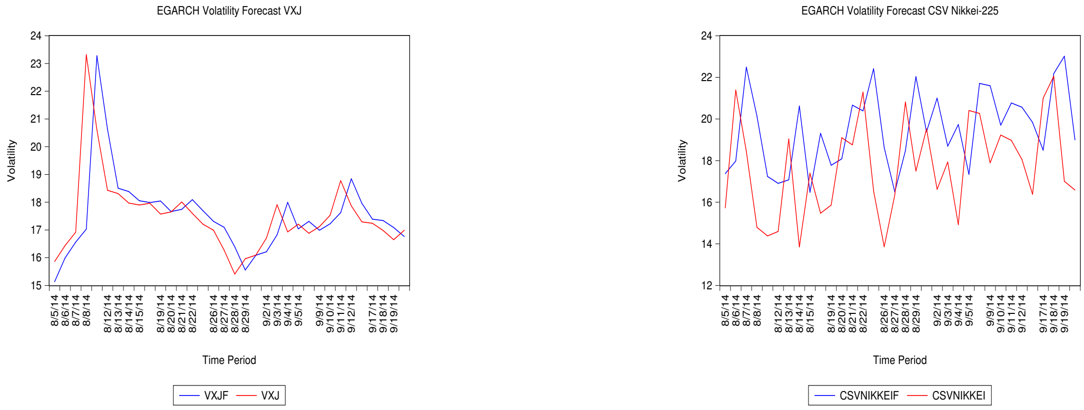


Figure 3.8: Volatility forecast of VXJ and Cross-Sectional Volatility Index(CSV) using E-GARCH in the Japanese market

3.5 Conclusion

In this study, we proposed the cross-sectional volatility index model to be applied in one of the Asian market, namely the Japanese market. This is obtained by finding consistent estimation of parameters in financial market model using a single cross-section of return data. The analysis of the relationship between the returns and the underlying assets and the volatility is aligned using the cross-sectional volatility and CBOE VIX index methodology. There are advantages on the used of cross-sectional volatility index method due to its model-free nature; also, this model may fit to any region, sector and style of the world equity market at any frequency. The model is independent and there is no need to resort to any auxiliary option market. Generally, the systematic and average specific volatility indicators are highly correlated since both reflect the aggregate uncertainty encountered by investors, financial institution and practitioner.

This thesis suggests that the cross-sectional volatility index is approachable in the Japanese market. To the best of our knowledge, this approach is the first to be examined in one of the Asian market. A small number of Asian countries have options market that would allow for the classic VIX approach to construct the volatility index measurement. So, based on our results, the Nikkei-225 CSV index is less volatile compared to the Japanese VXJ. The volatility index is dominantly low and consistent except during the uncertainty financial crisis. The main reason for constructing the CSV index is to allow the less derivative options market to measure the volatility index. It can be applied to markets that do not have an accompanying options component. We provide a statistical argument to support that an equally-weighted measure of average idiosyncratic variance would forecast market return and show that this measure displays a sizable correlation with economic uncertainty. From the results gained, there exist high correlation between the VIX index and the cross-sectional volatility index, possibly a model-free efficient and unbiased proxy for specific risk for Asian market. We have estimated measures of a cross-sectional rolling window of correlation in order to see the pattern of correlation between the CBOE VIX and CSV Index within the period of 252 days. The correlation moves the same direction between the US market and Japan market although it might not be consistent over time due to factors of changes in financial market conditions. Our results demonstrate a statiscally significant positive conditional volatility estimated using the GARCH and E-GARCH models. It is found that the CSV approach is also a good predictor of as that of the CBOE VIX model when estimating the idiosyncratics volatility. As a good volatility index model, the model should be able to forecast volatility, Engle and Patton (2001).

Chapter 4

The Prediction Performance of Cross-Sectional Volatility Index Model in Non-derivatives Asian Market.

4.1 Introduction

The effects of volatility of financial markets are unpredictable, and many researchers adopt many types of volatility model to reach an optimal prediction. Many of the researchers have conducted historical volatility, time series volatility and implied volatility models as to predict instability of financial markets but consensus has not yet been reached. In an unpredictable situation, achieving the least prediction error in a volatility model is one of an appropriate way to get a better forecast. A volatile market creates nervousness among the market participants, and fearful investors demand more hedge funds to protect their market positions in the short term. When there is a pressure demand on buying and selling options, the option seller will be responsible for higher premium. Moreover, when markets experience a spike in the volatility, option holders have more alternative in the short term for new strikes. These market conditions also provide potential profit from the fearful investors. More particularly, worries about the future state of the stock market reflect through volatility index. The volatility index, VIX or the VIX-styled index is constructed based on the pricing of derivative securities such as stock options and options on indices. So, naturally the market that applies the VIX and the VIX-styled index is attainable within the rapid growing derivatives market.

However, most markets in Asia do not have a derivative market. The Asia market depends on the power of investors to explore and invest in the derivatives market. Shamsher and Taufiq (2007) states that derivatives markets have only been introduced in 19 markets in Asia. Introducing the derivative demand in a market with spot trading completes the market-based price discovery process. Although, their study specific meager costs, the markets that have developed viable financial derivative markets during the post-1980s are Hong Kong, Japan, Korea and Singapore. However, emerging markets such as India, Malaysia and Thailand have also organized, in the 1990s, fast-developing financial derivative markets for interest rates, currency, futures and options however they are not entirely developed. There is no volume of trading in derivatives in these countries which shows that investors are not interested in derivatives. This is when the contribution of this study arises. As for instance, Ahmad and Haris (2012) proved that the use of derivatives among Malaysians companies are not as common as those in other developed countries due to lack of exposures on derivatives as well as derivatives are considered to be costly and complex products. Fratzscher (2006) mentioned that the market infrastructure and investor interest had been slightly developed, meaning that the trading volumes have remained low in Indonesia, Philippines, and Thailand.

The well-known benchmark indicator is the implied volatility index (VIX), mentioned earlier in the previous chapter, is currently expanding in the U.S market which is a leading indicator for measuring and predicting the performance of volatility index. The VIX model is proven to provide more comprehensive information and the trading guidance to investors through observing the changes in the future volatility of the stock market by monitoring the VIX index. However, as is indicated in the first case study, the VIX can only be applicable when accurate figures of current prices of S&P 500 index options are available as to reflect investors' expectations regarding the stock market volatility over the next 30 days. Whaley (2009) also stated that the VIX could only be implied in markets that comply with derivative options. The volatility index has attracted researchers and financial investors, and the Asian market is also able to expand their volatility measuring and prediction for better performance of stock market. According to the study of Yang and Liu (2012), the researchers came to compare the predictive performance of the historical volatility, implied volatility, the volatility index of Taiwan(TVIX), using GARCH volatility forecasts, regarding the future stock prices movement in Taiwan. From the results, the predictive power of the TVIX is relatively close to the implied volatility, irrespective of the models adopted. Apart from this, Aboura and Chevallier (2015a) also proposed a new empirical methodology for computing a cross-volatility index, coined CVIX, that characterizes the country risk understood as the financial market risk measurement. This method reveals that the CVIX is a better hedging performance than the VIX used as a benchmark. The unique of the CVIX is that it is representative index of global sources of risk which also compute the VIX as one of a source of risk to develop the CVIX. It leads to a motivation to the study by constructing the non-VIX styled index for this non-derivatives market in Asian. During fiscal stress periods, the VIX is no longer sufficient from a cross-asset perspective since it covers only U.S stocks but not other assets classes.

This research study is expanding the use of Cross-sectional Volatility (CSV) index from the previous chapter in non-derivatives market with a focus on the Asian market. Previously, Md Fadzil et al. (2017) has compared the CSV index with the implied volatility to measure the forecasting performance between the two approaches to two developed market. These developed markets was selected because both of these have applied the VIX and the VIX-styled approach model. A comparison has been carried out and the results show that the performance has a positive relationship with each other. So, to further this study, we propose to examine the CSV index model to the real non-derivatives market specifically on Asian non-derivatives market.

The Cross-sectional volatility (CSV) Index is an alternate approach that may possible to accomplish the value markets' co-movement and global risk estimation. Some implied volatility index approach experiences some drawbacks. One shortcoming is that the approach needs a local liquid derivative market. As stated to Goltz et al. (2011) the implied volatility index is constructed using the auxiliary option markets rather than the actual stock index returns. The options markets are likely to disrupt the volatility evaluation, hosting a minimal effect on the underlying stock or stock index returns. The CSV Index is a recent contemporary form of measure related to instability, see Goltz et al. (2011) for details. This new structure relies on observable and model-free volatility estimation at all data and recurrence. This new form of the index provides a good approximation of average idiosyncratic variance. The technical foundations of the new structure indices have been defined by Garcia et al. (2011). The results of the new form of volatility index can be used as a reliable proxy when such measures of volatility are not available. It has been a trend using the approach of idiosyncratic volatility for benefits of diversification. For instance, see Nartea et al. (2011), Campbell et al. (2001). Idiosyncratic volatility has also been the main focus among many researchers.

The primary purpose of this part of the thesis is to predict the volatility index of

Cross-Sectional Volatility Index (CSV) Index approach in the Asian markets that have no derivatives option prices. This method is proposed due to lack of option prices needed to compute the current implied volatility models or other related implied volatility prediction models. We shall predict the CSV Index using a few types of prediction model mainly based on time series. We are currently unable to compute the option prices due to lack of derivatives and little information of choices in the Southeast Asian market. We shall compare the prediction performance between all the of the GARCH models and observe the best predictive power. This study is to fill in the gaps that support and contributes the CSV Index is a reasonable alternative model to proxy the VIX index that is well-established in the U.S market.

4.1.1 Outline

The remainder of this chapter is organized as follows. Section 4.2 gives an account of previous work. Section 4.3 describes the methodology and research model, the distributions of error in GARCH models, HAR-RV model and measurements used to evaluate forecast performance. Our new and exciting results are described in Section 4.4. Finally, Section 4.5 gives the conclusions.

4.2 Background and Related Work

4.2.1 Previous literature

Derivatives topic has become an attraction among investors, researcher and policymaker. The common issue investigated by them is how the derivatives can impact the current global market. However, various markets show different results and some may contradict and quite controversial handling the derivatives issues. Many researchers have studied the effects of trading on the underlying market yet there are no conclusive results that exist while the growth of derivatives trading continued. Derivatives can be applied when there is a significant quantity of assets are traded, and this is called liquidity. Liquidity is an important factor because it can show and explain stock's return and time of aggregate returns, see Amihud et al. (2006) for instance. In the asset pricing principle, there are some methodology approaches that specify the connection of volatility, buying and selling options extent and liquidity.

In recent markets, the larger power of selling and buying of assets generates more significant liquidity in the market. Roşu (2009) mentioned that higher frequency of trading cuts down the amount of waiting time. Ultimately, the price effect is getting smaller which decreases the size of liquidity. For instance, to overview the relationship between the return and liquidity, Chordia et al. (2004) studied and examined the U.S stock market data from the year 1991 to the year 1998. It is shown that a significant positive relationship appears between them. Also, they found that the correlation between the liquidity and volatility was negative. Nonetheless, Gulen and Mayhew (1999) analyzed the effect of options and the underlying stock. The study concedes that highly volatile and larger trading volume and liquidity can benefit in determining the equity market competence. Chordia et al. (2001) estimated the liquidity and its competence of the financial market. They examined how the stock market absorb the inequitable during distinct liquidity conditions. When the growth of liquids takes place, they also detect that the stock market absorbs order imbalance. Xu et al. (2006) reveals that volatility and volume relates to each other constantly. They also expose that shorter observation period has an impact on the volatility and liquidity.

The stock market volatility index is essential because most passive investors probably have money in funds that track an index. If the index is extensive and represents a lot of diversified stocks, then the volatility can be the measure of the systematic risks of stocks. The market risk or called the systematic risk is the risk that cannot be removed through diversification but however the market risk can be hedged. The sources of this market risk are large macroeconomic factors. Most of the market has its methodology depending on the liquidity of the stock market. However, not all methodologies rest on any option pricing model and uses a relatively wide range of implied volatility smile. Borse (2005) proposed a methodology that is suitable for illiquid stock markets, such as the Spanish option market on IBEX-35, versus the alternative of focusing on a narrow set of options, which may preclude calculation of the volatility index because of lack of trades.

After the Asian economic crisis in 1997, Lim et al. (2008) states that the financial crash skeptically disturb the efficiency of most Asian stock markets with Hong Kong the most robust hit, followed by Malaysia, Singapore, the Philippines, Thailand, and Korea. For instance, the volatility of Malaysian market, Omar and Halim (2015) conducted a study to investigate the behaviour of stock return volatility of FTSE Bursa Malaysia KLCI. The study applied the GARCH model and its extension to examine the sample of their data during the financial crisis arose in 2008 until 2009. The results show that GARCH(1,1) express the presence of volatility clustering and persistence effects of the equity market volatility.

Looking at the Thailand market, Chaigusin et al. (2008) discussed that the economic growth of Thailand, both international and domestic economies factors can affect stock prices. The factors used in the study is the financial risk, commodity, loan rate and exchange rate. It is due most of the market has a relationship between with each other and shall give impact on one stock another. Some factors affect the Thai stock market because Thai stock market has unique characteristics. As for instance, the foreign stock index, the value of the Thai baht, oil prices, gold prices and many more, see Rimcharoen et al. (2005), Worasucheep (2007), Chaereonkithuttakorn (2005), Chotasiri (2004).

As for Indonesia, during the Asian financial crisis, Indonesia encountered a big slump from the Asian financial crisis towards the end of 2008. In the financial sector, the growth of its economy was still above 6 percent, a good performance. However, during the fourth quarter in 2008, the global financial turbulence started to bear down. The exports crashed down below target expectation followed by an impact on financial stability. It pressured the balance payment[1] and resulted in turmoil the money market as well. Indonesia Economic Report (Bank of Indonesia, 2008), the Indonesian Stock Market and Government Securities prices were plunged down sharply. This resulted in a widening of the risk spread.

4.2.2 Market information

4.2.2.1 Malaysia

In Malaysia, the stock trade and derivatives market is established through many stages. It is now called the Bursa Malaysia after demutualization in 2004. Initially, it was recognized as Kuala Lumpur stock exchange Berhad and integrated in 1976. There are subsidiaries in the Bursa Malaysia which are Bursa Securities Bhd and Bursa Malaysia Derivatives Bhd(BMD). BMD was formerly known as Malaysia Derivative Exchange Berhad (MDEX) and the derivatives contracts are not as widely operated as other developed derivative exchange markets. FTSE Bursa Malaysia KLCI was known as Kuala Lumpur Composite Index (KLCI). The index constituents of the FTSE Bursa Malaysia consist of 70 stocks, but due to a low volume of trading in the market, it has reduced to 30 stocks. The companies indexed in the FTSE Bursa Malaysia KLCI have at least a minimum of 15 percent free float. This free float factor is practiced to the market capitalization and index weighting for each of the company. Therefore, these companies are mandatory to provide at a minimum of 10 percent of their free floated shared that has been traded in the last

[1]Balance of payments(BOP)is a system to measure and guide all international financial transactions at a given period.

12 months before the annual index review.

4.2.2.2 Thailand

The Stock Exchange of Thailand (SET) is the Thailand centre of securities trading. SET offers a full range of products trading infrastructure and services for investors listed companies and other participants. The SET was formed in 1975 and initially began securities trading on April 30th, 1975. The main indices in SET are the SET index, SET50 index, SET100 index and MAI index. Each of the indexes has its definition and function. Since the study is focusing on all the listed common stocks, so SET index is used for the data analysis. The SET consists three types of products, namely; equity, bond, and derivatives. The SET index is the composite market capitalization-weighted price index that compares the current market value (CMV) of all listed common stocks with their market value on the base date of 30th April 1975 (base market value or BMV), which was when the stock market was established. On the base date , SET index was set to 100 points. The SET index formula is calculated as;

$$SETIndex = \frac{CurrrentMarketValue \times 100}{BaseMarketValue} \tag{4.1}$$

According to Sutheebanjard and Premchaiswadi (2010), Thailand economy is continually changing, and the factors influencing the Thailand stock market may be different from time to time.

4.2.2.3 Indonesia

Jakarta Stock Exchange (JSX) was the first stock exchange based in Jakarta. It was then changed to Surabaya Stock Exchange (SSX) in 2007. There are two primary stock market indices that are to measure value changes in representing stock groupings which is called the Jakarta Composite Index. Jakarta Composite Index is calculated using value-weighted index. The index base period is based on a specific base day for its calculation. Jakarta Future Exchange (JFX) is Indonesia's first future exchange which started trading in the year 2000. JFX buys and sells different commodities, indexes, and foreign exchange futures products. In 2004, JFX introduced a remote trading system called JAFeTS after the JFX trading increased its net income and daily trading during 2004. The corporate bonds in Indonesia are mostly listed in Surabaya Stock Exchange (SSX). SSX offers Over-The-Counter facility and empowers market shareholder to report their contract. SSX trades equities but less market activity than JSX. So, in September 2007, both Jakarta Stock

Exchange and Surabaya Exchange combined and are named Indonesian Stock Exchange (IDR).

4.2.2.4 Philippines

The Philippine Stock Exchange (PSE) is the oldest and only stock exchange in the Philippines. It has been operated since 1927 when the Manilla Stock Exchange was established. PSEi is the leading index for PSE. It is composed of a fixed basket of 30 listed companies and additional six sub-sectors aside from PSEi, namely, financial, industrial, holding firms, property, services, and mining and oil indices. The PSE has around 253 companies and 184 trading participants listed on it with the market capitalization of USD 202 billion[2]. The most common active study in the PSE is the measure of the relative changes in the free float-adjusted market capitalization by the PSEi. PSEi select companies based on specific set of the public float, liquidity and market capitalization criteria. The PSEi is the only index in the Philippines could monitor and is also one of the most observed economic indicators.

4.3 Methodology and Research Models

In the literature, there are three main classes of asset return volatility models that have been popular among researchers, they are the realized volatility model, implied volatility model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) class of models. These models are able to evaluate the performance of a volatility in financial risk market, equity market, commodity market and many more. So, this study aims to focus on the prediction model and how to perform and evaluate volatility index accurately, in financial terms. Since information of the survey is limited as to quantify the unpredictability of an absolute asset's return over the last month, we shall concentrate on the suitable model to forecast the volatility index. The primary prediction model that shall be examined in this study is the GARCH-type models and the Realized Volatility Model. This study approaches three types of GARCH model; namely the classic GARCH, E-GARCH and GJR-GARCH model. It will then be followed by the Realized Volatility model approach. Researchers and practitioners recognized that the fact that volatility is not directly observable, see Granger (2002) which is a little unclear when they refer to the same attribute. So, by adopting the financial time series exhibiting specific characteristics features such as clustering, leptokurtic and the generalized autoregressive

[2]See Chen and Diaz (2014) for more details.

conditional heteroscedasticity (GARCH) model gained its essential has finally able to solve this issue. Even sometimes fails to capture the fat-tail properties of financial data. This failure will lead to the use of non-normal distributions (Student's t and skewed Student's t), within many nonlinear extensions of the GARCH model, which is the E-GARCH and GJR-GARCH. According to Thorlie et al. (2015), the GJR-GARCH model is fitted to represent the evolution of conditional variances of the S&P 500 daily stock index returns capture asymmetry, but fails to achieve the leverages effect in the stock market.

4.3.1 Estimating the Cross-Sectional Volatility (CSV)Index

Based on the concept and theory of Cross-sectional Volatility index that is explained in the previous Chapter 3, the study will again apply the new construction of CSV index calculation approach to the Asian market. The selection of the non-derivatives market will then go through the same step as in Chapter 3 to build up the CSV index for each market. However, the markets are selected based on liquidity and volumes of the stock market. So, briefly, the CSV index is measuring the cross-sectional variance. In order to see this measure, we shall first allow $(w_t)_{t\geq 0}$ to be the weight factor process. Let the portfolio return be defined by the weight process w_t and be written as $r_t^{w_t}$ shown below;

$$r_t^{w_t} = \sum_{i=1}^{N_t} w_{it} r_{it} \tag{4.2}$$

We keep the target restricted to non-trivial weighting schemes making the portfolio return look as it is composed in a single stock. Besides that, we make sure the weights are positive at any given time of point. So, weighting schemes w_t must satisfy $0 < w_{it} < 1$ for all i, t. Refer to the previous chapter in Equation (3.3) where the CSV is defined as ;

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}(r_{it} - r_t^{(w_t)})^2.$$

As the focus on this study is on the equally weighted CSV, the measure is denoted as in Equation (3.4) in Chapter 3 corresponding to the weighting schemes $w_{it} = 1/N_t$ for all i, t;

$$CSV_t^{EW} = \frac{1}{N} \sum_{i=1}^{N_t} (r_{it} - r_t^{EW})^2,$$

showing that the r_t^{EW} is the return on the equally-weighted portfolio. According to Chapter 2, the study is simplified into two assumptions. The first assumption is when $\beta_{it} = \beta_t = 1$ for all i, namely the homogeneous beta assumption and $E(\varepsilon_{it}^2) = \sigma_\varepsilon^2(\varepsilon)(t)$

for all i, namely the homogeneous residual variance assumption, restricting the weighting schemes positively, as in Equation (3.5) in Chapter 3. So, it it proven based on Garcia et al. (2014), where the factor model decomposition is considered as;

$$r_t^{(wt)} = \sum_{i=1}^{N_t} w_{it}\beta_{it}F_t + \sum_{i=1}^{N_t} w_{it}\varepsilon_{it} \tag{4.3}$$

where F_t is the factor excess return at time t, β_{it} is the beta stock i at time t, and ε_{it} are the residuals.

$$r_{it} - r_t^{(wt)} = \left(\beta_{it} - \sum_{j=1}^{N_t} w_{jt}\beta_{jt}\right) F_t + \varepsilon_{it} - \sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt} \tag{4.4}$$

Let us have the betas assumption as;

$$r_{it} - r_t^{(wt)} = \varepsilon_{it} + \sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt} \tag{4.5}$$

and then

$$\left[r_{it} - r_t^{(wt)}\right]^2 = \varepsilon_{it}^2 - \left(\sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt}\right)^2 - 2\varepsilon_{it}\sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt} \tag{4.6}$$

to be

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}\left(r_{it} - r_t^{w_t}\right)^2 \tag{4.7}$$

$$= \sum_{i=1}^{N_t} w_{it}\varepsilon_{it}^2 + \left(\sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt}\right)^2 - 2\sum_{i=1}^{N_t}\sum_{j=1}^{N_t} w_{jt}w_{it}\varepsilon_{it}\varepsilon_{jt} \tag{4.8}$$

Note that

$$\left(\sum_{j=1}^{N_t} w_{jt}\varepsilon_{jt}\right)^2 = \sum_{i=1}^{N_t}\sum_{j=1}^{N_t} w_{jt}w_{it}\varepsilon_{it} \tag{4.9}$$

giving the final equation

$$CSV_t^{(w_t)} = \sum_{i=1}^{N_t} w_{it}\varepsilon_{it}^2 - \left(\sum_{j=1}^{N_t} w_{jt}\varepsilon_{it}\right)^2 \tag{4.10}$$

4.3.2 GARCH Volatility and its stylized pattern

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model has been extended from ARCH model by Bollerslev (1986). It is the same model as the ARCH but requires far fewer parameters to model the volatility process adequately. In the literature review in Chapter 2, the GARCH model has been similarly written as the ARCH model as;

$$Z_t = h_t e_t, \ \{e_t\} \sim IID(0,1)$$

where h_t makes the different from the ARCH model and is defined as:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i Z_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2$$

where $\alpha_0 > 0, \alpha_i \geq 0$ and $\sum_{i=1}^{max(p,q)}(\alpha_i + \beta_i < 1)$ and where $\alpha_i \equiv 0$ for $i > p$ and $\beta_j \equiv 0$ for $j > q$.

The GARCH model is a clustering volatility model, and it imposes restrictions on the parameters to have a finite fourth moment as was the case of ARCH model. The GARCH model have addition of lagged conditional variances, h_{t-j}^2, as well as the lagged squared returns, Z_{t-i}^2. The addition of the lagged conditional variances avoids the need for adding many lagged squared returns as was the case for the ARCH model to be able to model the volatility appropriately. As per Equation (2.17), the GARCH(1,1) conditional variance can be written as

$$h_t^2 = \alpha_0 + \alpha_1 Z_{t-1}^2 + \beta_1(\alpha_0 + \alpha_1 Z_{t-2}^2 + \beta_1 h_{t-2}^2) \tag{4.11}$$

where the recursive substitution is written as;

$$h_t^2 = \frac{\alpha_0}{1-\beta_i} + \alpha_1 \sum_{i=0}^{\infty} Z_{t-1-i}^2 \beta_1^i. \tag{4.12}$$

showing that the GARCH(1,1) model respond to an ARCH(∞) model with a certain structure for the value of the parameters of the lagged returns Z_{t-i}^2.

The E-GARCH model can allow asymmetric effects of positive and negative asset returns which has become the weakness of GARCH model. The GARCH model can model persistence of volatility so-called volatility clustering. E-GARCH has been extended from the GARCH model by Nelson (1991).

We have chosen the E-GARCH because it is an extension to the GARCH model which allows us to observe the symmetric effects of positive and negative asset returns, see Brandt and Jones (2006). There are two limitations that makes the GARCH and E-GARCH different. The limitation of the model assume that only the magnitude of unanticipated excess returns determines $log(\sigma_t^2)$. Another limitation is maybe the persistent of volatility shock. The E-GARCH model limit formulation is as:

$$\log(h_t^2) = \alpha_0 + \sum_{i=1}^{p} [\alpha_i Z_{t-i} + \gamma_i(|Z_{t-i}| - E(|Z_{t-i}|))] + \sum_{j=1}^{q} \beta_j \log(h_{t-j}^2), \tag{4.13}$$

where $\omega, \alpha, \beta, \gamma$, and λ are coefficients, and Z_{t-i} comes from a generalized error distribution. Using this model, we can expect a better estimate the volatility for asset returns due to how the E-GARCH counteracts the limitations on the classic GARCH model, see Engle and Patton (2001). Equation (4.13) has been further discussed in the literature review chapter.

The GJR-GARCH model is an alternative way of modeling asymmetric effects of positive and negative asset returns that was extended by Glosten et al. (1993). The properties of GJR-GARCH are quite similar to the E-GARCH model which both capture the asymmetric impact of positive and negative shocks.

The normal distribution is a symmetric distribution is which treats both the tails as asymptotic and equal. According to Yoon and Lee (2008), the GJR-GARCH gives more weight to left tail in the conditional volatility model. It is written as follows:

$$r_t = \mu_t + \varepsilon_t \tag{4.14}$$

where r_t denote as the daily log return, μ_t is the conditional mean, $\varepsilon_t = \sigma_t z_t$ and

$$\sigma_t^2 = k + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \xi_j I[\varepsilon_{t-j} < 0] \varepsilon_{t-j}^2 \tag{4.15}$$

where σ_t^2 denotes the conditional variance. The function $I[\varepsilon_{t-j} < 0]$ equals 1 if $\varepsilon_{t-j} < 0$, and 0 otherwise. It will capture the negative returns, which is more critical in risk examination.

Long persistence and extended memory properties of volatility is a new way of Corsi (2009) suggestion to measure volatility. We consider this in the next section.

4.3.3 Realized Volatility and its stylized pattern

4.3.3.1 Realized Volatility

Realized volatility is a common model-free indicator of volatility that is calculated using the daily squared returns. In this chapter, we shall compare the efficiency of forecasting the cross-sectional volatility index using realized volatility approach. We shall measure the inter-daily volatility generated from the CSV Index of each market. Let $p_{n,t}$ denote the time of $n \geq 0$ logarithmic price at day t. Based on the continuous-time stocastics volatility diffusion,

$$dp_{n,t} = \sigma_{n,t} dW_{n,t} \tag{4.16}$$

where $W_{n,t}$ denotes a standard Brownian motion. The time series of continuously compounded returns with N observations per day is defined by:

$$r_{n,t} = p_{n,t} - p_{n-1,t} \tag{4.17}$$

where $n = 1, ..., N$ and $t = 1, ..., T$. If $N = 1$, for any series, we shall ignore the first subscript n and thus r_t denotes the time series of daily return. Given the sample path of variance, $\{\sigma_{n,t}\}_{n=1,...,N;\, t=1,...,T}$, then the daily return is defined as

$$\sigma_t^2 = \int_1^N \sigma_{n,t}^2 dn \tag{4.18}$$

The continuous compounded daily squared returns may be decomposed as:

$$r_t^2 = \left(\sum_{n=1}^{N} r_{n,t}\right)^2 = \sum_{n=1}^{N} r_{n,t}^2 + \sum_{n=1}^{N}\sum_{m=1}^{N} r_{n,t} r_{m,t} = \sum_{n=1}^{N} r_{n,t}^2 + 2\sum_{n=1}^{N}\sum_{m=n+1}^{N} r_{n,t} r_{m-n,t}. \tag{4.19}$$

Assuming that $E[r_{n,t}] = 0$ holds, the squared daily return is, therefore, the sum of two components: the sample variance(at the regular unit) and twice the amount of $N - 1$ sample Autocovariances (at the 1/Nth day interval unit). The sample Autocovariances are measurement error and induce noise in the daily squared return measure.

4.3.3.2 HAR-Realized Volatility

According to Corsi (2009), Heterogenous Autoregressive model of Realized Volatility (HAR-RV) is a simple realized volatility forecast model in performance. The studies show remarkable outperforms results compared to the standard model which is steady and substantial. They are finding an alternative approach to construct an observable proxy for the latent volatility using high-frequency data. Their study approached the concept of latent integrated volatility using the stochastic volatility process. McAleer and Medeiros (2008) studied and extended the HAR-RV model by proposing a new method that merges long memory and nonlinearities. The HAR-RV model is made up of three heterogenous volatility components. The HAR-RV model at day $t+1$ is;

$$RV_{t+1}^{d} = c + \beta^{d} RV_{t}^{d} + \beta^{w} RV_{t}^{w} + \beta^{w} RV_{t}^{m} + \omega_{t}, \tag{4.20}$$

where ω is the mean zero error term, RV_t^d is the RV over day,d, t and RV_t^w, and RV_t^m are the average daily realized volatilities over the past week and month, respectively. In addition, the RV_t^w and RV_t^m are calculated as below

$$RV_{t}^{w} = \frac{1}{5}\left(RV_{t-1}^{d} + RV_{t-2}^{d} + RV_{t-3}^{d} + RV_{t-4}^{d} + RV_{t-5}^{d}\right). \tag{4.21}$$

$$RV_{t}^{m} = \frac{1}{22}\left(RV_{t-1}^{d} + RV_{t-2}^{d} + RV_{t-3}^{d} + RV_{t-4}^{d} + ... + RV_{t-22}^{d}\right). \tag{4.22}$$

In a very simple and parsimonious way, the HAR-RV model seems to reach the purpose of modeling the long memory behavior of volatility. Moreover, the form of logarithmic HAR-RV model can be shown as:

$$log(RV_{t+1}^{d}) = c + \beta^{d} log(RV_{t}^{d}) + \beta^{w} log(RV_{t}^{w}) + \beta^{w} log(RV_{t}^{m}) + \omega_{t}. \tag{4.23}$$

4.3.4 Evaluation of Volatility Forecast

To check the forecasting performance of the concurrent models, we employ the six accuracy statistics or loss functions as our criteria. The first measure used is the root mean squared error (RMSE) of the square of the out-of-sample observations. The best predictor is the one with the lowest RMSE of the squared out-of-sample observations discussed in Chapter 3 as;

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2}, \tag{4.24}$$

where $\hat{\sigma}_t^2$ is the forecasted volatility at time t, and σ_t is the actual CSV volatility at time t and N is the sample size. The MAE is dependent on the scale of the dependent variable but is less sensitive to large deviations than the usual squared loss which is

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{\sigma}_t^2 - {\sigma_t}^2\right|, \tag{4.25}$$

where N is the sample size, $\hat{\sigma}_t^2$ is the forecasted volatility at time t, and σ_t is the actual CSV volatilty at time t and N.

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{\sigma}_t^2 - {\sigma_t}^2\right|^2, \tag{4.26}$$

where N is the sample size, $\hat{\sigma}_t^2$ is the forecasted volatility at time t, and σ_t is the actual CSV volatilty at time t and N.

4.3.5 Data Source

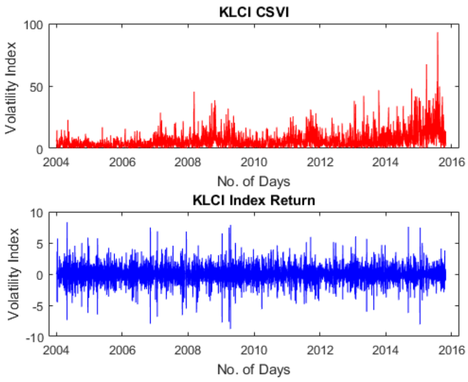
We consider the daily closing prices of four value-weighted CSV index markets covering the period January 2004 to November 2015, Malaysia, Philippine, Thailand, and Indonesia. These four countries have less derivative options prices to construct a proper VIX in Southeast Asian market. The indices are generated from the CSV Index model constructed in the previous chapter namely, Kuala Lumpur CSV Index (KLCI CSVI), Philippine CSV Index (PHP CSVI), Thailand CSV Index (THL CSVI) and Jakarta CSV Index (JSX CSVI Index). These indices were composed of the Kuala Lumpur Composite Index (KLCI), Philippine Stock Exchange (PSEI), Stock Exchange of Thailand Index (SET) and Jakarta Composite Index (JSX). These indices are collected from DataStream and in this study, the past returns from each index are composed of the filtered stocks to generate the volatility index for each market. We filter all available constituent stocks for the four non-derivatives Asian markets. We removed the unwanted stocks which are less liquid and less daily trading. Outliers are removed using the first principal component analysis (PCA) method. It is a way to reduce the dimensionality of data besides having the outliers removed. Using the PCA can detect the variables contribute the most to the occurrence of outliers, providing valuable information regarding the source of outlying data. The PCA analysis method has been explained in Chapter two.

The total number of the constituent list for each of the stock market index are 30 for KLCI, 473 for JSX, 551 for SET and 30 for PSEI. In order to perform the CSV Index, the daily stock prices are calculated in continuous compounds as $r_t = log(p_t/p_{t-1})$ where p_t and p_{t-1} are the prices on the days t and $t-1$ respectively. Then the returns of the stock market will be used to construct the equally weight of Cross-sectional Volatility index . We shall exhibit the statistical properties of the stock volatility index. Table 4.1 describes the statistical description of the four markets. We find that the return means index is negative for all markets except for Thailand market. The kurtosis is greater than 3, and the skewness is less than 0 shows that the characteristics of the return index are sharp peak and heavy tailed. The Jarque-Bera test describes this study has a higher value to represent the non-normality of the rate of return data. So, the distribution of the CSV index return is not a normal distribution.

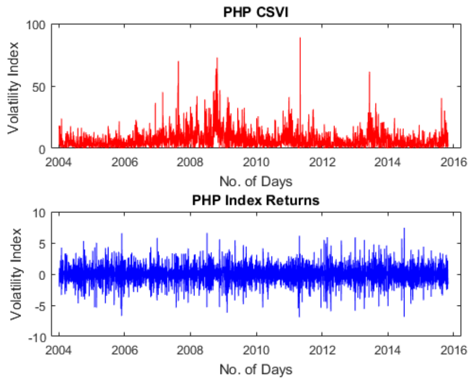
Figure 4.1 exhibits the price return index and the cross-sectional volatility index for each of the four non-derivatives markets. From the graph, the volatility changes over time and tends to cluster with periods of low volatility and periods high volatility. The turbulence and tranquility suggest the existence of volatility clustering in the graph of return. The volatility fluctuates consistently over most of the period. The volatility shown in Figure 4.1 has been generated after filtering the outliers and removing the illiquid returns. It is clear that volatility clustering phenomenon exists from the plot observations. In this case, GARCH models may be appropriate for explaining these data. We have also analyzed the correlation of the return volatility index by calling the sample autocorrelation function (ACF) and partial autocorrelation (PACF) function respectively shown in Figure 4.2. The test on ACF and PACF has been adopted to measure the independence among the observations in the series and take the value between -1 and +1 and also to generate accurate predictor variables. The ACF and PACF test determines the stationarity of the return series. The return series exhibit stationary when the serial lags are in the confidence interval. The test is applied to the four non-derivatives market along with the upper and lower standard deviation confidence bounds, based on the assumption that all autocorrelations are significant.

Table 4.1: Summary Statistics for CSV index Returns from January 2004 to November 2015

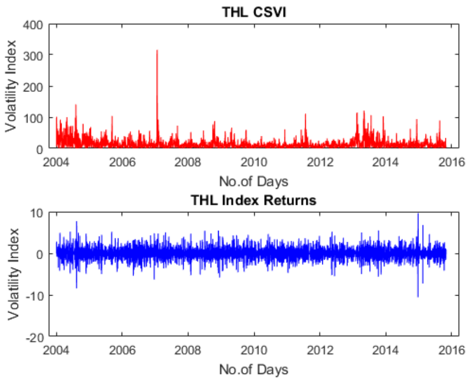
CSVI Market	Mean	Kurtosis	SkewNess	Standard Deviation	Jb-Stat	Critical Value
CSVI_KLCI	-0.0003	5.6982	-0.0335	1.6642	886.0829	5.8696
CSVI_JSX	-0.0009	4.9325	-0.0507	1.6456	449.8654	5.9966
CSVI_THL	0.0000	5.1917	-0.0585	1.6099	592.9027	5.9153
CSVI_PHP	-0.0008	4.6529	-0.0403	1.5965	330.7302	5.9997



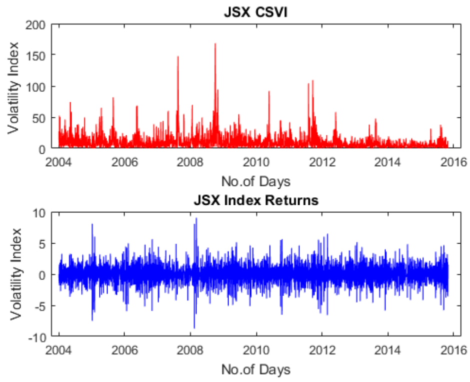
(a) Malaysia CSV index return



(b) Philippines CSV index return

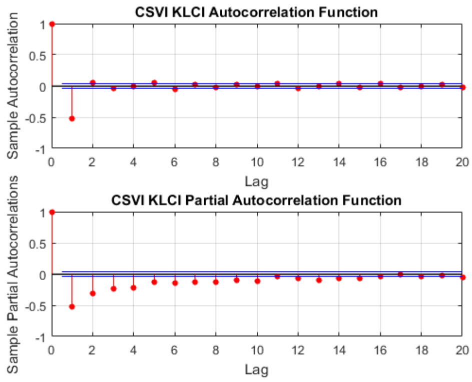


(c) Thailand CSV index return

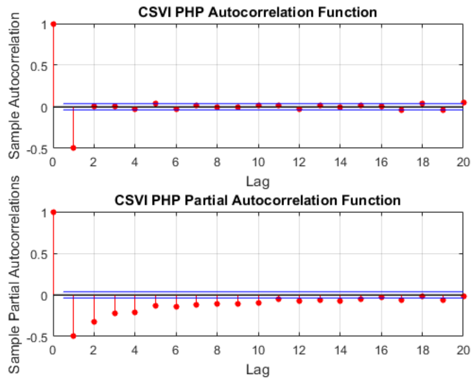


(d) Jakarta CSV index return

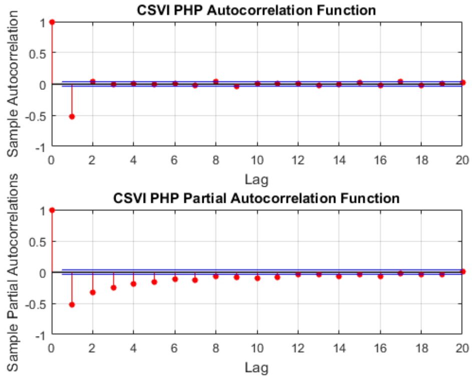
Figure 4.1: The Daily Cross-sectional Volatility index of Four Non-derivatives Asian Market



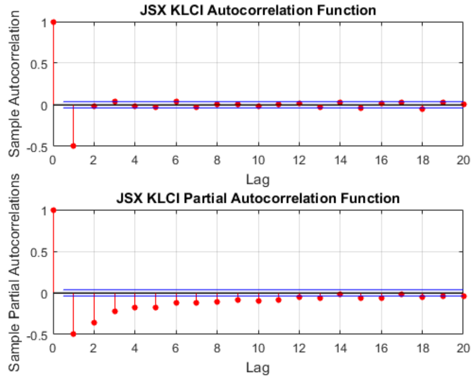
(a) Malaysia CSV index sample of autocorrelation



(b) Philippine CSV index sample of autocorrelation



(c) Thailand CSV index sample of autocorrelation



(d) Jakarta CSV index sample of autocorrelation

Figure 4.2: The sample of Autocorrelation and Partial Function of Four Non-derivatives Asian Market

4.4 Empirical Results

Forecasting efficiency of a model is usually tested by the mean square errors they produce. This comparison errors will not be informative as it is a point estimate. In this chapter, we did not only compute the errors which is provided iteratively but also plotted for the entire predicted and actual return volatility index to observe the convergence and divergence of the return index.

The estimation results of GARCH, E-GARCH, and GJR-GARCH in Table 4.2 - Table 4.5 show the first four coefficients constant, ARCH, GARCH and leverage are statistically significant and most of the coefficient of the lagged squared returns is positive for all indices. The results also indicate the presence of volatility clustering in the three models. The sum of ARCH and GARCH coefficients show the persistence of volatility and generally for all the model has sum up ARCH and GARCH coefficients close to 1. The ARCH and GARCH effect exist in the two market which is Malaysia and Thailand market. Malaysia and Thailand markets show the significance of both ARCH and GARCH which indicates that, lagged conditional variance and lagged squared disturbance have impact on the conditional variance. It also means that the news about volatility from the previous periods has an explanatory power on current volatility. The asymmetrical E-GARCH(1,1) results in Table 4.2 - Table 4.5 indicate that all the estimated coefficients are statistically significant. The parameter for the asymmetric volatility response or so called leverage is negative and significant for the four non-derivatives market. This result reflects the condition that volatility tends to rise in response to positive spikes and fall in response to negative spikes.

We estimate GARCH, E-GARCH, GJR-GARCH and HAR-RV models with normal and Students' t-distributions. Table 4.2 - Table 4.5 exhibits the symmetric and asymmetric effect which is the ARCH and GARCH effect for non-derivatives market. E-GARCH and GJR-GARCH models are assigned initially to every value to capture the importance of negative tail values and to give more weight to recent CSV Index return which is more important in hedging decisions. The t-value determines the strength of the coefficients, and normally they will be converted into probability values, and then they will be interpreted. For large samples, t-values of 1.66 are significant at the 10 percent level, and t-value of 1.96 is significant at 5 percent level. For instance, the CSVI KLCI market is significant as all the values using the E-GARCH and GJR-GARCH models are larger than 1.96, meaning that it is significant at 5 percent level.

Table 4.2: Malaysia autoregressive coefficients and t-values

	GARCH			E-GARCH			GJR-GARCH		
Parameter	Coeff	Std Err	t Value	Coeff	Std Err	t Value	Coeff	Std Err	t Value
C	1.8089	0.1010	17.8844	0.7868	0.0584	13.462 8	1.8483	0.1045	17.6755
$\alpha(1)$	0.3333	0.0311	10.6964	0.5114	0.0420	12.1523	0.1045	0.0217	4.8023
$\beta(1)$	0.5288	0.0659	8.0228	0.1213	0.0614	1.9732	0.0135	0.0443	0.3064
$\gamma(1)$				-0.1104	0.0258	-4.2824	0.3651	0.0702	5.1994

Table 4.3: Philippine autoregressive coefficients and t-values

	GARCH			E-GARCH			GJR-GARCH		
Parameter	Coeff	Std Err	t Value	Coeff	Std Err	t Value	Coeff	Std Err	t Value
C	1.8107	0.1143	15.8369	0.8772	0.0539	16.2522	1.9079	0.0847	22.5055
$\alpha(1)$	0.2729	0.0306	8.8974	0.4329	0.0402	10.7491	0.0151	0.0167	0.9042
$\beta(1)$				-0.0542	0.0647	-0.8384			
$\gamma(1)$				-0.1319	0.0257	-5.1183	0.3997	0.0678	5.8949

Table 4.4: Thailand autoregressive coefficients and t-values

	GARCH			E-GARCH			GJR-GARCH		
Parameter	Coeff	Std Err	t Value	Coeff	Std Err	t Value	Coeff	Std Err	t Value
C	1.6541	0.0962	17.1942	0.6759	0.0626	10.7881	1.6976	0.1306	12.9896
$\alpha(1)$	0.2868	0.0305	9.4032	0.3981	0.0395	10.055			
$\beta(1)$	0.0647	0.0351	1.8390	0.2031	0.0653	3.1079	0.1073	0.0630	1.7032
$\gamma(1)$				-0.1497	0.0296	-5.0534	0.4083	0.0710	5.7473

Table 4.5: Jakarta autoregressive coefficients and t-values

	GARCH			E-GARCH			GJR-GARCH		
Parameter	Coeff	Std Err	t Value	Coeff	Std Err	t Value	Coeff	Std Err	t Value
C	1.8547	0.1226	15.1277	0.8437	0.0620	13.5959	1.9419	0.0961	20.1886
$\alpha(1)$	0.2969	0.0294	10.0859	0.4645	0.0397	11.6889	0.0573	0.0194	2.9510
$\beta(1)$				0.0435	0.0675	0.6458			
$\gamma(1)$				-0.1230	0.0263	-4.6680	0.3799	0.0706	5.3772

For the GARCH(1,1) model in Table 4.2, the ARCH and GARCH coefficient (0.5288 and 0.3333) are statistically significant and exhibit the expected sign. However, Thailand in Table 4.4 shows the ARCH and GARCH coefficients (0.2868 and 0.0647) which describe the persistence of the ARCH and GARCH effects are weak. E-GARCH in Table 4.2 has the most influential ARCH, GARCH and Leverage effects (0.1213,0.5114 and -0.1104) and are also significant at a t value larger than 1.66. Then, followed by Thailand market, where Table 4.4 shows the total of the ARCH, GARCH and Leverage effects are 0.4515 which is still less than 1. However, GJR-GARCH has fewer effects on the study because the GJR-GARCH only gives impact on Malaysia market at Table 4.2 with the value of 0.4831 from the sum of ARCH, GARCH and leverage effects.

The primary results of forecasting Cross-sectional Volatility index using the GARCH model are represented in Table 4.6. The accuracy of the forecast is measured under the Root Mean Square Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Error (MAE). From the analysis exhibited in Table 4.6, it is recorded that the RMSE statistics indicate that the GARCH model provides the most accurate forecast for the Philippine market which is 0.6794. Overall, the RMSE suggests that Philippine market has the most precise forecast compared to other three non-derivatives market. The MAE statistics also indicate that the GJR-GARCH model has the most accurate forecast in the Philippine market. The Philippine market had the most accurate forecast of cross-sectional volatility index and followed by the Thailand market. In summary, MAE shows the best measure of the forecast for the four non-derivatives markets which the value measure is less than 1.0. It is consistently the best performing model compared to RMSE and MSE.

Table 4.7 indicates the result of CSV index return using the HAR-RV model. Summary results of HAR-RV model for CSVI.

Table 4.6: Forecasting performance of competing models with GARCH and its extension volatility model

	Performance Index	GARCH	E-GARCH	GJR-GARCH
Malaysia	RMSE	1.07170	0.9684	0.9876
	MSE	34.4540	28.1359	29.2650
	MAE	0.8019	0.6832	0.7724
Philippines	RMSE	0.6794	0.8089	0.7006
	MSE	13.8480	19.6329	14.725
	MAE	0.5822	0.5712	0.5469
Thailand	RMSE	0.9688	1.2501	1.3338
	MSE	28.163	46.8789	53.3729
	MAE	0.6535	0.6372	0.6949
Indonesia	RMSE	1.2529	1.552	1.6347
	MSE	47.0989	72.2600	80.1680
	MAE	0.9001	0.9260	0.9748

Table 4.7: HAR-RV model for Kuala Lumpur CSVI return

CSV KLCI HAR RV	Coefficient	Standard Error	t-Value	Prob ($> t$)
C	3.8244	2.8485	1.3430	0.1872
RV Daily	0.3577	0.1611	2.2210	*0.0322
RV Weekly	-0.5275	0.4257	-1.2390	0.2227
RV Monthly	-0.2089	1.3267	-0.1570	0.8757

Table 4.8: HAR-RV model for Philippine CSVI return

CSV PHP HAR RV	Coefficient	Standard Error	t-Value	Prob ($> t$))
C	1.7344	1.2165	1.4260	0.1610
RV Daily	-0.1275	0.1641	-0.7770	0.4410
RV Weekly	0.4733	0.4100	1.1540	0.2550
RV Monthly	-0.1730	0.5684	-0.3040	0.7620

Table 4.9: HAR-RV model for Thailand CSVI return

CSV THL HAR RV	Coefficient	Standard Error	t-Value	Prob ($> t$)
C	4.7698	2.2208	2.1480	0.0367*
RV Daily	0.1396	0.1550	0.9020	0.3713
RV Weekly	0.0216	0.3516	0.0610	0.9513
RV Monthly	-1.2990	0.9957	-1.3050	0.1981

Table 4.7 until Table 4.10 report the results of the estimation of the HAR-RV model for ten years of CSV Index of daily realized volatility for each market. According to Table 4.7, the HAR-RV regressors are not significant in most regressors, and when it is, only the lag is significant. CSVI Kuala Lumpur has the significant regression when the coefficient is significant at 5 percent level which is estimated 0.0322 percent. Figure 4.3 exhibit the conditional variance forecast of CSV index for four non-derivatives Asian Market. The CSV Index of non-derivatives market were predicted using the GARCH-family model by estimating the conditional variance. The time plots of the conditional variance indicates

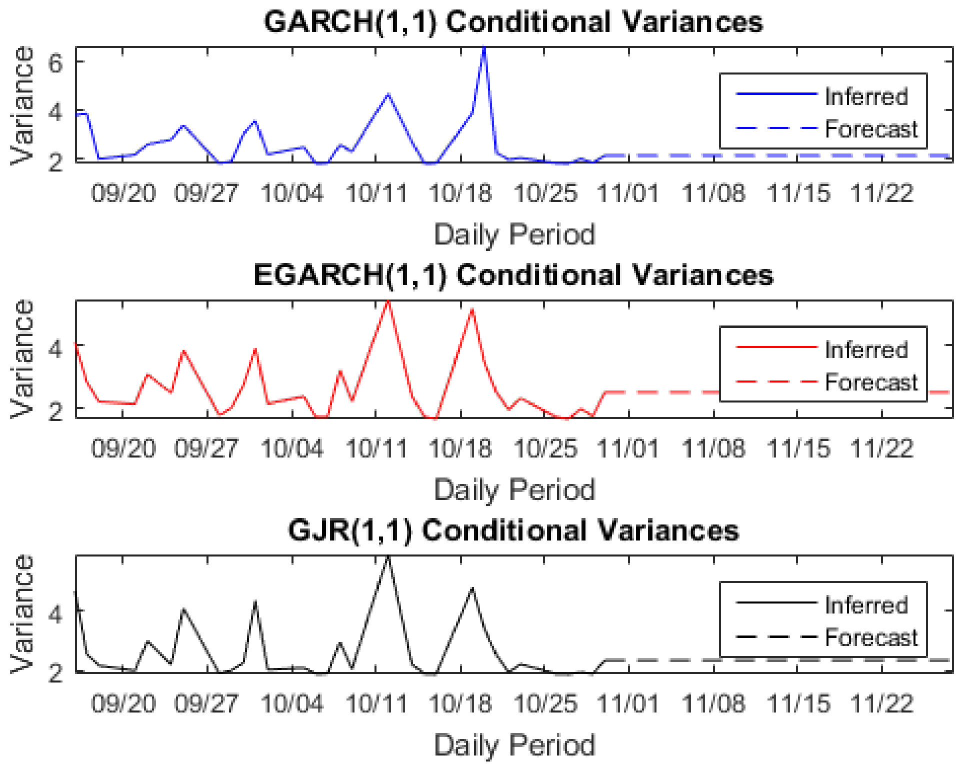
Table 4.10: HAR-RV model for Jakarta CSVI return

CSV JSX HAR RV	Coefficient	Standard Error	t-Value	Prob ($> t$)
C	10.9907	6.3470	1.7320	0.0915
RV Daily(-1)	0.2200	0.1741	1.2630	0.2142
RV Weekly(-1)	-0.2298	0.3566	-0.6440	0.5232
RV Monthly(-1)	-1.4862	1.4527	-1.0230	0.3127

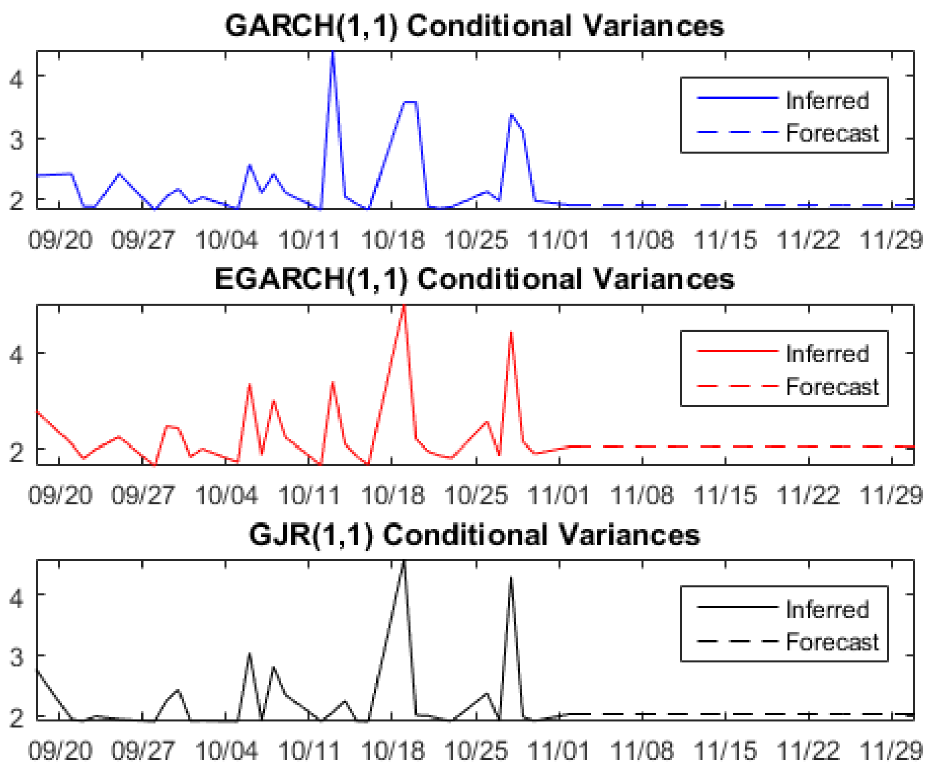
that the estimated conditional variance is extremely high for some periods and relatively low in others (time variant) which is quite common feature in most financial data. However, from the four market in this Figure, the CSV Index can be forecasted by looking at the forecast period increase at over time.

Figure 4.4 exhibit the conditional variance forecast asymptote for each market. The variance of the series seems to change. The inconsistency in ranking stress the importance of selecting an adequate loss function for the forecasting purposes. By generating Figure 4.4, it is found that E-GARCH forecast converge faster to the condition variance of the other two models implying that the latter process has a higher forecast memory.

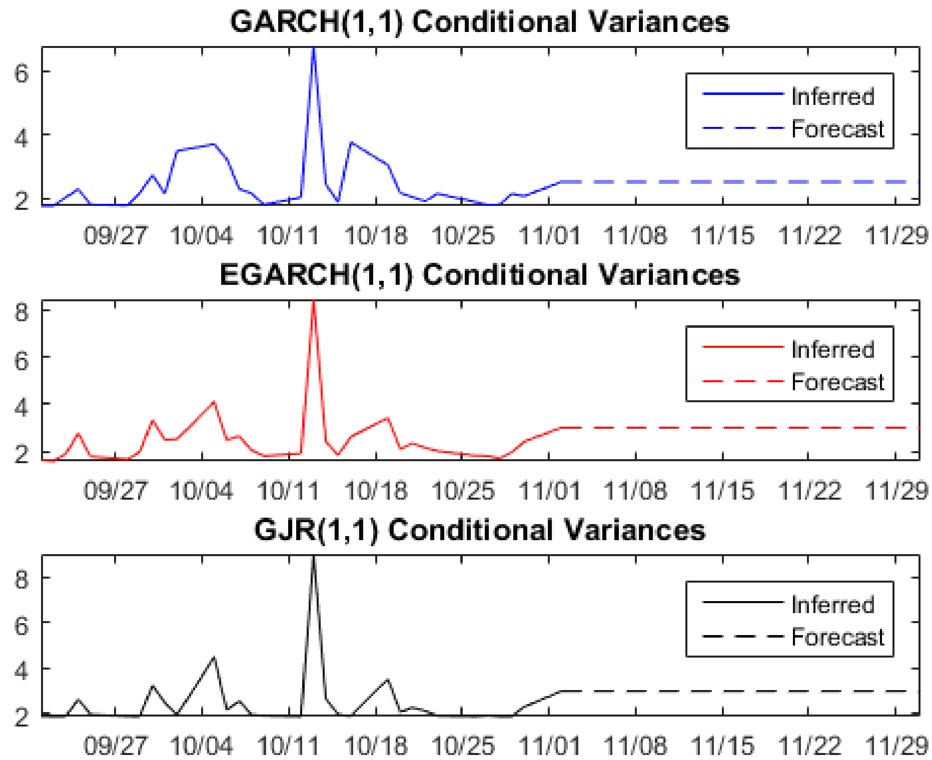
Figure 4.5 exhibit the CSVI HAR-RV model forecast. The observed HAR-RV and the forecast HAR-RV has a very small gap showing the accuracy is high. The most accurate prediction is the Kuala Lumpur (KLCI) CSVI HAR-RV.



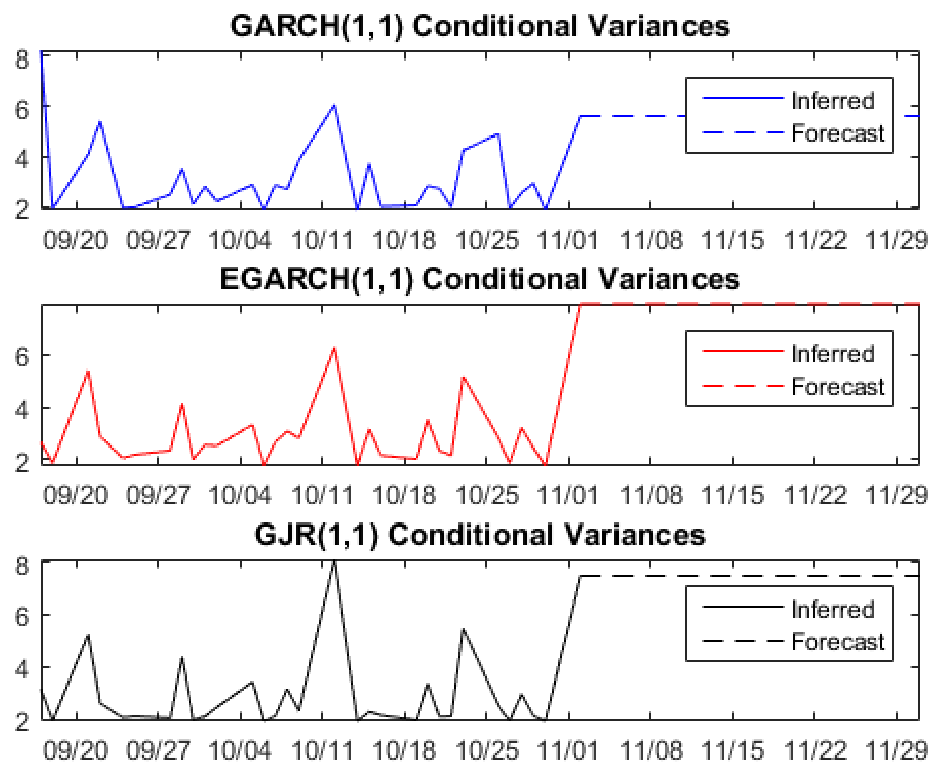
(a) Kuala Lumpur CSV index conditional variance



(b) Philippines CSV index conditional variance

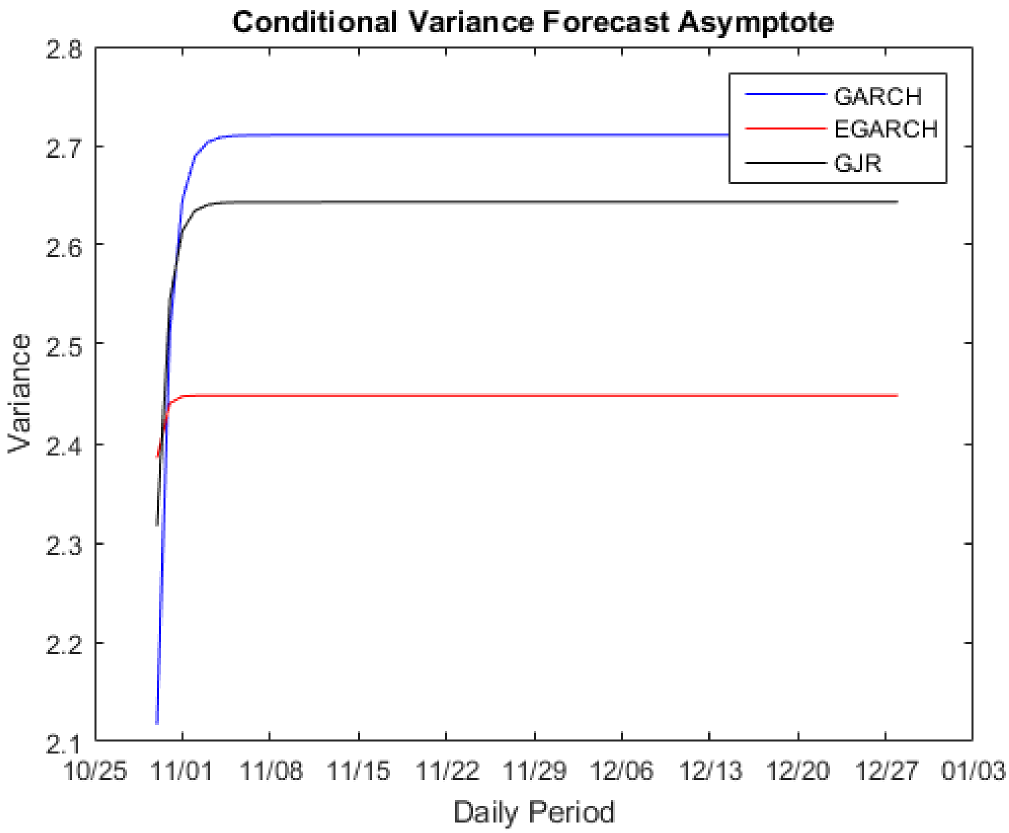


(c) Thailand CSV index conditional variance

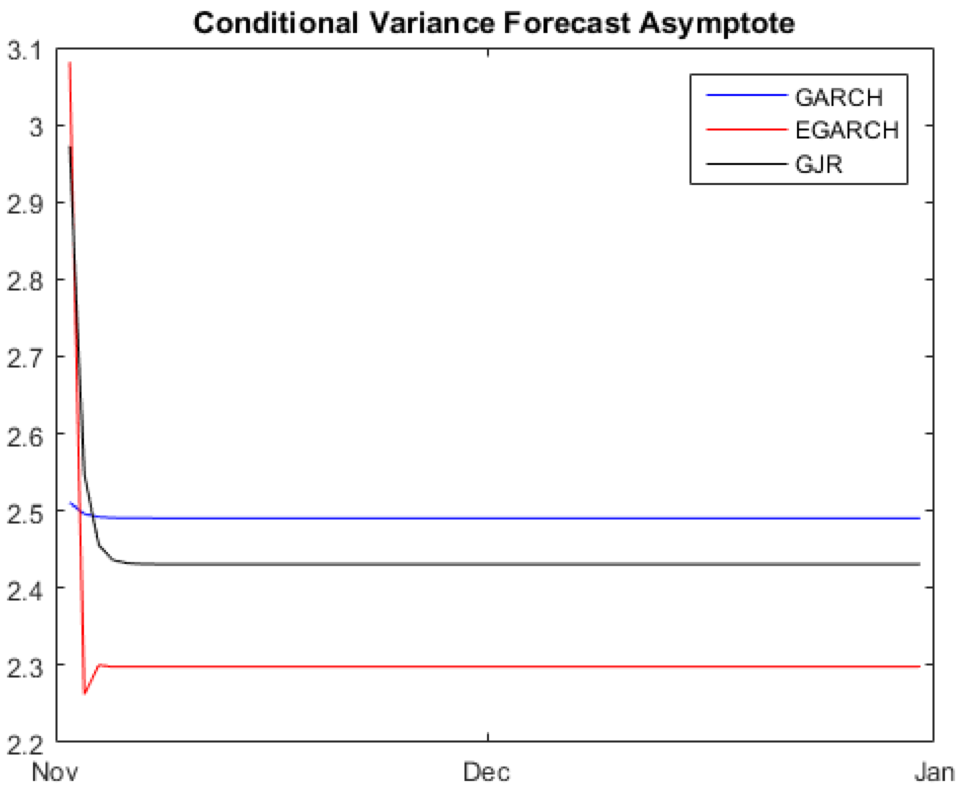


(d) Jakarta CSV index conditional variance

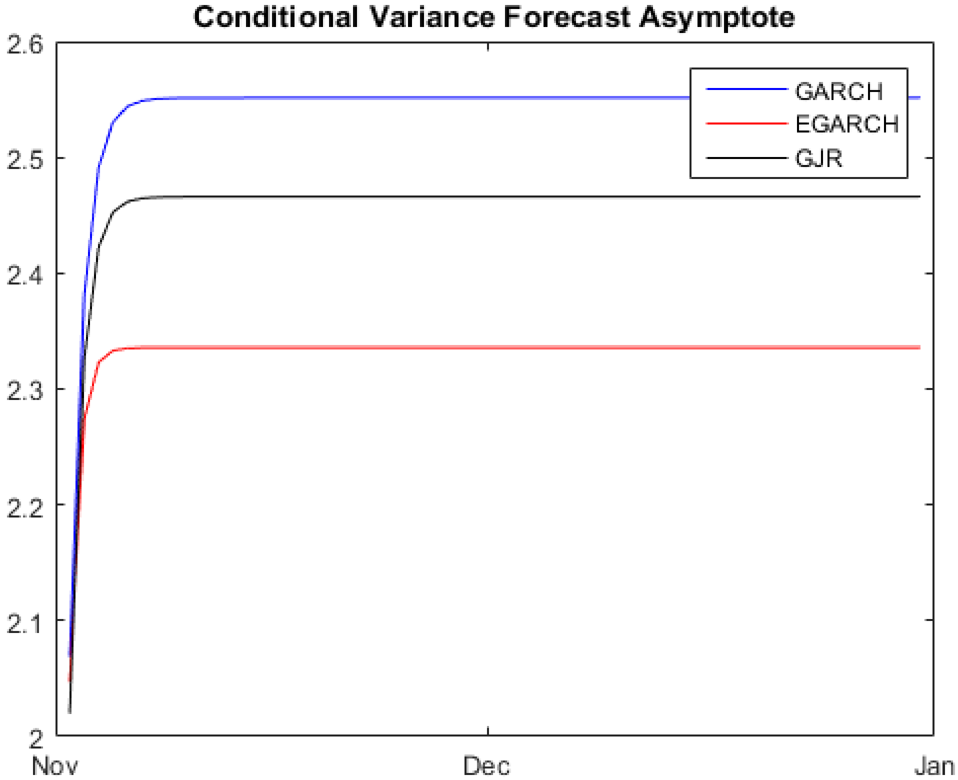
Figure 4.3: The Conditional Variance of CSV Index for Four Non-derivatives Asian Market



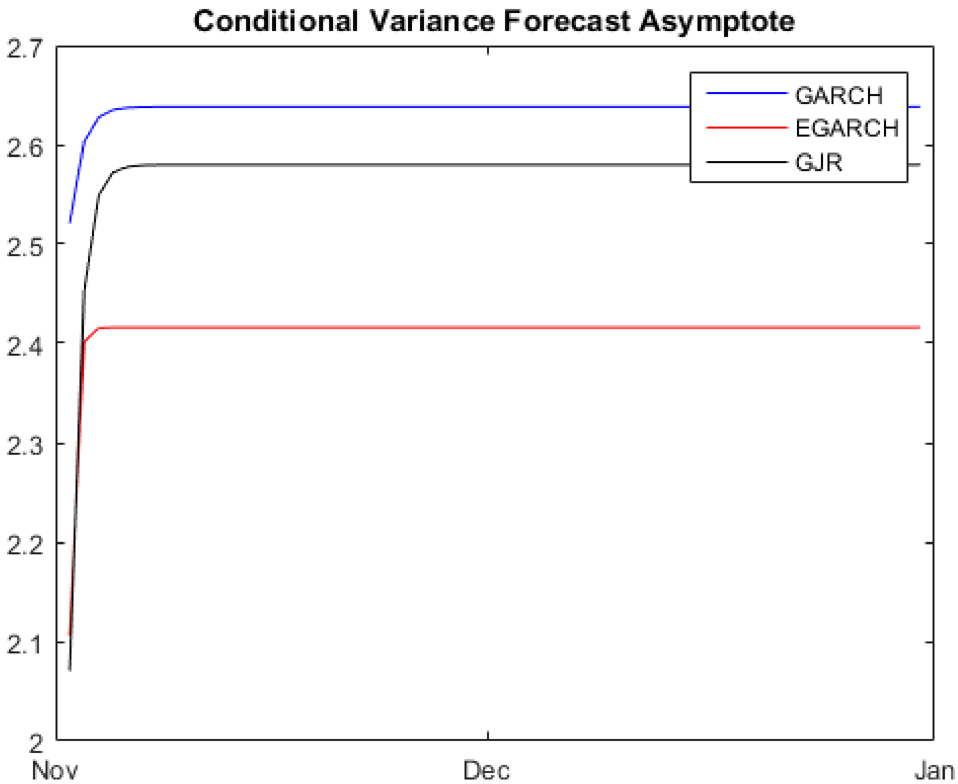
(a) Kuala Lumpur CSV index conditional variance forecast



(b) Philippines CSV index conditional variance forecast

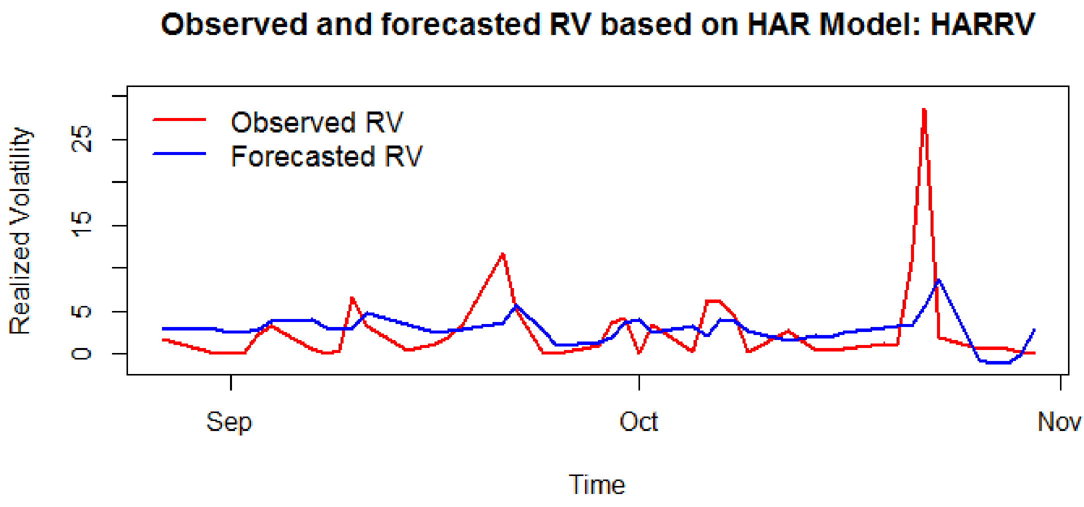


(c) Thailand CSV index conditional variance forecast

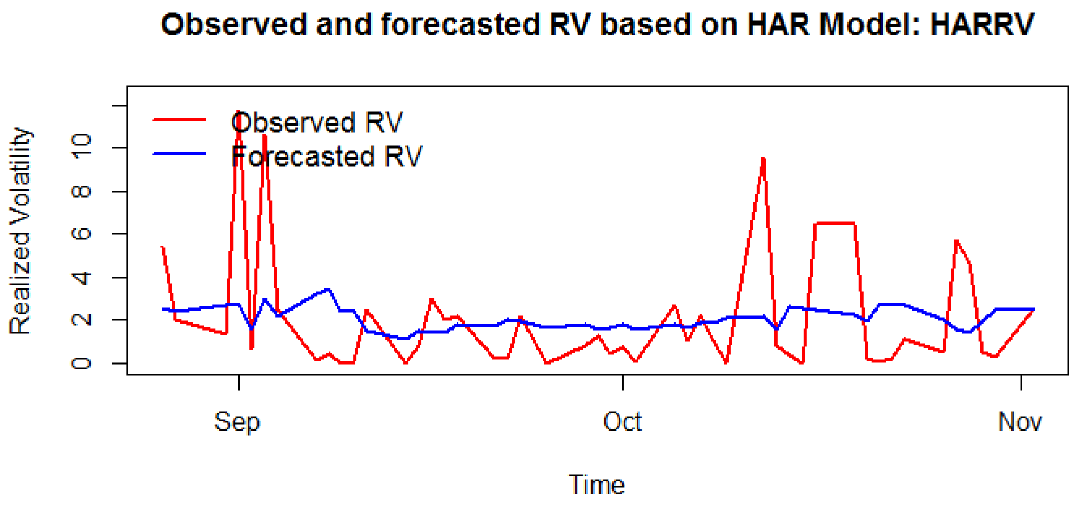


(d) Jakarta CSV index conditional variance forecast

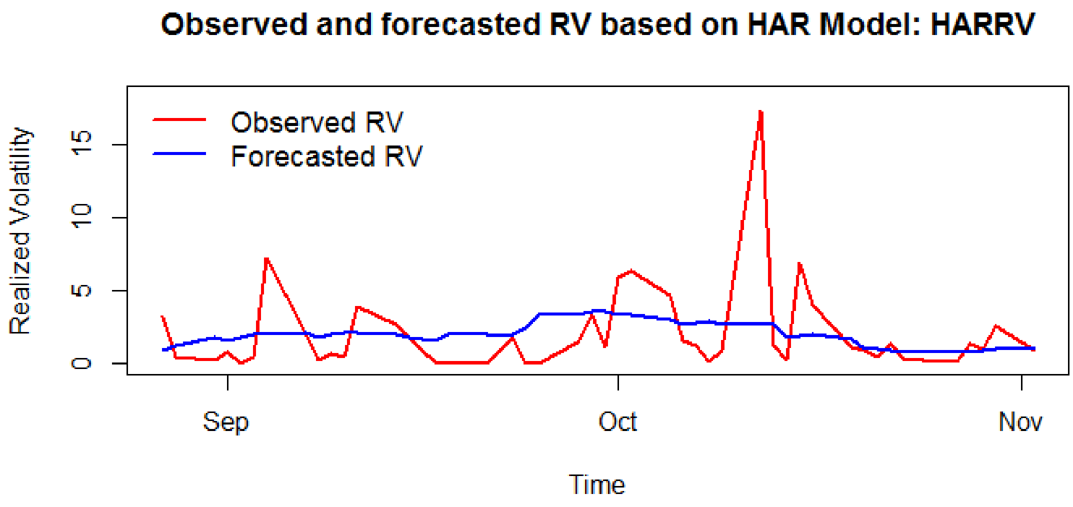
Figure 4.4: The Conditional Variance Forecast of CSV Index for Four Non-derivatives Asian Market



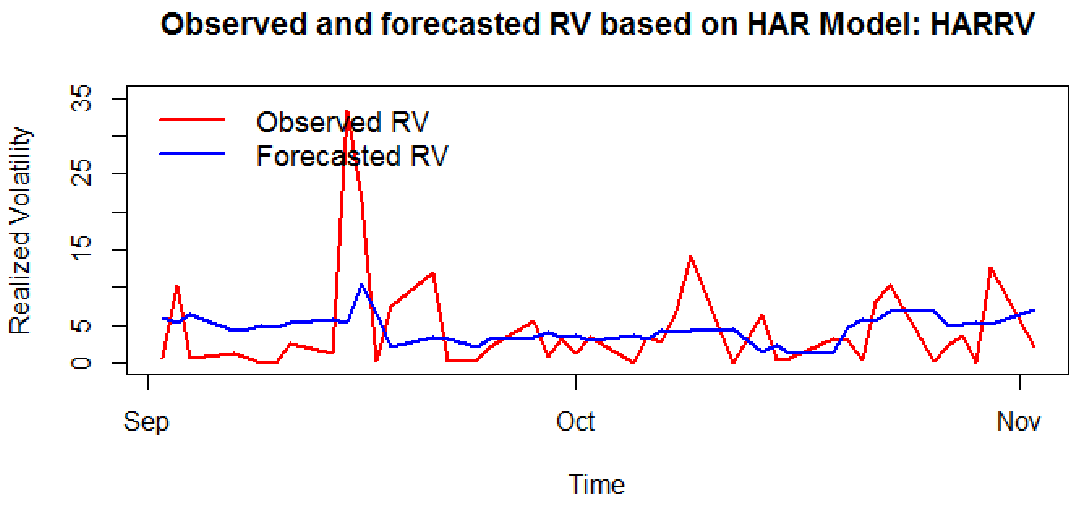
(a) Kuala Lumpur CSV index HAR-RV volatility prediction



(b) Philippines CSV index HAR-RV volatility prediction



(c) Thailand CSV index HAR-RV volatility prediction



(d) Jakarta CSV index HAR-RV volatility prediction

Figure 4.5: One-day Ahead Volatility Forecast from HAR-RV Model for Four Non-derivatives Asian Market

4.5 Conclusions

The purpose of this chapter was to propose the Cross-Sectional Volatility Index (CSV) index as an alternative to the VIX-styled index. It is a new form of volatility on observable and model-free volatility measures. This approach is particularly appropriate when a country's financial market does not trade local options. Suggesting that the CSV index should intimately relate to option-based implied volatility measures is by providing some interpretation of the CSV index as an indication for aggregate economic uncertainty. As to strengthen the performance of CSV index, this paper utilizes the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Heterogenous Autoregressive Realized Volatility (HAR-RV). These models are to explore the predictive power of CSV index in some Southeastern Asian market namely, Kuala Lumpur Composite Index (KLCI) of Malaysia, Jakarta Stock Exchange Composite Index (JKSE) of Indonesia, Philippine Stock Exchange Index (PSEi) of Philippine and The Stock Exchange of Thailand (SET).

This study adopts the GARCH, E-GARCH, GJR-GARCH and HAR-RV model to forecast the CSV index. It results in the analysis; not all markets have the ARCH and the GARCH effect. As the sum of ARCH and GARCH effect is not as close to one meaning that is not requiring to have a mean reverting variance process, indicating the performance of the error prediction is measured by Root Mean Square Root (RMSE), Mean Square Error (MSE) and Mean Absolute Error (MAE). The period of the data is from 3rd January 2004 until 2nd November 2015. The results capture symmetric and asymmetric effects on the volatility and yields for better predictive performance. Based on the results of the most accurate prediction for the CSV index is the Philippine market and E-GARCH model forecast faster implying that the latter process has a higher forecast memory. It has the least value of the RMSE and MAE measuring model which can assure that the forecast is most accurate. Simulation and empirical studies show that MAE(MSE) given by the best-fitted model is insignificantly different from that provided by the best forecast performance model. This study demonstrates that it is reliable to use the best-fitted model for volatility forecasting. So, therefore, the cross-sectional volatility index may be fit to be used in the four non-derivatives market.

Chapter 5

Cross-Mixed Volatility Index Hedging the Country Risk with Factor DCC

5.1 Introduction

This chapter proposes an empirical methodology of constructing a volatility index to measure the country risk. The methodology reflects the main sources of risks for any given country. A country risk is a combination of risks associated with investing in a foreign country that refers to economic, political and business risks that are unique to specific country. The country risk comes from primary risk sources of any given country. The risk mentioned here refers to changes in the macroeconomic and financial environment that affects the country financial systems. Liu et al. (2013) indicated that the country risk affects the performance of the economic and financial sectors in particular on the debt crisis countries, the turmoil that is happening in the Middle East, and the nuclear crisis in Japan. The risk mentioned comes from all the markets in a country, specifically, equities, foreign exchange, commodities and interest rates. Commonly, in asset management, prediction of volatility has been given the most attention, whether it is conditional volatility or implied volatility. However, there is less emphasis in the research literature a strategy on hedging the volatility risk directly. Risk analysis and risk hedging issues can be found in some of the discussion by Agliardi et al. (2012), Liu et al. (2013), Hassan et al. (2003) and Andrade (2009).

Research studies suggest extending the strategy of hedging risk by constructing an aggregate volatility index to provide investors with unique hedging techniques to alleviate, if not cancel, the country risk. The aggregate volatility index will comprise equities, volatility indices of the given country, foreign exchange, interest rates, and commodities. Also, in a financial market, a representative index of a global portfolio of various assets should be proposed as to monitor the unpredictable volatility. Therefore, this study needs first to establish a Cross-mixed Volatility index (CMV) that requires an appropriate methodology for calculating multivariate computing correlations to achieve this goal. The unique aspect about this chapter is that one of the variables in this aggregate volatility is derived from a Cross-Sectional Volatility Index (CSV). So, the chances of building the volatility index in a non-derivative market are high due to the CSV index can be applied to less derivative or non-derivative countries. The CSV index makes it easier to develop a benchmark risk index for the non-derivatives market. For instance, the VIX has been created by the Chicago Board of Options Exchange (CBOE) to keep tracks on an index based on the implied volatility of S&P 500 index options. It will be attractive to markets that have full options information specifically the developed markets. Upon the structuring the aggregate volatility index, there are several issues to carry out this task. Firstly, to capture the nature market of data precisely, determining the correct correlation function is an issue. Besides this, estimating the factor loading is the researcher's problem, mainly to find the right methodology to apply from the market data. Next question is the concern on the arbitrary choice of the number of factors. So, to resolve the issue of the construction of the aggregate volatility index, we construct the CMV index that captures the unpredicted risk and reduces the high dimension number of factors by implementing the framework of Zhang and Chan (2009) called Factor-DCC.

The Factor-DCC is a model that simplifies the estimation process of high-dimension of factors to a smaller number of factors regarding correlation function. It is different approach compared to the multiple pairwise DCCs. The factors approach appears due to economists to follow several time-series variables as proxies for the state of the economy. The Factor-DCC was explained earlier in Chapter 2. It is discussed further in Stock and Watson (2005, 2006), most of the information from every variable are combined and extracted to develop the factor model parsimoniously. As to minimize the number of factors of the Zhang and Chan (2009) model that allows an arbitrary choice of factors in the estimation of Factor-DCC, this paper applied an optimal criterion methodology to any statistical bias. The purpose of this research is to capture country risk factors in a single composite index of an equal-weighted based on the idiosyncratic risk in a non-derivative market, namely, Malaysia. It will be constructed to perform a benchmark index for the non-derivatives market that holds a large commodity asset. It will be named as Cross-Mixed Volatility Index, coined, CMV index. It is a combination of all the commodities volatility with other traditional asset volatility in foreign exchange, bonds, CSV Index, and equities. The aggregate volatility index encapsulates all the sources of risk stemming from the financial markets for the non-derivatives market. To our best knowledge, the Factor-DCC approach has never been implemented by mixing commodity markets with financial assets. As to develop the CMV index, this paper will focus towards the Malaysia market representing a non-derivative market. So, in this study, we construct an empirical methodology of CMV index in Malaysia market that combines the Factor-DCC method with elements filtered using optimal criterion. This volatility index, CMV index, serves for hedging the country risk at an aggregate level. From the results obtained, it is showing that the commodity assets are the country risk in Malaysia as it is more representative compared to the standard financial index. At the end of this study, this thesis revealed that the commodity assets represent 22 percent of the global risk in the CMV index. Next, the efficiency of the CMV Index is evaluated with the CSV index as a benchmark index for the given market. Referring to the VIX, it is a well-established volatility index using the implied volatility approach to hedge at global risk, but it is not applicable to the non-derivatives market due to lack of information on derivatives options. Then, the performance of the hedging is evaluated using the means of Ordinary Least Squares (OLS).

The CMV index is developed by mixing the volatilities stemming from commodity markets with traditional asset volatilities and the Cross-sectional Volatility (CSV) index. It is only applicable in the non-derivatives market, for instance, Malaysia, that is carried out in this study. Then, factor-DCC is fitted in two ways. Firstly, to extract the two factors, principal component analysis (PCA) is applied. Secondly, the estimated factors and the time-varying conditional correlation is determined. This methodology is considered new because when the PCA is used to extract the factors, it is static and de-correlated between factors averagely but not dynamically. This study then will make sure that the dynamic conditional correlation trend between factors remain close to zero despite some temporary peaks and troughs.

5.1.1 Outline

The remainder of this study is organized as follows. Section 5.1 gives an account of the purpose of the research. Section 5.2 provides information on the previous research work. Section 5.3 describe the data of the analysis in the research. Section 5.4 describes the methodology and research model, the Factor-DCC models, PCA model and hedging measurements used to construct the cross-market index and our new exciting results. Finally, Section 5.5 gives the conclusions.

5.2 Literature Review

Today, volatility hedging has been an issue to the world of the financial markets. Volatility risk plays a significant role in the management of portfolios of derivatives assets as well as holdings of vital assets. One of the purposes of this study is to review the literature related to the factors affecting market volatility and contagion effects. The increasing globalization has substantially raised the exposure of investors to risks associated with events in various countries. In this section, these findings are presented in an overview of some literature on the reason why cross volatility is a relevant index to be constructed, and from the results, all the findings in this study are used to put this thesis into perspective.

The reason for blending various assets is to compare a volatility index to represent a portfolio benchmark that reflects the primary sources of risk for the particular country. For instance, Agliardi et al. (2012) derived an overall index on economic, political and financial risk ranking of emerging countries. From the results, the leading contribution to sovereign risk is the financial risk, followed by the political and economic risks. It is another strong study that relates the reason to construct the CMV index in the non-derivatives market. Oetzel et al. (2001) were looking at a way to investigate the extent to which country risk measure can predict periods of intense instability. In this study, the researchers absorb currency fluctuations to surrogate for overall country risk. They found that by using the risk measures widely, it helps in providing benefits to predicting any significant crisis. It is related to the study to incorporate a mixed assets volatility that comprises country risk assets.

Besides that, Lin et al. (2013) found that changes in economic, financial and political country risk ratings have effects on five BRICS countries regarding response to positive and negative shocks. The BRICS countries are Brazil, Russia, India, China and South Africa. Since these five states have different characteristics in economies, financial, the risk ratings can be added to diversification benefits in portfolios.

The country risk defined in the introduction of this chapter gives impact not only on developed countries but also developing countries. The country risk, which includes the political risk, financial risk, and economic risk has provided an impact to the stock market return volatility and the future prediction. Hassan et al. (2003) examines the country risk impact towards the stock volatility in the Middle East and Africa. The results show how a portfolio of stocks can be formed from these countries to achieve mean-variance efficient portfolio. They found the country, political, financial and economic risks are significant determined and the investors benefit by diversifying the stocks market of the Middle East and African countries.

5.2.1 The Uncertainty Affects the Global Volatility Risk

Recently, the international financial and economic environment has become a pressure for all countries in the world. It is very challenging where to a large extent, the financial environment and economics are at uncertainty statistically. Firstly, is the uncertainty about the prospects for global growth in the aftermath of the Global Financial Crisis. The persistence of financial uncertainty is now having its implication on sentiment and confidence. Secondly, are the conditions in the commodity and financial markets that have become more volatile. The massive shifts in global liquidity are precipitating volatile capital flows with its immense implications on the asset and foreign exchange markets. Stock market return volatility and its prediction has been often related to uncertainty. It has been the most important indicators for investors and finance practitioners in today's globalization. The country risk with the association of political risk, financial risk and economic risk gives a great impact on the stock market return volatility . It is important for a country to decide direct investment globally as to diversify investment portfolios. Hassan et al. (2003) examined the volatility and predictor of stock market return in the Middle East and Africa. They found that the country risk significantly determine the stock market and its prediction.

There are various sources of macroeconomic volatility affecting countries. Asia Pacific region is the target among researchers which remains at the most dynamic part of the world's economy. Chow et al. (2017) examined 15 types of macroeconomic data series showing that three board categories of indicators that can be used to proxy macroeconomic volatility. It was reported in the study that the developing countries in the Asia Pacific were affected by factors such as global economic slowdown, geopolitical risks and volatile commodity prices. The study shows how important commodity risk could change the financial decision in a country. The recent work of Bali et al. (2014) exhibit the macroeconomic uncertainty and correlation risk related to hedge fund. There exist both macroeconomic risk and correlation risk when they examine the impact of uncertainty about future movements of market volatility on fund performance.

A further phenomenon affecting the global economic performance is the significant decline in global oil prices. While this has partially offset the weaker-than-expected growth momentum in some of the advanced countries, it has, in different degrees, adversely affected the oil exporting economies resulting in divergent growth performance across and within regions. Overall, however, the global economy is expected to benefit from the lower oil prices. A further recent development is the consequences of the unprecedented and divergent monetary policies being pursued in the major economies which have now resulted in significant policy spillovers to other parts of the world. Against this backdrop, the financial markets are therefore expected to remain in a state of heightened volatility during this year. Feng et al. (2017) forecast oil volatility risk to forecast stock market volatility. It is found that volatility risk premium on oil is statistically significant in-sample and out-sample of forecasting power. The analysis was conducted at G7 countries and the results appear to be robust when using alternative proxies for volatility of oil and stock. It is important nowadays, commodities give predictive power to stock market.

5.2.2 Country Risk

Country risk is dependent on changes in the macroeconomic and business environments affecting any of its financial markets (see Liu et al. (2009)). In the global economy, commodities enable investors to exploit the growth opportunities in just about every component of the production process. The most actively traded commodities include energy products such as crude oil and gasoline, agricultural products such as wheat and corn, soft products such as sugar and coffee and metals product such as gold, silver, and copper. Low correlations between these commodities and other assets is a way to diversify a portfolio among the investors. It helps to reduce risk and to boost return rather than investing in exchange-traded funds (ETFs), index funds, or mutual funds. Risk comes from all markets, namely interest rates, commodities, equities, foreign exchange and VIX. Aboura and Chevallier (2015a) mentioned that asset managers focused on volatility prediction, such as conditional volatility or implied volatility.

So, in the situation of the financial world market, the ability to monitor an index of a global portfolio of a variety of assets is important. Aboura and Chevallier (2015a) proposed a new empirical methodology for computing a cross-volatility index, coined CVIX, which characterizes the country risk understood as the financial market risk measurement. This methodology reveals that the CVIX is a better hedging performance than the VIX used as a benchmark. During financial stress periods, the VIX is no longer sufficient from a cross-asset perspective since it covers only U.S stocks but not other assets classes. Based on the CBOE platform of volatility index, they have recently established a commodity volatility index as a fear gauge index for the commodity. It is when the performance and prediction of the stock volatility index are positively accurate and well performed, the CBOE has constructed the volatility index for the commodity. The idea of CBOE is to let the investors turn to hedging strategies when markets start tumbling and fluctuating. So, they created some volatility benchmark indexes based on the sector-specific exchange-traded funds (ETFs) includes as:

- CBOE Crude Oil ETF Volatility Index(OVX)
- CBOE Gold ETF Volatility Index (GVZ)
- CBOE Silver ETF Volatility Index (VXSLV)

These volatility index benchmark of commodities are the new index published by CBOE since 2007 to track and analyze volatility measure with market's expectation of 30-day volatility. It uses the VIX methodology spanning a wide range of strike prices. The CBOE expands the VIX to the market that has derivative option prices. However, it does not suit the non-derivatives market. So, this study has come up with a methodology that allows non-derivatives market develop a Cross-mixed Volatility index reflecting the primary sources of risk which include all markets mentioned earlier. To construct the cross-volatility market index, the study proposes the Factor-DCC methodology implied by Zhang and Zhu (2006).

5.2.3 The Factor DCC model

The Factor-DCC method is conducted in the analysis of this study due to three reasons. First reason is to overcome problems that arise from the time-varying nature of market data especially in determining the correct correlation function. Secondly, by applying the Factor-DCC, it eases to estimate loading factors of the market data, and finally, the method is a platform to choose the number of factors with an arbitrary choice or it can be determined by using an appropriate methodology.

5.2.3.1 Factor

Assets managers have severe problems when solving and estimating high-dimension matrices of assets. Concurrently, they seem to incorporate two problems. Two issues that are faced by the asset managers are determining the correct correlation function when the nature market data is precisely captured and choosing the proper methodology to measure the market data factors. To overcome the two problems, this study will be constructing a new cross-market volatility index that captures the unpredicted risk. Secondly, issues of high dimension matrices can be solved by introducing the framework build by Zhang et al. (2010).

Zhang and Chan (2009) has come with a new framework to solve high dimensional matrices. The parameters used in some of the models, for instance, GARCH-extension model, are complex. However, a method was discovered to simplify the complex parameters efficiently. So, firstly their study estimates the factors used in their research based on the formal statistical approach by Alessi et al. (2010) to determine the number of factors. Then, each factor is calculated by the univariate GARCH model, and the conditional covariance matrix of return series is constructed. So, from the results of the study can be thought of as a hierarchical model, wherein the first level, the strong conditional correlation between return series is indicated regarding weak conditional correlation between factors, using linear transformation. At the second level, the dynamic conditional correlation (DCC) model estimates the weak conditional correlation accurately.

Determining the number of factors using the approach of Alessi et al. (2010) is a modified criterion from the model by Bai and Ng (2012). A positive real number multiplies the penalty function and as to allow penalization power by analog, another method of Hallin and Liška (2007) is used. Extraction of factors will first be sorted based on the principal component analysis. It is classified because the PCA approach allows the yielding factors that are de-correlated on average stays static during the computation although the factors are not dynamic at the given time. The PCA can only be exposed to a risk of re-correlation between factors. So, this shows the reason why the Factor-DCC approach is used to ensure the dynamic conditional correlation trend between factors remains zero. Although, despite some temporary peaks and troughs.

To extract the factors using the PCA approach, given k-dimensional random variable $r = (r_1, r_2, ...r_k)$ with covariance matrix $\sum_r$, which is explained in Tsay (2010). The PCA used a few linear combination of r_i. Then let $w_i = (w_{i1}, ..., w_{ik})'$ denoted as a k-dimensional real valued vector, with $i = 1, ..., k$. So, it shall randomly be written as r:

$$y_i = w_i^{'} r = \sum_{j=1}^{k} w_{ij} r_j \tag{5.1}$$

where r represents the returns of the k variables, and y_i shows the return of the portfolio assigning the weight w_{ij} to the jth variable. In the finding, the linear combinations w_i, the PCA should have:

1. y_i and y_j are uncorrelated for $i \neq j$;

2. variances of y_i are large as possible.

So, Tsay (2010) writes the variables randomly to the linear combination properties which more specifically look like;

$$Var(y_i) = w_i' \sum_r w_i, \quad i = 1, ..., k. \tag{5.2}$$

$$Cov(y_i, y_j) = w_i' \sum_r w_j, \quad i, j = 1, ..., k. \tag{5.3}$$

which resulting Var (y_i) maximizes the first principal component of r subject to $w_1' w_1 = 1$. The linear combination of the first principal component is written as $y_1 = w_1' r$. See Chapter 2 for further explanation regards to the PCA model.

5.2.3.2 DCC Model Approach

The implied volatility σ and its log-variation ς is denoted as $\varsigma = log(\sigma_t / \sigma_{t-1})$ at time t. Thus, ς_t is shows a $n \times 1$ vector of implied volatility log variations at time t, with an assumption of mean zero at a conditionally normal and covariance $n \times n$ matrix H_t:

$$\varsigma_t | \omega_{t-1} \sim N(0, H_t) \tag{5.4}$$

stating that ω_{t-1} represents the information set at time $t - 1$. The DCC model is also known as the dynamic conditional correlation estimates the weak conditional correlation accurately. The DCC model is decomposed as follows;

$$H_t = D_t R_t D_t, \tag{5.5}$$

where H_t represents the conditional covariance matrix, R_t is the $n \times n$ time-varying correlation matrix, $D_t = diag(\sqrt{h_{1,t}}, ..., \sqrt{h_{i,t}}, ..., \sqrt{h_{n,t}})$ is the $n \times n$ diagonal matrix of the time-varying standard deviations extracted from univariate GARCH models with $\sqrt{h_{1,t}} = \sigma^*_{i,t}$ or the ith diagonal. According to Engle (2002), the DCC model is written as;

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5.6}$$

where element R_t is formed as;

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t} q_{jj,t}}} \tag{5.7}$$

where $Q_t^* = diag(\sqrt{q_{ii,t}})$ is the square root of a diagonal elements of the covariance matrix Q_t. According to the covariance matrix Q_t, the DCC model evolves to

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B) + A'(e_{t-1}e_{t-1}^{'})A + B'(Q_{t-1})B \tag{5.8}$$

where the $n \times n$ vector of standardized residuals $e_{i,t} = \frac{\varsigma_{i,t}}{h_{i,t}}$ composed the unconditional covariance matrix Q. A and B are $n \times n$ diagonal matrix, where $A = diag(\sqrt{a})$ and $B = diag(\sqrt{b})$. It may be written as;

$$Q_t = (1 - \alpha_1 - \beta_1)\bar{Q} + \alpha_1 e_{t-1} e_{t-1}^{'} + \beta_1 Q_{t-1} \tag{5.9}$$

where α_1 and β_1 are parameters of the DCC model.

5.2.3.3 CD-DCC Model

The factor model expanded by Zhang and Chan (2009) is giving an idea in this study to specify the number of factors that outline the presence of all depend between assets return when a matrix of variance-covariance can be estimated. According to Alexander (2000, 2001) and Ding (1994), a PCA technique is used to set up a orthogonal GARCH (O-GARCH) model. The PCA is used to extract m principal components. Zhang and Chan (2009) attain three specifications for the Factor-DCC model which are

1. IF-DCC
2. BD-DCC
3. CD-DCC

The IF-DCC is the independent-factor DCC which estimates factors that is statistically independent as possible. The BD-DCC is the best-factor DCC that checks the criteria for each factor that are estimated to have the largest autocorrelation in squared value and the CD-DCC is called the conditional-decorrelation DCC that estimates factors which are conditionally as uncorrelated as possible. However, due to the study of Zhang et al. (2010) showing superior performance to model financial data, CD-DCC is chosen over the other two specifications criteria. To allow the orthogonality constraint of factor loading matrix is relaxed, Zhang and Chan (2009) resorted by using the set factor GARCH models. The set factor GARCH model is well suited to high-dimension data. There are two steps of estimation of the data factors. The first step is, the factors are estimated with some statistical criteria and the second step, each factor is estimated using the GARCH model. The latent uncorrelated factors $y_t = (y_{t,1}, ..., y_{m,t})'$ generates the innovation ϵ_t in a linear transformation form as;

$$\epsilon_t = Ay_t \tag{5.10}$$

where $A = diag(\sqrt{a})$. The $y_{i,t}$ represents the GARCH process as

$$h_{y_{i,t}} = (1 - \alpha_i - \beta_i) + \alpha_i y_{i,t-1}^2 + \beta_i h_{y_{i,t-1}}. \tag{5.11}$$

Then, only the conditional covariance matrix series, ζ_t can be inserted. Sometimes, the factor loading might still have some conditional correlation; this is when Zhang and Chan (2009) proposed the Factor-DCC to remain the time-varying condition correlation between the DCC model and the factors. It is an extension of the factor GARCH model to model the conditional correlation between factors. So, the following equation is the conditional covariance matrix between factors:

$$D_t R_t D_t \tag{5.12}$$

where R_t represents the conditional correlation matrix of y_t shown in the form of equation (5.6). The D_t denotes the diagonal matrix composed of the square root of the diagonal elements of the conditional covariance matrix Σ_t of factors $y_{i,t}$ with $i = 1, 2, ..., m$, with $m < n$ and is written as $diag(\sqrt{h_{y_{i,t}}})$. However, the CD-DCC model is selected because it provides the best fit to financial data. So, we introduced to create a cross-mixed commodity volatility index.

5.2.4 Performance Measure

As to assess hedging performance of the CMV index, it is good to have a least one approach measure to compare with the actual relative informational content against the VIX index. Unfortunately, it can not be done due to insufficient information of options prices. So, the CSV index approach will be the main approach method to compare with the CMV index methodology. This is the nearest relevant methodology as the CSV index represents the volatility benchmark index for the non-derivatives market, see Md Fadzil et al. (2017) for further method explanation.

5.2.5 Data Sources

5.2.5.1 Malaysia Market

Trade, investment and income channels have been growing recently in the Malaysia market. It encourages positive spillovers on the domestic economy. Export performance in Malaysia can benefit from higher growth among key trading partners and the projected recovery in commodity prices. Malaysia today has a diversified economy and has become a leading exporter of electrical appliances, electronic parts and components and natural gas. Malaysia continues to grow after the financial crisis in 1997-1998 and average of 5.7 growth raters after Malaysia was hit by the global financial crisis in 2009.

Malaysia was one of those Asian crisis countries that suffered from destabilization in the capital market due to insignificant foreign exchange trading in the late 1990s. The traditional measures that are taken up to stabilize the capital inflows during any financial crisis are raising the interest rate and devaluation of the currencies. But this strategy did not work in the late 1990s in Malaysia, and this led to thin foreign exchange trading in Malaysia. The volatility transmission and time-varying volatility are some of the factors that affect the foreign exchange market of Malaysia.

Both the domestic and international financial markets play a significant role in regulating the foreign exchange market Malaysia. The economic factors like government budget deficits or surplus, inflation levels, economic growth strategy taken up by the central bank of Malaysia Bank Negara Malaysia, trade balance, etc. influence the foreign exchange market of Malaysia. The exchange rate of Malaysian Ringgit is always changing following a slight change in the money value of the Ringgit and other currencies of the world. The current exchange rates of one Malaysian Ringgit with some of the major currencies of the world are as follows:

5.2.5.2 Bursa Equity Market (KLCI)

Bursa Equity Market (KLCI) is the leading stock index of 30 listed public companies in Malaysia individually and collectively influence the economy of Malaysia, Southeast Asia, and the world profoundly. The listed companies are aggregated in Malaysia's to form FTSE Bursa Malaysia Kuala Lumpur Composite Index or abbreviated as FBM KLCI or simply KLCI.

5.2.5.3 Kuala Lumpur Cross-Sectional Volatility Market (CSV KLCI)

Kuala Lumpur Cross-Sectional Volatility Market (CSV KLCI) is a volatility index that uses the cross-section methodology to calculate the volatility index. It is constructed in Chapter 3 to indicate the fear index of equity volatility to proxy the VIX. The approach is simply based on Equation 3.13.

5.2.5.4 Foreign Exchange Market (MYR-USD)

In Malaysia, the rate of exchange rate depends on various economic and political factors of Malaysia. The foreign exchange market in Malaysia compromises the trading of Malaysia currency Ringgit with other currencies of the world.

5.2.5.5 10 year Government Bond Market (RETGB)

Government bonds are issued by the Malaysia's government to increase funds from the local domestic market to finance the government's development expenditure. They are marketable debt and also used to raise the fund to work capital for the government project transformation. It is one of the most developed and dynamic bond markets in the region. As of 31 December 2011, the market has reached the size of MYR848 billion.

5.2.5.6 Commodity market

Malaysia is one of the biggest suppliers of natural rubber which is 70 percent of the world contribution after Indonesia and Thailand. It has been Malaysia's primary exports for many years. Natural rubber production is increasing in the year 2011 compared to 2010 with the total of production from 966,210 to 939,241 tonnes. The industry has manufactured more than 500 latex products including tyres and tyre-related products. From the natural rubber sources, the industry contributed 18.1 billion to the country's export earnings in 2011, and is quite a huge contribution.

The palm oil production in Malaysia is the second world largest producer of the commodity after Indonesia. It currently produces 39 percent of palm oil in the world production and 44 percent of world exports. Malaysia accounts for 12 percent and 27 percent of the worlds total production and exports of oils and fats. Malaysia has to fulfill the growing global need for oils and fats sustainable. The palm oil prices are very much driven by international supply and demand. Malaysia exports palm oil at 85 percent and the palm oil is traded in the form of physical market, paper market, and the futures market. The futures exchange is traded in the Bursa Malaysia. It is the most important indicator to show the palm oil prices in the world. Crude palm oil (CPO) has also been the primary export commodity in Malaysia. It is traded on a regulated exchange, Bursa Saham Malaysia. The futures market of CPO shows significant changes in their trading volume and open interest over the years.

Gold has been played as a hedging tool for many centuries mainly during the political and economic uncertainty exists, see Baur and Lucey (2010). Due to the high performance of return in the Malaysia market and risk reduction effectiveness, gold has become one of the outstanding commodities among other commodities.

Malaysia has become the major exporter of sawn timber in the world. The wood-based industry is one of the significant resource-based industries and one of the most important sectors contributing to Malaysia's economy. The wood-based industry can be divided into two subcategories, namely primary and secondary wood processing. Primary wood processing mills process logs to produce sawn timber and veneer. Secondary wood processing turns primary products and other solid wastes such as small branches, off-cuts, edging or slabs, chipping and sawdust into downstream value-added products. Export of sawn timber in 2008 amounted to RM 2.6 billion and major species exported by Malaysian are Kapur, Keruing, Meranti, and Mersawa.

Malaysia Crude Palm Oil and palm kernel oil is currently the most popular contract by trading volume and open interest. It started trading in Kuala Lumpur Commodity Exchange (KLCE) before merging with the Monetary Exchange (MME) in November 1998 becoming the Commodity and Monetary Exchange (COMMEX). Then, the COMMEX was renamed as Bursa Malaysia Derivatives Bhd (BMD). The palm kernel oil is a co-product to palm oil at a ratio production volume of 10 to 13 percent. Malaysia palm kernel oils have expanded its production by 20 percent, see Nasir et al. (1994).

5.3 Data

Table 5.1 shows the descriptive statistics of return mixed assets. The data is retrieved from DataStream, and there are ten time series that have been collected in monthly frequency over a period of ten years from January 2005 to March 2015. These data can be composed of subgroups. The total number of observations is equal to 2310.

1. Bursa Equity Market (KLCI): It is the FTSE Bursa Malaysia KLCI price index.

2. Kuala Lumpur Cross-Sectional Volatility Market (CSV KLCI)(RETCSVI): CSV KLCI is the cross-sectional volatility index of the price index.

3. Foreign Exchange Market (MYR-USD)

4. Ten year Government Bond Market (RETGB)

5. Commodity market

    - Rubber (RETRUBB) spot price.
    - Palm Oil (RETPO) spot price.
    - Gold (RETGOLD) spot price.
    - Crude Palm Oil (RETCPO) spot price.
    - Palm Kernel Oil (RETPKO) spot price.
    - Sawn Timber (RETSTIM) spot price.

The CSV KLCI is constructed using the method discussed earlier in Chapter 3. The CSV KLCI maybe one of the country risk factor and it is the reason to compute the index with the other combination of data sources of risk index. Figure 5.1, Figure 5.2 and Figure 5.3 display the monthly time-series of price data of commodity and financial assets. The monthly price of each commodity and financial risk varies. The CSV KLCI index seems to be a stationary process with a mean close to zero compared to other assets monthly prices. Other commodity assets such as the Gold, Rubber, Palm Kernel Oil and Palm Oil exhibit relatively calm periods followed by turbulent periods. The government bond monthly price decreases gradually through out ht Then, Figure 5.4, Figure 5.5 and Figure 5.6 exhibit the monthly time-series of returns price on commodity and financial assets. This is to observe the volatility changes across markets and periods. The pattern of each asset is not the same but motivates to our new cross-market volatility index that combines all sources of risks.

Table 5.1 shows the descriptive statistics of returns in commodity assets and financial assets market. From this table, we can observe how risky the commodity assets and the Cross-Sectional Volatility index compared to the other financial assets. The variability, standard deviation and the kurtosis of commodity assets and CSVI KLCI are higher than the other assets. It means that their speculative component might be higher than for other assets. The highest volatility in this study relates to the representation of high trading volumes in the market given their nature of strategic consumption assets. According to the Markowitz approach, the 'good' dimension is captured on the expected return on an investment and the 'bad' dimension is the variance in that return. So, the standard deviation, skewness, and kurtosis of the returns show the dimension of risk. The CSVI, Palm

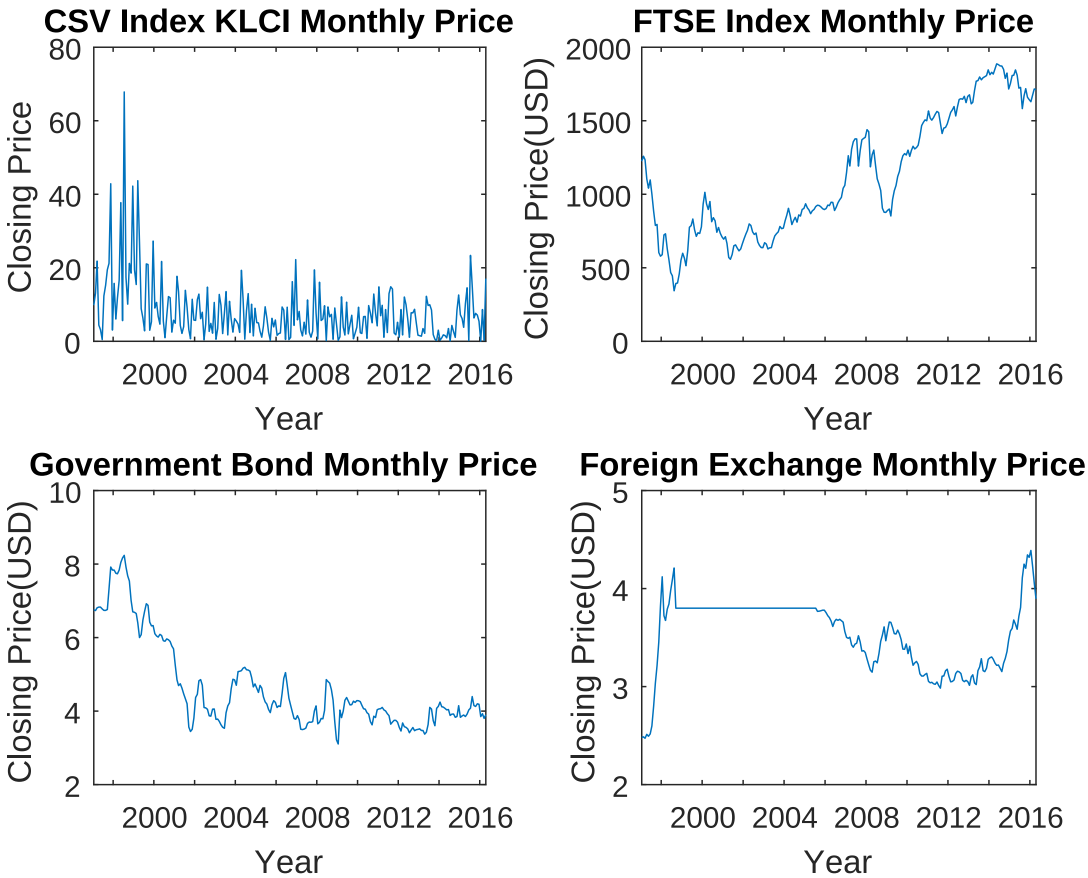


Figure 5.1: Monthly Price Data of all Mixed Assets

Oil, Palm Kernel Oil and Crude Palm Oil display negative skewness meaning possibility due to its leading role as a primary ingredient for world population feeding.

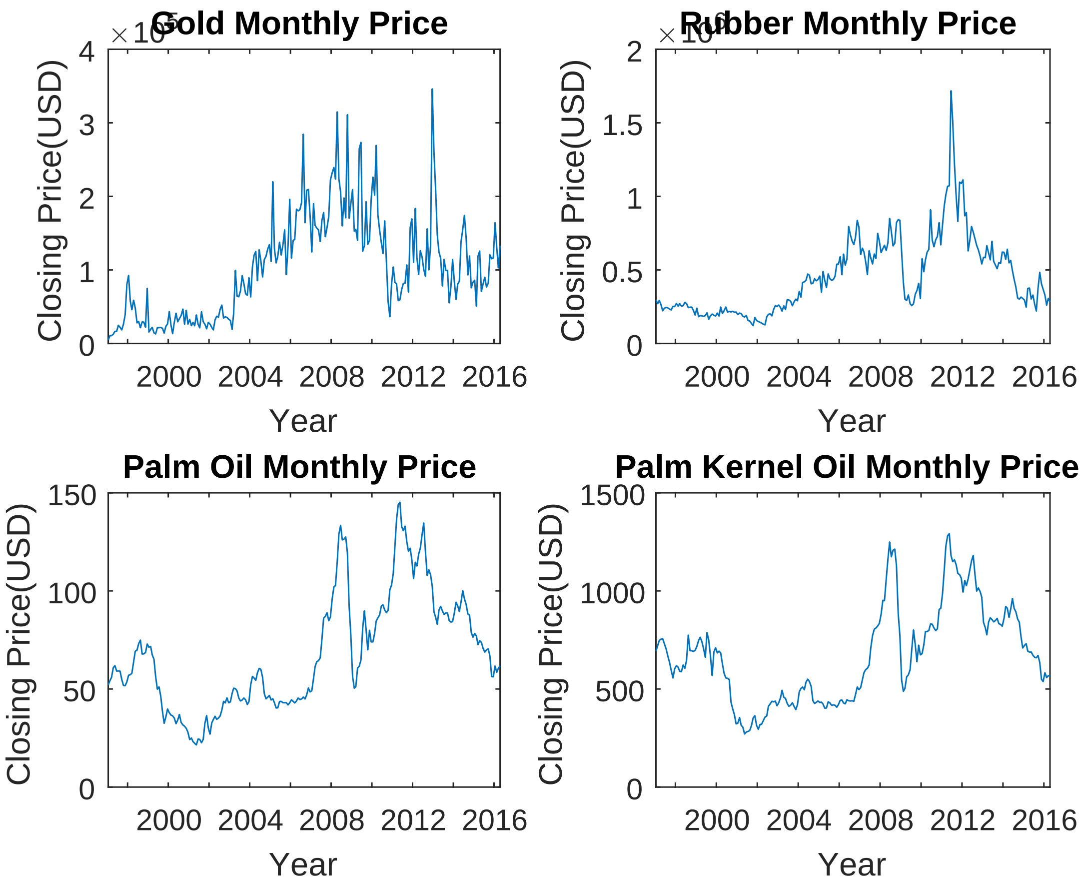


Figure 5.2: Monthly Price Data of all Mixed Assets

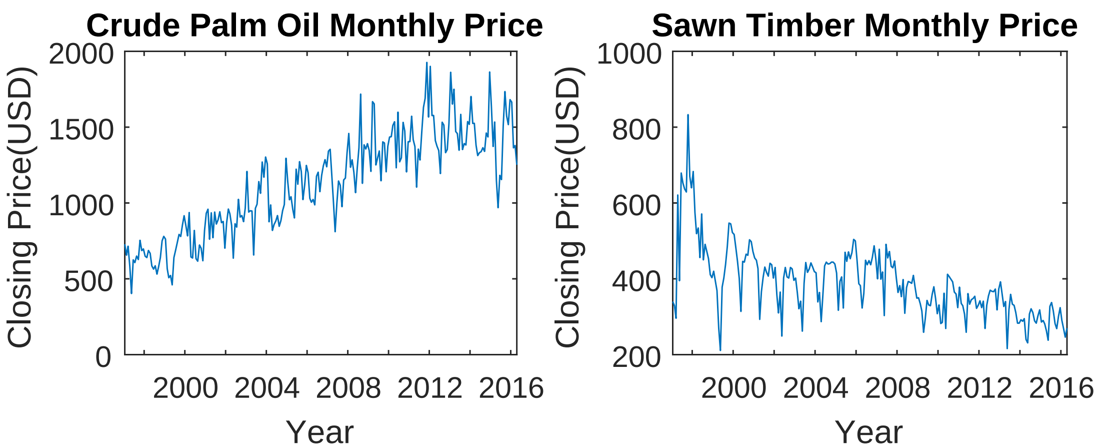


Figure 5.3: Monthly Price Data of all Mixed Assets

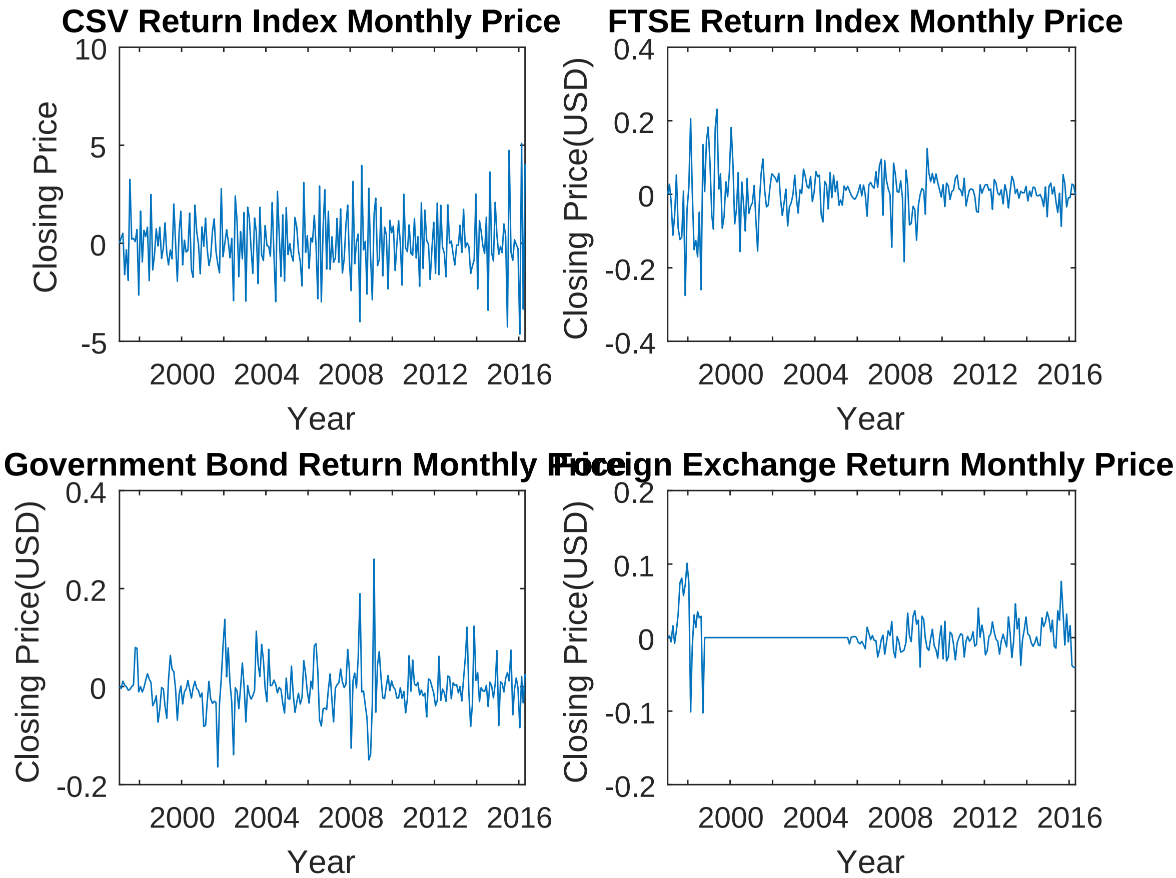


Figure 5.4: Return Price of Mixed Assets

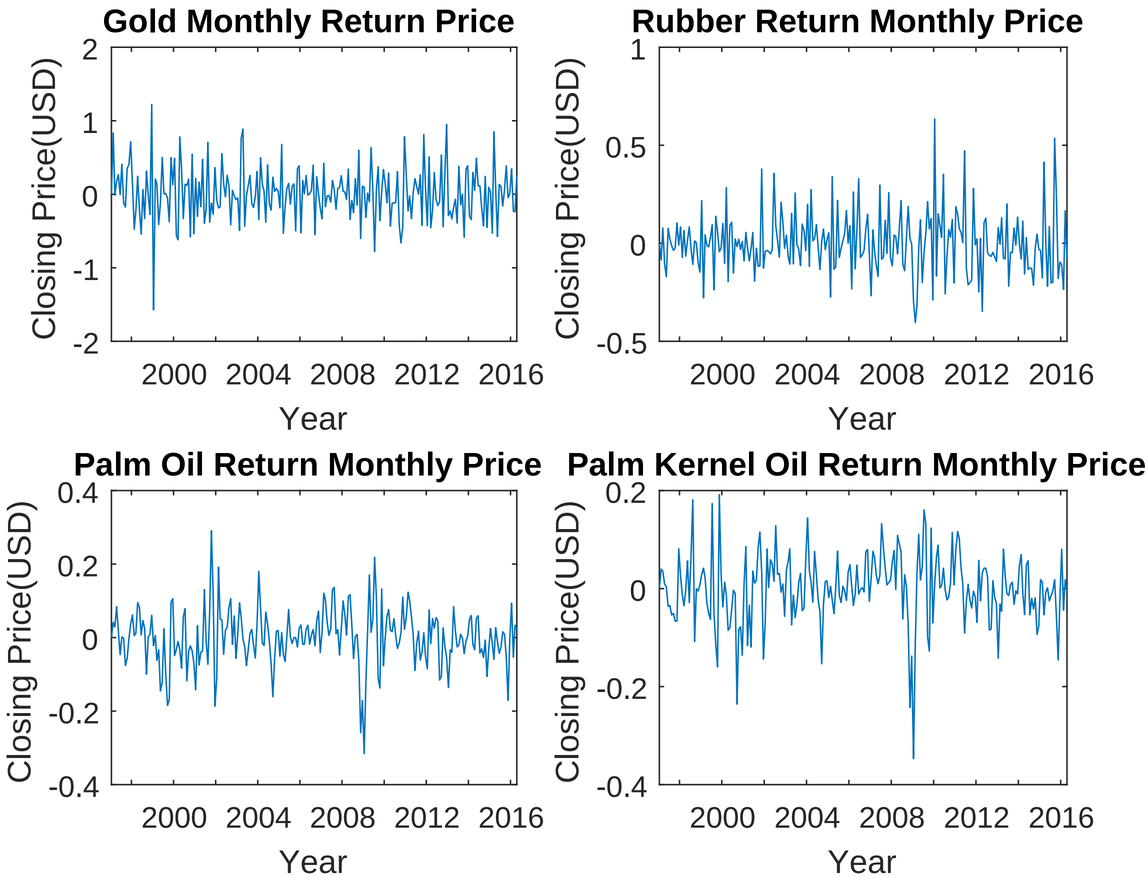


Figure 5.5: Return Price of Mixed Assets

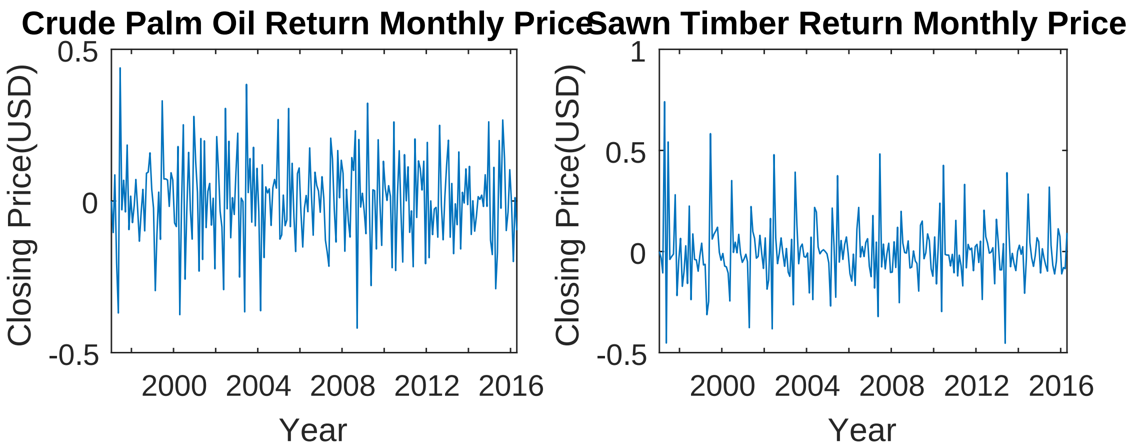


Figure 5.6: Return Price of Mixed Assets

Table 5.1: Descriptive Statistics on Returns of Assets

	RET_CSVI_KLCI	Ret_KLSE	RET_FE	RET_GB	RET_GOLD	RET_RUBB	RET_PO	RET_PKO	RET_CPO	RET_STIM
Mean	0.0023	0.0014	0.0019	-0.0024	0.0144	-0.0001	0.0007	-0.0008	-0.0234	-0.0009
Median	-0.0979	0.0087	0.0000	-0.0037	0.0092	-0.0170	0.0055	0.0022	0.0007	-0.0113
Standard Deviation	1.5905	0.0645	0.0221	0.0485	0.3628	0.1549	0.0767	0.0706	0.1476	0.1614
Kurtosis	0.5802	3.6778	6.9564	5.2922	1.3636	1.6180	2.1485	2.9774	0.2433	3.4935
Skewness	0.1649	-0.4828	0.3482	0.8058	0.0319	0.6934	-0.2509	-0.6667	-0.0554	0.9472
Minimum	-4.6360	-0.2753	-0.1024	-0.1639	-1.5722	-0.4044	-0.3155	-0.3469	-0.4192	-0.4536
Maximum	5.0991	0.2314	0.1010	0.2602	1.2214	0.6342	0.2907	0.1917	0.4388	0.7409

Table 5.2: Correlation of Returns Between All Mixed Assets

	RET_CSVI_KLCI	Ret_KLSE	RET_FE	RET_GB	RET_GOLD	RET_RUBB	RET_PO	RET_PKO	RET_CPO	RET_STIM
RET_CSVI_KLCI	1	0.0175	-0.0464	0.1122	-0.0058	-0.1533	-0.0157	0.0073	-0.1253	-0.1802
Ret_KLSE	0.0175	1	-0.4358	-0.0630	-0.0038	0.0321	-0.0033	0.0383	-0.0115	-0.0737
RET_FE	-0.0464	-0.4358	1	0.1588	0.0525	-0.00065	-0.0131	-0.0273	0.0500	0.0769
RET_GB	0.1122	-0.0630	0.1588	1	0.0425	-0.0441	-0.0446	-0.0476	0.0047	0.0551
RET_GOLD	-0.0058	-0.0038	0.0525	0.0425	1	-0.0386	-0.0259	-0.0242	0.0244	0.0342
RET_RUBB	-0.1533	0.0321	-0.0006	-0.0441	-0.0386	1	0.0366	0.0592	0.2729	0.3320
RET_PO	-0.0157	-0.0033	-0.0131	-0.0446	-0.0259	0.0366	1	0.8364	-0.1156	-0.0447
RET_PKO	0.0073	0.0383	-0.0273	-0.0476	-0.0242	0.0592	0.8364	1	-0.1080	-0.0472
RET_CPO	-0.12531	-0.0115	0.0500	0.00472	0.0244	0.27299	-0.1156	-0.1080	1	0.3740
RET_STIM	-0.1802	-0.0737	0.0769	0.0551	0.0342	0.3320	-0.0447	-0.0472	0.3740	1

Table 5.2 exhibits the correlation between each of assets. The highest relationship of the mixed assets is between the Palm Kernel Oil and the Palm Oil at the value of 0.8364 followed by the Crude Palm Oil and the Sawn Timber with the value of 0.3740. The value means that the relationship between these assets are strong and will give impact on each other in future results analysis. Table 5.3 shows the correlation between the factor loading extracted using the principal component analysis (PCA). From the five principles, the highest correlation is exhibit mostly in Principle Component 1 and Principle Component 2. The first principle component increases with the increases in palm oil and palm kernel oil scores. Based on Table 5.3, the highest correlation 0.8226 is the primary measure of Palm Kernel Oil followed by the Palm Oil with the value of 0.8185.

Table 5.3: Correlation between the assets return and the PC's component

	PC1	PC2	PC3	PC4	PC5
RET_CSVI_KLCI	0.1738	-0.4129	0.1183	0.4702	0.3543
Ret_KLSE	0.1756	-0.1261	-0.7575	0.3036	-0.0187
RET_FE	-0.2140	0.1647	0.7848	-0.1370	-0.0193
RET_GB	-0.1299	-0.0651	0.3889	0.6650	0.2938
RET_GOLD	-0.0831	-0.0746	0.1198	0.4469	-0.8642
RET_RUBB	-0.2189	0.6355	-0.2356	0.0548	0.1610
RET_PO	0.8185	0.4681	0.1367	0.0613	-0.0118
RET_PKO	0.8226	0.4680	0.1007	0.0909	-0.0058
RET_CPO	-0.4727	0.5098	-0.1521	0.1683	0.0613
RET_STIM	-0.4255	0.6297	-0.0532	0.1743	0.0509

5.4 Empirical Analysis

Using the approach by Zhang et al. (2010), the Factor-DCC model is estimated in two separate steps. We first use Principle Component Analysis (PCA) to extract factors. The recovery of the factors can be considered as a pre-processing step. Second, we turn to the estimation of the DCC for modeling the conditional covariance matrix of factors. The reason to specify the number of factors is to summarize all the current dependence between asset returns from which a matrix variance-covariance is estimated. These factors will show the correlation function over time. In a previous study by Alexander (2002) PCA is applied to extract m Principal Components by setting up the GARCH (O-GARCH) model.

So, the first-factor extraction, the choice of the number of factors are subjected to an arbitrary choice using the formal statistical approach by Alessi et al. (2010) and Bai and Ng (2012) to identify the number of factors. When a large idiosyncratic disturbance occurs, it is best to use Alessi et al. (2010). It is a modification criterion of Bai and Ng (2012) model in order to avoid overparametrization, where minimization is subject to penalization. The original procedure is modified by multiplying the penalty function by a positive real number, which allows to tune the penalizing power. It is generally an iterative criterion application of the Bai and Ng (2012). So, the study chooses the method by Alessi et al. (2010) which is also applying the criterion of Bai and Ng (2012) at the same time when running the analysis.

Denote $\hat{r}^{T}_{c,N}$ as the number of factors described by Alessi et al. (2010) criterion with T as the time and N is the cross-section dimensions of the data set. There are two information criteria to be used in the statistic test which are:

$$IC^{T*}_{1,N}(k) = log[V(k)] + ck\left(\frac{N+T}{NT}\right) log\left(\frac{NT}{N+T}\right), c \,\epsilon\, \mathbb{R}^{+} \tag{5.13}$$

$$IC^{T*}_{2,N}(k) = log[V(k)] + ck\left(\frac{N+T}{NT}\right) log\left(min\left\{\sqrt{N}, \sqrt{T}\right\}\right)^{2}, c \,\epsilon\, \mathbb{R}^{+} \tag{5.14}$$

when V is the residual variance of the idiosyncratic components, c is an arbitrary positive real numbers, and k common factors. The estimated number of factors is function of c and, depending on the criteria chosen, which is given by:

$$\hat{r}^{T}_{c,N} = \underset{0 \leq k \leq r_{max}}{argmin}\, IC^{T*}_{a,c,N}(k),\ a = 1, 2. \tag{5.15}$$

where r_{max} represents the maximum number of factors and $\hat{r}^{T}_{c,N}$ is consistent as n and T diverge, see Bai and Ng (2012) in Chapter 2 for more details. c also represents the degree of freedom and can be exploited when criterion is implemented. Then the stability of the estimated number of factors can be evaluated by the empirical variance S_c concerning to sample size. It is written as:

$$S_c = \frac{1}{\tau}\sum_{j=1}^{J}\left[\hat{r}^{\tau_j}_{c,n_j} - \frac{1}{\tau}\sum_{j=1}^{J}\hat{r}^{\tau_j}_{c,n_j}\right]^{2} \tag{5.16}$$

taking account of the subsamples of sizes (n_j, τ_j) with $j = 0, ..., J$ such that $n_0 = 0 < n_1 < n_2 < ... < n_j = N$ and $\tau_0 = 0 < \tau_1 < \tau_2 < ... < \tau_j = T$.

From the criteria mentioned, the study represents the results achieved from the Principal Component Analysis. Table 5.4 displays the fraction of the total variance explained

Table 5.4: Share of variance explained by factors.

Assets	Factor 1 (44.81 %)	Factor 2 (55.19%)
RET_CSVI_KLCI	0.02	-0.27
Ret_KLSE	0.04	-0.08
RET_FE	-0.05	0.12
RET_GB	-0.06	0.00
RET_GOLD	-0.04	0.02
RET_RUBB	-0.01	0.49
RET_PO	0.9	0.11
RET_PKO	0.91	0.12
RET_CPO	-0.19	0.52
RET_STIM	-0.14	0.67

by the two factors, along with the time-series in the data set that each of them is most strongly correlated with. The cumulative variance of factors is given by the sum of their eigenvalues. The total variance is the sum of the variances of the individual volatility series in the data set, measured as the sum of their eigenvalues. Table 5.4 shows that Factor 1 reports for almost 44.81 percent of the variability contained in the dataset, while Factor 2 accounts for 55.19 percent of the total variation. This allows that the Factor-DCC model captures a significant fraction of the total variation of the ten time-series contained in the dataset. It represents 100 percent of the total variance. This amount validates the factor-DCC methodology as being in the presence of various time series of volatilities with different patterns. These Factor 1 and Factor 2 are characterized by a mix of commodities and financial assets. Factor 1 and Factor 2 captures mainly influences from the commodity assets. Palm Oil and Palm Kernel Oil are the most influence in Factor 1 with 0.9 and Sawn Timber, Crude Palm Oil and Rubber are the most influence in Factor 2.

Figure 5.7 and 5.8 illustrate the factor loadings for two components. It shows the contribution of each series to each factor.

DCC estimates occur in the next step wherein Table 5.5 explained the estimation of Factor-DCC parameters on the mixed asset returns. It is shown that it is significant and comparable to the GARCH-family models. The correlation between the two factors is negative, -0.08, meaning the two factors are unlikely correlated which suits the purpose of CD-DCC model. In conditional de-correlation DCC model, the factors should appear to uncorrelated as much as possible, especially in the multivariate financial time series. Both

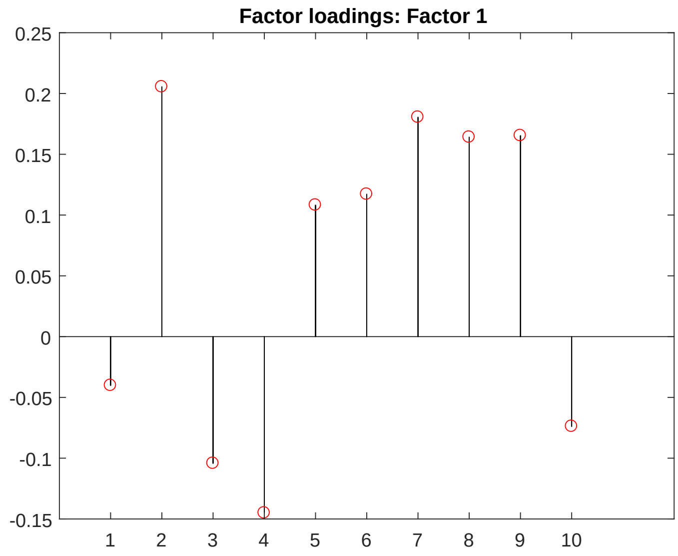


Figure 5.7: Factor loadings of First Principle Component Analysis

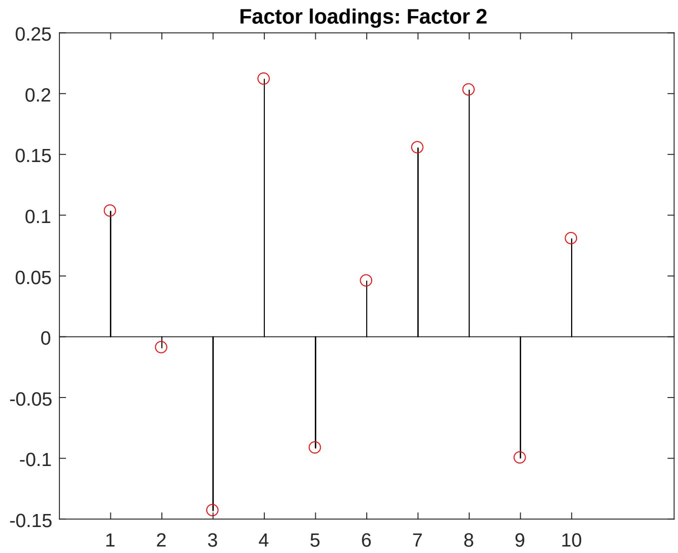


Figure 5.8: Factor loadings of Second Principle Component Analysis

the alpha and beta sum up is approximate equals to one. The best multivariate financial time series is best when factors are de-correlated in DCC condition method.

Then in Figure 5.9 exhibits the conditional correlation between the first and second factors estimated by the PCA. It shows that the conditional correlation calculated using the CD-DCC model is time-varying with an almost zero average correlation around 0.02 percent. This result indicates the objective of the CD-DCC GARCH model is fulfilled. The dramatic changes of magnitude are observable between the 100 to 150 months which is specifically between April 2005 and June 2009. The changes of magnitude could be the impact from the Asian financial crisis that occurs in this period.

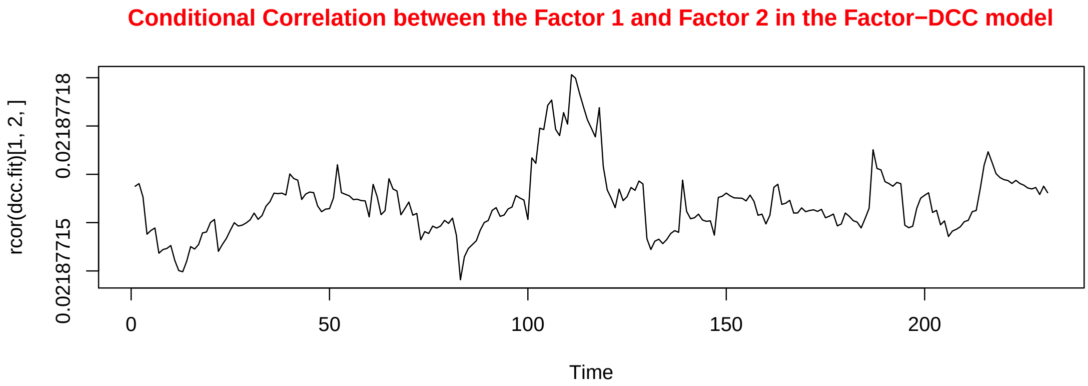


Figure 5.9: Conditional correlation between the CD-GARCH factors 1 and 2 estimated by the DCC Model

As to compose the cross-mixed commodity volatility index composition, there are a few steps required after extracting factors from the factors loading. This methodology is a straightforward to use and it can be computed easily by practitioners. The intuition of this methodology is based on the output of the Principal Components Analysis (PCA). The purpose of building the volatility index composition is to capture the contribution of the ten series to each factor, and the contribution to each factor of the two factors to the cross-mixed volatility index,(CMV Index). The weighting scheme is built in three steps. The first step is to compute the absolute value, as a measure of magnitude, of each series' contribution to each factor. The second step is to standardized the percentage and finally, to plug the weights into the original data to create the CMV Index time series.

In order to compute the weights index, $S_{i,n}$ represents each bar of the plot illustrate in

Table 5.5: Estimation of Factor-DCC on the return assets

Model	CD-DCC
Parameters	
Alpha_DCC	0.2211**
Beta_DCC	0.7778**
Diagnostics	
Log-L	1239.57
Akaike	-1.0698
ρ	-0.08

Figure 5.7 and 5.8. The plot illustrates that the loadings alternate between positive and negative signs. So, change the loadings value to absolute value. Then, the absolute values from the both mentioned figures, compute the sum of the loadings for each factor, and divide each absolute value by its respective sum. The objective of this step is to average out the loadings' contribution. These are the three steps to employ the weighting scheme of the composition of CMV index:

1. Each factor loading $F_i, i = 1, 2$, the absolute value of each series' $S_{i,n}$ contribution, with $n = 1, ..., 10$.

2. The absolute value $|S_{i,n}|$ is divided by the sum of each factor loading's absolute value $\sum_{n=1}^{10} |S_{i,n}|$ and multiplied by 100.

3. The contribution of each series to the index is computed as the average percentage between the two factor loadings contributions $\omega_n = \frac{|S_{1,n}+S_{2,n}|}{2}$ with $\sum_{n=1}^{10} \omega_n = 1$.

Creating ω as the quantity is to not favor one factor over another. It denotes the weight of each time series in the CMV index by implying an equal share for each factor. Based on the PCA simplicity, the ω sums to one. Then, each series would allow contributing in percentage to the CMV index.

Next step is to compute the index time series. Stemming from the composition in percentage, the CMV index time series is created by computing as an average of the ten time series (TS) composing the index, weighted by their respective contribution which is written as $CMV_t = \sum_{n=1}^{10} \omega_n TS_{n,t}$ which is also similar to $CMV = \sum_{t=231} \sum_{n=1}^{10} \omega_n TS_{n,t}$. The weight of each time series is multiplied by the raw time series as to create the CMV index. The study reports the contribution in the percentage of each of the CMV index in the pie chart in Figure 5.10.

Figure 5.10 represents the composition of the cross-mixed volatility index, CMV index pie chart. There are a few steps to generate the CMV Index. The first step is computing the weights of the index and the second step is calculating the index time series by stemming from the composition in percentage. The contribution in percentage in each volatility is reported as to obtained the graph of CMV index, as prescribed in the pie chart. The average participation of each class of asset is equal to 10%, with a minimum of -25% and a maximum of 36%. Gold and Palm Kernel Oil have the highest composite of the CMV index. It is likely to be a safe-haven during a bear financial markets followed by recessions.

Figure 5.11 and Figure 5.12 display the graph of two volatility index with a different approach. One is generated with factor loading to the composition, and the other is repro-

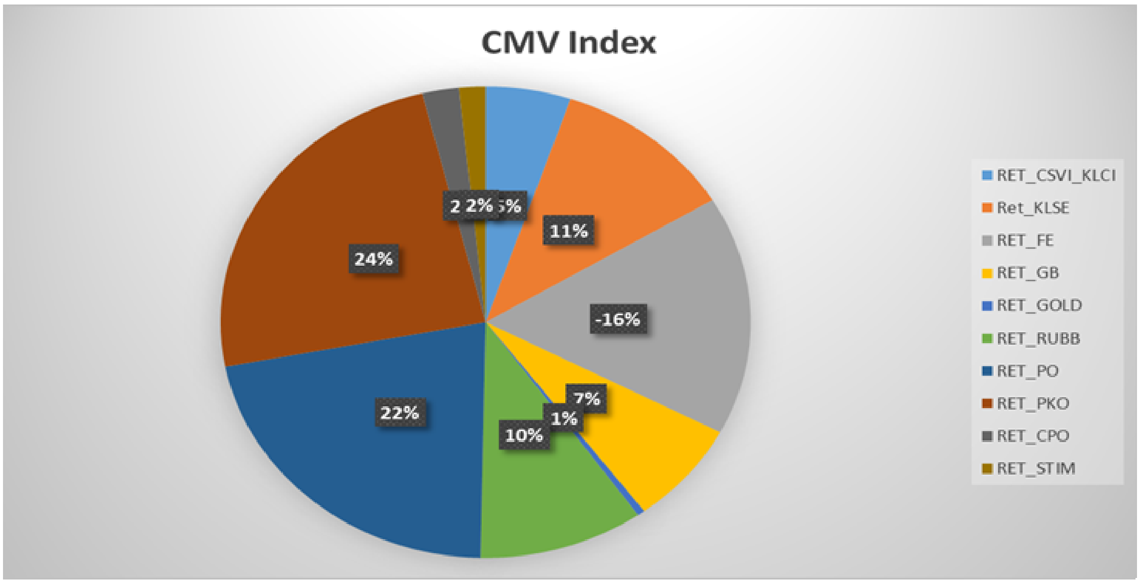


Figure 5.10: The Composition of the cross-market index for the mixed assets

duced using the cross-sectional volatility index approached. It looks strongly correlated, but the difference is the composition and weight of this two graphical volatility presentation. The Cross-Mixed Volatility Index is more weighted contribution on the Palm Kernel Oil and the Gold commodity.

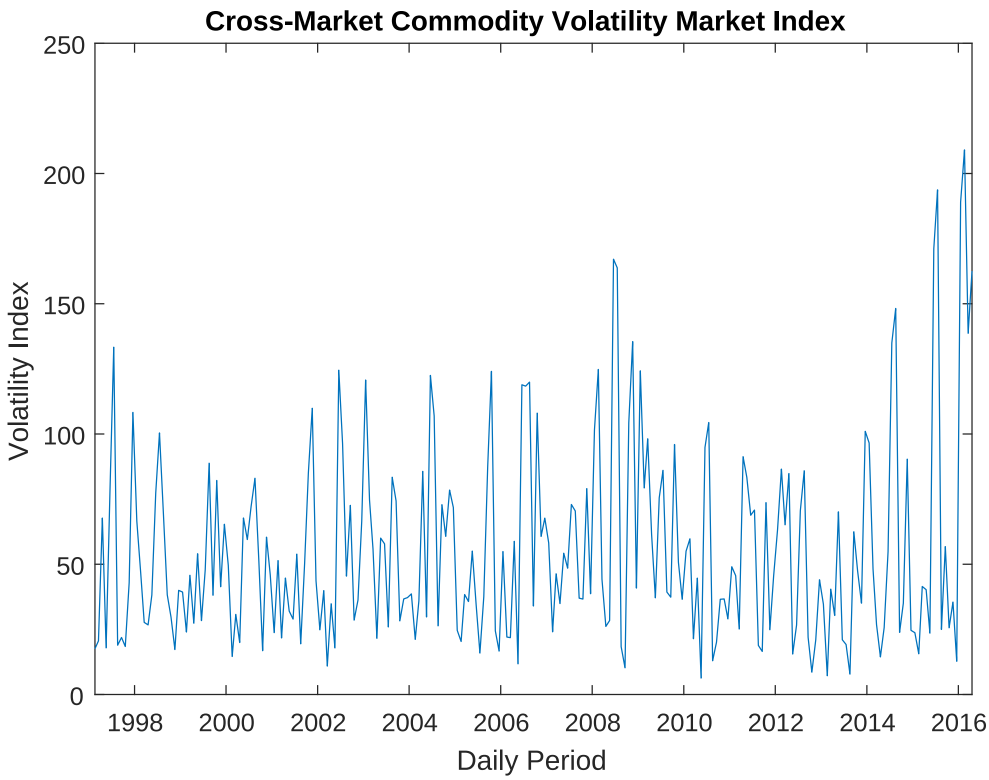


Figure 5.11: The Cross-Mixed Volatility Index

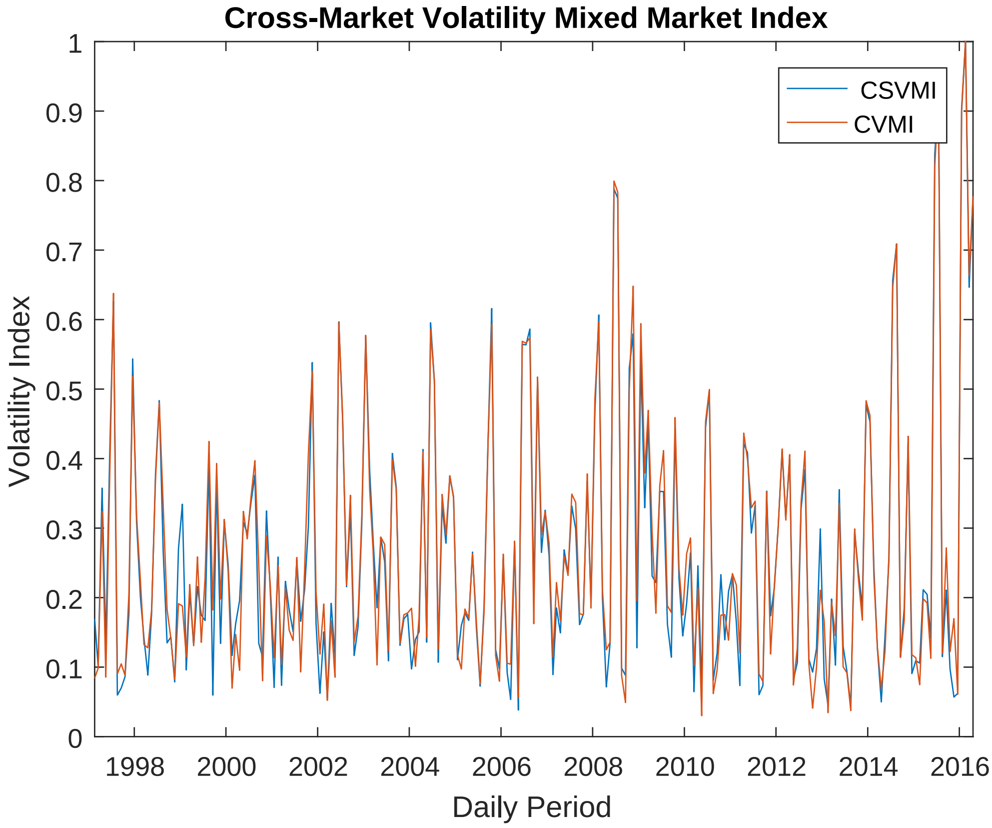


Figure 5.12: The comparison of the CMV index Approach with the CSV index

The CMV index can be interpreted as a measure of aggregated volatility, meaning that it is a volatility computed from other volatility indexes in any sources of risk. The important observation of this study is that the CMV index is calculated over several ranges of market volatility segments including equities, bonds, foreign exchanges, and commodities. The CMV index measures the volatility hikes effecting one market another. The CMV index can capture the uncertainty dimension similar to the CSV index, which may be an indicator of the expected volatility of the CSV index approach. The advantage of the CMV Index to the CSV Index in a comparative way is that the market investors are provided with an aggregate measure of uncertainty. It is not only focused on equities, but also from a cross-market perspective. Based on Figure 5.11, the aggregate volatility is visualizing the overall uncertainty jumps almost all year round. The reason for this hike is because the contribution each factors mostly influenced by commodity market. Commodity market especially the Crude Palm oil and the Palm Kernel may have factors influencing them such as unexpected volumes and liquidation in the daily trading market. In fact, in the economic explanation is related to the combination of various factors including declining inflation. Maybe a longer perspective might reveal a more stable outlook as volatility in the long run typically mean-reverting. From Figure 5.12, the study exhibits the comparison of the CMV index with the CSV index approach. The CMV index represents the cross-section volatility of both the financial market and the commodity market, and CMV index shows the new form of cross-mixed volatility by the Factor-DCC approach. The magnitude and sign of the volatility are almost similar between both of the volatility index although different approach.

5.5 Conclusion

The study proposes a new empirical methodology of commodity benchmark index to be used in one of the Southeast Asian country specifically Malaysia. It is based on the Factor-DCC model by Zhang et al. (2010) as to construct the Cross-Mixed Volatility Index. This also involves the Bursa Saham CSVI approach. This approach is characterized as the country risk where the method is allowing each source of risk stemming from the financial markets for any given country in two steps. The first step is by applying the Principal Component Analysis (PCA) which isolates the principal components from given series in a manner that these components are de-correlated. The second step is to make the DCC multivariate GARCH model to investigate the main links between the components of the index. This study proposed a new way of creating a Cross-mixed asset as a part of financial innovation approached combining a de-correlation method that extracts principal components from the original series and then applied the ordinary DCC model to the filtered data.

The application of this method is concentrating on the Southeast Asian economy focused on the non-derivatives market, specifically Malaysia. The volatility index is composed of assets index characterizing the equity market, the FX, fixed income market and the commodity market. The results showed that the Palm oil and Sawn Timber with 22 percent and 24 percent were the most prominent contribution of the composition index, the CMV index. The new methodology may be attractive to the risk managers since it provides an investor with a unique volatility index to hedge against any country risk.

The asset managers and practitioners may find the study of constructing a cross-mixed volatility index is useful and a benefit to them. Both asset managers and practitioners may see it is an essential exposure to the domestic market when the research can determine the allocation of financial and commodity assets by the weights. So, the asset managers may plan to invest and purchase the CMV index. It allows the asset managers and practitioners to minimize the risk of the cash portfolio, as well as the costs of hedging. The CMV index is built from a cross-asset perspective so that the CMV index may outperform differently with the sole VIX but similar to CSV index in the volatility performance.

Chapter 6

Conclusion and Discussion

This final chapter of the thesis presents and discuss the conclusions drawn from empirical results. Then, future research of this study will also be addressed at the end of the segment.

There are three main themes in this thesis, where the first theme focus on the construction of a volatility index. The reason for the development of a volatility index is due to finding an alternative benchmark to the VIX. VIX is a benchmark developed by the Chicago Board Options Exchange (CBOE) to capture the impact of global financial conditions and hence perceived risks exposure in a developed market. VIX is mostly applicable when a market uses a derivatives options to determine the market anxiety level. However, in those countries that have a smaller or no derivative options market will not able to use this fear index, VIX. So, the study applied the CSV Index to promote the benchmark of the volatility of the non-derivatives market to countries to measure the volatility as much as the VIX. So, the validity of the CSV has been analyzed by producing the CSV and comparing the CSV with the VIX. To perform the analysis, we applied the CSV method approached a country that uses the derivatives options for measuring the level of the volatility benchmark index.

Two markets that have been pointed out to the validity of the CSV approach are the US market and the Japanese market. Both of these markets have a VIX-styled index. So, we predicted the performance of volatility index by using the GARCH and its extension, namely GARCH and E-GARCH models. From the results, the correlation moved in the same direction in the CSV index approached with the VIX-styled model. The result demonstrated a statistically significant positive condition volatility in both GARCH and E-GARCH model. Since the results were giving positive outcome, the CSV index approach may be a useful forecast as that of CBOE VIX model.

The second theme in this thesis is the continuation of the CSV index approach to an actual non-derivatives market. The study identified a few countries that have fewer derivatives options and these countries were situated in the Southeast Asian market. The study has adopted four main countries that have less derivatives options market namely, Malaysia, Thailand, Indonesia and Philippines. These market were tested and analyzed using the CSV index model approach. The primary objective of this study was to predict the performance level of the CSV index using the GARCH-styled and HAR-Realized Model. Both of these models could estimate the volatility by only using the observation of the past returned data. The GARCH-extension used in the analysis and prediction were GARCH, E-GARCH, and GJR-GARCH. These three models have their conditions of parameters that allows the test to perform better. The HAR-RV model was also used to predict the performance of volatility index because it was a common model-free indicator of volatility which is estimated using the daily squared return. The CSV index approach was compared concerning its prediction volatility captured so that the CSV index was a good proxy to the VIX-styled index.

From the analysis and performance of the prediction, the results showed the most accurate prediction was in the Philippines market. It was because the value of RMSE and MAE have the least value meaning that the forecast was most accurate. It supports the CSV index approach to be used in the non-derivatives market.

Finally, the final theme of the thesis was to find the country risk benchmark index. The country benchmark index has accounted the primary risk sources of the countries that allow CSV index method estimation. So, therefore, we created the CMV index that combined risk from all mixed sources stemming from the commodity market with the traditional financial asset volatilities, namely the foreign exchange market, bonds, and equities. As to construct the CMV index, the study adopted the Factor-DCC approach.

Factor -DCC approach helps to simplify the estimated process of high-dimensions factors to a smaller number of factors specifying the correlation function. The purpose of forming the cross-mixed volatility index was also to capture the country risk factors as a single composite index. So, we took the Malaysia market as to conduct the study because the data sources of risk were available in this country, especially the commodity market. The commodity market in Malaysia, for instance, were rubber palm oil, sawn timber, crude palm oil, and gold. We adopted the Factor-DCC model using two steps. The first step, we extracted the number of factors that form the PCA model. Then, by using the criterion factors by Bai and Ng (2012) and Alessi et al. (2010), we restricted extraction of factors in the first two outcomes of PCA model. We found that both of the first two factors were likely to be influenced by the commodity market which was the palm oil and the palm kernel oil. It means that the main assets to hedge against the sources of risk of Malaysia was the commodity market. The model used to estimate the condition correlation was the CD-DCC model. We found that this model used time-varying with a zero-average correlation. The average conditional correlation between the two factors was equal to -0.08, which means that two factors were almost decorrelated as was the objective of the CD-DCC model.

The composition of the CMV shown in the results explained that the average contribution of each class asset was 10 percent with the maximum of 30 percent, namely the Palm Kernel Oil. It is likely to be a safe haven in a financial crisis or recession. The performance of the CMV index that was mainly showing commodity market was evaluated with the CSV index approach but using the mix-assets without applying the Factor-DCC. The results revealed that the CMV index has similarity on its magnitude and sign with the CSV index approach model.

We can finally conclude that the CSV index can be used as a proxy of VIX in the non-derivatives a market. The CSV index is a part of the blending approach of constructing the CMV index allocating the mix-assets to capture the essentially political nature of country risk. The political risk intrinsic to each country is reflected in the commodity fluctuation rate more than other indicators. So, the investor is able to price the country risk more appropriate.

To further increase the methodology of the cross-sectional volatility in its performance, one could consider the difference of forecasting schemes, looking at different horizons and more complex conditional mean. We can investigate the use of other error distributions and extend the method of conditional var-models in the next research. Furthermore, the cross-mixed volatility index should assess the hedging performance using Ordinary Least Squares (OLS) and followed by the stress level test analysis to see if the CMV index is capable of explaining country's macros financial stress as an operating hedging tool.

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Appendix A

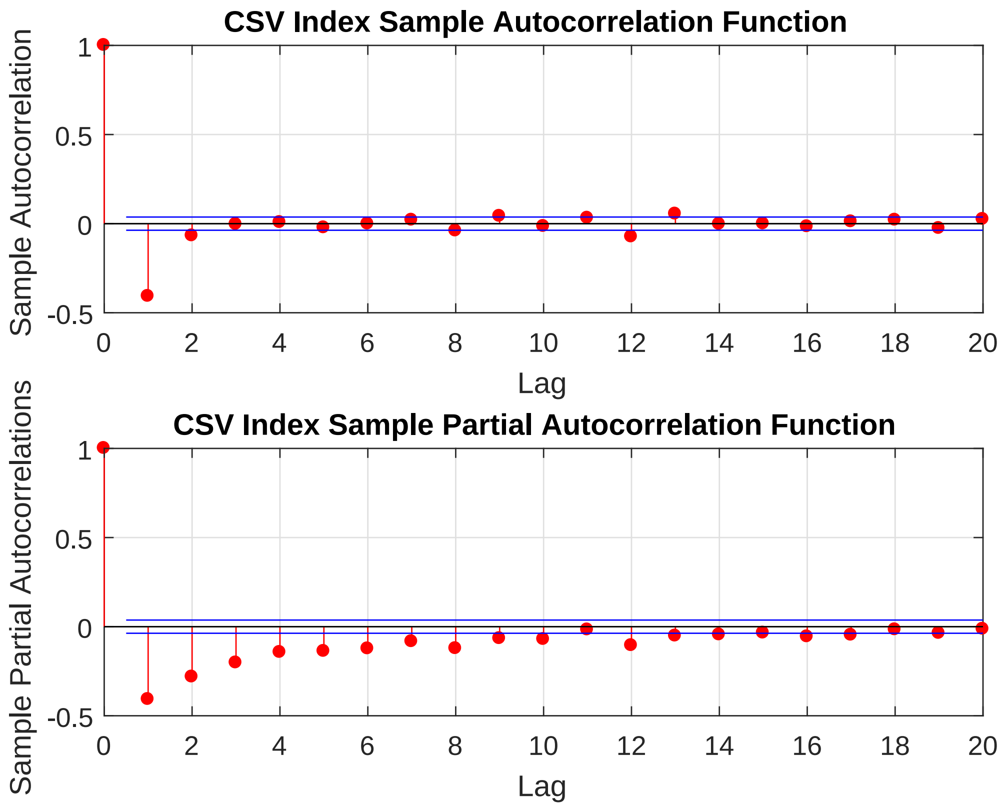

Figure A.1: Autocorrelatian Function and Partial Autocorrelation Function of CSV Index