FORECASTING MALAYSIAN STOCK RETURNS USING GEOPOLITICAL RISK AND ECONOMIC POLICY UNCERTAINTY: AN IN-SAMPLE AND OUT-OF-SAMPLE ANALYSIS.

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DECLARATION

We hereby declare that:

1. This undergraduate Final Year Project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

2. No portion of this Final Year Project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

3. Equal contribution has been made by each group member in completing the FYP.

4. The word count of this report is 38967 words.

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LIST OF ABBREVIATIONS

ALS	Adjusted OLS
APT	Arbitrage Pricing Theory
AR	Non-stationary Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving-average
CAPM	Capital Asset Pricing Model
CBOE	Chicago Board Options Exchange
EMH	Efficient Market Hypothesis
EPU	Economic Policy Uncertainty
FGLS	Feasible Generalized Least Squares
GPR	Geopolitical Risk
KLCI	Kuala Lumpur Composite Index
MSCI	Morgan Stanley Capital International
OLS	Ordinary Least Squares
OVX	Crude Oil Volatility Index
U_1	Theil U Coefficient
U_2	Theil U2 Coefficient
VAR	Value at Risk
VIX	Volatility index

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PREFACE

Subject of UBFZ 3026 Research Project is compulsory to be taken as one of the requirements for completing our course in Bachelor of Finance (HONS). The title of the research that we conducted is 'Forecasting Malaysian stock returns using Geopolitical risk and Economic policy uncertainty: An in-sample and out-of-sample analysis.'

Through this study, Geopolitical risk (GPR) and Economic policy uncertainty (EPU) are taken as the variables as determining their predictability on forecasting the Malaysian stock returns. Besides, the analysis of in-sample test and out-of-sample test will be conducted to check whether any discrepancy between the result which generated from both test above.

Furthermore, this study is established to contribute a better understanding for the potential investors, future researchers as well as policymakers towards the predictability of GPR and EPU on Malaysian stock returns. It will be reported about the predictive power of GPR and EPU which may provide significant impact for those characters above in the decision making process.

ABSTRACT

From earliest infancy, human being tend to classify the world into categories, forecast how things work, and assess those predictions. Such thinking, which is one of the human nature, is now being expanded into economics, business, management and finance contexts. That is why nowadays there are growing literature and empirical studies which examined the forecasting extreme by applying several types of predictors, since they wished to search for the most accurate forecasting method and predictors for different contexts. In finance context, especially on stock returns forecasting, prior studies focused on the assessment of the predictive power of macroeconomic determinants and financial ratios on stock returns.

Thus, this paper focuses on the application of the latest risk indicators which comprises of economic policy uncertainty (EPU) and geopolitical risk (GPR) on forecasting Malaysian stock returns by using monthly data that covered from January 2005 to April 2019. This studies makes three contributions to the literature on forecasting Malaysian stock returns. First, we examine the predictive ability of EPU and GPR by undertaking in-sample tests on the FGLS model of both predictors. Through this, we find that both predictors have the ability to predict Malaysian stock returns. Second, by comparing the in-sample and out-of-sample results of both predictors, both tests provide a consistent outcome by showing that EPU and GPR are favourable in forecasting Malaysian stock returns. Third, through the comparison between the predictive ability of EPU and GPR by implementing the out-of-sample analysis, GPR is said to be performed even well in forecasting Malaysian stock return than EPU by referring to Theil U2 coefficient.

CHAPTER ONE: RESEARCH OVERVIEW

1.0 Introduction

This chapter delivers an introduction that related to the fundamentals of forecasting, the overview of Malaysian stock market, and the overview of economic policy uncertainty (EPU) as well as geopolitical risk (GPR), which served as the predictors of Malaysian stock return in this research. Besides, this chapter also covers the problem statement, research questions, research objectives, development of hypothesis statement, significance of study, and the organization of this study.

1.1 Research Background

One of the human nature is being scientific by sorting the world into categories frequently, predicting how things work and examining those predictions. The main initiative of people to predict and forecast is it might ease in revenue and profit earning. According to Polat (2008), the common strategy in decision making is constantly based on assumption as there is insufficient future information at the time of decision making. Polat (2008) also suggested that forecasting is one of the variety managerial instruments and techniques that might aid in producing strategic information to achieve financial goals and objectives. Generally, every investor made investment decision with the objective to earn financial return. In particular, investors invest in stock market to receive stock returns in the form of dividend or capital gain, while corporates invest for the purpose of market and future cash flow growth. Thus, an invaluable, functional and reliable forecasting that able to make substantial gain is essential for them during investment decision making.

That is why there are growing literature and empirical researches done to examine the forecasting extreme by using various type of predictors such as price multiples, macroeconomic variables, corporate actions, and measure of risk to forecast various items, ranging from commodities prices, inflation rate, exchange rates to returns and volatility of financial assets. Within the forecasting literature, the variables that used to forecast oil price are including U.S. Energy Information Administration (EIA) short-term oil price (Baumeister & Killian, 2012, 2013a; Alquist, Kilian & Vigfusson, 2013), current oil price (Davies, 2007; Hamilton, 2009), and West Texas Intermediate (WTI) price (Baumeister & Kilian, 2013a). Besides, the researches that focus on the issue of inflation predictability by using predictor variables of monetary policy (Zhang & Clovis, 2010), money supply (Jianfei, 2009; Zhiyong, 2008), and output gap (Hallman, Porter & Small, 1991) have done in studies as well. Moreover, forecasting exchange rate volatility by using exchange rate return (Clement & Samuel, 2011; Bala & Asemota, 2013; Rofael & Hosni, 2015), and other macroeconomic variables (Pelinescu, 2014) also have been included in the past studies.

Apart from that, past literature have identified that the price of other vegetable oils (Amiruddin, Rahman & Shariff, 2005; Kumar, Acharya & Suresh, 2014), economic growth (Rosa & Vasciaveo, 2008; Nazlioglu & Soytas, 2012), exchange rates (Headey & Fan 2008; Cespedes & Velasco, 2012), and price of crude petroleum oil (Abdullah & Wahid, 2010; Nazlioglu & Soytas, 2012) can affect towards the predictability of crude palm oil price. Furthermore, some popular variables that used to study the movements of stock returns include oil price (Narayan & Sharma, 2011; Driesprong, Jacobsen & Maat, 2008; Sim & Zhou, 2015), financial and macro variables (Campbell & Thompson, 2008; Westerlund & Narayan, 2015; Rapach, Strauss & Zhou, 2010; Gupta, Hammoudeh, Modise & Nguyen, 2014), US market returns (Rapach, Strauss & Zhou, 2013), credit standards (Chava, Gallmeyer & Park, 2015), technological innovation (Hsu, 1999), EPU (Bekiros, Gupta & Majumdar, 2016; Brogaard & Detzel, 2015), the consumption, wealth, income ratio (Lettau & Ludvigson, 2001), output gap (Cooper & Priestley, 2009), and investor sentiment (Baker & Wurgler, 2007).

Although there are many studies focused on the forecasting extreme, the research on forecasting of stock returns still considered as one of the focus points for researchers over the past decades. Since the stock return is not only significant for the investors in increasing their wealth over time, but it also acts as a critical role to enhance the financial competitiveness of a country. Therefore, many researchers have emphasized that stock returns can be applied as an indicator to assess and measure the economic performance of a country.

Before discussing the foresting of stock returns, one should understand the forecasting tests and its differences. According to Inoue and Kilian (2005), the forecasting tests for any variables can be carried out by applied the in-sample fit of a model or refer to out-of-sample fit derived based on a sequence of rolling or recursive regressions. The rolling regression or approach referred to the application of particular windows of data to re-estimate the estimators ranging from the out-of-sample period, while for the recursive approach, it will re-estimate the models by utilizing an increasing window. (Eurostat, n.d.). Hence, in order to explain the tests in a more detailed manner, it can be understood as the statistical tests of a forecasting model's performance that are frequently conducted by splitting a provided data set into an in-sample period that used for the estimation of initial parameter and model selection, whereas for out-of-sample period applied to examine the forecast performance (Hansen, 2012). As for the previous studies, they mostly focused on the application of full sample in fitting the models of interest. The common in-sample tests that applied by researchers are F-tests or standard t-tests to evaluate the significance of the estimators or the significance of the overall model.

However, a good fit does not necessarily lead to a good result in forecasting which means that the in-sample proof of predictive content of a specific variable mostly does not indicate an improvement in forecast accuracy, especially in finance context. It can be supported by Herwartz and Morales-Arias (2009), who stated that the in-sample return predictability does not certainly imply out-of-sample return forecastability in both emerging and developed financial markets. Besides, based on Hansen (2012), the empirical findings according to out-of-sample forecasting test is typically recognized as more reliable than findings based on in-sample test that might be more sensitive to outliers and data mining. In this regard, it causes many researchers to view the performance of out-of-sample forecasting test as the "ultimate test of a forecasting model" (Stock & Watson, 2007). In the latter studies, they tied to mimic the data constraints that a real-time forecaster faced. Some examples of out-of-sample tests are the tests of forecast encompassing and the tests of equal predictive accuracy (Inoue & Kilian, 2005).

Normally, in the view of forecasting indicators, most of the researchers have considered the financial ratio as the main instrument or indicator on predicting the stock market return. Those financial ratios could be categorized as price earnings ratio, dividend payout ratio, return on asset ratio, current ratio etc. undoubtedly are commonly used in predicting the return of particular stock, which is justified by several seminal researches (Fama & French, 1988; Campbell & Shiller, 1988; Chen, 2009). Besides, Chan, Hamao and Lakonishok (1991) stated that those financial ratios like book-to-market ratio, dividend yield etc. are important on forecasting the earning or return of stocks in Japanese country. They found that the earning yield and stocks return have an indirect relationship when observing the stock market in Japan; thus, they are significantly related with one another. Kothari and Shanken (1997) proved that the book-to-market ratio and dividend yield consist of notable impact towards the stock return in US market over the period of year 1926 until 1991. Mukerji, Dhatt and Kim (1997) demonstrated about there exists linear relationship between the book-to-market ratio, dividend earnings etc. and stock returns on Korean stock market ranging from the period of year 1982 until 1992. Briefly, the financial ratios provided significant effect on the estimation of stock market return among the stock market of different nations. Furthermore, a risk indicator, crude oil volatility index (OVX) is widely treated as one effective measure for recording as well as analyzing the future oil prices' volatility (Chen, He & Yu, 2015). On the other hand, volatility index (VIX) refers to a sentiment indicator that mainly aids in detecting any unexpected crisis on the particular market of nation ("VIX -- Volatility Index -- Definition & Example", 2019). Both indicators above are usually used for estimating the risk involved and the index is estimated through the data collected by Chicago Board Options Exchange (CBOE).

However, instead of financial market, most investors actively participated in the stock market for predicting the stock returns since it is an efficient channel to gain a greater return in a short period with sufficient knowledge and skills. In reality, there are full of uncertainties or risks that could influence the stock market dramatically or even lead to a huge hit on the investors' confidence towards the market.

1.1.1 Global Issues Contribute to Uncertainties

In this era of globalization, the new invention of technology and telecommunication have advanced timely as long as fulfilling the satisfaction of market demand domestically or internationally. Meanwhile, the competition or rivalry is aggressively taken place in every nation in order to fight for their greater well-being as well as strengthen their competitive advantage to be the independent one. From the reports of International Monetary Fund (2019), we found out that the global economy activity is experiencing a slow growth period which is not ideal with the market expectation compared to year 2017 and 2018. The economists unanimously believed that the downturn of global economy is probably caused by few serious issues that been discussed recently.

First, US-China trade war is one of the most well-known cases which attracted the most attention from every nation since both countries are listed as the major parties in influencing the global economy significantly. Therefore, the trade disputes would affect the whole global economy activities instead of the involving nations. Thus, those countries which engage in trading business with US and China such as Vietnam, Taiwan, Malaysia, etc. have suffered the negative effect towards nation economy especially the stock market. For an example, Shamsudin (2018) reported that Malaysia experienced a great volatility to the net trading of stock for various investors and less demand in trading activities during that period. In addition, Malaysia faced a loss of approximately RM270 billion in the stock market within the crisis period (Rasid, 2019).

Besides, the ‘Brexit’ news about United Kingdom that is going to exit from the European Union (EU) also generate a particular effect among the investors who actively involving in UK property development especially the Malaysians. As UK is popular in providing the outstanding education program; hence, most Asian students are willing to further their education achievement in UK as well as create the opportunities for property development. As ‘Brexit’ issue breakout, the financial performance of UK economy dropped abruptly which lowers the confidence level the foreign investors as well as indirectly affects the financial stability of the foreign stock market like in Malaysia (Angie, 2016).

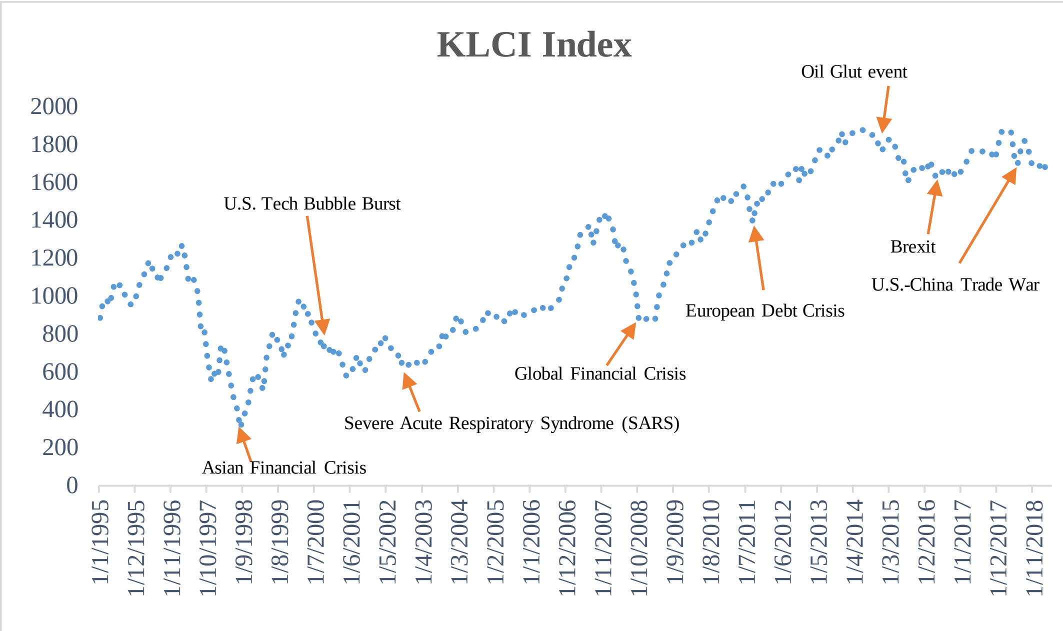
Moreover, the conflict between US and Iran about the plane attacking case has raised up the concern globally as it leaded to an increasing on oil prices that pressure the economy towards the nations which participate in oil production. Hence, this issue dramatically influenced the Asian stock market badly as long as conflict is going to be solved if both nations could come out to a meaningful agreement to resolve this market tension (Sano, 2019). Briefly, Malaysia is one of the Asian countries that have experienced a greater impact from these crisis events. Therefore, the economy of Malaysia would be affected as well, especially in the view of stock market.

1.1.2 Overview of FTSE Bursa Malaysia KLCI (FBM KLCI)

According to FTSE Russell (2019), Kuala Lumpur Composite index (KLCI) was introduced on 4th April 1986 and undergone a transition to FTSE Bursa Malaysia KLCI (FBM KLCI) on 6th July 2009. FBM KLCI is the headline index of the FTSE Bursa Malaysia Index series and it consists of 30 largest Malaysia companies on Bursa Malaysia’s Main Board by full market capitalization which meets the FTSE Bursa Malaysia Index Ground Rules’ eligibility requirements. These 30 companies’ stock index is representative, liquidity and transparency in order to provide local and international investors with an enhanced index for Malaysia market’s assessment. FTSE Russell also suggest that the major objective of FBM KLCI is used for the index tracking funds' creation, derivatives and also performance benchmark. Moreover, the value of FBM KLCI is computed according to price and methodologies of total return, both end-of-day and in real time basis.

Figure 1.1.2:

FBM KLCI index value



Source: Bloomberg (2019).

Figure above shows FBM KLCI index value from 3rd January 1995 to 30th April 2019. It depicts a significant change in the index's movement during Asian Financial Crisis in between 1997 to 1998. Zakaria, Hussin, Noordin & Mohamed Sawal (2010) mentioned that legal infrastructure, deficiencies in risk management, speculative attacks, form of corporate governance and equity markets were the major reasons of Malaysia financial crisis. Besides, Global Financial Crisis which happened due to liquidity shortfall in the banking system of United also resulted in a 45% plunge in FBM KLCI ranging from the period of 14th January 2008 to 12th September 2008 (Angabini & Wasiuzzaman, 2011). In contrary, FBM KLCI index achieved the highest value in Malaysia history with 1895.18 on 19th April 2018 before the General Election 14 on 9th May 2018 (Joseph, 2018). Joseph (2018) proposed that the peak of FBM KLCI was caused by the fund buying of banks, a fall in oil price as well as the recovery in aluminum price which lead to a rise in Petronas-linked stock and Press Metal stock. Besides, US tech Bubble Burst arise during 2000 and Severe Acute Respiratory Syndrome (SARS) in the period of 2002 to 2003 also lead to unfavorable FBM KLCI index performance. Furthermore, European Debt Crisis in 2011 and Oil Glut event which happened in the mid-year of 2014 that caused a significant drop of more than 40% in crude oil price, give rise to a negative fluctuation in FBM KLCI index. Apart from that, the news of Britain exits from European Union (Brexit) that emerged unexpectedly result in a loss of FBM KLCI with 28 points but it had a recovery of 22 points in 24^{th} June 2016 (New Strait Times, 2016). At the same year, in November, FBM KLCI declined by 16.2 points due to the victory of Donald Trump on Republican US presidential election which will cause to an US policies uncertainty on global political and economic conditions (Billy, 2016). Subsequently, FBM KLCI index value was higher in 2017 by 9.89% compared to the adverse growth between 2014 and 2016, although it might be the second-worst in the performance of Asian stocks (The Malaysian Reserve, 2018). Moreover, Cecelia (2019) remarks about FBM KLCI 2018 end up with 1690.58 points and lose 5.91% throughout the year. Cecelia (2019) also mentioned that FBM KLCI 2018 has the worst annual performance in 10 years because of a surge in US interest rate, volatile oil prices and US China trade war tension. Recently, US China trade war was the most popular and ongoing issue that will continually influence FBM KLCI in the future. Therefore, we will apply Economic Policy Uncertainty index (EPU) and Geopolitical Risk index (GPR) to capture the event.

1.1.3 Overview of Economic Policy Uncertainty (EPU)

The uncertainty regarding fiscal, regulatory, or monetary policy which resulted by government policymakers that can bring an impact towards the financial and economic fundamentals (Brogaard & Detzel, 2015), which we consider as Economic Policy Uncertainty (EPU). Policy inaccuracy is hugely reflected in the uncertainty of policy arrangements, which are the political demands of the relevant interest collectives and will be reflected through the adjustment and formulation of relevant policies and systems. Uncertainty about the future has actual impacts towards economic agents' behavior (Dixit, 1989; Bloom, 2009; Bernanke, 1983;

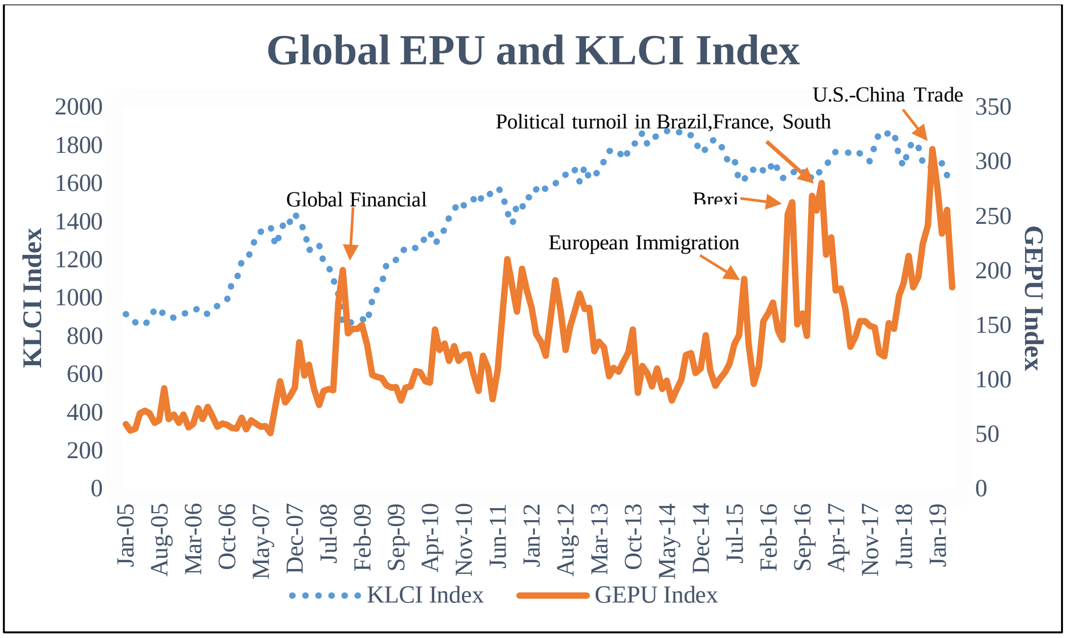
Bloom, Bond & Van Reenen, 2007). Thus, this measure is recognized as a good proxy for real world uncertainty related particullary to the economic policy of government and is applied wisely (Li & Peng, 2017; Wang, Chen, & Huang, 2014; Li, Balcilar, Gupta & Chang, 2016; Ajmi *et al.*, 2015).

The EPU index is consisted on three components. First component measures the number of occurrence of newspapers references to economic policy uncertainty. It treats coverage of policy which particularly related to economic uncertainty in leading newspapers as an indicator by automated text-search results from major newspapers which comprise terms in three assortments pertaining to uncertainty, the economy, and policy. The second component reflects the number of scheduled tax code expirations. The amount of federal tax code provisions set to expire are a source of uncertainty whether to extend them, undermining stability in and certainty towards the future path of taxes. The third component uses the degree of forecaster disagreement over future inflation and government expenses. It exploits individual-level forecast data for inflation, expenses of goods and services incurred by the federal, state and local government.

Next, the impacts of EPU can present in several channels. First and foremost, policy uncertainty might lead to shift or delay decisions made by business organizations and other economic participants especially for investment, employment, saving and consumption decision (Gulen & Ion, 2016). Besides, policy uncertainty might cause a rising in financing and production costs that may influence towards both channels of supply and demand, resulting economic contraction and intensifying disinvestment (Julio, 2012). On the other hand, EPU causes the financial markets' risks to increase in particular by diminishing the amount of protections given by the government (Pastor & Veronesi, 2012). Lastly, economic uncertainty affects interest rate, inflation and expected risk premiums (Pastor & Veronesi, 2013).

Figure 1.1.3:

Global EPU and KLCI index value



Source: Scott Baker, Nicholas Bloom & Steven J. Davis (2018).

Notes: Global EPU index is measured by using GDP-weighted average of monthly national economy (E), policy (P) and uncertainty (U) indexes for 21 countries, which are including Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom and United States.

The chart above reveals that it was a non-linear relationship between global EPU and FBM KLCI index. The global EPU index spikes near tight the global financial crisis, European immigration, Brexit and other major shocks. Recently, U.S.–China trade war has caused the global EPU index rose to historic highs and been a key factor in weakening Malaysian stock market performance. The outlook for Malaysian stocks market remained shaky as sentiment continued to be affected by the trade tensions between US and China. From the historical perspective, the prominent role of U.S.-China trade policy results in the highly unusual swings towards the FBM KLCI index.

1.1.3.1 Economic Policy Uncertainty (EPU) as a Predictor.

The EPU measure is largely reflected in recent studies that examined the impact of EPU on unemployment (Caggiano, Castelnuovo & Figueres, 2017), inflation and output (Jones & Olson, 2013), tourism (Demir & Gozgor, 2018), policy inaccuracies (Tsai, 2017), economic development (Scheffel, 2016), crude oil (Antonakakis, Chatziantoniou & Filis, 2013), monetary policy effect (Aastveit, Natvik & Sola, 2013), commodity market (Wang, Zhang, Diao & Wu, 2015), real housing returns (Christou, Gupta & Hassapis, 2017),exchange rate expectations (Beckhmann & Czudaj, 2017), corporate governance (Zhang, Han, Pan & Huang, 2015), corporate investment (Wang, Chen & Huang, 2014), co-movement of stock market (Li & Peng, 2017), stock and bond market correlation (Li, Zhang & Gao, 2015), stock market volatility (Liu & Zhang, 2015), industry betas (Yu, Fang, Du & Yan, 2017), financial stress (Sun, Yao & Wang, 2017), and sources of global stock market risk (Tsai, 2017). These studies have brought to the evidence that EPU has act as a significant variable towards both economic fundamental and stock market performance.

Among the research done to study the issue of EPU, there are still scarce of studies that examined the EPU-stock return relationship. Li *et al*. (2016) showed that stock market return and EPU are negatively related in the sense of economic policies uncertainty. It causes investors to harbor pessimistic consideration about discount rates and expected future dividends, which might result the share price to drop. Pástor and Veronesi (2012) measured the government policy uncertainty as the variance of policy change and also reported that EPU and stock returns are negatively related. Additionally, Brogaard and Detzel (2015) used the measure from Baker, Bloom and Davis (2016) to capture the EPU in U.S. and found that EPU can significant positively forecast excess market returns. Moreover, Bekiros, Gupta and Majumdar (2016) revealed that EPU comprises valuable out-of-sample information, in particular when the market condition is neutral and has a slight upward trending behavior, and not in highly bullish market condition.

Several studies document that raising in EPU results stock return in the U.S. market to be lower by applying several model, namely, dynamic conditional correlation (DCC) (Antonakakis, Chatziantoniou & Filis, 2013), linear and non-linear Granger causality tests (Ajmi *et al.*, 2015), vector autoregression (VAR) (Kang & Ratti, 2013; Kang, Gracia & Ratti, 2017) and the quantile regression approach (Bekiros, Gupta & Majumdar, 2016). Apart from that, the research done in European countries (Demir & Ersan, 2018; Gao & Zhang, 2016), India (Bhagat, Ghosh & Rangan, 2013; Li *et al.*, 2016), China (Yang & Jiang, 2016; Li *et al.*, 2016; Kang & Ratti, 2015) and other international markets (Ko & Lee, 2015; Chuliá, Gupta, Uribe & Wohar 2017; Lam & Zhang, 2014) have drawn a conclusion that EPU and stock market performance are negatively related.

1.1.4 Overview of Geopolitical Risk (GPR)

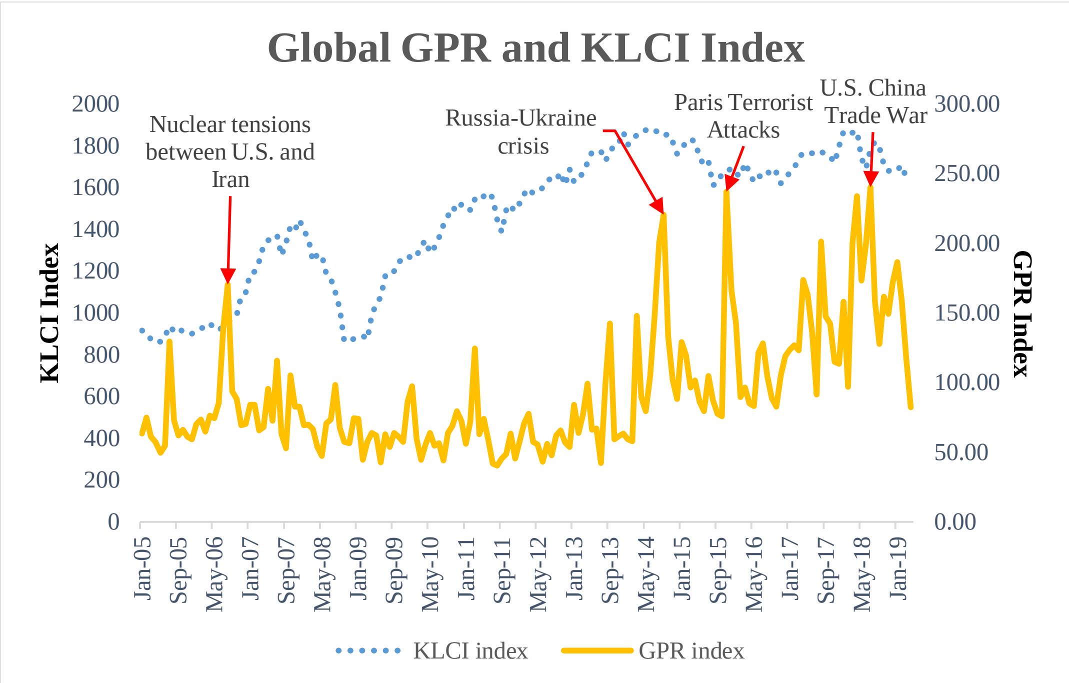
In recent years, GPR has become the concern of market participants over the political and economic uncertainty as investors start to worry about the economic effect of the various military as well as the diplomatic issues happening around the world (Ladbury, 2019). Thus, it is crucial for public to have a better understanding about GPR.

Before discussing the GPR, one should understand about the geopolitics, a signification of general concern with geography and politics. The literal meaning of geopolitics is an investigation of the influence of such components as economics, demography and geography on policy, mainly on the foreign policy of a state (Dittmer & Sharp, 2014). Besides, Morrison (n.d.) defined geopolitics as the study of how economics and geography affect politics as well as the relations between countries. One of the reasons why geopolitics has become popular among the foreign policy makers, strategic analysts and academics is due to its ability to capture the comprehensive version of the world political map. In other words, it is able to address the “big picture” and provides a way of relating local as well as the regional dynamics to the global system as a whole (Dittmer & Sharp, 2014).

Due to this reason, public start to concern and put more attention on GPR, with GPRs often cited by business investors, financial press as well as the central banks as one of the critical market factors of investment decisions since it is perceived to influence the business cycles and financial markets (Caldara & Iacoviello, 2018). Based on Caldara and Iacoviello (2018), GPR is commonly referred as the risk of one country's foreign policy affecting or upsetting domestic social and political policy in other countries or regions, but its scope is much wider. Basically, geopolitical uncertainties involve civil wars, terrorist's attacks, military conflicts, sanctions and tensions between countries which might contribute a disruption to harmony in the international relations. In this regard, GPR index has been developed by Caldara and Iacoviello with the main purpose of capturing the risk of these events or the new risks associated with a growth of existing events.

Figure 1.1.4:

Global GPR and KLCI index value



Source: Caldara & Iacoviello (2018).

The chart of FBM KLCI index and GPR index above depicts that the GPR index reached the spikes during the 2006 United States-Iran nuclear tensions, 2014 Russia-Ukraine crisis and the 2015 Paris terrorist attacks. So far, these past events for sure have little discernible effects on markets worldwide, especially the terroristic incidents which threaten the security of countries and undermined the confidence of consumers as well as the investors. However, the impacts of these events did not necessarily connote a negative effect to all the countries, it might bring a positive influence to certain countries as well.

Thus, based on the chart above, it shows that a positive relationship between KLCI index and GPR index, with both index move in tandem. This can be supported by Bernama (2017) which reported that the government of Malaysia has monitored closely the development of geopolitical events that happened around its neighbor countries with measures or decisions taken in accordance with the interests of country. Furthermore, according to NST Business (2017), MIDF research mentioned that there still would be an uptrend in GDP of Malaysia despite the rising of geopolitical risks. In this regard, the stability of Malaysia in facing geopolitical events might be able to attract more foreign investors to invest in Malaysian market which leads to a rise in FBM KLCI index. Recently, the emergence of serious events such as Notre Dame Cathedral fire and US trade war will drive the GPR index to a spike again in 2019 (Zheng, 2019). Thus, the public start to become concerned when there is an exogenous change in GPR since it is an increasing threat that might depress the economic activities and stock returns, especially in advanced economies (Caldara & Iacoviello, 2018).

1.1.4.1 Geopolitical Risk (GPR) as a Predictor

Market attention to GPR has hit a high in recent years. GPR has become popular and mostly used in recent studies as a risk indicator or market factor to determine its effect on various aspects. From the past until now, GPR often been applied in predicting the stock market volatility (Chen & Siems, 2004; Drakos, 2004; Eldor & Melnick, 2004; Johnston & Nedelescu, 2006; Arin, Ciferri & Spagnolo, 2008; Nguyen & Enomoto, 2009; Karolyi & Martell, 2010; Aslam & Kang, 2015; Apergis & Apergis, 2016; Apergis, Bonato, Gupta & Kyei, 2017). Nowadays, in recent researches, GPR has been widely used to examine its effects on financial assets and commodities such as gold's safe haven status (Baur & Smales, 2018), oil returns (Antonakakis, Gupta, Kollias & Papadamou, 2017), national stock indices

(Plakandaras, Gogas & Papadimitriou, 2019), Islamic equity and bonds returns (Bouri, Demirer, Gupta & Marfatia, 2018), gold price movement (Banerjee, Ghosal & Mukherjee, 2019), Bitcoin returns as well as its volatility (Aysan, Demir, Gozgor & Lau, 2019). Through these studies, GPR has been proved to be significant in affecting the global markets, ranging from stock market volatility to financial assets as well as the commodity prices.

However, the study that analyzed non-financial indicators such as GPR on stock returns are rare. The current research that examined the effects of GPR on stock returns has been done by Apergis, Bonato, Gupta & Kyei (2017) which involved the GPR as a risk indicator to predict the movements of stock returns and volatility of the major players in the leading defence industry. This study showed that GPR from global geopolitical events was less likely to forecast returns, with the effect more focused in changing the future risk profile of defence firms. Furthermore, the research done by Bouras, Christou, Gupta and Suleman (2018) depicted that GPRs do have a positive impact on stock returns by analysing the role of country-specific and global GPRs on the returns of 18 emerging market economies through a panel Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach.

1.2 Problem Statement

As stated by Caldara and Iacoviello (2018), geopolitical risks (GPR) is the crucial element that will influence investment decisions and stock market from point of view of the entrepreneurs, market participants, and central bank officials. Caldara and Iacoviello (2018) suggested that a high level of GPR will give rise to a continuous fall in real activities, lower stock returns and capital flows move towards advanced economies and away from emerging economies. Moreover, Cheng and Chiu (2018) proved that when there is exogenous uncertainty shock, emerging economies will deteriorate more severe decline in private consumption and investment than US and other developed countries.

Based on Caixa Bank Research (2018), a high GPR will lead to a low level of Composite global Purchasing Managers' Index (PMI), an index which used to gauge for the United Kindom's manufacturing, construction and service activities. Caixa Bank Research (2018) discovered that GPR affect world GDP growth negatively. In particular, decline in GDP growth in the emerging economies is 1.45 larger than advanced economies during the peak of GPR shock. Furthermore, geopolitical factors explained the discrepancy in global growth by 49% during 2000 to 2007. This might be caused by the tone down of geopolitical tension excluding the period of 2001 to 2003 which the 9/11 attacks and the invasion of Afghanistan and Iraq occurred simultaneously. In contrast, only 13% of the global growth was explained by the geopolitical factor during 2008 to 2012 since these were the period with financial crisis. However, the significance of geopolitical factors on global growth rise again to 30% in 2012 to 2017 (Caixa Bank Research, 2018). Therefore, GPR is an important index that can be used to gauge global economic prospects as well as stock returns. Apart from the importance of GPR, limited researches on stock returns predictability by using GPR such as Apergis, Bonato, Gupta and Kyei, 2017; Bouras, Christou, Gupta and Suleman, 2018 is the main inducement for us to use GPR for predicting Malaysia stock returns.

Besides, since EPU is recognized as a good proxy for real world uncertainty related particularly to the economic policy of government and is applied wisely (Wang, Chen & Huang, 2014; Li & Peng, 2017; Li *et al*., 2016; Ajmi *et al*., 2015). Therefore, it is worth in investigating whether EPU have bring significant impacts towards economic fundamentals and stock market performance and, especially whether this can lead to predictability accuracy of stock return in real world condition. Moreover, the current existing literature reported that EPU is driven either positively or negatively towards stock returns. However, we aimed to fulfill this research by examining the predictability of EPU. In addition, although numerous researches have been studied on the issue country-specific EPU to linkage its country's stock market performance (e.g. Kang & Ratti, 2015; Brogaard & Detzel, 2015), there are still insignificant numbers of researcher paying attention on the integration among global EPU and its country's stock market performance. In fact, it is important for taken global EPU into consideration as previous research (e.g. Dakhlaoui & Aloui, 2016) reported that both economic and financial system shocks in particular country may be significantly transferred to other countries. Therefore, it been highlighted whether global EPU has provided any valuable economic prove for the market participants. In brief, there is no past studies on predicting stock returns by using GPR and EPU simultaneously. Hence, this research gap leads to the general objective of this paper.

Next, according to Zhang, Zeng, Ma and Shi (2018), forecasting stock returns can be considered as a subject of great interest to both academics and practitioners in finance; yet, it is notoriously difficult. That is, the degree of returns forecastability is ultimately an empirical issue. Even through ample studies often conclude that there is significant evidence of returns predictability by applying a variety of economic variables, these existing papers only put its attentions on in-sample tests. Clark and McCracken (2012) mentioned that the in-sample results or evidence of a specific variable's predictive content mostly does not certainly imply an improvement in forecast accuracy. According to Welch and Goyal (2008), there is a long list of indicators from the literature are found to be incapable in providing consistent superior out-of-sample forecasts of the stock returns relative to a simple forecast in accordance to the historical average. Furthermore, according to Campbell (2000), the extant literature that mainly relied on in-sample tests of stock returns predictability might face the issue of data mining or overfitting. In a precise manner, it referred to the absence of sufficient data to accurately estimate the parameters of the model prior to forecasting. Based on Clark and McCracken (2012), there are various possible causes for such problem to occur as well, including the presence of parameter estimation noise and the existence unmodeled structural change.

Therefore, in recent studies, the general consensus is that the empirical results of out-of-sample forecast is considered as more trustworthy and it is more likely to reveal the information available to the real time forecaster (Hansen & Timmermann, 2012). Besides, according to Rapach and Wohar (2006), it is normally perceived that out-of-sample foresting tests offer a measure of protection against model overfitting or data mining, since the statistical models will be tested by applying out-of-sample observations which are not applied in the prediction of the model itself. It is fascinating to note that the relatively few researches which utilize out-of-sample tests of returns predictability basically obtain negative outcomes. The discrepancies between in-sample and out-of-sample results in the literature lead to the overall assessment of returns predictability to remain controversial. In this research, we undertake an extensive assessment to examine the out-of-sample predictive ability of GPR and EPU by comparing to the in-sample test outcomes by using the feasible generalized least square (FGLS) approach which proposed by Westurlund and Narayan (2011).

Lastly, in this thesis, Malaysia is chosen as research subject since it is quite interesting and important to be a subject in study. First of all, Malaysia is recognized as a small open economy nation among the Asian countries; however, its economy condition will be affected by various global economy issues positively or negatively in obvious. Datuk Seri Mustapa Mohamed, the former minister of International Trade and Industries (MITI) mentioned that Malaysia is one of the crucial beneficiaries from its openness as well as globalization towards overall global economy. He noted that most of the Malaysian companies have expanded their business operation over worldwide to achieve the concept of multinational business. Therefore, the Malaysian have received some particular benefits from the foreign direct investment (FDI) as long as involving themselves in the foreign market especially the stock market.

Furthermore, Malaysia has offered an effective banking presence in every Asean country which indicated about the high capabilities of Malaysia in building business internationally (Rosli, 2017). Thus, the strength of Malaysia is quite interesting to be explored among the other countries. As refer to research background above, Malaysia has experienced different impacts from few serious global issues that are received the attention from global. For an example, the US and China trade war has influenced the global economy condition dramatically since US and China are considered as the major market player in global economy. Hence, the stock market of the Malaysia also been affected since it is one of the trading partners with US and China respectively. Lee (2019) reported that both Union Bank of Switzerland (UBS) and Hong Kong and Shanghai Bank Corporation (HSBC), both well-known banks in Europe have recommended the stock of Malaysia as a defensive stock against the period of US and China trade war. This is mainly due to the economic growth of Malaysia has accelerated by an additional 0.1 percentage point even facing the effect of US and China trade war. To sum up, the stock market of Malaysia is fluctuated drastically which reflects the unexpected impacts from the global economy issues. In short, the issues stated above leads to following research objectives of this study.

1.3 Research Question

Headers of this research are to response the following research questions: -

1.3.1 Is there any discrepancy in the in-sample and out-of-sample test results of GPR?

1.3.2 Is there any dispute between the in-sample and out-of-sample test results of EPU?

1.3.3 Does GPR or EPU have the superior out of sample foresting power in predicting Malaysian stock returns?

1.4 Research objectives

1.4.1 General Objective

To analyse the predictability of geopolitical risk (GPR) and economic policy uncertainty (EPU) to Malaysian stock returns through the usage of monthly data from January 2005 to April 2019.

1.4.2 Specific objectives:

Specifically, there are three specific objectives of this paper are as following: -

- To examine the out-of-sample predictive ability of GPR by comparing to in-sample test results.

- To investigate the out-of-sample forecasting power of EPU by comparing to in-sample test results.

- To determine a better predictor in forecasting the Malaysian stock returns by comparing the predictive power of GPR and EPU.

1.5 Hypothesis Development

With the purpose in achieving the objectives of this study, there are three hypothesis tests will be carried out as follows: -

1.5.1 Hypothesis statement 1

H_0: There is no discrepancy in the in-sample and out-of-sample results of GPR.

1.5.2 Hypothesis statement 2

H_0: There is no dispute between the in-sample and out-of-sample results of EPU.

1.5.3 Hypothesis statement 3

H_0: GPR has the superior out-of-sample forecasting power in predicting Malaysian stock returns.

1.6 Significance of Study

To fulfill present study, we extend the previous studies in numerous dimensions. First and foremost, we trying to fill up the literature gap by subjecting our predictor variables to extensive out-of-sample forecasting tests. Several studies showed that stock return predictability is primarily and predominantly conducted by in-sample test; and it is not robust to evaluation of out-of-sample tests (Brennan & Xia, 2005; Bossaerts & Hillion, 1999; Ang & Bekaert, 2007; Goyal & Welch, 2003; Butler *et al.*, 2005; Cochrane, 2008; Lettau & Van Nieuwerburgh, 2008; Rapach & Wohar, 2009; Hjalmarsson, 2010; Rangvid, Schmeling & Schrimpf, 2014). Thus, this study we examine the predictability of the Economic Policy Uncertainty (EPU) and Geopolitical Risk (GPR) on stock returns by not solely based on the data frequency used but it also taken the forecasting tests into consideration.

Besides, the present study applied the Feasible Generalized Least Squares (FGLS) forecasting approach for both in-sample and out-of-sample stock return horizon. Narayan and Westerlund (2012) have employed this approach initially to predict U.S. stock returns, revealing that FGLS forecasting test are statistically significant and also achieve economically superior, as it accounts for all three features which include the persistency, endogeneity and heteroscedasticity of the estimator. Furthermore, Phan, Sharma and Narayan. (2015) also found that FGLS is outperform to the Ordinary Least Squares (OLS) and adjusted OLS (ALS) as well as generally perform better compared to the historical average model in the out-of-sample evaluation test. Hence, FGLS test is expected to perform well than the competitor tests in predicting the stock return.

As for many earlier studies, any apparent statistical significance models were often used the data for the years up to and in particular on the years of the oil shock ranging from the period of 1973 to 1975 (Pesaran & Timmermann, 1995; Barsky & Kilian, 2004; Cambell & Thompson, 2008; Driesprong *et al.*, 2008; Goyal & Welch, 2008; Hamilton, 2008). Nowadays, most models are insignificant and have performed poorly for out-of-sample test performance. Our study examines the empirical evidence as of early of 2005. It provides initial empirical evidence on the relationship between recent market conditions and out-of-sample forecast performance.

To date, there are many variables and empirical researches done to study the issues of return predictability, including oil price (Narayan & Sharma, 2011; Driesprong, Jacobsen & Maat, 2008; Sim & Zhou, 2015), financial ratios and macro variables **(**Gupta *et al.*, 2014, Campbell & Thompson, 2008; Rapach, Strauss & Zhou, 2010), US market returns (Rapach, Strauss & Zhou, 2013), credit standards (Chava, Gallmeyer & Park, 2015), technological innovation (Hsu, 2009), and EPU (Bekiros, Gupta & Majumdar, 2016; Brogaard & Detzel, 2015). However, there are lack of studies that used both GPR and EPU as predictor variables in stock returns forecasting. Thus, our study contributes and fulfill to the past literatures by including both GPR and EPU in this set of predictor variables for the purpose of further examine their effects towards return forecasting.

By focusing on the common forecasting framework of forecasters, which also can be known as the future researchers, do realized that there is lack of forecasting research regarding to both EPU and GPR predictors. Thus, the empirical relationship established in this study may provide some insights or valuable evidences for researchers because it examines if EPU and GPR can improve the predictive ability of return and provide an estimate on the accuracy of magnitude of possible real-time gain between both of them. As a result, an analysis and comparison on the result of this study with other research can be carried out. By equipping with details comparison, forecaster might have a clearer picture of the impact on the stock market performance and which can assist them to make a correct judgment and evaluation on return forecasting.

Furthermore, this research might beneficial for investors as well. According to Camargo and Azzoni (2016), they concluded that before any decision made by investors, they should equip a better and immediate understanding on the stock market condition. For instance, any changes in market factors may generate favorable or unfavorable consequence on the stock market performance which will directly impact the investor’s profitability. Therefore, our research could assist investors to time-vary their portfolio allocations between debt and equity by referring to their understanding.

In conclusion, this study expected would be the reference point for researchers, forecasters and investors in their investment decision making. It enables them to examine the factors that will influence the Malaysian stock market performance as well as assist them to time the market in real time.

1.7 Organization of study

The outline of the research which consists of five chapters, the remaining chapters are structured as follows: -

Chapter 2: This chapter will present the theoretical framework and provide in-depth discussion on empirical results of previous studies that used GPR and EPU as a predictive variable to forecast the Malaysia stock market returns.

Chapter 3: Chapter 3 presents the details of methodology of this research which includes the collection of data, techniques used and the ways to analyze in-sample as well as the out-of-sample results.

Chapter 4: Chapter 4 will provide the discussion on empirical findings, analysis and interpretation of the results according to the research objectives of this study and the agreement with the findings of relevant research studies done by the previous researchers.

Chapter 5: A brief summary on the previous chapters, discussion, limitations and recommendations for future research of this topic will be presented in the final chapter of this paper.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

In this chapter, the results from previous studies on investigating the relationship between dependent and independent variables will be reviewed. The purpose of this chapter is to provide a better understanding and a clearer picture in the related area of study by presenting different opinions suggested by different researchers. Independent variables which include economic policy uncertainty (EPU) and geopolitical risk (GPR) in globalize form, whilst the dependent variable is stock market's returns in Malaysia. In addition, relevant theories in this study such as efficient market hypothesis (EMH) and arbitrage pricing theory (APT) are also being discussed, where their respective linkages with the independent variables will be explained in detail as well.

2.1 Theoretical Framework

2.1.1 Efficient Market Hypothesis Theory (EMH)

In finance related researches and literature, efficient market hypothesis theory (EMH) is an essential theory as academics and practitioners are keen to study about EMH due to its disputable results. There are a lot of opposite opinions against the EMH theory; however, its origin and the evolution of the way of studies on it during the last decade are still essential. Basically, EMH is relevant to stock market analysis, technical analysis, fundamental analysis and share asset valuation. It is developed by Eugene Fama in the mid-1960s with his studies (Fama, 1965; Fama, 1970; Fama 1991). According to Fama (1970), the capital market is efficient when the price of securities "fully" reflects the available and fundamental information of the company. When securities price fully reflects the company's information, none of the investors have the opportunity to gain abnormal profits from the efficient stock market transactions (Titan, 2015). Fama (1995) also explained efficient market as a market with huge amount of rational investors who are having active competition with each other so as to attempt on future individual stock value prediction in the condition that everyone receives the same essential current information. In other words, stock market can't be beaten by anyone.

From Fama (1970), EMH comprise of weak form efficiency, semi strong form efficiency and strong form efficiency. Sewell (2012) defined weak form efficiency as a set of available information which consists only the historical stock price. It is a condition that investors who refer to the changes in the previous stock prices are incapable to predict the future stock price. In simple words, a rise in today stock prices does not indicate that there will be an increase in tomorrow stock prices. Thus, it will cause the market stock returns or stock volatility to be unpredictable. In weak form efficient market, it is not sufficient to constantly produce excess returns by applying the techniques of technical analysis but certain forms of fundamental analysis techniques might still possible to generate excess returns (Manasseh, Ozuzu & Ogbuabor, 2016).

As stated by Leković (2018), correlation test is to test weak form market efficiency with the aim to analyze the existence of linear correlation between current and past stock returns:

$$R_t = \alpha + \beta R_{t-1-T} + \varepsilon_t$$

Where:

R_t = return on securities at the period t

α = expected return on securities not influenced by past return,

β = correlation coefficient between return on securities at the period t and return on securities in period $t - 1 - T$

R_{t-1-T} = return on securities at the period $t - 1 - T$

ε_t = random error

From the test above, if $\beta = 0$, which means the correlation coefficient is equal to zero, observed returns do not correlated with each other, and future return can't be predicted by past return. Nevertheless, if $\beta \neq 0$, then the future return is possible to be predicted and it indicates no weak form market efficiency. Particularly, when $\beta > 0$, i.e. the return on securities correlates positively which implies that this following period will repeat the positive and negative returns of past period. While for $\beta < 0$, it depicts a negative correlation between the series of securities' return with a reversal effect.

In terms of empirical findings, Dickinson and Muragu (1994); Dockery and Vergari (1997); Karemera *et al*. (1999); Olowe (1999) suggested that Nairobi stock exchanges market, Budapest stock exchange market, Turkey's stock market, and Nigerian stock exchanges market are efficient in weak form efficiency respectively. In contrast, Wheeler *et al*. (2002) showed that Warsaw Stock Exchange market of Poland does not hold the weak form efficiency. Besides, Gimba (2012) also found that Nigerian stock market is weak form inefficiency. For Malaysia, Singh and Kumar (2018), Ling and Ruzita (2016) suggested that Kuala Lumpur stock market is weak form inefficiency. In other words, investors who are expert in applying technical analyses have a high possibility of gaining abnormal profit from the timing the stock market.

Besides, weak form efficiency is corresponding to random walk theory (Sharma & Marhendru, 2009). When the random walk theory holds, weak form market efficiency must hold too (Ko & Lee, 1991). Hence, market efficiency exists when evidence is provided to support the random walk theory. Nonetheless, when random walk theory violates, it cannot conclude that market is weak form efficiency (Shamshir & Mustafa, 2014). According to one of the popular researches on random walk theory, Fama (1995), an efficient stock market that follows random walk theory is a market where the consecutive changes in the prices of stock is independent or do not have memory. Particularly, the price of stock does not have relationship with previous stock market price pattern. Besides, Dupernex (2007) proposed that the stock price in efficient market must follow a random walk where movement of stock price is on random path. This is because when previous stock price is freely available, investors will have competition with each other and causes all the non-random fluctuations about stock price intrinsic value become smaller (Van Horne & George, 1967). By performing random walk, investors are unable to generate abnormal profit from the trading that based on information as all of them react immediately to the available information. This can be proved by Alam, Hasan and Kadapakkam (1999) where the finding depicted that except for stock market of Sri Lanka, other emerging stock markets comprising Hong Kong, Bangladesh, Malaysia and Taiwan follow random walk theory. Munir, Ching, Furouka and Mansur (2012) provided similar findings where stock market of Malaysia and Thailand follow random walk theory. However, there are a few studies rejected the random walk hypothesis in Bangladesh, Taiwan and Vietnam's stock market respectively (Mobarek, Mollah & Bhuyan, 2008; Nguyen, Chang & Nguyen, 2012; Phan & Zhou, 2014).

Subsequently, when a stock market price reflects both the information of historical price and current public information, the stock market is semi-strong form efficiency (Fama, 1970). Moreover, Ayodele, Oshadare and Ajala (2017) suggested that the main idea of semi-strong form efficiency is public information must able to be collected from public sources such as newspaper, news release and computer information database. Furthermore, semi-strong form efficiency has the capabilities to process information when it meets two aspects (Ayodele, Oshadare & Ajala, 2017). The first aspect is all the relevant historical, current and foreseeable future information which can be acquired from public resources can predict the stock price level accurately. While the second aspect is when public resources have new information, the stock prices must have the ability to react fully and instantaneously. In semi-strong form market, both techniques of technical analysis and fundamental analysis are unable to generate excess returns (Manasseh *et al.*, 2016). Dhar, Satyajit and Chhaochharia (2008) supported semi-strong form efficiency where the results verified that Indian stock market hold semi-strong form efficiency. For Malaysia, Hussin, Ahmed and Teoh (2010) found that in semi-strong form, Malaysian stock market is partially efficient. On the other hand, Nickolas, Laws and Nikos (2000) concluded that Cyprus stock market, an emerging stock market is semi-strong form inefficiency. Moreover, Robinson and Bangwayo-Skeete (2017) proposed that low trading activities due to international terrorist attacks, natural disasters, credit rating reviews of sovereign, political elections, events in between the period of global financial crisis and Brexit events will lead to semi-strong form market more inefficient.

Next, as proposed by Fama (1970), when stock market is in strong form efficiency, except for public information will be reflected by the stock price, private information like forthcoming announcement by a corporate about merger and acquisitions will also be reflected by the stock price. The market is very efficient until none of the investors comprising that company top management, employees, manager can earn excess profit from the stock market although they might have insider information from the company. It can be supported by research conducted by Brown, Richardson and Trzcinka (2003) who found that strong form efficiency was held in Canadian stock market. However, Kara and Denning (1998) provided a contradict result and rejected the strong form efficiency in stock market of US. Moreover, Sheefeni (2015) also suggested that Namibian stock market was strong form inefficiency although it was weak form efficiency.

In conclusion, those researches which regarding the validity of EMH on stock markets showed contradict results and some even do not provide clear answer. However, based on the past findings on EMH in other countries, it assumes that stock market returns cannot be predicted by various factors in the efficient market. Hence, if Malaysia stock market (KLCI) is efficient, stock return generally cannot be predicted over the long run, and vice versa.

2.1.2 Arbitrage Pricing Theory (APT)

Before discussing the APT, one should have a brief understanding on the asset pricing theory, a significant theory in the finance context with its vital role in valuing the financial assets. The main objective of the asset pricing theory is to determine the investor’s required return on the financial asset by considering the risk-return element. According to Galagedera (2007), there are five main categories under the asset pricing theory, and the most common category that people discussed is the Capital Asset Pricing Model (CAPM) theory which proposed by Sharpe (1964) and Lintner (1965). This theory is frequently used in explaining the relationship between the systematic risk and the expected return of an investment, especially for equities. Systematic risk or non-diversifiable risk that captured by CAPM is related to the overall activities in general market, thus, it is mostly cannot be diversified through the diversification process by constructing a good portfolio.

According to Fama and French (2004), CAPM is perceived as a crucial tool and it is still broadly applied in applications, for examples, it has been applied in the assessment of cost of equity, assessment of managed portfolio performance, valuation of investments, assessment of strategies for portfolio diversification, etc. However, in the recent years, proliferation of studies has been done to examine the validity of CAPM and most of the researchers found that the expected returns of an investment or portfolio could not be explained by a single factor alone (Mollik & Bepari, 2010; Verma, 2011; Das & Barai, 2013). For instance, there is an increase in the instability of beta when two different periods are tested, known as intra-period and inter-period (Mollik & Bepari, 2010). Since there are several studies found that the application of single factor is not enough to describe the return of an investment, numerous models have been developed to estimate the stock returns — arbitrage pricing theory (APT) model, for example.

APT is the alternate form of CAPM and also considered a well-known multi-factor approach in predicting the price of assets. It can be defined as an asset pricing theory which perceives that the return of an asset can be estimated through the linear relationship between the expected return of an asset and the macroeconomic components that capture the market risk. APT was developed in 1976 by an economist, Stephan Ross. According to Ross (1976), instead of referring to single factor, APT model will consider more risk measures in determining the elements that might be used to explain the asset’s return. In other words, APT assumed that the stock return will depend on several macroeconomic components, such as exchange rates, inflation, movements of interest rates, etc.

Besides, there are several assumptions of APT, such as APT assumes that the market is efficient and all participants tend to maximize their profit in any trade associated with stocks. Furthermore, APT assumes that there is no arbitrage opportunity since the market participants will always engage in the market which result the market prices back to its equilibrium levels. Moreover, under APT, the markets are assumed to be frictionless, with no transaction fees, taxes and short selling is allowed as well.

The formula of APT is presented as follows: -

$$E(Y) = R_f + b_1RP_1 + b_2RP_2 + b_3RP_3 + \cdots + b_nRP_n$$

Where:

E(Y) = expected return rate of a risky asset

R_f = return rate from the risk-free security

b_n = the risky asset's sensitivity in relation to particular factor

RP = risk premium related to particular factor.

From the APT formula, it indicates that the expected return of the investment is in a linear form by taking into account multiple factors which might influence the asset's price and the sensitivity of asset to several macroeconomic risks. In other words, under APT, the return can be predicted through various macroeconomic factors or risks. It can be supported by the research of Bower, Bower and Logue (1984) which found that APT is better in explaining and estimating return variations across assets and through time by using the monthly returns data of all corporations that listed on NYSE and multiple APT factors, for instances, inflation rate, exchange rates, etc.

Besides, the APT's validity has been approved since it found to be efficient in forecasting the future stock returns through the usage of macro-variables such as money supply and oil prices. (Iqbal, Khattak, Khattak & Ullah, 2012). Thus, through the previous studies, it showed that APT assumes that the return of an asset can be estimated through multiple factors. This can be supported in the recent studies as well. For examples, Demir, Gozgor, Lau and Vigne (2018) found that the EPU has the power in predicting the Bitcoin returns and the returns have negative relationships to EPU's changes. Moreover, one of the risk indicators — GPR, has been proved as a relevant feature in forecasting the gold movement (Banerjee, Ghoshal & Mukherjee, 2018). In this regard, it depicted that APT is perceived to hold in recent studies as well with the usage of different risk indicators in predicting returns.

However, APT suffers from a various number of drawbacks, for instances, under APT, it is necessary for every portfolio to be evaluated singularly. According to Gaille (2018), APT is suitable to examine only one item for risk, so it might virtually impossible when attempting to evaluate a whole portfolio with diverse securities. Hence, the entire portfolio has to be evaluated through the application of APT instead. Since it might account only for the portfolio, there are few assumptions that shall be made during the assessment to ensure the accuracy of its outcomes.

Besides, the results generated by APT might not be guaranteed. In a detailed manner, APT might not ensure the occurrence of profits. That is why several securities are underpriced by the market due to the reasons which lay outside of the range of what APT looks at (Gaille, 2018). Several risks might not the "real" risks, as these risks were being included by the investors themselves in pricing mechanisms, due to having a certain fear of particular investments in certain economic or market conditions. Another limitation of APT is that APT does not recommend any specific factors in this model which creates the difficulty in identifying the factors for a particular asset (Elbannan, 2015). Under APT, the investors are required to perceive the sources of risk or estimate of factor sensitivities. In fact, one asset will be more sensitive to a single component than another. Therefore, in APT, the real challenge for research and investor is to identify the single factor or factors that affect a specific stock; the required return for every factors as well as the sensitivity of asset toward each of the factors (Kumar, 2016).

Although there is an absence of formal theoretical guidance in selecting the appropriate group of risk or macro-variables to be involved in the model, however, APT does suggest that stock return is predictable (Rasiah & Kim, 2011). Thus, it leaves to an open question to the empirical research.

2.2 Empirical Review

2.2.1 Financial Ratio

Throughout the past few centuries, financial ratio is important in estimating the stock market return and being widely used by the market players as well. The existence of financial ratios implies that the effectiveness of forecasting the market returns with the given available information in the market. Thus, few empirical researches are prepared to highlight the effect of financial ratios on stock market return performance.

Refer to a study prepared by Din (2017) who investigated the financial ratio role on predictability of the stock return in PSX 100 Index companies ranging from the period of year 2001 until 2014. The sample size taken is 65 listed companies under the PSX 100 Index in form of panel data. OLS is conducted to estimate the significance of parameters within the dependent variable (yearly stock return). The outcome shows that the part of the financial ratios and market variables such as return on sales, debt ratio, market return and firm size consist significant positive effect towards the stock return performance. Besides, there is another similar study prepared by Musallam (2018) who specialized in determining the relationship of financial ratio between stock market return to assist those government policymakers in decision making process. The scholar has selected sample which are 26 companies that are from Qatar Stock Exchange. The 7 years' time period is taken for analysis from year 2009 to 2015. The method of Weighted Least Square (WLS) is used in evaluating the predictive regression model. Hence, the result of the sample indicated that the ratio of earnings yield, dividend yield (DY) and earnings per share (EPS) affect the market stock return positively and showed that the independent variables have significant relationship with dependent variable.

Moreover, Karami and Talaeei (2013) aimed to explore the effect of financial ratio on forecasting the stock market returns and the correlation between both variables. They have covered few financial ratios which are market-to-book value (M/B), DY, capital gain and price to earnings ratio (P/E) as well in this study. The sample size consisted of the organizations which listed on Tehran Stock Exchange over the year 1998 until year 2007 with 10 years period. The method of posteriori is conducted in this study as a simple linear regression model is applied by using the panel data. Consequently, it reported that the capital gain and M/B significantly affect the stock return predictability. A similar research is studied by few scholars such as Jais, Jakpar, Doris and Shaikh (2012) who purposed to investigate the potential financial ratios in predicting the stock returns. They collected all the financial information on Bursa Malaysia (KLSE) between the time period of 2000 to 2009 as their empirical evidence. The method of Least Square regression is applied as their methodology for examining the relationship of the financial ratios between stock market return as well. The findings justified that most of the financial ratios (eg: P/E, return of equity (ROE), debt to equity) have significant positive relationship with stock market return. It indicated that the financial ratio based on historical cost enable to analyzing the stock return predictability.

Furthermore, Auret and Sinclaire (2006) studied that the specific relationship between M/B and returns since M/B is classified as one of the financial ratios. They have selected all the stocks available under the Johannesburg Stock Exchange (JSE) as sample data. Then, they also took the sample period which extends from year of 1990 through 2000. The method of OLS is applied to examine the relationship of the financial ratios between stock market returns accurately. Lastly, the outcome indicated the M/B played the role as proxy of particular risk and possessing a positive relationship with stock market return under JSE.

Khan, Gul, Rehman, Razzaq and Kamran (2012) studied that the predictability of the financial ratios on estimating the stock returns by investigating 100 non-financial organizations from the Karachi Stock Exchange. They selected a sample period within 7 years between 2005 till 2011. Then, they have applied the method of Generalised Least Square (GLS) to run over the panel data model. Refer to their study, they found out that those financial ratios enable in estimating the stock return effectively especially the M/B and DY have high predictive power towards the stock return predictability. Besides, Kheradyar, Ibrahim and Nor (2011) examined that the availability of financial ratio on predicting the stock market return. They have taken the sample of 960 organizations that are from Malaysia stock exchange which is Bursa Malaysia. The sample is focused which starting from January year 2000 to December year 2009 in 10 years period. They have taken dividend per share (DPS), EPS and M/B as the independent variables. They also applied generalized least square (GLS) method to predict the regression model efficiently. Therefore, the outcome stated that the financial ratios above able in estimating the stock market return and the result on predicting the stock market return could be shaped by the combination of financial ratios.

Moreover, Wijesundera, Weerasinghe, Krishna, Gunawardena and Peiris (2015) also studied about the predictability of financial ratio on stock market return forecasting to construct an effective portfolio for investors. The sample size is included 60 listed companies on Colombo Stock Exchange by considering the 10-years sample period from 2004 till 2013. Method of Ordinary Least Square (OLS) is carried out on estimating the significance for five financial ratios such as P/E, return on equity, EPS, DY and M/B in forecasting stock market return. Subsequently, the result indicated that the financial ratios have predictive power towards the stock return significantly even though they have the weak performance on it. A research is prepared by Cheung, Chung and Kim (1997) who likely in investigating the predictive ability of certain financial ratios on return forecasting. They aimed in examining the sample size of all non-financial firms under the database of Hong Kong from Pacific-Basin Capital Market (PACAP). The sample period is taken from year 1980 to year 1991 over 11-years period. They also reported the summary statistics in calculating the variable changes on the daily stock market return from Hong Kong stock market. Hence, the result from their research mentioned that certain financial ratios which are book-to-price ratio and P/E are useful on estimating the stock market return effectively. Both of them contributed different impacts on particular aspect of stock market as they are important in influencing the stock return well.

Furthermore, Alexakis, Patra and Poshakwale (2010) are purposely examining the predictability of stock return by utilizing the accounting information in constructing the financial ratios out. There are 47 firms from Greek which listed under the Athens Stock Exchange (ASE) are taken as sample size as well as the considering the data from year 1993 until year 2006 over the 13-years period. The application of Generalized Method of Moments (GMM) specification is carried out to estimate the relationship of the stock return between the financial ratios without the problem such as endogeneity. In result, they found that some particular financial ratios provided the significant information in estimating the stock return on AES. Agirman and Yilmaz (2018) have examined the issue about the availability of financial ratios on estimating the stock market return effectively. Since they have undertaken 4 common financial ratios, they collected the sample size about the quarterly data of 47 BIST companies that listed under Istanbul Stock Exchange. The sample period is observed from second-quarter of year 2004 until the forth-quarter of year 2014. They also applied the method of panel data analysis as the regression tool for predicting the stock return as well as determining the relationship among the variables. Therefore, the result disclosed that the 3 out of 4 financial ratios have significant predictive power on estimating the stock market return. It also examined that the ratio on firm size is considered great in predictability as comparing among the other ratios.

A research done by Morelli (2007) also studied that the role of size and M/B as the measurements to explain the stock returns of UK stock market. There are 300 securities which are obtained from the London Share Price Database (LSDP) selected as the sample size. Meanwhile, the sample period will extend from July of year 1980 until June of year 2000. The study also adopted the method that proposed by Fama and MacBeth (1973) which involved 3 steps like portfolio formation, estimation of beta and testing. Through the result, it examined that the role of M/B is considered as a significant determinant towards the stock market return as well as the showing the importance of financial ratio. Thus, Lewellen (2004) investigated about whether most well-known financial ratios which are DY, P/E and etc. able on predicting the stock return. The sample size is collected from the Centre for Research from the Security Prices (CRSP) database. Thus, the time period is taken from year 1946 till year 2000 within 54 years-period. They have conducted the OLS method to run over the predictability of financial ratio on stock return forecasting. In result, they found out that those financial ratios have weak predictive power on stock return; however, it also indicated the significant impact from financial ratios on returns as well.

Otherwise, some of the financial ratios could brought certain negative impact or even no influence towards the stock returns. For example, P/E seems to play the vital role on predicting stock return. Thus, according to Fun and Basana (2012), they have investigated the effectiveness of P/E on affecting the changes of stock return by selecting the sample of Liquidity 45 stocks that listed under Indonesia Stock Exchange (IDX). The period is taken from August year 2005 to January year 2010. They also employed the method of OLS to evaluate the slope and intercept with minimized sum squared of error. The result of this study determined that the stocks which consist of low P/E would be expected in generating the greater return in future vice versa.

Refer to Din (2017), it concluded that some financial ratios which are asset turnover ratio and EPS have negatively affected in forecasting the stock returns by observing the sample collected from 65 listed companies from PSX 100 Index at time period of year 2001 till year 2014. Besides, Musallam (2018) also indicated that some financial ratios may direct a negative effect on the stock return over particular period such as ROA, P/E, NPM, M/B, return on equity and DPS. The result is conformed after taking the consideration on the data of 26 organizations from Qatar Stock Exchange. Karami *et.al* (2013) examined that few ratios such as DY and P/E showed no predictive effect on the stock returns after investigating those firms all listed on Tehran Stock Exchange within the time period of 1998 until 2007. Briefly, financial ratio is found to able in affecting the stock return predictability neither positively or negatively from discussion above.

Furthermore, Agirman *et al.* (2018) studied that the predictability of few common financial ratios which included price-to book, P/E, dividend per share and also firm sizes on forecasting the stock return. They found out that a relationship between the stock return and all variables except P/E. This is concluded with the sample size of 47 organizations under Istanbul Stock Exchange from year 2004 to year 2014. A similar study prepared by Morelli (2007) who found out that the size did not contribute any relationship with the stock return; in other words, it lacks of predictive power on stock return forecasting.

2.2.2 Macro Variables

Apart from financial ratios, macro variables are important factors which might influence the stock market returns and many researchers have shown interest on their relationship. For instance, Chia and Lim (2015) applied autoregressive distributed lag (ARDL) bounds testing procedure and error correction Granger causality tests to examine how Malaysian stock market will response on the macro variables comprising exchange rate, interest rate, inflation rate, industrial production and money supply (M1) over the period from year 1980Q1 to year 2011Q3. The findings depict that interest rate and money supply will affect Malaysian share prices positively while inflation rate affect negatively in long-run coefficients. Besides, fluctuation of exchange rate causes stock prices movement and it is an appropriate variable that can explain the stock returns. Jamaludin, Ismail and Manaf (2017) who analyze how inflation rate, exchange rate and money supply will influence conventional and Islamic stock market returns in Malaysia, Singapore and Indonesia also shows a similar results. Jamaludin et al. (2017) used the techniques of panel least square regression and obtained the monthly data from Data Stream for all variables from January 2005 to December 2015 and found that inflation rate has greater negative effect on stock market returns. For exchange rates, finding revealed that it has significant and positive relationship with stock market returns. However, money supply has insignificant relationship with stock market returns. It means that money supply has no impact on stock market returns. Moreover, Lai, Yee and Chelliah (2017) examined the impact of local macro variables including inflation rate, interest rate and exchange rate and foreign macro variables which comprising gold price and Dow Jones Index. This study extracted monthly data from January 2000 to December 2013 from DataStream database and applied Unit Root Test, Granger Causality Test and Juselius Co-integration test. Lai *et al.* (2017) verified that all the local and foreign macro variables can influence

KLCI significantly in long run while Dow Jones Index and exchange rate fails to influence KLCI in short run. In terms of Granger causality test, only inflation rate, interest rate and gold price can granger cause KLCI significantly. At the same time, results also depicted that KLCI can granger cause exchange rate and inflation rate respectively.

Subsequently, the study of Chen (2009) used Markov-switching model for estimation before applying filtered probability to identify bear market. In addition, in-sample and out-of-sample tests also applied in this study to test the macro variables' level of stock predictability. Chen (2009) obtained the data, S&P 500 price index from February 1957 to December 2007. While all the independent variables (macro variables) comprising yield spreads, unemployment rates, inflation rates, federal fund rates, money stocks, aggregate output, nominal effective exchange rates, and federal government debts are obtained from Federal Reserve Economic data (FRED II). Moreover, the result shows that macro variables have better performance in bear market prediction than stock market prediction. At the same time, Chen (2009) mentioned yield spread and inflation rates are the most useful when predicting US stock market during recession. The result of Chen (2009) is consistent with Gupta and Modise (2013) who proposed that inflation rate has extremely strong ability to predict the stock return over the medium to long run horizons for the period of out-of-sample. Gupta and Modise (2013) who applied data-mining-robust bootstrap procedure examines the ability of in-sample and out-of sample in predicting the stock returns of South Africa by using macro variables. In terms of in-sample, t-statistic correlated with slope coefficients in a predictive regression model has been conducted while MSE-F and the ENC-NEW t-statistics was applied in out-of-sample. The macro variables are inflation rate, unemployment rate, interest rate, money stocks, aggregate output, term spreads on bonds, world oil production and crude oil price where the data is acquired from Bloomberg, South African Reserve Bank, Statistics South Africa and US Energy Information Administration websites. Besides, the data period is from January 1990 to December 1996 for in-sample while out-of-sample is from January 1997 to June 2010. Briefly, in-sample results depict that interest rate variable can predict in short run while money supply and world oil production can predict at certain horizon. In contrast, out-of sample results show that inflation rate has high ability of prediction while term spread, relative treasury-bill rate, growth of narrow money supply, money stock and the world oil production has low ability of prediction.

According to Rapach, Wohar and Rangvid (2005), data-mining-robust bootstrap procedure, in-sample and out-sample tests was conducted to test macro variables predictability which include term spread, inflation rate, unemployment rate, money stocks, interest rates, and industrial production on the 12 industrialized countries. Monthly data for 12 industrialized countries and macro variables data was applied and obtained from DATABASE. Furthermore, this study aims to attain a better understanding on the real nature of stock return predictability in worldwide data. In terms of result, it shows that interest rate and inflation rate have the in-sample and out-of-sample predictability but interest rate is more consistent and trustworthy predictor for most of the industrial countries' stock returns as compared to other macro variables. Besides, interest rate has significant out-of-sample predictability over the period of 1990s in a lot of countries. Yet another finding of Fang and Blassler (2017) also supported the finding of Rapach *et al.* (2005). The research objective of Fang and Blassler (2017) is to test whether interest rate can aid in forecasting China stock returns by conducting prequential approach, bivariate VAR model and univariate autoregressive model. In addition, bootstrap-like simulation method and a nonparametric kernel-based simulation method has been applied to generate the out-of-sample probability forecast. Shanghai Stock Exchange Composite Index and interest rate are the data of this study which collected in daily basis from year 2013 to year 2015. Based on the results, vector autoregressive regression (VAR) model performs better than autoregressive (AR) model and forecasting on China stock returns will be more reliable when model includes interest rate. Furthermore, Aono and Iwaisako (2007) researches on the predictability of price-earnings ratio, lagged stock returns and interest rate with proxy of ten-years Japanese government bond yield (JGB) on Japanese aggregate stock return also support the finding of Rapach *et al.* (2005) and Fang and Blasser (2017). From Aono and Iwaisako (2007), single variable regression model and multivariate regressions are conducted and time series data is collected from Tokyo Stock Exchange with the results depict that both interest rate and aggregate stock return are useful predictors for Japan stock market returns. However, the study of Kadir, Selamat, Masuga and Taudi (2011) who predict KLCI returns and volatility by using interest rate volatility and exchange rate volatility based on GARCH (1,1) found that interest rate has weak predictive power while exchange rates have strong predictability power on KLCI returns. Besides, the findings also depict that both interest rate and exchange rate fail to predict KLCI volatility. This study adopted monthly data from Yahoo Finance in between January 1997 to November 2009. While end of month exchange rates and three months Treasury bill rate are collected from International Financial Statics.

2.2.3 Risk Indicator

On top of that, there are also researches which predict stock market return by using risk indicators. For examples, Yang and Liu (2012) study on the predictability of historical volatility, implied volatility, the Taiwan stock options' volatility index (TVIX) and GARCH forecast volatility (GFV) on stock market of emerging countries by applying GARCH model. The data such as implied volatility, trading volume, detailed transactions data, Taiwan stock index options' open interest, volatility index (TVIX), are taken from TAIFEX database in daily basis with the period from 1st December of 2006 to 31th March of 2010, which is the time where TAIFEX promoted TVIX aggressively. The finding of Yang and Liu (2012) showed that the predictability of TVIX on future stock market volatility has parallel result with put options' implied volatility. While comparing to the call options' implied volatility, the predictability of TVIX performed better. In addition, TVIX is proved to be an effective predictor for future realized Taiwan's stock market volatility. The result of Yang and Liu (2012) is corresponding with Bahadur and Kothari (2016) who not only study the relationship between India VIX and India stock market volatility but also examine the predictability of India VIX on India stock market volatility. This study applied time series data which included India VIX and daily closing values of CNX Nifty 50 index with the sample sizes of 1656 in between the period from March 2009 to December 2015. The data above is acquired from the National Stock Exchange (NSE) of India. Based on the results, India VIX is proved to be a good indicator and has good forecasting ability in future short-term market volatility. Moreover, the forecasting accuracy of India VIX is higher for lower stock price movements as compared to high magnitude of future price movements. Besides, Habibah, Rajput and Sadhwani (2017) compare the ability of Investor Fear Gauge Index (VIX) and Google Search Volume Indices (GSVIs) to explain and predict the returns of S&P 500 by conducting autoregressive distributed lag (ARDL) model and nonlinear autoregressive lag (NARDL) model. In terms of weekly data, opening prices and volume of S&P, VIX and GSVIs which comprising market crash and bear market is obtained from Yahoo Finance, Chicago Board Options Exchange (CBOE) and Google Trend respectively within 1st January of 2004 to 31th December of 2015. In short, the results depicted that VIX has stronger S&P 500 returns predictability than GSVI. Yet another study of Chen, Jiang, Lu and Tu (2017) analyzed the predictability of international volatility risks (ΔVIX) on China stock market returns by applying in-sample and out-of-sample test. This study obtained data from RESSET over the period from 4th January of 2003 to 30th September of 2013 and the proxy of international volatility risks is the volatility index of seven international markets which include UK, US, German, France, Euro zone, Hong Kong and Japan. The findings depicted that Chinese daily overnight stock market returns can be forecasted negatively and significantly by international risks while next-day Chinese daytime stock returns can be forecasted positively.

Aside from VIX, Crude Oil volatility index (OVX) is another risk indicator which will affect the stock market returns. Dutta, Noor and Dutta (2017) analyze whether crude oil volatility index (OVX) is an essential factor to explain the emerging stock market returns' trend from a global perspective by conducting GARCH-jump model. In terms of data, this study used daily data of world emerging market index, Morgan Stanley Capital International (MSCI) which consists of 23 emerging countries including United Arab Emirates, Brazil, Turkey, Chile, South Africa, Colombia, Russia, Egypt, Qatar, Czech Republic, Poland, Greece, Mexico, China, Taiwan, Korea, Peru, Hungary, Philippines, India, Malaysia, Thailand and Indonesia. Besides, the daily data of West Texas Intermediate (WTI) have been used to represent the conventional oil prices too. The major source of data of this study is Thomson Reuters DataStream database and website of Chicago Board Options Exchange and the results depicted that stock returns of emerging country have a positive respond to the changes in OVX and time-varying jumps occur in the stock market returns. Moreover, the sensitivity of emerging market equity returns to oil volatility shock is high and the impact of the OVX magnitude is slightly larger than oil market returns of WTI. However, the study of Vu (2019) appeared to contradict the results of Dutta *et al.* (2017). Vu (2019) utilized EGARCH model and GARCH-jump model to examine the relationship between international oil indices with the proxy of OVX and Southeast Asian stock market which included 6 Asian nations comprising Malaysia, Indonesia, Thailand, Singapore, Philippines and Vietnam. The daily data of Morgan Stanley Capital International (MSCI) indices and crude oil volatility index (OVX) are obtained from the website of Chicago Board Options Exchange and DataStream database over the period from May 2007 to December 2017. Next, finding shows fluctuations of oil price will affect stock returns positively while OVX will influence the stock returns negatively. In other words, when future oil prices uncertainty increase, stock markets will move downwards. Luo and Chin (2017) who conducted Augmented Dickey-Fuller test, Phillips-Person test and unrestricted vector auto-regression (VAR) model to analyze how OVX shocks and oil price shock influence Chinese stock market returns and returns of industrial, commercial, real estate, utility and conglomerate sectors discovered a similar result with Vu (2019). Luo and Chin (2017) revealed that Chinese stock market returns and the returns of another five sectors are affected by oil price stocks positively but negatively by OVX shocks. Hence, when OVX shocks increase, all returns will decrease. Next, the daily data of this study is from 10th May 2007 to 31th Dec 2015. There are two sample period which are crisis period from 1st Dec of 2007 to 30th June of 2009 and post-crisis period from 1st July of 2009 to 31th Dec of 2015), so they specifically discovered the role of global finance crisis from those issues.

Apart from the effect of OVX on stock market returns, predictability of OVX also has been studied by some researcher. For instance, Wang, Wei, Wu, and Yin (2018) has an idea to depict that stock volatility is predictable with the crude oil volatility in the short-term from the perspectives of both in-sample and out-of-sample analysis by utilizing regression-based approaches and autoregressive (AR) model. The daily price of S&P 500 index is from Yahoo Finance while West Texas Intermediate (WTI) crude oil and Brent oil is from Energy Information Administration website in between January 1991 to December 2015. There are few findings from this research which include the crude oil volatility distributes various information from macro variables and predictability of crude oil volatility on stock volatility is sufficient to be captured by simple regression model. Moreover, few forecasting analyses revealed that crude oil volatility cannot predict stock volatility for longer periods of 9 months. While for portfolio return volatilities, recent major portfolios are predictable with the crude oil volatility.

2.2.4 Economic Policy Uncertainty

The EPU measure is largely reflected in recent studies which examine the impact of EPU on both economic and financial market performance. An investigation about the impact of Chinese EPU on Hubei carbon price by using weekly data frequency from April 2014 to December 2017 has done by Ling-Ling and Wen-Jun (2019). The data for news-based EPU index is developed by Baker *et al.* (2016), while the closing price of Hubei Emission Allowance (HBEA) is retrieved from the website of China Carbon Emissions Trading. The empirical results from the Markov Switching Vector Autoregressive (MSVAR) model showed that Chinese EPU has significantly positive impact on Hubei carbon price. The impulse response analysis shows that the impact of Chinese EPU on Hubei carbon price is relatively larger over the low volatility period than the high volatility period on carbon market. Besides, Castelnuovo (2019) has investigated the relationship between both financial uncertainty and the yield curve by using monthly frequency data ranging from year 1962 till year 2018 in local projection (LP) model setting. The main findings showed that the yield curve responds significantly negative to an uncertainty shocks; and the response of the short end of the yield curve is relatively robust than the long end one. In other words, it means that a financial uncertainty shock results a temporary steepening of the yield curve. The research done by Aastveit, Natvik and Sola (2013) aimed to estimate how economic uncertainty constructed by Bloom (2009) influences the transmission of monetary policy shocks which sourced from national statistical office, over the period 1971Q1 to 2011Q3 in structural VAR model setting. An evidence shows that when the uncertainty level is high, the economic activity is affected by monetary policy shocks considerably weaker, which support and consistent with “real-options” effects suggested by models with non-convex adjustment costs. Another evidence also proved that investment reacts two to five times weaker especially when uncertainty is in its upper instead of its lower decile. In addition, Zalla (2017) examined the impacts of monthly policy uncertainty towards the stock exchange, interest rate, industrial production, and employment from January 1985 to January 2016 in VAR model setting. The source of data for Irish Stock Exchange (ISEQ), the interest rate and the employment rate are derived from Central Statistics Office (CSO) of Ireland; the industrial production data is obtained from the International Monetary Fund (IMF); and the EPU index is developed by Baker *et al*. (2015). The estimated effects demonstrated that policy uncertainty innovations in Ireland have negative impacts on macroeconomic and financial variables.

Besides, Ribeiro Scarcioffolo and Etienne (2018) aims to evaluate the importance of EPU on both price fluctuations and volatility in the crude oil and natural gas market in U.S. from 1994 to 2017. The data for EPU is collected from Baker *et al*. (2017) and both price of crude oil and natural gas are downloaded from the Bloomberg. The results based on VAR and MGARCH models reveals that the relationship between innovations in EPU and the volatility of oil and natural gas returns is negatively related, whereas the innovations in the two energy market are positively affects the volatility of the EPU. According to Czudaj (2019), a research done to analyze the impact of different extents of uncertainty on momentum trading in WTI crude oil future market by applying Bayesian time-varying structural VAR model from the period February 2006 to December 2014 in daily data frequency. The data for WTI crude oil future closing prices is collected from Stevens Analytics via Quandl and the data for uncertainty are separated into two measures, which are U.S. stock market volatility with the proxy of VIX provided by Jurado, Ludvigson and Ng (2015). While daily news about the stance of EPU index in U.S. is suggested by Baker *et al*. (2016). This study employed wavelet techniques to split crude oil futures price into several time horizons. The findings revealed that both uncertainty measures influence momentum trading on the crude oil future market in different periods, in particular during the great recession between year 2007 and year 2009. For the decomposed futures prices, the findings reported that the reaction of uncertainty are subjected to change over various frequencies. High frequencies generate a very short-lived reaction to uncertainty while low frequencies generate a persistent reaction to uncertainty shocks. Kang and Ratti (2013) have done a research by employing monthly frequency data on the crude oil price, U.S. EPU index, and aggregate U.S. stock returns. The objective of the study is to determine the impact of policy uncertainty with allow for the endogenous relationships towards real stock returns. Killian (2009) is applied structural VAR model to examine the interrelationship effect between oil price shocks and EPU toward stock market returns. The source of data for crude oil price, EPU index and aggregate stock returns are retrieved from the U.S. Department of Energy, Baker *et al*. (2011) and the Center for Research in Security Prices (CRSP) respectively over the year 1985 to\ill 2011. For the country of U.S., an unanticipated rise in EPU has generate a significant negative impact towards real stock returns. A positive demand shock of oil market significantly raises EPU and reduces real stock returns. The results also reported that EPU and oil-market specific demand shock account for 19% and 12% of the long-run variability in real stock returns respectively.

A research that studies on how annual time-series EPU affects corporate capital structure in a market-based system of the U.S. and a bank-based system of Germany done by Li and Qiu (2018) in panel regression specified model setting. This research employed the EPU index of Baker *et al*. (2016); and both the end-of-year share price data and world scope accounting data for each firm are retrieved from DataStream database. Based on a sample of 5,360 U.S. firms from 1985 to 2015, both market-value and book-value based financial leverage ratios are positively (negatively) related to the U.S. EPU News Index in tranquil (crisis) periods in the U.S.; representing that during the crisis periods, U.S. firms become more prudent in levering up but not tranquil periods. A similar result is found for the book-value based leverage ratios of 717 German firms from 1993 to 2015. However, the market-based leverage ratio of German firms responds negatively to an increase in EPU News index in both tranquil and crisis periods; suggesting that German firms tend to borrow less in general when policy uncertainty is high. Moreover, Brogaard and Detzel (2015) examine the role of EPU plays in asset price in the cross section and time series from year 1985 to 2012, which extended the measure from the research of Baker *et al*. (2013). This framework employed monthly EPU index constructed by Baker *et al*. (2013) and the CRSP value-weighted index as a measure indicator of overall U.S. stock market performance, based on Merton's (1973)

Intertemporal CAPM (ICAPM) model. They find evidence that one standard deviation increase in EPU is associated with a contemporaneous 1.31% decrease in market returns and a 1.53% increase in future 3-month log excess returns. Furthermore, the finding also reveals that EPU has no statistically discernable effect on dividend growth either over one to twenty-four month horizons. A study done by Carvalho (2017) investigated the relationship between EPU and the returns on stocks and bond markets for G7 countries (U.S., U.K., France, German, Japan, Canada and Italy) from the period January 2000 to December 2016 in GARCH model setting. This research employs monthly EPU index developed by Baker *et al.* (2016), and the stock and bond market index for G7 countries are retrieved from the Bloomberg. The results for the stock market in U.S., U.K., France, German and Japan show a statistically significant impact from EPU and they are following a negative correlation, but for Canada and Italy whose current returns are unaffected by the changes in EPU. Moving on to the bond market, there is resounding evidence of the non-existing impact of EPU on the current zero-coupon bond returns, for most countries. The exception are U.S. and Italy, where the EPU index presents a statistically significant influence at 1% significance level.

Based on Christou, Cunado, Gupta and Hassapis (2017), they done a research to analyze the role of EPU on stock market returns for numerous Pacific-rim countries, which include Australia, Canada, China, Japan, U.S. and Korea, from period 1998 to 2014 on monthly data frequency and based on a panel VAR (PVAR) model setting. The key findings reported that stock market returns is oppositely related toward increased of policy uncertainty levels. Furthermore, when taken the uncertainty spillovers into consideration, all countries generated a significant non-linear relationship between stocks market returns and U.S. EPU shocks, except in Australia, which suggesting that there is a favorable opportunity that investors could earn by making investment in Australia, after a rising in EPU levels under the U.S. economy. The research of Tsai (2017) explored the impact of EPU in four countries which are U.S., China, Japan and Europe towards the contagion risk of investments in worldwide stock market by implementing VAR model setting. The worldwide returns of 22 stock markets ranging from year 1995 till year 2015 are examined and retrieved from the DataStream database to determine which region's EPU index constructed by Baker *et al*. (2015) exhibits the huge impact on regional systematic risk in the international stock market, and also on volatility risk for individual stock market. Firstly, the markets of different continents and the spillover indices of the developed and emerging markets are computed with the purpose of examining both regional systematic risk and the contagion risk effect of EPU. The findings reported that China's EPU has the most influencing power and its contagion risk spreads to different regional markets, except for Europe; the impact of EPU in the U.S. is weaker to that in China; EPU in Japan solely impacts contagion risk in emerging markets; contagion risk in Europe is unaffected by the four EPU indices; and EPU in Europe is unaffected by contagion risk in the worldwide stock market. However, based on the volatility risk in individual market, the EPU in Europe and China respectively have the most influencing power towards the Asian and European countries. These findings are attributable to the extremely high trade dependence among these countries as the international enterprises performance is predominantly affected by the economic policies which hold by their trading partners. Moreover, Asgharian, Christiansen, Gupta and Hou (2016) employ mixed data sampling (MIDAS) approach to study the importance of EPU for the long-run U.S. and U.K. stock market movements over the period of 1997 to 2016. The news-based EPU indices for the both countries are generated in the monthly data frequency from Baker *et al*. (2016) while the intra-daily transaction prices for both stock markets are collected from the Thomson Reuters SIRCA database. They found a strong evidence that U.S. long-run stock market volatility is significantly rely on its own EPU shocks while the U.K. is rely significantly on both countries' EPU. The long-run correlation between U.S. and U.K. stock market is strongly and positively related to the U.S. EPU shocks. Overall, the results suggest that U.K. investors need to concern mainly on U.S. policy uncertainty, even when investing in a domestic stock portfolio.

Nevertheless, Li and Peng (2017) done a research to examine the impact of innovations in U.S. EPU index on the co-movements of China's A/B stock markets with the U.S. stock market, as covered from January 1993 to December 2014 in weekly data frequency. The source of data for EPU index is developed by Baker *et al*. (2016) while for both China and U.S. stock market index are derived from DataStream database. The Asymmetric Dynamic Conditional Correlation (ADCC) model is applied that incorporates the EPU innovations as an exogenous variable, and examine whether a structural change on the model. The results reported that an absolute change in the U.S. EPU generate a non-linear relationship on the co-movements. In other words, it implies that shocks in U.S. EPU may particularly influential on the purchases and sales in the U.S. stock market, whereby resulting to negative consequences in the co-movements between China and U.S. stock market. Antonakakis, Chatziantoniou and Filis (2013) study of time-varying correlations between stock market returns, implied volatility and policy uncertainty. The study employed monthly S&P 500 returns series from FRED database, the S&P 500 VIX data series from DataStream, and the policy uncertainty index of Baker *et al*. (2012), ranging from January 1985 till January 2013, in dynamic conditional correlation (DCC) model of Engle (2002). The findings show that the dynamic correlation are consistently negative between policy uncertainty and stock market returns over period, except for the latest financial crisis, whereby correlations became positive. In addition, the results revealed that an increase in EPU and stock market volatility significantly dampen stock market returns. Moreover, Baker, Bloom and Davis (2016) has developed a new-based EPU index for the U.S. and others of 11 major economies countries to examine the impacts of policy uncertainty towards firm-level stock price volatility implied by employment growth rates, firm-level investment rates and equity options on aggregate employment, output and investment, by using monthly data frequency from year 1985 to 2014 in a panel VAR (PVAR) model setting. The key results consistent with the theories and highlight that economic effects of uncertainty shocks in the U.S. and Europe have resulted negative influential towards macroeconomic condition.

The research from Li, Balcilar, Gupta and Chang (2016) assess the causal relationship between EPU and stock returns by using a twenty-four months rolling-window approach ranging from February 1995 till February 2013 in China and February 2003 till February 2013 in India. The results reported that EPU and stock market performance is negatively related as uncertainty of economic policies lead investors to harbor pessimistic considerations towards discount rates and expected future dividends, which subsequently a dropping in the share price. Additionally, Ozoguz (2008) investigates empirically the dynamics of investor’s beliefs and Bayesian uncertainty on the state of the economy as variable that measure the time-variation in investment opportunities. The key findings discovered that stock returns and level of economic uncertainty is negative related by employing state probabilities generated from two-state regime-switching models of aggregate stock market returns and of aggregate output. Furthermore, Pastor and Veronesi (2012) examined how adjustments made in government policy influence stock prices by measuring government policy uncertainty as the variance of policy change. The findings proven numerous evidence. The level of policy uncertainty is non-linear correlates with stock returns, the stock price significantly declined if uncertainty change of government policy is large in increasing the volatilities and correlations among the stocks. They also find that when policy uncertainty is larger, it may result the stock returns to be more volatile and more correlated. The research measured that whether EPU in the nation of U.S. has any influential on the returns for stock market of BRIC (Brazil, Russia, India and China) countries is studied by Sum (2012) by employed the Granger causality tests. The results find evidence that the EPU of U.S. with stock market returns in Brazil, India and Russia are negatively related; subsequently at the 10% level for Brazil and at the 1% level for India and Russia. The EPU of U.S. and stock returns in China is negatively related as well, but this effect is not statistically significant**.** In addition, Mensi, Hammoudeh, Reboredo and Nguyen (2014) includes South Africa as the BRIC countries to analyze the effect between EPU of U.S. and influential global factors for the period from 1997 to 2013. The results find no evidence in explaining that EPU of U.S. affect daily South African stock returns by using the quantile regression framework. Moreover, Arouri, Estay, Rault and Roubaud (2016) contributed to the past literature by examining the effect of EPU on U.S. stock markets ranging from 1990 till 2014 with monthly data frequency by using both linear and market switching models. The U.S. stock index is represented by S&P 500 extended from the Shiller's version (Shiller, 2000), while EPU index is retrieved from Baker *et al*. (2014). The finding find that a rise in degree of policy uncertainty resulted a significant reduction on the stock returns, which indicate that EPU and stock returns is non-linear related and the impact generated by EPU towards stock returns is stronger and persistent over extreme volatility periods such as elections. This study highlights how the importance for the U.S. political unit to enhance the stability and transparency in the process of implementation and adjustment for economic policies in order to avoid the negative effects on stock market performance. The key message from above studies is that

EPU is statistically important and shift either positively or negatively based on both economic fundamentals and financial market performance.

However, studies that focus to the predictability of EPU on economic fundamental and financial market are merely done by numerous researchers. First of all, André, Bonga-Bonga, Gupta and Mwamba (2015) done a research to analyze whether the measure of EPU developed by Baker *et al*. (2013) can forecast both real housing returns and its volatility, which sourced from Shiller (2015) by covered the period from year 1953 to year 2014 in monthly data frequency. The results reported that structural breaks and non-linearity in relationship between EPU and real hosing returns in AR and VAR model setting. In addition, a k-th order non-parametric Granger-causality test proposed by Nishiyama, Hitomi, Kawasak and Jeong (2011), which is robust to such features. They find a strong evidence that information from EPU is useful for investors in predicting for future returns as well as in analyzing the related risks. Besides, Antonakakis, Babalos and Kyei (2016) analyzed predictability of sustainable investments returns using the U.S. Dow Jones Sustainability Index (DJSI) and a broad set of uncertainty measure indicators by employed a novel nonparametric causality-in-quantile approach at a monthly frequency over January 2002 till December 2014. The data of U.S. DJSI and EPU index are derived from DataStream of Thomson Reuters and Baker *et al*., (2013) respectively. The findings show that the aggregate economic policy uncertainty (EPU) indicator has predictability power for real returns of the U.S. sustainable investment index. In addition, if the sample data decompose the period of global financial crisis into before and after basis, the findings reveal that predictor variables carry causal information for real returns only in the after crisis period. Nevertheless, a research studied by Balcilar, Gupta and Kyei (2015) analyzed whether the stock returns for South African can be predictable based on a measure of EPU of South Africa and twenty other developed and emerging markets (Australia, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Mexico, The Netherlands, South Korea, Spain, Sweden, Switzerland, U.K. and U.S.) over a monthly period of 1990 till 2012. The Johannesburg All Share Index (ALSI) is employed as the measure of stock prices in South Africa and is downloaded from the International Financial Statistics database, while the index on EPU for the 21 countries is obtained from the Access World News database. The results reveal that linear granger causality approach unable generate an evidence of predictability, excluded from Japan and Russia, but nonparametric causality-in-quantiles approach generated robust evidence of causality from all the EPUs. Furthermore, predictability power is hold over the whole conditional distribution of stock returns when the stock market of South Africa is underlying in a normal mode condition. As the result, this study highlights that the stock market of South Africa cannot be considered to be efficient by using EPUs in predicting stock returns, as concluded in previous literatures like Gupta and Modise (2012a, b, 2013) and Aye, Gupta and Modise (2013).

A study that examined the stock returns predictability and its volatility of Hong Kong, Malaysia and South Korea by employed domestic and global (China, Japan, U.S., and the European Area) EPU over a monthly period of January 1997 to March 2012 is done by Balcilar, Gupta, Kim and Kyei (2015). The stock index data for these three countries are derived from International Financial Statistics database, while data for domestic and global EPU index are obtained from the Access World News database. The linear granger causality tests unable to found an evidence of predictability, excluded from South Korean's EPU which is forecasting on its own stock returns. However, when non-parametric causality-in-quantiles test was applied, this study found some valuable evidence as follow: (1) Local and global EPUs neither predict stock returns nor its volatility for Hong Kong; (2) For Malaysia, local and global EPUs has the predictability power on stock returns volatility, but no evidence for stock returns, and; (3) For South Korea, local EPU carry huge information for predicting stock returns volatility, whereby global EPUs is significant in forecasting stock returns. As a results, this study highlight the significance of accounting for non-linearity when forecasting stock returns and its volatility by employed the predictor of EPUs, in particular for the case of Malaysia and South Korea. Furthermore, a research done by Phan, Sharma and Tran (2018) aimed to examine the forecasting power of EPU on stock excess returns, which covers 16 countries with sample size range from 160 to 378 observations, based on autoregressive predictor regression model in monthly data frequency. The time series of EPU indexes are considered into two groups which are EPU from particular countries and globe EPU. The source of data for EPU index is obtained from EPU website and all stock data are retrieved from the DataStream database.

This study provides the following evidence; they found that stock excess returns are predictable by employed EPU. Secondly, they show that predicting of returns is country-dependent (sector-dependent), implying that EPU is significant for particular countries (sectors) compared to others. Thirdly, the result supports that predictability of EPU is from discount rate channel rather than the cash flow channel. Lastly, they found an asymmetric predictability results when employing both positive and negative EPU shocks to forecast stock returns. By referring to past literature, research that particularly focuses on the predictability of EPU on stock market return are limited and insignificance. So, it has become the motive to us for carrying out a research in taking EPU as predictor variable for predicting Malaysian stock returns.

2.2.5 Geopolitical Risk

Before the development of GPR index by Iacoviello and Caldara, war and terrorist activities are perceived to be the main factors which derived the geopolitical risk to all the countries. Since terrorism will have a huge impact on both national and international economy which in turn will affect the financial market, many researches have been done to examine the effects of terrorism on capital market in terms of volatility as well as the returns of an asset.

Based on the study of Arin, Ciferri and Spagnolo (2008), an investigation on the implications of terrorist activities on the financial markets of six nations in terms of volatility and stock returns has been done, with the application of VAR analysis. In this study, terror index in a daily frequency and market index of six different countries (Israel, Spain, Thailand, Turkey, UK and Indonesia) have been collected to perform the test. As a result, they found that the volatility of terror index will influence the returns of these stock markets, however, among the six countries, Spain and UK are found to be more resilient to the volatility of those index. Besides, Drakos (2010) which explored the effect of terrorism on the daily returns of stock market for a sample of 22 nations, found that terrorist activity was perceived to influence the mood of investor which in turn led to significantly poorer returns. In this study, it covered a longer time span from 1994 to 2004 by collecting the number of terrorist incidents and the daily closing values of stock indices for each country, with the application of Pooled Panel GARCH to evaluate the effect. The findings depicted that terrorism indeed has brought a negative impact on stock returns and the effect is significantly amplified when the incidents led to higher psychosocial effect. Moreover, Brounen and Derwall (2010) has investigated the influence of terrorism on international stock markets, i.e., stock markets of Canada, France, Japan, Italy, Germany, the Netherlands, the US and the UK. By considering 31 terrorist incidents that happened from 1990 to 2005 and the daily prices for stock indices of these countries, they found that terror attacks will generate negative impact on stock market, but the magnitude of the impact might differ across nations. The research by Kollias, Papadamou and Stagiannis (2011) have examined the impacts of two main terrorist events – bomb attacks in Madrid and in London – on equity markets by utilizing GARCH family models. They collected the daily prices of three stock indices of Spain and the stock indexes of London as well as the sample for the terror event that happened in London with a period of 2004 to 2006. This paper reported a significantly negative reaction on the equity markets in Spain and in London once the incidents happened, but all markets differ in their recovery rate which measured by the number of days required by the markets to rebound, i.e., London – recover with only one trading day. Furthermore, the research of Alam (2013) has evaluated the relationship between terrorism in Pakistan and the development of its stock market, by using Engle-Granger approach to examine the causality evidence between both variables. In order to conduct the test, daily Terrorism Impact Factor index and KSE 100 index have been collected with the period of 2001 to 2011. Its result indicated that stock market returns will be affected negatively by terrorism in the long term; yet in short period, there is insignificant relationship between returns and terrorism. While in the research of Essaddam and Karagianis (2014), which examined the effects of terrorism on the stock returns' volatility in America, have collected daily MSCI index as the proxy for the market portfolio and 44 terrorist events which targeted the firms in America, with the application of GARCH model. This study observed that on the day of the terrorist activity, American firms experienced an abnormal stock return's volatility on the measures of terrorist activity exposure.

In the last decade, the meaning of geopolitical risk has been expanded by including the changes of foreign policy, sanctions, riots, etc. Thus, many researchers started to examine the effects of GPR on the stock markets of various emerging countries by applying GPR index. For instances, according to Cheng and Chiu (2018), they examined the effects of global geopolitical risks on various emerging countries, which covered up to 38 emerging countries by applying a variance decomposition analysis. They employed annual data on the 38 emerging countries from 1980 to 2011 and they collected the benchmark Geopolitical Risk Index (GPRB) as well as the historical Geopolitical Risk Index (GPRH). In this study, they found that shocks to global geopolitical uncertainty bring considerable business cycle implications for these nations which will provide a significant impact on the countries' stock market volatility. Moreover, based on the study of Lee (2018), it applied a copula approach on the stock markets of 37 countries around the world by covering a large sample size, ranging from June 1997 to December 2017. The results showed that the actions in relation to geopolitical uncertainty is more often negatively related to the stock market performances. Furthermore, according to Hoque, Low and Zaidi (2019), by applying factor augmented SVAR method on analyzing the monthly time-series variables which covered from January 2009 to March 2017, they found that GPR have insignificant direct effects on the stock market. However, GPR has significant indirect impacts on stock market by the transmission through global EPU and oil shock channels.

Besides, instead of examining the effects of GPR on stock market, GPR has become a popular predictor in forecasting several assets' returns and volatility in recent studies. For instance, Aysan *et al.* (2019) examined the predictive ability of GPR on Bitcoin's price volatility and returns. In order to conduct this research, they have collected the global GPR index and daily Bitcoin's returns and the price volatility over the time period of July 2010 to May 2018. By applying Bayesian Graphical Structural Vector Autogressive (BSGVAR) method, they found that the price volatility and returns of Bitcoin are predictable by using GPR. Instead of forecasting the volatility and returns of Bitcoin, GPR is considered as one of the popular measures in the recent studies for these two years in forecasting the volatility and returns of commodities such as gold and crude oil. For examples, Banerjee *et al.* (2019) examined the predictive ability of GPR in forecasting the movement of gold prices by applying support-vector machine (SVM) model, with the GPR index which includes of the major adverse events such as riots, terrorist attacks, nuclear missile tests, violent conflict in case of the Middle East and North Africa as well as Korean Peninsula region. The empirical finding of this study also showed that the GPR is a critical feature when it comes to forecasting the gold prices. Furthermore, Gkillas, Gupta and Pierdzioch (2019) have done a research on the GPR's predictive ability on realized gold volatility by comparing its in-sample and out-of-sample results. They have considered the GPR index and the gold intraday futures data to derive the realized volatility on the daily basis for a period of December 1997 to May 2017. By utilizing a quantile-regression heterogeneous autoregressive realized volatility (QR-HAR-RV) model, GPR is suggested to have the predictive ability for realized gold volatility, especially at a greater forecasting horizon. While for Plakandaras, Gupta and Wong (2018), they have investigated the dynamic relationship between global GPR and oil prices for the emerging economies by using Dynamic Model Averaging (DMA). They compiled the WTI oil prices and global GPR index on a monthly basis which span the time period of 1985 to 2017. As a result, in the short run, global GPR which associated with wars has the superior forecasting power in predicting the returns for the emerging markets, given a negative relationship between oil returns and GPR. Next, Demirer, Gupta, Ji and Tiwari (2019) have analyzed the predictive power of GPR on oil market return and volatility. They applied the nonparametric causality-in-quantile approach to the daily six oil benchmarks data (Brent, Dubai, Tapis, ORB, Bonny Light, and WTI). This paper indicated that GPRs and oil returns have extremely non-linear relationship, thus, the liner Ganger causality test is not reliable. In terms of predictability, GPR is able to estimate the oil returns of ORB, Bonny Light and Tapis only, while for its volatility, GPR is observed for almost all of the oil prices, except for the case of Dubai. The study of examining the forecastability of GPR on the returns for both commodities has been done by Asai, Gupta and McAleer (2019). They studied the predictive power of GPR on the returns for crude oil and gold futures by collecting WTI crude oil and gold prices and monthly GPR index, with the 2 kinds of time period which are Period 1: October 2007 to August 2015 and Period 2: October 2011 to May 2017. Through the application of Conditional Wishart (CW) model, the involvement of GPR in the model often improves the prediction of the returns for the crude oil and gold futures.

Even though GPR has become a popular predictor in recent studies, the research that investigate the forecasting power of GPR in relation to stock returns is rare. The current research that examined the effects of GPR on stock returns has been done by Apergis, Bonato, Gupta & Kyei (2017) which involved the GPR as a risk indicator to predict the movements of stock returns and volatility of the major players in the leading defense industry. It involved the application of nonparametric causality test with the monthly data of GPR and the daily closing share prices of 24 global defense companies listed on several stock market. This study showed that GPR from global geopolitical events was less likely to forecast returns, with the effect more focused in changing the future risk profile of defense firms. Besides, the study of Bouras *et al.* (2018) has investigated the role of global and country-specific GPR on the volatility and return of 18 nations by utilizing the monthly data, ranging from December 1998 to June 2017, with the application of panel GARCH approach. Its empirical findings showed that the global and country-specific GPRs have no significant impact on forecasting the stock returns. Furthermore, Bouri *et al*. (2018) has applied the nonparametric causality test and collected the monthly GPR data and monthly prices of Islamic stock indices (DJIA) to evaluate the causal effect of GPR on equity returns as well as the volatility dynamics for Islamic bond and stock market, with the period from 1996 to 2007. This research has generated the similar findings as the previous studies by stating that GPR is found to affect the measures of volatility for Islamic equity market, rather than stock returns which means that GPR is normally not found to have the forecasting power over stock returns.

2.3 Summary of Literature Review and Literature Gap

As referring the empirical review of our study, it disclosed that the EPU and GPR have significant predictive power on stock return forecasting. Most of the researches used to prove the predictability of EPU on forecasting the stock return such as Nishiyama, Hitomi, Kawasak, and Jeong (2011), Antonakakis, Babalos, and Kyei (2016), Phan, Sharma, and Tran (2018) etc. Those studies mainly explain about the predictive power of EPU on return forecasting. On the other hand, GPR is less likely to be proved towards its predictability; however, few researches are conducted to observe the importance of GPR on return forecasting such as Plakandaras, Gupta and Wong (2018), Gkillas, Gupta and Pierdzioch (2019), Demirer, Gupta, Ji and Tiwari (2019) etc. Briefly, limited research is contributed to investigate the predictive power of both EPU and GPR on forecasting the stock returns. Hence, this thesis aims to include the combination of GPR and EPU as the predictor variables to determine their accuracy on forecasting.

Furthermore, the issue of in-sample and out-of-sample test has been debated in the past few decades about their accuracy and effectiveness in prediction. In-sample test is well-known to be conducted as the outcome usually is significant. As justifying by Inoue and Kilian (2004), they aimed to examine the trustworthiness of in-sample evidence, and their outcome seems to be more reliable in comparing with out-of-sample when justifying the predictability of relevant variables. However, out-of-sample test also provides a trustworthy result although only few researchers studied about the effectiveness of out-of-sample test. Hence, the discrepancy between the in-sample and out-of-sample result always been discussed by the scholars. For example, Rapach and Wohar (2006) studied on the ability of forecasting power towards the in-sample and out of sample test on estimating the stock returns as well. In order to overcome the potential problems such as heteroscedasticity, bias of small sample size, etc. by using OLS estimation; thus, a bootstrap procedure and standard asymptotic distribution are applied to observe any discrepancy between their in-sample and the out-of-sample results. In consequence, their findings showed that the results of both tests are approximately similar to each other, increasing the accuracy of their study. Therefore, in order to have a more reliable outcome, our study will examine the predictability of both predictors by comparing their in-sample result with the out-of-sample outcome instead of focusing solely on in-sample test.

CHAPTER THREE: METHODOLOGY

3.0 Introduction

This chapter aims to deliver a detailed description on the collection of data and the research techniques used to conduct this study, including the sources of data, the description about the data used, the explanation about all applicable methodology as well as tests which applied in this research. Furthermore, the evaluation approaches for each test have been discussed as well in this chapter in order to ensure the effectiveness and accuracy in analyzing the outcomes, which will be conducted in the following chapter.

3.1 Research Design

Based on Dulock (1993), research design is the framework which specifically derived to answer the enquiries of the research and to monitor variance. There are two paths in developing the framework such as qualitative approach and quantitative approach. This study adopted the quantitative technique in examining the forecastability of GPR and EPU to Malaysian stock returns. Quantitative research could be defined as a systematic process that used to describe or examine the relationships between variables via mathematical, statistical or computational ways (Burns & Grove, 1993).

3.2 Data Collection Method

As to the general objective which aims to investigate the forecastability of predictors (GPR & EPU) to Malaysian stock returns, GPR index, EPU index and FBM KLCI index will be utilized to conduct this research. Besides, the sample size of this paper consists of 172 observations since a monthly frequency will be used for each of the predictors, with sampling period which covered up to approximately 14 years ranging from January 2005 to April 2019. The sample period has covered up to April 2019 since we wished to include and capture the effects of the current issue, US-China trade war that happened in January of 2019. Subsequently, a monthly data for FBM KLCI index is sourced from Bloomberg and these data will be used to compute a set of log returns. Besides, the vital measure of geopolitical risk applied in this research is the Global GPR index which derived by Caldara and Iacoviello.

While for Global EPU index, it is sourced from the website of Economic Policy Uncertainty. We will log both GPR and EPU index to ensure that we have a uniform data set. Furthermore, based on the full sample, we will consider three different forecasting periods for conducting the out-of-sample test; (1) January 2005 to May 2008, (2) January 2005 to February 2012, (3) January 2005 to September 2015. The three different forecasting horizons, which separated into 25%, 50% and 75% of the full sample, were set according to the suggested allocation by Westerlund and Narayan (2012). The choice of considering the subperiods is due to the motivation by the previous studies which argued on the forecast accuracy of out-of-sample which might be influenced in part by the choice of the sampling period (Lettau & Nieuwerburgh, 2008; Boudoukh, Richardson & Whitelaw, 2006).

The table below depicts the definition and sources of data for each of these variables.

Table 3.2:
Sources and definition of data

Variables	Proxy	Data Sources	Definition
Malaysian stock return	MSR	Bloomberg (2019)	**FBM KLCI Index** A capitalisation-weighted equity market index which comprised of 30 largest listed enterprises on Bursa Malaysia, by market cap (ie. Market capitalization) which achieve the eligibility requirements of FTSE Bursa Malaysia Index Ground Rules.
Geopolitical Risk	GPR	Caldara and Iacoviello (2019)	**Global GPR Index** An index which assess the likelihood of occurrence of terms that associated to geopolitical tensions in top newspapers of the world.
Economic Policy Uncertainty	EPU	Economic Policy Uncertainty (2019)	**Global EPU Index** A GDP-weighted mean of national EPU indexes for 21 nations.

3.2.1 FBM KLCI Index

FBM KLCI index is constructed from the 30 leading listed enterprises on the stock exchange of Bursa Malaysia. These listed companies must achieve many requirements before they are chosen as one of the 30 constituent companies. For an example, there are two key eligibility requirements that need to be met by the companies such as liquidity and free float requirements. These companies have to meet the liquidity requirement which aims to assure the stocks of the company are adequately liquid to be transacted by market players. While for the free float requirement, it is applied to each of the company's market cap based on the banding stated in the ground rules of FTSE Bursa Malaysia. This free float factor is applied in assessing the attribution of the firm's market events in this KLCI index. Thus, in order to fulfil the free float requirement, there is necessary for every companies to maintain their free float shares at a minimum of 15%.

This KLCI index is computed according to a value-weighted formula and the free float element will be used to adjust the index, through the application of real period as well as the closing prices obtained from Bursa Malaysia. These KLCI index values are derived and dispersed on a real-time basis, every 15 seconds. The continuity of this KLCI index values represents the performance of the stock market of Malaysia and it also acts as a benchmark which reveals the economic growth in Malaysia.

3.2.2 Global EPU index

The Global EPU index consists of the national EPU indexes for 21 countries which comprised of Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom and United States (Baker, Bloom & Davis, 2016). Each of the country-specific EPU index reveals the relative frequency of newspaper articles of the country which contain some terms relating to the economic, legislation, and uncertainty. Thus, in order to construct the Global EPU index, the national EPU indexes for these 21 nations will be normalized to an average of 100 from year 1997 to year 2015. Next, there is necessary to impute the missing values for few countries such as Greece, India, Australia, Spain and the Netherlands by applying a regression-based approach. Through this method, it derived a balance panel with a monthly frequency for the values of EPU index of 21 countries from year 1997 onwards. Lastly, Global EPU index will be computed on a monthly basis as the GDP-weighted mean of the EPU indexes for 21 nations by utilizing the GDP data which is obtained from IMF's World Economic Outlook Database.

3.2.3 Global GPR index

The GPR index is derived on a monthly basis and it normally considers the automated text-search outcomes of the electronic records archives of 11 international as well as national newspapers namely The Daily Telegraph, The Boston Globe, Financial Times, Chicago Tribune, The Globe and Mail, Los Angeles Times, The New York Times, The Guardian, The Washington Post, and The Wall Street Journal (Caldara & Iacoviello, 2018). The index is calculated by focusing on the number of articles associated to geopolitical risk in each newspaper per month. After that, the index is normalized to a value of hundred in 2000 to 2009 decade.

According to Caldara and Iacoviello (2018), GPR index includes the search that recognizes articles comprising references to six main categories of words: Group 1 involves words related with explicit indications of GPR, and brings up of military-related tensions including the large regions of all nation as well as a U.S. involvement. Group 2 comprises words straightly associated to nuclear tensions, while Groups 3 and 4 encompass mention associated to the threats of war and terrorist, respectively. Lastly, for Groups 5 and 6, both focus on capturing the press coverage of actual negative geopolitical incidents which can be reasonably predicted to cause a rise in geopolitical uncertainty, for instances, the beginning of a war or terrorist acts.

3.3 Methodology

3.3.1 Predictive regression model

As our study focuses the predictability of EPU and GPR to Malaysia stock returns, we have constructed a basic predictive regression model as shown below:

$$MSR_t = \alpha + \beta x_{t-1} + \varepsilon_t \quad (3.1)$$

MSR_t is our predicted variable, Malaysia stock returns with the proxy of FBM KLCI index at the time t while x_{t-1} is the predictor variable which might able to predict MSR_t. In our study, x_{t-1} is either one period lagged EPU or one period lagged GPR, where α is an intercept term and ε_t is an error term. According to previous studies (Campbell & Thompson, 2008; Phan, Sharma & Tran, 2018; Phan, Sharma & Narayan, 2015; Welch & Goyal, 2008; Westerlund & Narayan, 2012), the following predictive model regression 3.2 can be used to predict stock returns. While equation 3.2.1 is the predictive model regression when we assume h = 1.

$$MSR_{t+h} = \alpha + \beta x_t + \varepsilon_{t+h} \quad (3.2)$$

$$MSR_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \quad (3.2.1)$$

Based on the equation 3.2.1, ε_{t+1} is a predictive error term at one-period ahead. By applying in-sample test method, the stock returns' predictability of x_t can be tested under the null hypothesis that $\beta = 0$. If null hypothesis being rejected, it implies that EPU and GPR can predict stock returns in future and vice versa. Although equation 3.1, 3.2 and 3.2.1 is simple and easy to estimate stock returns, but they have high possibility to suffer from three significant econometric issues comprising persistency, consistency and heteroscedasticity. Subsequently, we will provide the explanations and consequences about those issues in three different sections.

3.3.1.1 Persistency

Persistency occurs when the situation of variable is persistent and high serial correlation happen at the same time in the dynamic model. As stated by Gujarati and Porter (2009), dynamic model is a model where either the predicted or predictor variable or both variables contain lagged variables. Our predictive regression model is likely to incur persistency issue since it consists of lagged predicted variable. Caporale and Pittis (2001) explained persistence as the extent to which the event in current period will impact on the whole future history of random process. Based on Westerlund and Narayan (2012), persistency of predictor is to exasperate the OLS bias result from endogeneity. In order to demonstrate the persistency issue, first-order autoregressive scheme, AR (1) model of EPU and GPR has been written below as:

$$x_{t+1} = v(1-\rho) + \rho x_t + \mu_{t+1} \tag{3.3}$$

Gujarati and Porter (2009) suggested that AR (1) process is simpler to be used than higher-order autoregressive scheme and numerous applicants provide evidence that AR (1) is quite useful. The predicted variable in autoregressive model must has stationary process in level form and error term is assumed to consist of white noise process. Where ρ is the coefficient of auto-covariance. Suppose equation 3.3 follow AR (1) scheme, autoregressive coefficient, ρ is constant in between -1 and +1. When $|\rho| \leq 1$, i.e. the value of ρ is less than or equal to 1 which indicates the AR (1) process specified in the time series EPU and GPR is stationary. When the time series is stationary, its variance and mean will not fluctuate systematically over the time. In contrast, $|\rho| \geq 1$, i.e. the value of ρ is more than and equal to 1 implies that time series EPU and GPR are non-stationary. Yet, if $|\rho| = 1$, it depicts unit root problem, that is nonstationarity. As a result, EPU and GPR are then considered as persistent predictors if $|\rho| \leq 1$ (Lanne, 2002). The consequences of persistent predictor for prediction is it will lead to bias estimated parameter and spurious result. Hence, the result will be misleading and not reliable.

3.3.1.2 Endogeneity

Endogeneity problem occurs when predictor variable correlate with error term (Abdallah, Goergen & O'Sullivan, 2015). The following model is derived to capture the endogenous effect from our predictive regression models.

$$\varepsilon_t = \theta\mu_t + e_t \tag{3.4}$$

From model 3.3, ε_t is the residual, the difference between observed value and the estimated value of predicted variable from the predictive regression models of 3.1, 3.2 and 3.2.1. Next, μ_t is the stochastic error term of EPU and GPR in equation 3.3, e_t and μ_t are mean zero which indicates that both of them are independent, e_t is the white noise error term where the error term assumes to follow white noise process and satisfies all the classical assumptions. EPU and GPR are endogenous when coefficient θ is not equal to zero, where the MSR plays two different roles as predicted and predictor variable. In other word, Malaysia stock returns not only will influenced by EPU and GPR but also can influence both of them. Contrarily, when coefficient θ is zero, there is no relationship between ε_t and μ_t, which implies EPU and GPR are exogenous. Particularly, EPU and GPR do not have relationship with the error term of Malaysia stock returns. If EPU and GPR found to be endogenous, predictive regression models above have violated one of the ordinary least square (OLS) regression analysis' basic assumptions where all the predictor variables must not be endogenous. Therefore, OLS method does not fit well with our predictive regression model which consists of endogenous variable. Consequently, if we apply OLS method to predict our models, ε_t will no longer normal distributed, where x_t and ε_t varies simultaneously. This will lead to autocorrelation and heteroscedasticty problem. Then, the estimated parameter will become biased, inconsistent and hence result in simultaneous-equation bias.

3.3.1.3 Conditional Heteroscedasticity: ARCH and GARCH effect

Gujarati and Porter (2009) explained heteroscedasticity as unequal variance of the error term. There are two forms of heteroscedasticity which are conditional and unconditional. In our study, we applied conditional heteroscedasticity since it is able to identify inconstant volatility when later periods of high or low volatility cannot be identified. Those error terms in equation 3.4 are generally to be assumed that they have constant variances over the time. Nonetheless, in reality, almost all stock returns are discovered to be heteroscedastic consistently. There are several methods to capture heteroscedasticity while autoregressive conditional heteroscedasticity (ARCH) is one of the well-known approaches for time series data. Based on our case of e_t from equation 3.4, the following equation 3.5 has been written to represent the ARCH approach:

$$var(e_t|I_{t-1}) = \sigma^2_{e,t} = \lambda_0 + \sum_{i=1}^{q} \lambda i \ e^2_{t-1} \qquad (3.5)$$

Where I_t can be defined as the information at time t which can be obtained while $var(\mu_t|I_{t-1}) = \sigma^2_{\mu,t}$ is assumed to be applied by a similar equation. $\sigma^2_{\mu,t}$ is the variance of e at time t which indicates that variance of Malaysia stock returns no longer constant. Basically, equation 3.5 describe squared error term $\hat{e}^2_t$ in the form of AR(q) model where the unconditional variance of ε can be estimated by applying it. The AR root of model 3.5 cannot be changed or improved when equation 3.5 is in the inverse form. When $\lambda_0 > 0$ and $\sum_{i=1}^{q} \lambda i < 1$, it indicates that the unconditional variance e_t can be rewritten in the following equation:

$$var(e_t) = \sigma^2_e = \frac{\lambda 0}{1 - \sum_i^q \lambda i} \qquad (3.6)$$

Now, the unconditional variance of the residual ε_t can be written in the equation as:

$$var(\ \varepsilon_t) = \sigma^2_\varepsilon = \gamma^2 \sigma^2_\mu + \sigma^2_e \qquad (3.7)$$

As mentioned above, if we apply OLS method on model that consists of endogeneity and persistency problem, it will lead to bias estimated parameter. While for heteroscedasticty by corresponding to the classical regression theory, it will cause an inefficient estimator. According to Westerlund and Narayan (2014), an estimator able to provide essential efficiency gain when it captures ARCH effect in the model. In sum, estimator from our model 3.1, 3.2 and 3.2.1 also have the same consequence when ARCH effect being detected.

3.3.2 The Innovation of Estimator

3.3.2.1 The Ordinary Least Square Estimator (OLS estimators)

Practically, the equation 3.1 and 3.2 are constructed by applying the well-known linear function which commonly practiced by everyone. Thus, the outcome of the model could be estimated through the method of ordinary least square (OLS). However, by using OLS method, the OLS estimators are found to be biased due to the existence of regressor persistency, heteroscedasticity (Midi, Rana &Imon, 2013) and endogeneity (Abdallah, Goergen & O'Sullivan, 2015). Hence, owing to these potential econometric problems, the outcome of estimator will become biased as well as no longer efficient consequently in case of applying the OLS method directly in the model 3.1 and 3.2 by ignoring the possible issues mentioned above. Notwithstanding, for investigating the comparison between the outcome of different estimators used in estimation; so, the predictive regression models will be estimated by using OLS method in the beginning of modelling.

3.3.2.2 The Adjusted Least Square Estimator (ALS)

In view of the discussion above, the problems of endogeneity and persistency still exists when forecasting a model. Hence, Lewellen (2004) proposed the bias-adjusted least square (ALS) estimator for the regression model after referring the original version of ALS estimator that developed by Stambaugh (1999). The proposed ALS estimator is mainly to show whether the predictive regression model is conditional to time series effect, t and a new equation is created by substituting both equation 3.3 and 3.4 into the model 3.2. New equation is presented:

$$MSR_{t+h} = \alpha + \beta x_t + \theta(x_{t+h} - \rho x_{t+h-1}) + e_{t+h} \quad (3.8)$$

where $\alpha = \beta_1 - \theta c(1 - \rho)$. Nonetheless, the equation 3.8 above is considered as infeasible due to there is an unknown value towards the autoregressive coefficient (ρ) during the process of modelling. As the value of ρ could not be determined from the model above; thus, Lewellen (2004) stated that the unknown ρ can be replaced with a fitted value which make the equation easier to be understand as well as efficient in explaining. This is leading to the following test regression:

$$MSR_{t+h} = \alpha + \beta_1 x_t + \theta(x_{t+h} - \rho_1 x_{t+h-1}) + e_{t+h} \quad (3.9)$$

From equation above, ρ_1 plays the role of fitted value while β_1 is considered as the bias-adjusted coefficient since the β_1 equals to $\beta - \theta(1 - \rho_1)$. In following, the regression above can be estimated through OLS simply as long as the whole regression fulfils the characteristic of feasible. Therefore, Narayan and Westerlund (2012) assumed that the value of ρ equals to 1 as it is also a parameter in measuring the degree of persistency for x. Thus, the ρ_1 will be substituted into value of 1 which contributing to the equation 3.10 below:

$$MSR_{t+h} = \alpha + \beta x_t + \theta(\Delta X_{t+h}) + e_{t+h} \quad (3.10)$$

In addition, the symbol of Δ represents the operator of difference in the equation as well. According to the equation above, it captures the issue of persistency and endogeneity effectively towards the independent variables from the model. Hence, this equation successfully examined the present of both issues and consistent with the outcome of Narayan and Westerlund (2012).

3.3.2.3 The Feasible Generalized Least Square Estimator (FGLS)

As refer to equation 3.10, it has taken the ALS estimator instead of OLS one meanwhile it is exempted from the issues of persistency and endogeneity. However, instead of overcoming both issues above, the equation will still suffer the effects of ARCH which directly resulted in the existence of heteroscedasticity problem to the equation as it neglected this problem. As long as the heteroscedasticity problem exists, the estimator will become biased and inefficient which leads to an invalid outcome. According to Narayan and Westerlund (2012), they reported that every ALS estimator should be weighted by $1/\sigma_\varepsilon^2$ which could in return to form more effective estimators. Besides, the value of σ_ε^2 can also be taken by predicting the error variance which is presented in the equation 3.7 in applying an appropriate ARCH model regression. Consequently, a new equation is going to be created as below:

$$MSR_{t+h} * = \alpha^* + \beta^* x_t + \theta^* (\Delta x_{t+h}) + e_{t+h} * \qquad (3.11)$$

where; $MSR_{t+h} * = MSR_{t+h} / \sigma_\varepsilon^2$; $\alpha * = \alpha / \sigma_\varepsilon^2$; $\beta * = \beta / \sigma_\varepsilon^2$; $\theta * = \theta / \sigma_\varepsilon^2$ and $e_{t+h} * = e_{t+h} / \sigma_\varepsilon^2$. Then, after all the estimators divided by $1/\sigma_\varepsilon^2$, new estimators are created such as $\alpha *$, $\beta *$ and θ^* as well as they also play the role as the feasible generalized least square (FGLS) estimators in this regression model. All in all, this model can be concluded that it could efficiently robust to the presence of 3 main issues that we reviewed from the beginning of modelling which are persistency, endogeneity and heteroscedasticity from this model.

3.3.3 In-Sample Analysis

The statistical procedure of one sample t-test is used to determine whether a sample of observations could have been carried out by a process with a specific mean. The hypotheses for one sample t-test would classified into two, the null hypothesis (H_0) and the alternative hypothesis (H_1). The null hypothesis assumes that the variable is insignificant, whereas the alternative hypothesis vice versa. The one sample t-test is purposely used to determine if the null hypothesis should be rejected in favour of the alternative hypothesis, given on the sample data. As a parametric procedure, the one sample t-test generates certain assumptions, for instances, it requires the sample data to be numeric and continuous; the observations should not depend of one another; the dependent variable should be approximately normally distributed; and the dependent variable should exclude any outliers. The overall statistic framework for one sample t-test have to fulfil the assumptions above, otherwise the inference breaks down. Subsequently, if the test statistic is less than the lower critical value or greater than the upper critical value, which means that the variable is fitted and significant. The formula applied to calculate one sample t-test has denoted as follow:

$$t = \frac{\hat{\beta}}{SE_{\hat{\beta}}} \tag{3.12}$$

3.3.4 Out-of-Sample Analysis

According to the earlier researches (Welch & Goyal, 2008; Campbell & Thompson, 2008; Rapach, Strauss & Zhou, 2010), in order to perform the out-of-sample forecasting, a recursive method will be applied to derive an accurate result. By applying the recursive method, the total sample size, T, will be divided into an in-sample portion composed of the first T_0 observations, and an out-of-sample portion composed of the last, say, P observations. Furthermore, several different choices of in-sample periods will be applied, comprising of 25% (January 2005 to July 2008), 50% (from January 2005 to February 2012), and 75% (from January 2005 to September 2015) of the total sample. Through this idea, it enable us to assess the robustness of the outcomes and, in the process, obviate the problem of data mining. Besides, it is critical to examine predictive accuracy by utilizing genuine forecasts. In other word, it is invalid to focus on how well a regression model fits the actual historical data; the accuracy of prediction should be determined by taking into account how well the model performs on new data which were not applied when forecasting the model. Based on Hyndman (2014), when selecting models, it is often to utilize a portion of a set of available data for testing, and apply the remaining data for predicting the model. Through this, the testing data will be used to evaluate how well the model is likely to predict on new data. Some studies describe the data for testing as the “out-of-sample data”, while the training data have been described as the “in-sample data” (Hyndman, 2014). In order to assess the accuracy of a forecast, there are various forecast accuracy measures that have been applied in the previous studies.

According to Fair (1986), there are four common metrics to measure the accuracy of forecasting, namely mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE) and Theil inequality coefficient (Theil U). These metrics have been applied to examine the accuracy of ex ante and ex post forecasts. Mostly, forecast accuracy measures will be divided into few groups such as scale-dependent measure (i.e. MAE, RMSE and MSE), percentage-based measure (i.e. MAPE), and the standardized RMSE which can be known as Theil’s inequality coefficient (i.e. Theil U and U2).

3.3.4.1 Scale-Dependent Measures

The first group also can be referred as the absolute forecasting error since it based on the absolute error computation. It consists of the estimates that based on the computation of the forecast errors (u_i).

$$u_{i=}(y_t - f_t) \tag{3.13}$$

where u_i referred to forecast error and the measured or calculated value at time t is y_t, forecasted value at time t is f_t .

Mean Absolute Error (MAE) is measured by the formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|u_i| \tag{3.14}$$

Where n referred to forecast periods. Mean Square Error (MSE) is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left|u_i^2\right| \tag{3.15}$$

Therefore, Root Mean Square Error (RMSE) is derived using the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i^2)} \tag{3.16}$$

However, these scale-dependent measures have some potential drawbacks such as the scale dependency, high influence of noise or outliers in data on the evaluation of forecast performance, and the low reliability of RMSE as well as MSE which derived various results depending on diverse fraction of data.

3.3.4.2 Percentage-based measure

It includes the percentage errors that are computed according to the value P_t.

$$P_t = \frac{|u_t|}{y_t} \tag{3.17}$$

Mean Absolute Percentage Error (MAPE) is computed according to:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} 100 \cdot |p_i| \tag{3.18}$$

However, there are some shortcomings for this measure, for instance, outliers will have significant influence on the result and the error measure is biased which might lead to an inappropriate evaluation. Thus, Theil's inequality coefficient has been proposed and it is one of the statistical forecasting evaluators commonly cited in the literature (Minai & Gupta, 2019; Gurung, Singh, Paul, Panwar, Gurung &

Lepcha, 2015; Baghestani & Toledo, 2017). In this regard, Theil U_1 and U_2 will be applied to evaluate the forecast accuracy in this study.

3.3.4.3 Theil's inequality coefficient

It is important procedure to incorporate the Theil's inequality coefficient within the out-of-sample forecasting of the stock returns. There are main two categories under the specifications of Theil's inequality coefficient, which are U_1 (Theil, 1958) and U_2 (Theil, 1966) respectively and has been denoted as follows:

$$(1)\ U_1 = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(u_i)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n} y_t^2}+\sqrt{\frac{1}{n}\sum_{t=1}^{n} f_t^2}} \qquad (3.19)$$

$$(2)\ U_2 = \frac{\sqrt{\sum_{t=1}^{n-1}(\frac{f_{t+1}-y_{t+1}}{y_t})^2}}{\sqrt{\sum_{t=1}^{n-1}(\frac{y_{t+1}-y_t}{y_t})^2}} \qquad (3.20)$$

Where y_t denoted as n observations on a variable of interest and f_t denoted as a set of related forecasts.

By looking at the statistics as shown above, both are differ in terms of their formulation and interpretation. First, by referring to U_1, it is a (0, 1) bounded statistic, with perfect forecasting (i.e. $y_t = f_t \ \forall \ t$) resulting in U_1 equals to zero. Greater values of U_1 approaching the upper bound of 1 are then normally argued to show increasingly imprecise forecasts. In comparison, the U_2 statistic is differ in terms of interpretation by comparing to U_1. While perfect forecasting (i.e. $y_{t+1} = f_{t+1} \ \forall \ t$) delivers a value of zero for U_2 statistic, the value of 1 represents a threshold where forecasting accuracy is equivalent to a naïve no change extrapolation.

Some of the previous studies such as Bliemel (1973) and Granger and Newbold (1973) have discussed on the weaknesses of U_1. For instance, it can be seen that when $U_1 = 1$, either one of y_t or f_t should equal to zero in all periods. To illustrate this weakness, consider a hypothetical situation in which a set of forecasts applies the value zero throughout the forecast period while y_t applies non-zero values. In these situations, the numerator and denominator of the statistic become equal and $U_1 = 1$ will result irrespective of the values of y_t and the proximity of f_t to these values. Subsequently, it is possible for one set of near zero forecasts to return a greater value for the U_1 statistic than an alternative less accurate set of forecasts which are further from the value being forecast in every period considered.

Besides, U_1 is that the denominator which relies on the forecasts and therefore it is not appropriate to conclude that U_1 is exclusively determined by the mean square prediction error. Furthermore, Hirsch and Lowell (1969) illustrate the weaknesses of U_1 by provided following example: "Suppose that the forecaster realizes that y = 0 and also realizes the standard deviation S_y, and nothing more. The forecaster might simply forecast zero change, in such case he would have a mean square error of S_y^2 and a $U_1 = 1$. Alternatively, he might assumes his forecast randomly from a distribution with mean zero and a variance of S_y^2. Although the second strategy is manifestly worse than the first, but it receives a better rating in terms of U_1, namely $U_1 = \sqrt{1/2}$ rather than unity.

Next, one might argue against that proposing better forecasting models will be better than the naïve no change forecasting model, and thus U_1 will be appropriate for comparing "better" models in the region where U_1 is small. In the context of forecasting, "better" forecasts do not seem warranted. Proof to this account is provided by Zarnowitz (1967) through the comparison the forecasts made by professional teams to the no change alternative by computing $\overline{R}_t$, the ratio of mean square error of the experts' forecasts to the mean square error from the no change model. Zarnowitz (1967) found that less than one-eight of them exceeds the ratio of 1.0, only about one quarter are less than 0.6 when determining the reliability of forecasting approaches.

In contrast, the coefficient of U_2 is unambiguous and easy to understand. When there is perfect forecasts, U_2 will hit its lower boundary of $U_2 = 0$. The statistic assumes the value of 1 when a forecasting approach provides forecasts with the similar standard error as the naïve no change extrapolation. It increases monotonically as the standard error forecasting improves over the no change extrapolation. Besides, the forecasting method applied will be rejected if U_2 is larger than 1 because it unable to beat the most simple no change extrapolation. Due to the superiority of U_2 coefficient, it receives support and being preferable in previous studies, for instances, Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984). In this research, we planned to apply the coefficient of U_2 to determine which variable has the superior forecasting power in predicting Malaysian stock returns as it gives more accurate and meaningful information since it less sensitive to the outliers compared to U_1.

3.4 Diagnostic Testing

3.4.1 Autoregressive Conditional Heteroscedasticity (ARCH)

In econometrics, Autoregressive Conditional Heteroscedasticity (ARCH) is one of the tests which introduced by Engle (1982) which used to detect whether a time series model is encountering from heteroscedasticity problem (Nelson, 1991). Long and Ervin (1998) stated that heteroscedasticity incurs when there is inconsistent variance of the error terms between the observations. The conditional variance relies on the observation, including variability relies on the mean of the data, or variability relies on one or more explanatory factors (Payne, 2014).

Heteroscedasticity can lead to several impacts in the disturbances of a linear model. Firstly, it may influence the distribution of coefficient as it has violated the minimum variance property by raising the variances of the distribution, which may cause the Ordinary Least Square (OLS) method to be inefficient and no longer hold the Best Linear Unbiased Efficient (BLUE) assumptions. However, the coefficients of OLS estimators are still considered as consistent and unbiased because the explanatory variables and the error term are uncorrelated with each other (Gujarati

& Porter, 2009). Secondly, it tends to underestimate the standard errors and variances of a model. An inaccurate standard error eventually leads to a large value of T statistic and F statistic. As a consequence, the null hypothesis tends to not be rejected and subsequently caused all the conclusions of hypothesis testing to be invalid.

There are consist of several tests which used to detect whether heteroscedasticity problem is existing in the model. The test can be categorized into two main groups which are informal and formal tests. The examples of informal test consist of nature of problem and graphical method. While, the formal tests are consist of White test, Park test, Breusch-pagan test, Glesjer test, and ARCH-LM test.

Since the research topic of our study is closely related to the stock market returns and the model is also consisting of time series data, which behavior is considered as very uncertain. The ARCH-LM test planned to be applied in this study for the objective of diagnostic checking and to ensure that the reliability of the hypothesis testing in this research is valid. Firstly, the null hypothesis states that error terms are homoscedasticity, while alternative hypothesis as heteroscedasticity. Secondly, this study rejects the null hypothesis by comparing the *p*-value and significance level of 5 % ($\propto = 0.05$). The decision rule to reject the null hypothesis if the *p*-value is smaller than significance level of 5%, otherwise, tend to not reject the null hypothesis. If the null hypothesis does not be rejected, it indicates that the model does not suffer from heteroscedasticity and the variance of error term is being constantly presented as well.

3.4.2 Breusch-Godfrey Serial Correlation LM test

According to Gujarati (2003), autocorrelation can be understood as the correlation or relationship between a series of data that ordered in time. In this regard, serial correlation violates one of the assumptions of Ordinary Least Squares (OLS) which stated that the error term for all observations are uncorrelated. Besides, based on Gujarati (2003), autocorrelation issue is often to be happened in the time series data.

Thus, for researchers who are working with time series data, it is often for them to conduct a test to detect the autocorrelation issue in a time series. Conducting diagnostic tests to detect autocorrelation is crucial since any neglected autocorrelation might lead to inappropriate inference on the conclusion of the hypothesis testing.

Based on Hyun, Mun, Kim and Jeong (2009), two statisticians, namely, Breusch and Godfrey (1978) have proposed the Breusch-Godfrey test which also can be known as LM test, is frequently used in the studies that applied time series data compared to other tests such as Durbin-Watson d test or the Q statistics. One of the reasons of applying the LM test is due to its ability in preventing some of the drawbacks of the Durbin-Watson d test. For instances, DW test only considered the AR (1) alternative, which always means that it did not allow for higher-order AR schemes. Furthermore, the assumption of d test is generally difficult to retain in economic models which involved time series data, since it assumed that the explanatory variables are non-stochastic, that is, the value of regressors are fixed or constant in the repeated sampling.

In this respect, the LM test is usually more applicable for the models that include the time series data since it allows for (1) higher-order AR schemes, for instances, AR (2), AR (3), AR (4), etc; (2) higher-order or simple moving average (MA) of white noise error terms; and (3) non-stochastic regressors, that is, the lagged values of the dependent variable (Gujarati, 2003). To discuss the LM test in detailed manner, a regression model with two variables can be used as follows:

$$Y_t = \beta_1 + \beta_2 X_t + u_t \qquad (3.21)$$

Assume that u_t in the equation 3.23 follows the following structure:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3} + \cdots + \rho_p u_{t-p} + v_t \qquad (3.22)$$

Where v_t is the white noise error term which mentioned previously.

According to Gujarati (2003), in order to detect the autocorrelation, the null hypothesis can be stated as there is no autocorrelation problem ($H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_p = 0$). Subsequently, we will compare the chosen significance level (α = 0.05 or 5%) with the p-value from the estimated chi-square statistic. If the p-value is lesser than α = 5%, a decision will be made to reject the null hypothesis; otherwise, do not reject the null hypothesis. If we reject the null hypothesis, it indicates that there is an autocorrelation in the model which causes the estimator to be inefficient. Thus, it might draw a misleading conclusion in the hypothesis testing, which will affect the judgment of researchers.

3.5 Chapter Summary

All in all, we have undertaken the quantitative technique by collecting the data of GPR index, EPU index and FBM KLCI index for examining the predictability of GPR and EPU towards Malaysia stock return. As overall data will be collected in monthly basis, total of 172 observations are taken as the sample size of this research, with the sampling period of 14 years which from January 2005 until April 2019. Under the section of methodology, the regression model with the FGLS estimators will be conducted to overcome the issues of persistency, endogeneity and heteroscedasticity in case of applying the OLS estimators. Furthermore, in-sample and out-of-sample test will be taken to examine any discrepancy on the result of both analyses. For the out-sample-analysis, the coefficient of U_2 is applied in determining the forecasting power of the variables on Malaysian stock returns. Besides, ARCH and Breusch-Godfrey serial correlation LM test are conducted for detecting any issues such as heteroscedasticity and autocorrelation from the model respectively. Hence, the outcome which is generated in Chapter 3 will be interpreted in the following chapter, Chapter 4.

CHAPTER FOUR: EMPIRICAL RESULT

4.0 Introduction

This chapter commences by providing the empirical results obtained based on the methodology introduced in the previous chapter. The discussions on the results of unit root test, persistency and endogeneity test, in-sample analysis, diagnostic tests, as well as the out-of-sample analysis will be also covered in this chapter. Lastly, a summary on the critical findings of this research will be provided at the end of this chapter.

4.1 Unit Root Test

Unit root is the non-stationary autoregressive (AR) or autoregressive moving-average (ARMA) under the process of time series. The application of unit root test often been conducted in economics and finance sector by examining the stochastic intercept or trend that generated from test above. Hence, unit root test usually is held for addressing the null hypothesis about the variable is unit root non-stationary and classified as an AR (1) model with noticeable intercept and linear trend. Otherwise, an alternative hypothesis always told about the variable is in stationary process without any evident trend (Herranz, 2017). Therefore, we decided to perform the unit root test for examining whether both GPR and EPU are unit root stationary or non-stationary in the model.

Table 4.1:

Result of unit root test for each predictor.

Predictors	Probability (p-value)
GPR	0.0000
EPU	0.0000

Notes: This table reports the probability of each predictor (GPR & EPU) when undertaking the unit root test.

Figure 4.1:

Line graph of GPR

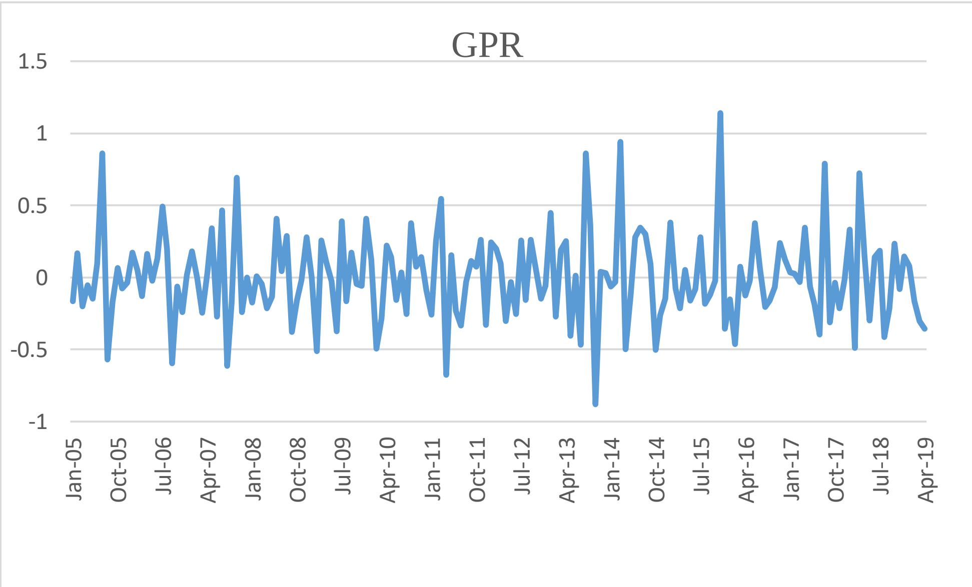
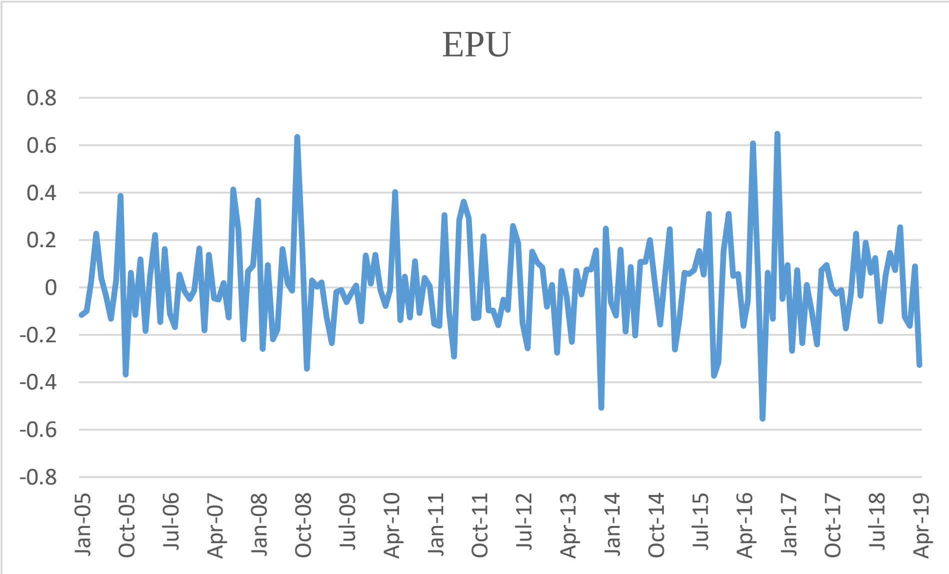


Figure 4.1.1:

Line graph of EPU



Refer to the table 4.1, the probability (p-value) of GPR is 0.0000. In this situation, the p-value is lesser than significant level of 0.05 which is taken as the benchmark. When p-value is lesser than the 0.05, the null hypothesis about the variable is unit root non-stationary can be rejected. Hence, it concluded that the data of GPR is stationary under this model. Besides, EPU has faced the similar outcome with GPR since its p-value is 0.0000 too which is lower than the 0.05. Hence, EPU data is stationary as well. Regarding to the diagram 4.1.1 and 4.1.2, they presented the line graph without showing any noticeable linear trend. Therefore, both EPU and GPR are under the stationary process. Based on the final result, we directly utilized the data without taking the first difference of sample data since both predictors are stationary in this model. In other words, both predictors moved under stationary at level form with the stochastic-trend line graph.

4.2 Persistency and Endogeneity Tests

The inefficiency and bias of the predictor variables resulted by both persistency and endogeneity issues has been shown and been the concentrating point on previous studies (see Westerlund and Narayan (2012, 2015), Lewellen (2004), and Stambaugh (1999).Thus, in this study, we have analyzed whether our model has encounter the aforementioned issues through persistency and endogeneity test.

Table 4.2:

Results of persistency and endogeneity test of the variables.

	Persistency Test		**Endogeneity Test**	
Predictors	**Coefficient**	**Probability**	**Coefficient**	**Probability**
EPU	-0.155216	0.0443	-0.052939	0.0001
GPR	-0.247146	0.0012	0.017182	0.0469

Notes: This table reports results of persistency and endogeneity test in the total sample ranging from January 2005 to April 2019. The first and second column of each data present the coefficient and the probability of persistency test, while the last two columns of each data present the coefficient and the probability of endogeneity test.

First, referring on persistency test, both EPU and GPR predictors does not hold the null hypothesis at 5% and 1% level respectively, suggesting that both predictors hold alternative hypothesis of predictors have encounter the issue of persistency. Besides, for endogeneity test, both EPU and GPR predictors are significant at the level of 1% and 5% respectively, suggesting that the null hypothesis of exogenous for both predictors are rejected. Hence, conclude that, both predictors are endogenous.

Overall, the preliminary results statistically reveal that both persistency and endogeneity of the predictors are existed in the predictive regression model. Hence, the FGLS model is used and expected to perform well than other competitive models in predicting the stock returns, as mentioned in chapter 3.

4.3 In-Sample Analysis (FGLS Model)

Table 4.3:

Results of in-sample predictability test.

Predictors	**T-Statistic**	**Coefficient**	**Probability**
EPU	-3.548570	-0.043280	0.0005***
GPR	2.454461	0.017472	0.0151**

*Notes: This table reports the results of in-sample predictability test by employed both EPU and GPR as selective predictors on Malaysian stock returns. The result reported included the t-statistic, the coefficient, and the probability of the variable. The significance levels of 10%, 5% and 1% are denoted by *, **, *** respectively.*

In Table 4.3, we report the t-statistics and the coefficient of the FGLS test associated with the null hypothesis of “zero predictability power” for both predictors. When we employed EPU as a predictor for stock returns, we found that there is evidence of predictive ability at the significance level of 1%. However, for the GPR, the null hypothesis of “zero predictability power” is easily rejected at the 5% significance level, but it does not hold at the significance level of 1%. Overall, EPU is more prominent than GPR in the in-sample predictability test.

4.4 Diagnostic Test

4.4.1 ARCH Test

As stated by Gujarati and Porter (2009), heteroscedasticity occurs when the variance of error term (ε) depends on the values of predictor variables exactly. In our case, we have applied the standard approach, autoregressive conditional heteroscedasticity (ARCH) test, one of the well-known tests for heteroscedasticity detection, to detect the problem of heteroscedasticity in our model.

Table 4.4.1:

Result of ARCH test for both estimators of ALS model.

Predictors	Probability (p-value)
EPU	0.0621
GPR	0.0139

Notes: Probability (p-value) is referred to the Probability Chi-Square with lag length of 6.

Based on the result from ALS model, the p-values of EPU is 0.0621 while GPR is 0.0139. According to the statistical decision rule, if p-value more than significance level, we do not reject null hypothesis, where there is no heteroscedasticity problem. In contrast, if p-value less than significance level, we reject null hypothesis and heteroscedasticity problem exists. Under 10% significance level, it shows that both variables' p-values are less than 10%, where 0.0621 < 0.10; 0.0139 < 0.10. Thus, we reject null hypothesis and conclude that both EPU and GPR in ALS model have heteroscedasticity at the significance level of 10%.

Owing to the present of heteroscedasticity of EPU and GPR at 10% significance level, it depicts that the estimators in the model are still linear and biased but no longer best. Hence, we have transformed the model into FGLS model to overcome this problem since FGLS model performs better than ALS model (Westerlund & Narayan, 2012; Bentes & Menezes, 2013).

Table 4.4.1.1:

Result of ARCH test for both estimators of FGLS model.

Predictors	**Probability(p-value)**
EPU	0.7122
GPR	0.9178

Notes: Probability (p-value) is referred to the Probability Chi-Square with lag length of 6.

In FGLS model, the p-values of EPU and GPR are 0.7122 and 0.9178 which is larger than the significance level of 10% where 0.7122 > 0.10; 0.9178 > 0.10. As a result, we do not reject the null hypothesis for the both variables. In other words, heteroscedasticity does not arise in EPU and GPR after we transformed ALS model to FGLS model.

4.4.2 Breusch-Godfrey Serial Correlation LM Test

Gujarati and Porter (2009) defines autocorrelation issue as the correlation between a series of observations that ordered in time and it mostly will arise in the model which comprises of time series data. Moreover, autocorrelation problem arises when error term of current period and past period are correlated. Therefore, it can be expressed concisely as $E(\varepsilon i, \varepsilon j) \neq 0$ where $i \neq j$, period. In our case, we have applied Breusch-Godfrey Serial Correlation LM test to check for the existence of autocorrelation.

Table 4.4.2:

Result of LM test for both estimators of ALS model.

Predictors	Probability (p-value)
EPU	0.0733
GPR	0.0568

Notes: Probability (p-value) is referred to the Probability Chi-Square with lag lane of 6.

Same as ARCH test, we use significance level of 10%. As stated in table 6, the p-values of EPU and GPR from ALS model are 0.0733 and 0.0568. Based on the decision rule, we reject null hypothesis for both variables as their p-values are less than 10% significance level, where 0.0733 < 0.10; 0.0568 < 0.10. Hence, we concluded that there is autocorrelation on EPU and GPR at 10% significance level. Due to the presence of autocorrelation, the estimators in the ALS model are no longer efficient although they are still linear, unbiased, consistent as well as normally distributed. Thus, we have transformed the ALS model to FGLS model likewise with heteroscedasticity to capture autocorrelation problem.

Table 4.4.2.1:

Result of LM test for both estimators of FGLS model.

Predictors	Probability (p-value)
EPU	0.4058
GPR	0.3143

Notes: Probability (p-value) is referred to the Probability Chi-Square with lag lane of 6.

In FGLS model, the p-values of EPU and GPR are 0.4058 and 0.3143 which are larger than the three significance level of 10%, where 0.4058 > 0.10; 0.3143 > 0.10. As a consequence, we do not reject null hypothesis for both variables. Particularly, autocorrelation does not arise in EPU and GPR after we transformed ALS model to FGLS model.

4.5 Out-of-Sample Analysis

In order to derive the out-of-sample results, we have applied several in-sample periods with the proportions of 25%, 50% and 75% of the full sample in forecasting the Malaysian stock returns. Hence, the out-of-sample periods will comprise of January 2005 to May 2008, January 2005 to February 2012, and January 2005 to September 2015. Besides, the evaluation for out-of-sample forecasting is done by referring the Theil Inequality Coefficient (i.e., Theil U and Theil U2) of the estimators. If the Theil U statistic of the estimator is less than the Theil U statistic of historical average model, then the estimator is normally good at forecasting stock returns, vice versa. While for Theil U2, if it is less than 1, then the estimator is considered to have the superior power in predicting stock returns, whereas if it is greater than 1, the estimator applied is to be rejected as it is unable to beat the simplest no change extrapolation.

Table 4.5:

Out-of-sample result for the estimators and benchmark.

Sample	**U1**			**U2**		
	EPU	GPR	Benchmark	EPU	GPR	Benchmark
25%	0.8110	0.8256	0.8973	1.0630	0.9778	0.9105
50%	0.7655	0.8168	0.9161	1.0587	0.9185	0.9533
75%	0.7605	0.7898	0.9080	1.0420	0.9981	1.0307

Notes: U1 is the Theil U statistics. U2 is the Theil U2 statistics.

By referring the results reported in the table, it depicts the Theil U statistics and Theil U2 statistics for EPU and GPR, while the statistics of historical average model act as the benchmark when comparing the Theil U statistics. By comparing the Theil U coefficient of both estimators with the benchmark, the Theil U coefficients of EPU and GPR are less than the benchmark for all three out-of-sample periods. This shows that both estimators have the predictive power to forecast Malaysian stock returns for all horizons.

However, in order to make comparison between the predictive power of EPU and GPR, Theil U2 statistics will be used to assess which estimator has the superior power in predicting stock returns. Hence, by considering Theil U2 statistics, GPR performs best for all horizons, with 0.9778 in 25%, 0.9185 in 50%, and 0.9981 in 75% of the full sample, which are less than 1. While for EPU, its Theil U2 statistics for all out-of-sample periods are greater than 1, with 1.0630 in 25%, 1.0587 in 50%, and 1.0420 in 75% of the full sample. In brief, by referring to Theil U coefficient, both estimators are favourable in predicting Malaysian stock returns, however, by referring to Theil U2 coefficient, GPR turns out to perform better than EPU in predicting the Malaysian stock returns.

This result which shows that EPU has the predictive ability is the same as the one in the study of Balcilar *et al.* (2015) and Phan *et al.* (2018). The study of Balcilar *et al.* (2015) mentioned that Malaysia is vulnerable to the global uncertainties, thus investors are more likely to rely on information of uncertainty related with its major trading partners which are China and the US. Besides, Phan *et al.* (2018) stated that global EPU has the ability to predict excess returns for various countries, i.e., the UK, Australia, Brazil, France, Germany, China, through discount rate and cash flow channels. While for GPR, the result is inconsistent with the previous studies which showed that GPR is normally not found to have forecasting power over stock returns (Apergis *et al.*, 2017; Bouras *et al.*, 2018; Bouri *et al.*, 2018). This might due to the use of different data frequencies and types since most of the previous studies focused on country-specific GPR instead of global GPR when evaluating the predictability of GPR on stock returns.

4.6 Summary of the Findings

In the nutshell, the EPU and GPR are stationary under this model. In the other words, both of them experienced the stationary at the level form instead of considering the first difference on sample data. In this study, FGLS model is employed because the preliminary results show that the existence of persistency and endogeneity in our predictor variables. Besides, the results of in-sample predictability (FGLS test) reported that both EPU and GPR have the forecasting ability toward Malaysian stock returns. Apart from that, we have sufficient evidence to conclude that both EPU and GPR does not encounter the heteroscedasticity problem by applying FGLS model as compared to ALS model. It also implies that the variance of error term (Ɛ) in FGLS model can be known as constant as well. Furthermore, similar with the result of heteroscedasticity, autocorrelation absences for both variables by transforming ALS model to FGLS model. This depicts that even though ALS model accounts for endogeneity and persistency for the EPU and GPR, but it is still inefficient due to the presence of heteroscedasticity and autocorrelation problems. Hence, FGLS model is proved to be more robust than ALS model since FGLS model accounts for endogeneity, persistency, heteroscedasticity and autocorrelation problem. Besides, by considering Theil U statistic, both estimators are said to have the ability to predict the Malaysian stock return. However, by focusing on Theil U2 statistic, GPR turns out to perform even well in forecasting Malaysian stock return, since the result of EPU is unable to beat the historical average model.

CHAPTER FIVE: CONCLUSION AND IMPLICATION

5.0 Introduction

This chapter is devoted to deliver a discussion of key findings for our hypothesis testing, implications of the research and limitations, complement with recommendations for the future study.

5.1 Summary of Major Findings

First of all, by referring to the empirical result in Chapter 4, we realized that both predictors, GPR and EPU have experienced stationary under the level form. Hence, we will not be going to consider the first difference of sample data under the regression model. Besides, FGLS model is employed because the preliminary results show that persistency and endogeneity does exist in our predictor variables. Apart from that, the results of in-sample predictability (FGLS test) reported that both predictor (EPU and GPR) have the forecasting ability toward Malaysian stock returns. Furthermore, although ALS accounts for endogeneity and persistency, it is not efficient in addressing heteroscedasticity and autocorrelation problem. Thus, FGLS model is founded to be more superior than ALS model since it captures heteroscedasticity and autocorrelation for both EPU and GPR at significance level of 10%. Moreover, by undergoing the out-of-sample test, we found that EPU and GPR have the ability to forecast Malaysian stock returns, however, by referring to Theil U2 in comparing the predictive power of both estimators, GPR is found to be more favourable than EPU in forecasting Malaysian stock returns.

5.2 Discussion of Key Findings

This study applies GPR and EPU to forecast Malaysian stock returns by using KLCI index. FGLS forecasting model, which proposed by Westerlund and Narayan (2012), has been applied in this paper as it takes into consideration the potential problems in a predictive regression, which namely, predictor endogeneity, persistency and heteroskedasticity issue. Thus, the discussion of the main findings is as follows.

First, based on the in-sample results of GPR, it shows that GPR has a significant effect and predictive power in forecasting Malaysian stock returns. In addition, by considering GPR’s out-of-sample result, we found that GPR is able to forecast Malaysian stock returns for all forecasting horizon periods (25%, 50%, and 75%). Since Malaysia is a small and open economy, the accelerating of geopolitical tensions in the world, especially in Asian countries, are expected to present a risk on Malaysia’s economy, which might directly have an impact on the nation’s stock returns. For example, the increasing of geopolitical tensions in Middle East and North Asia are likely to expose the global economy to a risk that might directly have a bearing on the economy of Malaysia (Tan, 2018).

Second, according to the in-sample results of EPU, it depicts that EPU has a significant effect and predictability to forecast Malaysian stock returns and it is more prominent than GPR. Besides, the out-of-sample result of EPU is in line with its in-sample result since it shows that EPU has the ability to forecast Malaysian stock returns for three horizon periods by referring to Theil U coefficient. In economic context, as an emerging economy such as Malaysia, it most probably will be affected by the uncertainties in the global economic environment due to the changes in government policies of other countries. The worsening trade tensions which created by global events such as Brexit and the trade negotiations between US as well as China will generate impact on Malaysia’s economic growth which might influence the confidence level of investors towards Malaysia stock market.

Third, the out-of-sample results obtained show that GPR and EPU have the ability to forecast Malaysian stock returns for all horizons by referring to Theil U coefficient. This result is consistent with the APT theory, which mentioned in Chapter 2, by saying that the stock returns is predictable through the usage of appropriate macro-variable. Nevertheless, by considering to Theil U2 coefficient in comparing the predictability of both estimators, we found that GPR has the superior forecasting power in predicting the stock returns of Malaysia. According to Hoque, Low, and Zaidi (2019), geopolitical tensions might generate uncertainties which could influence the risk behaviour of investors through global policy uncertainty. Thus, the occurrence of shock in geopolitical risk magnified the effects of global EPU towards Malaysia stock market, which explains why GPR is more favourable since it carries direct and indirect impact to Malaysian stock returns.

5.3 Implications of the Study

5.3.1 For the Potential Investors

The present research has revisit the field of the macroeconomic factors and the risk factors towards the stock returns, in the sense that, this research can provide valuable knowledge in constructions of portfolio and risk management in the stock market. The deep understanding on the macroeconomic and the risk factors are the key focus point for the future investors as they will be better in time-varying of the portfolio allocations in accordance to the market conditions. This subsequently implies that consideration of both macroeconomic and risk factors is significant for the investors before stepping into the stock market. According to the discussion of our findings, it statistically suggests that investors have to be more concentrate on the movement of GPR and EPU in the prediction making process as both predictors have the predictive ability toward Malaysian stock returns.

Besides, investors are also able to make an improvement on extant prediction analysis as this study has provide another alternative as predictor (EPU and GPR), which strengthen the forecasting power in aspect of Malaysian stock returns. With that, the consideration of stock market response can be forecasted accurately and which are very important for hedging and diversification strategies because upward and downward movements in EPU and GPR by the same magnitude are not likely to have the same effect on the stock market. In addition, they are able to analyze and make the judgment precisely regarding on how and when to take a short or long position in the stock market by taken both significant variables into consideration. For an example, if investors are well-informed about the possible movement of EPU and GPR by expecting a rise in both variables in the future, they have to take a short position instead of long position in the stock market. Since an expected increase in EPU and GRP reveals a signal of high market uncertainty in the future, most of the market participants will lose confidence in such economic situation that might influence the stock returns negatively. Hence, in order to reach better portfolio investment, investors have to constantly alert on the movement of both EPU and GPR so that the development of portfolio performance can be enhanced and maximized.

5.3.2 For the Forecaster and Future Researcher

Refer to existing literature framework, there is lack of forecaster studied on determinants of the stock market performance by analyzing both EPU and GPR factors at the same time. However, this research helps in uncovering another prospective results for the future researchers by formulating a new model which comprises of selective variables such as the economic policy uncertainty (EPU), geopolitical risk (GPR) and Malaysian stock returns. Thus, financial market analysts may have to fit in this information while formulating their predictive model for stock returns. In other words, this study could provide some insights or valuable evidence for future researchers who are interested in studying and examining the factors of the stock market performance. However, in order to make this study more comprehensive, logical extension of the study is necessary.

5.3.3 For the Policymakers

This study can provide insights on the predictability between the macroeconomic factors and the performance of Malaysian stock returns towards the policymakers. The results reported that both EPU and GPR variables are found to be significant in affecting the performance of Malaysian stock market. Thus, it suggests that policymakers have to constantly concern on the movements of both variables and subsequently make their policy decision accordingly. For example, policymakers can place government policy into consideration such as change in regulations, monetary policy and fiscal policy. All the actions taken will subsequently reflect on EPU as this predictor is defined as the uncertainty regarding fiscal, regulatory, and monetary policy which resulted by government policymakers towards the financial and economic fundamentals. Nonetheless, the implementation of the related policies must be proceeded carefully and transparency as it may result negative consequences towards the stock market performance.

5.4 Limitations of Study

Although Feasible Adjusted Least Square (FGLS) model outperforms Ordinary Least Square (OLS) model and Adjusted Least Square (ALS) in capturing the endogeneity, persistency heteroscedasticity and autocorrelation issues, but it is still encountering with limitation. Particularly, only one predictor can be used in the FGLS model due to mathematical limitation from the model itself (Westerlund & Narayan, 2012). If there is an extension to two predictors, the model will become complicated. As stated by Westerlund and Narayan, the author of FGLS model, the model currently has not reached the condition of extension to two predictors; nevertheless further development on this model are in progress.

Apart from that, recent US-China Trade War has caused the global EPU rose to historical high and global GPR to a spike after year 2015 of Paris terrorist attacks. The performance of Malaysia stock market also has been affected negatively since Malaysia engage in trading business with US and China. Hence, US-China trade war undoubtedly will affect the result of our study. However, since we conduct our research in May 2019 where the US-China trade war still ongoing, we encounter with the issue of lack of available data since we are not able to collect the data after May 2019. Therefore, in this case, it has resulted in limiting the scope of our analysis and size of sample.

Subsequently, the country-specific EPU index for Malaysia is not available. Hence, in our study, we applied both global EPU index and global GPR index to run the FGLS model. The global EPU is a GDP-weighted mean of national EPU indexes of 21 countries but not include Malaysia while the global GPR is an index which assess the likelihood of appearance of words that associated to geopolitical tensions in top newspapers of the world. Similarly, newspapers of Malaysia are not involved in the indexes. In other words, both predictors have the likelihood in failing to capture the events from Malaysia which might affect the Malaysian stock returns or they probably will involve some events which have no effect on Malaysian stock returns. Therefore, if there is available country-specific EPU index for Malaysia, our results on forecasting the Malaysian stock returns by applying Malaysian EPU and GPR indexes might be different or even better as compared to the application of global EPU and GPR indexes.

5.5 Recommendations for Future Researches

First of all, we realized that each equation in the FGLS model only can use one predictor for explaining its relationship with the dependent variable. According to Narayan and Westerlund (2012), the authors has mentioned that they will continuously develop an advanced FGLS model which could take two or more estimators as multiple regression. Therefore, the researchers are recommended to wait for the introduction of advanced FGLS model in the future. As long as the FGLS model can be developed into mutli-regression, it assumed that those variables are no autocorrelated with one another unless failed the diagnostic test of autocorrelation. Hence, the researchers could generate the result easier and effectively by examining the effect from different estimators under one FGLS model as well as confirm the model is excluded any econometric problem such as heteroscedasticity, autocorrelation etc.

Furthermore, we suggested that the sample size should be large enough for enhancing the accuracy of outcome presented in the research. Based on the Classical Normal Linear Regression Model (CNLRM) assumption, the error term will be normally distributed unless the sample size tend to be small or finite (Gujarati & Porter, 2009). In other words, as the sample size increases, the estimated outcome will be getting more accurate with the actual outcome one. Besides, the larger sample sizes are more likely to fully capture some significant or important crisis which happened in the target country. Hence, it is vital to obtain large sample size; otherwise, the future researchers could extend the sample period more by collecting data with daily or monthly basis in case of time-series model or panel data model. For instances, in order to fully capture the US-China trade war issue, the future researchers could extend the data period up to February of 2020 as the first sign of a truce was seen in mid-January 2020 due to the signing of Phase One Trade Deal and the outbreak of COVID-19 pandemic (Klein, 2020).

Lastly, future researchers are recommended to examine the particular sector of target country with local determinants. As we mentioned above, the global determinants might indirectly influence the estimated outcome to be less precise since the data may capture the external effect from different country. Instead of taking the global determinant, they could conduct the research with the determinants which specifically reflect the changes in the condition of target country. Therefore, the estimated outcomes tend to be more accurate as well as the research can be conducted effectively with the relevant data given.

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Appendices

Appendix 1.1:

The 30 Companies that composed FBM KLCI in year 2019

	Company Name	Code	Sector
1.	Malaysia Airport Holding Berhad	5014	Transportation and Logistic services
2.	AMMB Holdings Berhad	1015	Banking
3.	Axiata Group Berhad	6888	Telecommunications services providers
4.	CIMB Group Holdings Berhad	1023	Banking
5.	Dialog Group Berhad	7277	Energy Infrastructure, Equipment & Services
6.	Digi.com Berhad	6947	Telecommunications services providers
7.	Genting Malaysia Berhad	4715	Travel, Leisure & Hospitality
8.	Genting Berhad	3182	Travel, Leisure & Hospitality
9.	Hap Seng Consolidated Berhad	3034	Diversified Industrials
10.	Hartalega Holdings Berhad	5168	Health Care Equipment & Services
11.	Hong Leong Bank Berhad	5819	Banking
12.	Hong Leong Financial Group Berhad	1082	Banking
13.	IHH Heathcare Berhad	5225	Health Care Providers
14.	IOI Corporation Berhad	1961	Plantation
15.	Kuala Lumpur Kepong Berhad	2445	Plantation
16.	Maxis Berhad	6012	Telecommunications services providers
17.	Malayan Banking Berhad	1155	Banking
18.	MISC Berhad	3816	Transportation & Logistics Services
19.	Nestle (Malaysia) Berhad	4707	Food and Beverages
20.	Public Bank Berhad	1295	Banking
21.	Petronas Chemical Group Berhad	5183	Chemicals
22.	Petronas Dagangan Berhad	5681	Retailers
23.	Petronas Gas Berhad	6033	Gas, Water & Multi-utilities
24.	Press Metal Aluminium Holdings Berhad	8869	Metals
25.	PBB Group Berhad	4065	Food and Beverages
26.	RHB Bank Berhad	1066	Banking
27.	SIME Darby Berhad	4197	Automotive
28.	SIME Darby Plantation Berhad	5285	Plantation
29.	Tenaga Nasional Berhad	5347	Electricity
30.	Top Glove Corporation Berhad	7113	Health Care Equipment & Services

Source: Bursa Malaysia (2019).

Appendix 4.1: Unit Root Test

4.1.1 EPU predictor

Augmented Dickey-Fuller Unit Root Test on EPU
Null Hypothesis: EPU has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.95075	0.0000
Test critical values:	1% level	-3.468980	
	5% level	-2.878413	
	10% level	-2.575844	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EPU)
Method: Least Squares
Date: 03/12/20 Time: 16:41
Sample (adjusted): 2005M03 2019M04
Included observations: 170 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EPU(-1)	-1.385306	0.115918	-11.95075	0.0000
D(EPU(-1))	0.197682	0.076373	2.588379	0.0105
C	0.010336	0.014405	0.717554	0.4740

R-squared	0.591225	Mean dependent var	-0.001334
Adjusted R-squared	0.586329	S.D. dependent var	0.291414
S.E. of regression	0.187430	Akaike info criterion	-0.493338
Sum squared resid	5.866683	Schwarz criterion	-0.438000
Log likelihood	44.93372	Hannan-Quinn criter.	-0.470882
F-statistic	120.7688	Durbin-Watson stat	2.052758
Prob(F-statistic)	0.000000		

4.1.2 GPR predictor

Augmented Dickey-Fuller Unit Root Test on GPR
Null Hypothesis: GPR has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.37925	0.0000
Test critical values:	1% level	-3.469214	
	5% level	-2.878515	
	10% level	-2.575899	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GPR)
Method: Least Squares
Date: 03/12/20 Time: 16:43
Sample (adjusted): 2005M04 2019M04
Included observations: 169 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GPR(-1)	-1.943796	0.170819	-11.37925	0.0000
D(GPR(-1))	0.565973	0.126277	4.481988	0.0000
D(GPR(-2))	0.209311	0.077015	2.717800	0.0073
C	0.005840	0.022108	0.264168	0.7920

R-squared	0.666523	Mean dependent var	-0.000898
Adjusted R-squared	0.660460	S.D. dependent var	0.492924
S.E. of regression	0.287227	Akaike info criterion	0.366297
Sum squared resid	13.61240	Schwarz criterion	0.440377
Log likelihood	-26.95206	Hannan-Quinn criter.	0.396360
F-statistic	109.9289	Durbin-Watson stat	2.057511
Prob(F-statistic)	0.000000		

Appendix 4.2: Persistency Test and Endogeneity Test

4.2.1 Persistency Test - EPU Predictor

Dependent Variable: EPU
Method: Least Squares
Date: 01/21/20 Time: 11:15
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007858	0.014562	0.539623	0.5902
EPU(-1)	-0.155216	0.076597	-2.026394	0.0443

R-squared	0.023721	Mean dependent var	0.006636
Adjusted R-squared	0.017944	S.D. dependent var	0.191996
S.E. of regression	0.190265	Akaike info criterion	-0.469169
Sum squared resid	6.117939	Schwarz criterion	-0.432425
Log likelihood	42.11399	Hannan-Quinn criter.	-0.454260
F-statistic	4.106271	Durbin-Watson stat	2.045929
Prob(F-statistic)	0.044297		

4.2.2 Persistency Test - GPR Predictor

Dependent Variable: GPR
Method: Least Squares
Date: 04/02/20 Time: 15:43
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002173	0.023175	0.093778	0.9254
GPR(-1)	-0.247146	0.074775	-3.305180	0.0012

R-squared	0.060716	Mean dependent var	0.001525
Adjusted R-squared	0.055158	S.D. dependent var	0.311764
S.E. of regression	0.303044	Akaike info criterion	0.461752
Sum squared resid	15.52026	Schwarz criterion	0.498496
Log likelihood	-37.47976	Hannan-Quinn criter.	0.476661
F-statistic	10.92421	Durbin-Watson stat	2.123276
Prob(F-statistic)	0.001159		

4.2.3 Endogeneity Test - EPU Predictor

Dependent Variable: RESID_EPU
Method: Least Squares
Date: 01/21/20 Time: 11:19
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDEPU01	-0.052939	0.013141	-4.028544	0.0001

R-squared	0.087146	Mean dependent var	6.01E-19
Adjusted R-squared	0.087146	S.D. dependent var	0.034020
S.E. of regression	0.032503	Akaike info criterion	-4.009110
Sum squared resid	0.179601	Schwarz criterion	-3.990738
Log likelihood	343.7789	Hannan-Quinn criter.	-4.001656
Durbin-Watson stat	1.834003		

4.2.4 Endogeneity Test - GPR Predictor

Dependent Variable: RESID_GPR
Method: Least Squares
Date: 04/02/20 Time: 16:14
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDGPR01	0.017182	0.008582	2.002221	0.0469

R-squared	0.023038	Mean dependent var	3.04E-19
Adjusted R-squared	0.023038	S.D. dependent var	0.034204
S.E. of regression	0.033808	Akaike info criterion	-3.930429
Sum squared resid	0.194303	Schwarz criterion	-3.912057
Log likelihood	337.0517	Hannan-Quinn criter.	-3.922975
Durbin-Watson stat	1.692749		

Appendix 4.3: FGLS model

4.3.1 EPU and Stock Returns

Dependent Variable: STOCKRETURN/SD
Method: Least Squares
Date: 06/11/19 Time: 21:52
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.110381	0.077104	1.431592	0.1541
EPU(-1)/SD	-0.061833	0.018548	-3.333747	0.0011
D(EPU)/SD	-0.043280	0.012196	-3.548570	0.0005

R-squared	0.074634	Mean dependent var	0.094512
Adjusted R-squared	0.063618	S.D. dependent var	1.040072
S.E. of regression	1.006445	Akaike info criterion	2.868114
Sum squared resid	170.1725	Schwarz criterion	2.923231
Log likelihood	-242.2237	Hannan-Quinn criter.	2.890478
F-statistic	6.774896	Durbin-Watson stat	1.942384
Prob(F-statistic)	0.001480		

4.3.2 GPR and Stock Returns

Dependent Variable: STOCKRETURN/SD45
Method: Least Squares
Date: 06/11/19 Time: 22:16
Sample (adjusted): 2005M02 2019M04
Included observations: 171 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.086462	0.081768	1.057405	0.2918
GPR(-1)/SD45	0.048697	0.007252	6.714691	0.0000
D(GPR)/SD45	0.017472	0.007118	2.454461	0.0151

R-squared	0.900748	Mean dependent var	0.331807
Adjusted R-squared	0.899566	S.D. dependent var	3.363142
S.E. of regression	1.065822	Akaike info criterion	2.982758
Sum squared resid	190.8441	Schwarz criterion	3.037875
Log likelihood	-252.0258	Hannan-Quinn criter.	3.005122
F-statistic	762.3304	Durbin-Watson stat	1.816752
Prob(F-statistic)	0.000000		

Appendix 4.4: Diagnostic Test

4.4.1 ARCH Test

4.4.1.1 ALS model- EPU and Stock Return

Heteroskedasticity Test: ARCH

F-statistic	2.064303	Prob. F(6,158)	0.0603
Obs*R-squared	11.99431	Prob. Chi-Square(6)	0.0621

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/12/20 Time: 16:55
Sample (adjusted): 2005M08 2019M04
Included observations: 165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000650	0.000247	2.630827	0.0094
RESID^2(-1)	0.021563	0.077108	0.279646	0.7801
RESID^2(-2)	0.087289	0.077150	1.131412	0.2596
RESID^2(-3)	0.047682	0.077458	0.615582	0.5391
RESID^2(-4)	-0.011249	0.077480	-0.145192	0.8847
RESID^2(-5)	-0.011516	0.077147	-0.149276	0.8815
RESID^2(-6)	0.245386	0.077152	3.180553	0.0018

R-squared	0.072693	Mean dependent var	0.001054
Adjusted R-squared	0.037479	S.D. dependent var	0.002233
S.E. of regression	0.002191	Akaike info criterion	-9.367478
Sum squared resid	0.000758	Schwarz criterion	-9.235710
Log likelihood	779.8169	Hannan-Quinn criter.	-9.313989
F-statistic	2.064303	Durbin-Watson stat	2.109080
Prob(F-statistic)	0.060345		

4.4.1.2 ALS model- GPR and Stock Return

Heteroskedasticity Test: ARCH

F-statistic	2.823271	Prob. F(6,158)	0.0123
Obs*R-squared	15.97716	Prob. Chi-Square(6)	0.0139

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/12/20 Time: 16:56
Sample (adjusted): 2005M08 2019M04
Included observations: 165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000639	0.000276	2.315581	0.0219
RESID^2(-1)	0.096468	0.076529	1.260547	0.2093
RESID^2(-2)	0.070359	0.076772	0.916472	0.3608
RESID^2(-3)	0.032507	0.076955	0.422417	0.6733
RESID^2(-4)	0.024839	0.076947	0.322801	0.7473
RESID^2(-5)	-0.058370	0.076781	-0.760213	0.4483
RESID^2(-6)	0.274718	0.076542	3.589132	0.0004

R-squared	0.096831	Mean dependent var	0.001151
Adjusted R-squared	0.062534	S.D. dependent var	0.002750
S.E. of regression	0.002662	Akaike info criterion	-8.977654
Sum squared resid	0.001120	Schwarz criterion	-8.845887
Log likelihood	747.6565	Hannan-Quinn criter.	-8.924165
F-statistic	2.823271	Durbin-Watson stat	2.097639
Prob(F-statistic)	0.012266		

4.4.1.3 FGLS model- EPU and Stock Return

Heteroskedasticity Test: ARCH

F-statistic	0.610308	Prob. F(6,158)	0.7218
Obs*R-squared	3.737460	Prob. Chi-Square(6)	0.7122

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/12/20 Time: 17:01
Sample (adjusted): 2005M08 2019M04
Included observations: 165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.007537	0.243283	4.141415	0.0001
RESID^2(-1)	-0.034576	0.079231	-0.436390	0.6631
RESID^2(-2)	0.091250	0.079373	1.149636	0.2520
RESID^2(-3)	-0.049863	0.079404	-0.627975	0.5309
RESID^2(-4)	-0.091840	0.079453	-1.155900	0.2495
RESID^2(-5)	-0.002580	0.079342	-0.032513	0.9741
RESID^2(-6)	0.069715	0.079308	0.879040	0.3807

R-squared	0.022651	Mean dependent var	0.990295
Adjusted R-squared	-0.014463	S.D. dependent var	1.757411
S.E. of regression	1.770074	Akaike info criterion	4.021418
Sum squared resid	495.0397	Schwarz criterion	4.153185
Log likelihood	-324.7670	Hannan-Quinn criter.	4.074907
F-statistic	0.610308	Durbin-Watson stat	2.015042
Prob(F-statistic)	0.721822		

4.4.1.4 FGLS model- GPR and Stock Return

Heteroskedasticity Test: ARCH

F-statistic	0.326432	Prob. F(6,158)	0.9223
Obs*R-squared	2.020321	Prob. Chi-Square(6)	0.9178

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/12/20 Time: 17:02
Sample (adjusted): 2005M08 2019M04
Included observations: 165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.090809	0.270734	4.029082	0.0001
RESID^2(-1)	0.037278	0.079579	0.468448	0.6401
RESID^2(-2)	-0.075001	0.079605	-0.942169	0.3475
RESID^2(-3)	0.016114	0.079751	0.202048	0.8401
RESID^2(-4)	0.055800	0.079747	0.699712	0.4851
RESID^2(-5)	0.015886	0.079575	0.199633	0.8420
RESID^2(-6)	-0.026376	0.079492	-0.331811	0.7405

R-squared	0.012244	Mean dependent var	1.117364
Adjusted R-squared	-0.025265	S.D. dependent var	1.994128
S.E. of regression	2.019162	Akaike info criterion	4.284741
Sum squared resid	644.1686	Schwarz criterion	4.416508
Log likelihood	-346.4911	Hannan-Quinn criter.	4.338230
F-statistic	0.326432	Durbin-Watson stat	1.990893
Prob(F-statistic)	0.922341		

4.4.2 Breush-Godfrey Serial Correlation LM Test

4.4.2.1 ALS model- EPU and Stock Return

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.952061	Prob. F(6,162)	0.0755
Obs*R-squared	11.52949	Prob. Chi-Square(6)	0.0733

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 03/12/20 Time: 17:06
Sample: 2005M02 2019M04
Included observations: 171
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000136	0.002464	-0.055222	0.9560
EPU(-1)	0.001983	0.020535	0.096585	0.9232
D(EPU)	-0.002732	0.013403	-0.203820	0.8388
RESID(-1)	0.056012	0.079679	0.702968	0.4831
RESID(-2)	0.062652	0.080274	0.780480	0.4362
RESID(-3)	0.192775	0.079219	2.433457	0.0160
RESID(-4)	0.008864	0.079029	0.112155	0.9108
RESID(-5)	0.122816	0.079036	1.553923	0.1222
RESID(-6)	-0.063928	0.079499	-0.804132	0.4225

R-squared	0.067424	Mean dependent var	1.30E-18
Adjusted R-squared	0.021371	S.D. dependent var	0.032503
S.E. of regression	0.032154	Akaike info criterion	-3.985348
Sum squared resid	0.167491	Schwarz criterion	-3.819997
Log likelihood	349.7472	Hannan-Quinn criter.	-3.918255
F-statistic	1.464045	Durbin-Watson stat	1.982146
Prob(F-statistic)	0.174167		

4.4.2.2 ALS model- GPR and Stock Return

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.082038	Prob. F(6,162)	0.0580
Obs*R-squared	12.24221	Prob. Chi-Square(6)	0.0568

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 03/12/20 Time: 17:07
Sample: 2005M02 2019M04
Included observations: 171
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.76E-05	0.002552	-0.010799	0.9914
GPR(-1)	0.001129	0.013555	0.083266	0.9337
D(GPR)	0.000921	0.008646	0.106484	0.9153
RESID(-1)	0.131064	0.078439	1.670908	0.0967
RESID(-2)	0.122492	0.079496	1.540855	0.1253
RESID(-3)	0.067343	0.080664	0.834857	0.4050
RESID(-4)	-0.012593	0.080156	-0.157103	0.8754
RESID(-5)	0.140587	0.078702	1.786315	0.0759
RESID(-6)	-0.082273	0.078895	-1.042813	0.2986

R-squared	0.071592	Mean dependent var	1.20E-18
Adjusted R-squared	0.025745	S.D. dependent var	0.033808
S.E. of regression	0.033370	Akaike info criterion	-3.911146
Sum squared resid	0.180392	Schwarz criterion	-3.745795
Log likelihood	343.4030	Hannan-Quinn criter.	-3.844054
F-statistic	1.561528	Durbin-Watson stat	1.985382
Prob(F-statistic)	0.140212		

4.4.2.3 FGLS model- EPU and Stock Return

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.008451	Prob. F(6,162)	0.4217
Obs*R-squared	6.156894	Prob. Chi-Square(6)	0.4058

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 03/12/20 Time: 17:05
Sample: 2005M02 2019M04
Included observations: 171
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002580	0.077129	-0.033452	0.9734
EPU(-1)/SD	-0.001353	0.019339	-0.069984	0.9443
D(EPU)/SD	-0.003974	0.012705	-0.312795	0.7548
RESID(-1)	0.015871	0.080067	0.198223	0.8431
RESID(-2)	0.021536	0.081004	0.265860	0.7907
RESID(-3)	0.153649	0.080116	1.917823	0.0569
RESID(-4)	-0.009363	0.079930	-0.117141	0.9069
RESID(-5)	0.105589	0.079098	1.334919	0.1838
RESID(-6)	-0.000729	0.079549	-0.009164	0.9927

R-squared	0.036005	Mean dependent var	6.49E-17
Adjusted R-squared	-0.011599	S.D. dependent var	1.000507
S.E. of regression	1.006293	Akaike info criterion	2.901620
Sum squared resid	164.0454	Schwarz criterion	3.066971
Log likelihood	-239.0885	Hannan-Quinn criter.	2.968712
F-statistic	0.756338	Durbin-Watson stat	1.993562
Prob(F-statistic)	0.641680		

4.4.2.4 FGLS model- GPR and Stock Return

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.164628	Prob. F(6,162)	0.3278
Obs*R-squared	7.070978	Prob. Chi-Square(6)	0.3143

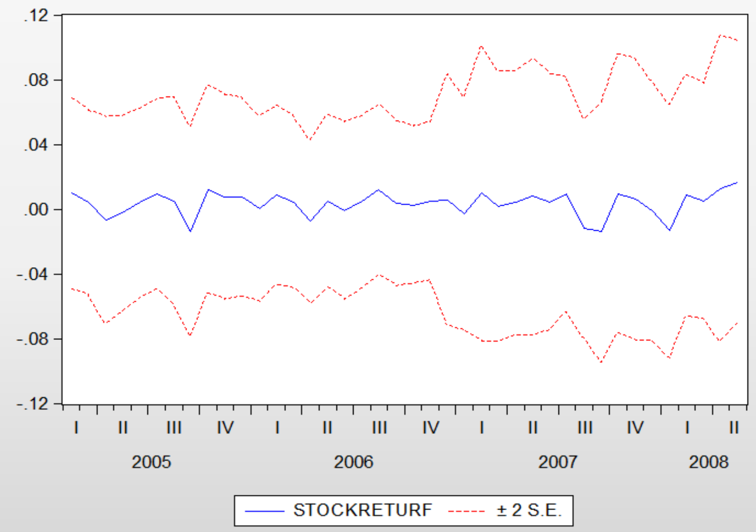
Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 03/12/20 Time: 17:08
Sample: 2005M02 2019M04
Included observations: 171
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001283	0.081565	-0.015730	0.9875
GPR(-1)/SD45	6.32E-05	0.007307	0.008646	0.9931
D(GPR)/SD45	-0.000105	0.007201	-0.014534	0.9884
RESID(-1)	0.102450	0.078713	1.301564	0.1949
RESID(-2)	0.030393	0.078647	0.386456	0.6997
RESID(-3)	0.068836	0.081144	0.848321	0.3975
RESID(-4)	-0.084525	0.078704	-1.073962	0.2844
RESID(-5)	0.150892	0.078629	1.919045	0.0567
RESID(-6)	-0.023421	0.079263	-0.295480	0.7680

R-squared	0.041351	Mean dependent var	1.39E-16
Adjusted R-squared	-0.005990	S.D. dependent var	1.059534
S.E. of regression	1.062703	Akaike info criterion	3.010703
Sum squared resid	182.9525	Schwarz criterion	3.176054
Log likelihood	-248.4151	Hannan-Quinn criter.	3.077796
F-statistic	0.873471	Durbin-Watson stat	1.997156
Prob(F-statistic)	0.540212		

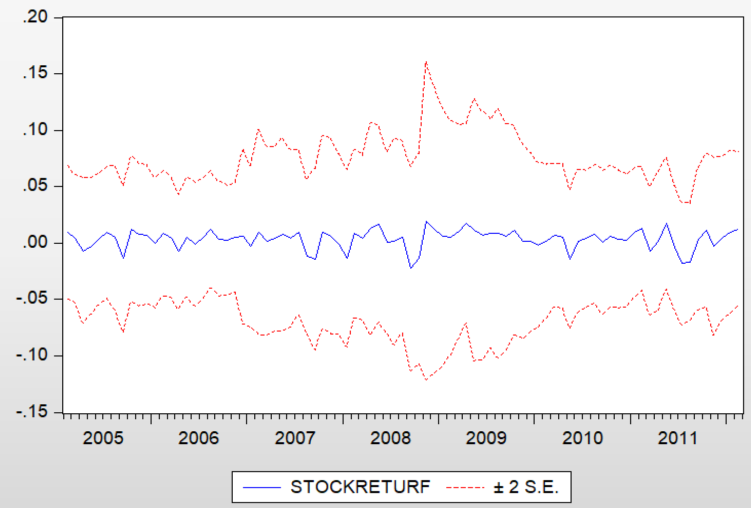
Appendix 4.5: Out-of-sample Test

4.5.1 EPU and Stock Return (Forecasting period: 25%)



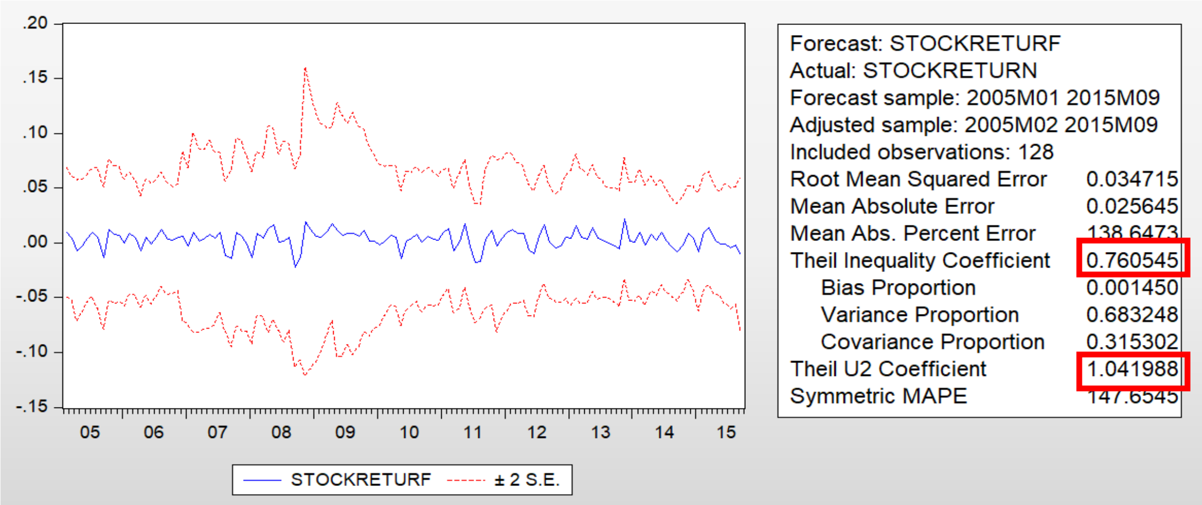
Forecast: STOCKRETURF	
Actual: STOCKRETURN	
Forecast sample: 2005M01 2008M05	
Adjusted sample: 2005M02 2008M05	
Included observations: 40	
Root Mean Squared Error	0.036347
Mean Absolute Error	0.028470
Mean Abs. Percent Error	116.8567
Theil Inequality Coefficient	0.811033
Bias Proportion	0.019085
Variance Proportion	0.607838
Covariance Proportion	0.373076
Theil U2 Coefficient	1.062990
Symmetric MAPE	151.0231

4.5.2 EPU and Stock Return (Forecasting period: 50%)

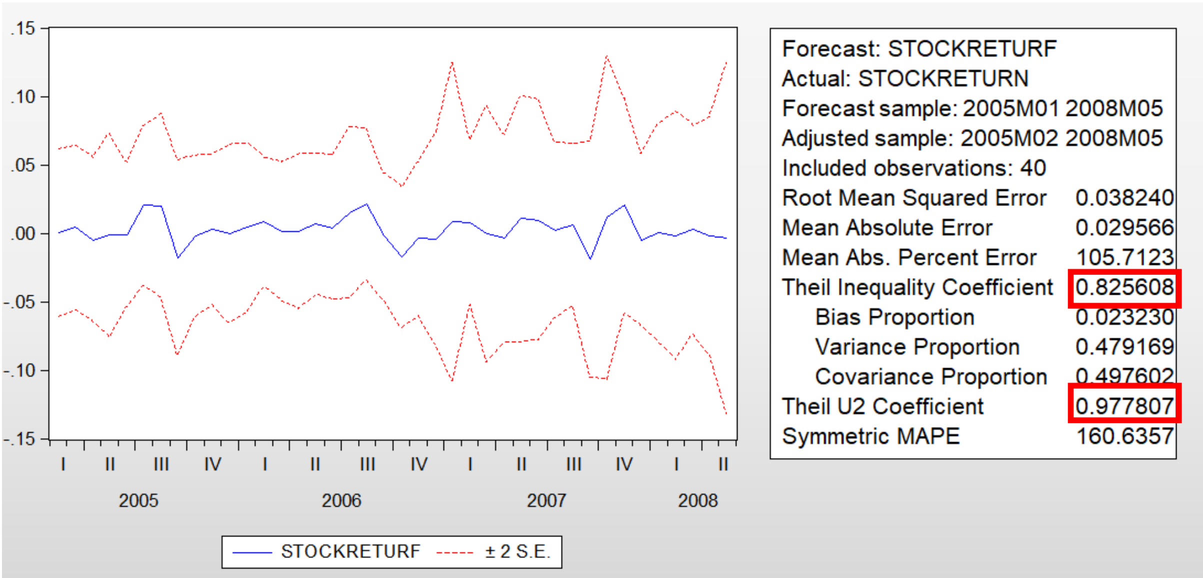


Forecast: STOCKRETURF	
Actual: STOCKRETURN	
Forecast sample: 2005M01 2012M02	
Adjusted sample: 2005M02 2012M02	
Included observations: 85	
Root Mean Squared Error	0.039405
Mean Absolute Error	0.029380
Mean Abs. Percent Error	140.7027
Theil Inequality Coefficient	0.765549
Bias Proportion	0.005697
Variance Proportion	0.728026
Covariance Proportion	0.266277
Theil U2 Coefficient	1.058695
Symmetric MAPE	146.8230

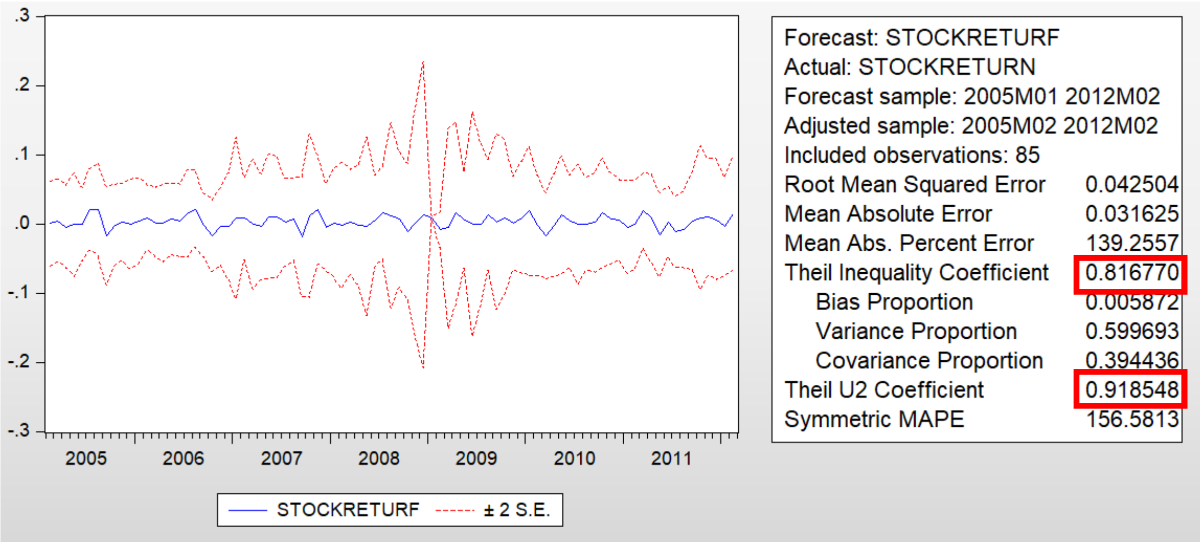
4.5.3 EPU and Stock Return (Forecasting period: 75%)



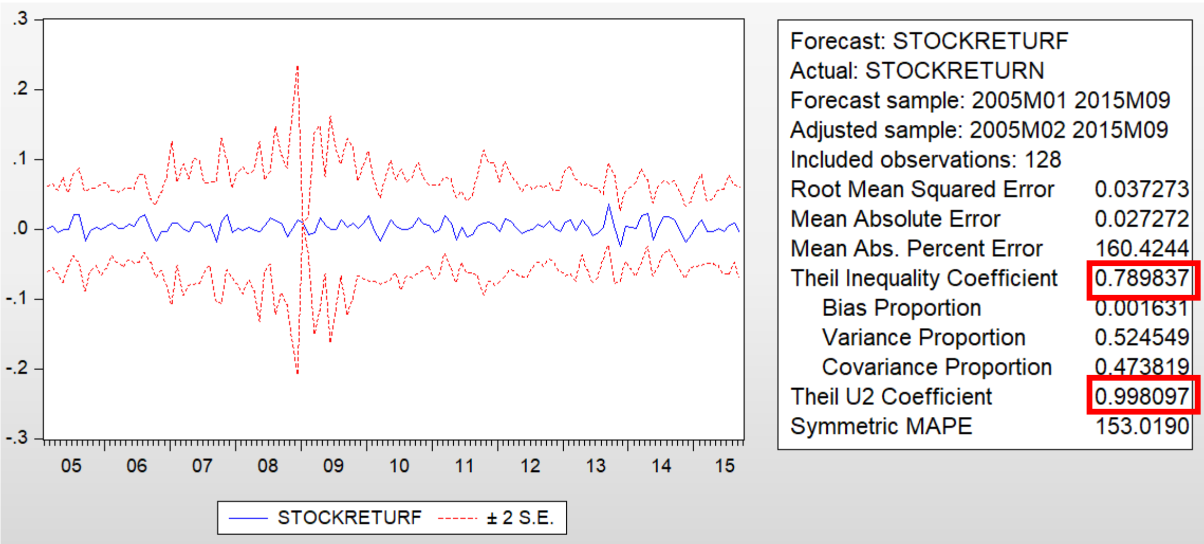
4.5.4 GPR and Stock Return (Forecasting period: 25%)



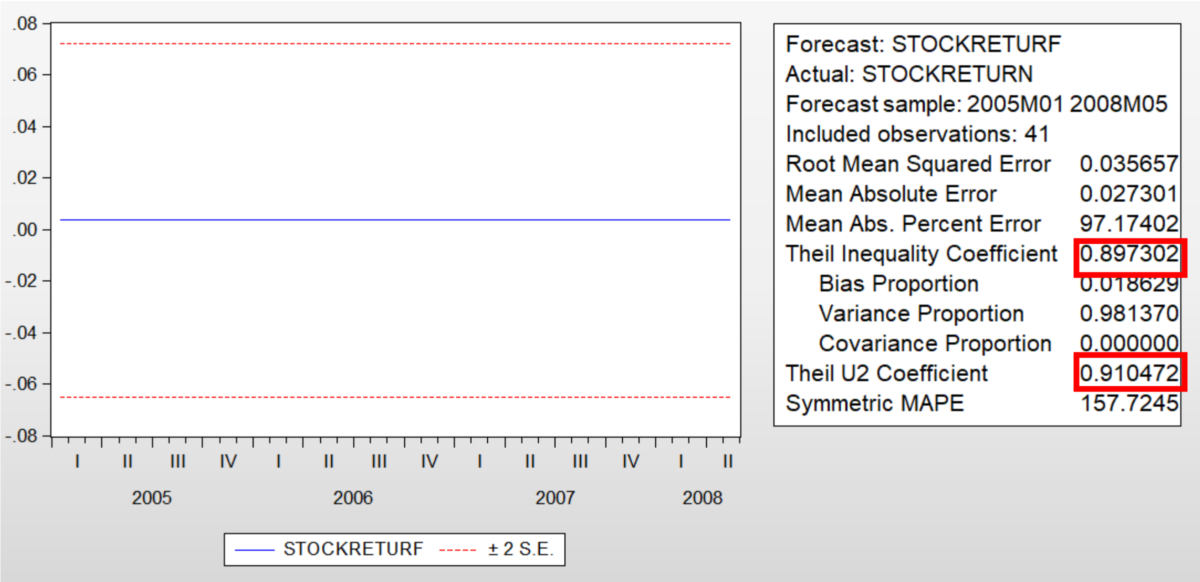
4.5.5 GPR and Stock Return (Forecasting period: 50%)



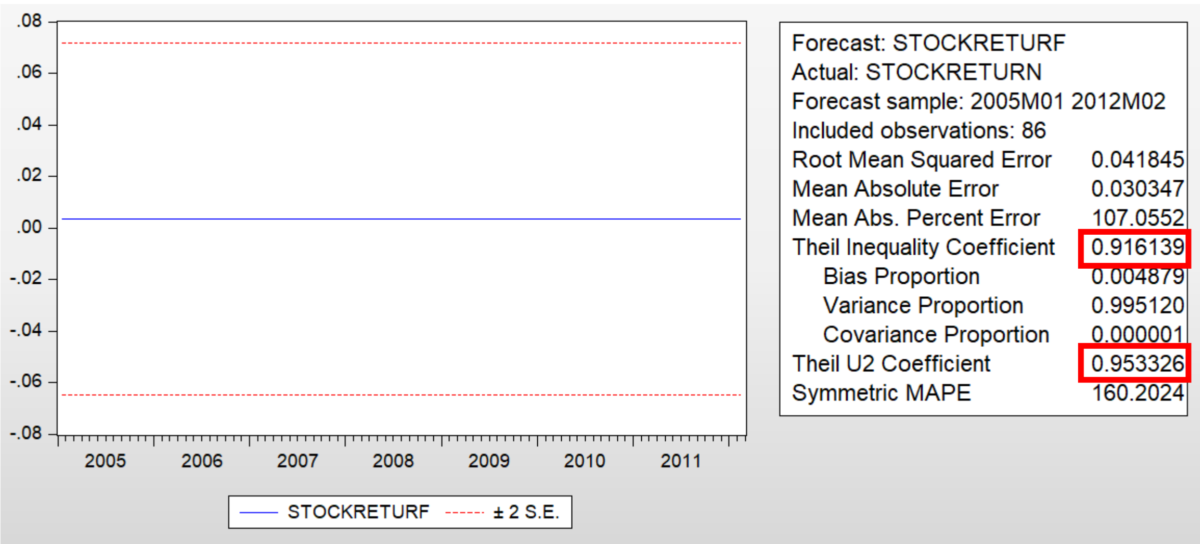
4.5.6 GPR and Stock Return (Forecasting period: 75%)



4.5.7 Benchmark model (Forecasting period: 25%)



4.5.8 Benchmark model (Forecasting period: 50%)



4.5.9 Benchmark model (Forecasting period: 75%)