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30 June 2017

Online at <https://mpra.ub.uni-muenchen.de/101229/>
MPRA Paper No. 101229, posted 28 Jun 2020 12:55 UTC

Stock returns and macroeconomic factors in an emerging economy: Malaysian evidence

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Abstract

This paper investigates the relationship between stock returns and macroeconomic variables in an emerging economy. Malaysia is taken as a case study. The evidence based on variance decompositions tends to indicate that interest rate is relatively most exogenous followed by stock returns, while consumer price index has been most endogenous. The findings reveal that all other endogenous variables are highly affected by stock returns. Impulse Response Functions to one standard deviation shock to the equation for Stock Returns and Exchange rate received significant responses from other variables. However, none of the variables reacted to a shock on oil price. The results have strong policy implications.

Keywords: Interest rate, Inflation, Oil price, Industrial production, Stock returns, Money supply, Exchange rate.

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1. INTRODUCTION

It has been argued that certain macroeconomic variables have significant relation to stock returns. Portfolio holders' expectations about future values of macroeconomic variables can influence the stock prices and macroeconomic variables become risk factors in their portfolio substitution. Thus, a rational understanding of stock volatility is very important for investors, regulators as well as academic researchers.

Financial theories suggest that the returns of stocks are determined by systematic risk and unsystematic risk. Unsystematic risk is assumed to be diversifiable by constructing a portfolio of assets. Ross, Westerfield, Jordan (2006), stated that the unsystematic risk is essentially eliminated by diversification, so a portfolio with many assets has almost no unsystematic risk. However systematic risk is said to be non-diversifiable due to the fact that the risks are bound to all of the stocks in the market.

Therefore, it is crucial for investors to know about the systematic risk factors that influence the stock prices. Finance literature suggest the macroeconomic variables as systematic risk factors.

The objective of this study is to conduct an empirical analysis in order to identify the relation between macroeconomic factors and the stock market returns. The variables used in this study are; Industrial production, Money supply (M2), Interest rate, Inflation, Global crude oil price and Exchange rate, Kuala Lumpur Composite Index (KLCI).

In order to conduct our study, we examine whether there is any relation obviously seen in the variables and treat KLCI as the target dependent variable. These variables are believed to be relevant, based on the hypothesis and verifications from other studies as well.

The main significance of this study is the technique used which is the time series technique. The study covers the very recent time period, which includes monthly data from January 1997.

This study could also contribute to the finance literature on the relationship between macroeconomic variables and stock returns in other emerging markets like Indonesia and Thailand. Although there have been many studies conducted on this area for many emerging markets, no such study has been conducted using recent data as in this study,

The rest of this paper is organized as follows. Section 2 reviews the related literature. Section 3 explains the data and methodology Section 4 analysis and findings. The concluding remarks and recommendations are revealed in Section 5.

2. LITERATURE REVIEW

Several studies have been conducted to examine the relationship between macroeconomic variables and stock returns.

Yilmaz (2008) studied the role of seven macroeconomic factors in Turkish stock markets. He observed a significant relationship between stock prices and exchange rate, interest rate, as well as world equity index. However industrial production, money supply, oil price and inflation do not appear to affect the Turkish stock returns.

Chen, Roll and Ross (1986), observed a set of economic variables as systematic risks on the U.S stock market returns and examined their influence on asset pricing. They found that consumption and oil prices are not significant to predict stock returns, while industrial production, changes in risk premium and twists in the yield curve are found to be significant. Chen (1991) conducted a second study on U.S. market and found that default spread, term spread, one-month T-bill rate, industrial production growth rate, Dividend - Price ratio are significant predictors of stock returns. Bulmash and Trivoli (1991) found that stock prices are predicted by various lagged economic variables such as money supply and interest rate in the U.S economy. Flannery & Protopapadakis (2002) reevaluated the effect of some macroeconomic variables on U.S stock returns. They found employment, consumer price index, money supply (M1), and producer price index as predictor of stock returns. However, they have surprisingly found that the two popular measures of aggregate economic activity, namely real GNP and industrial production do not appear to be related to stock returns.

Clare and Thomas (1994) investigated the effect of 18 macroeconomic factors on U.K stock market. They found that oil prices, retail price index, bank lending and corporate default risk to be important risk factors. Cheng (1995) examined the relationships between security returns and economic indicators in the U.K stock market and found a positive relationship between stock price and money supply, government securities price index and unemployment.

Mukherjee and Naka (1995) investigated whether co-integration exists between the Tokyo Stock Exchange index and six macroeconomic variables, namely the exchange rate, money supply, inflation, industrial production, long-term government bond rate, and call money rate. They found that there is a co-integration and a relationship between stock prices and the variables.

Apergis and Eleftheriou (2002) investigated the relationship between stock prices, inflation and interest rates in Athens Stock Exchange (ASE) and found that inflation is significant while interest rate does not have a close relationship between the two. Dritsaki and Dritsaki (2004) found a significant relationship between stock prices and macroeconomic variables such as industrial production, inflation and interest rates in Greece.

Ibrahim & Aziz (2003) examined the relationship between Malaysian equity market and macroeconomic variables by employing four macroeconomic factors namely; industrial production, money supply (M2), consumer price index, and exchange rate. They found that stock prices are not affected by industrial production and consumer price index in a long-run. However, stock prices have negative relationship with money supply and Ringgit exchange rate. Islam (2003) studied the Kuala Lumpur Stock Exchange and found a significant relationship between interest rate, inflation, exchange rate and industrial productivity to the stock returns.

Islam and Watanapalachaikul (2003) observed a strong, significant long-run relationship between stock prices and macroeconomic factors such as interest rate, bonds price, foreign exchange rate, Price-Earning ratio, market capitalization, and consumer price index in Thailand.

Kwon, Shin, and Bacon (1997) studied the Korean stock market and found that exchange rates, trade balance, money supply, production index are sensitive to stock returns.

Bailey and Chung (1996) examined the relationship between macroeconomic variables and equity market of Philippines and found that financial fluctuations, exchange rate movements and political changes on owners of Philippine equities, cannot explain Philippine stock returns.

Mookerjee & Yu (1997) investigated the effect of macroeconomic factors on Singapore stock market. They found that stock prices are co-integrated with M1 and M2 as well as aggregate

Foreign Exchange Reserves. However exchange rates do not have a long-term relationship with stock prices.

While using real oil price, total personal consumption, money supply (M1) and GNP as macroeconomic factors, Cheung and Ng (1998) examined the situation of number of countries consist of Canada, Germany, Italy, Japan and U.S. They found a long-run relationship between the selected variables and stock returns.

Wongbangpo and Sharma (2002) examine the role of GNP, the consumer price index, the money supply, the interest rate, and the exchange rate on the stock prices in Indonesia, Malaysia, the Philippines, Singapore and Thailand and found causal relationships from the macroeconomic variables to stock prices. They observe that the stock prices are negatively related to inflation. Interest rate is negatively related with stock prices in the Philippines, Singapore and Thailand, but positively related with stock prices in Indonesia and Malaysia. The exchange rate variable is positively related to stock prices in Indonesia, Malaysia and the Philippines, but negatively in Singapore and Thailand.

Al-Khazali (2003) investigated short and long-term relationship between stock prices, inflation and industrial production for 21 emerging markets. He found a negative relationship between real stock return and inflation in the short-term except Malaysia. In the long run, the relationship was found to be positive.

Basher and Sadorsky (2006) examined the impact of oil price changes on the stock market returns of 21 emerging economies and found a strong evidence of the effect of oil prices being positively significant to stock market returns for most of the countries studied.

3. DATA AND METHODOLOGY

3.1 Data Description

The data used in this study are monthly starting from January 1997. All macroeconomic data were extracted from Data Stream. All variables were tested for unit root in log form and log differenced form.

KLCI represents the return on stock in Malaysia and is used as the target dependent variable whereas the macroeconomic variables are considered to be independent variables. The selected independent variables are; INP as the growth rate of industrial production index, MS as the amount of money supply (M2), OIL as the change in global crude oil price, INT as the change in short-term deposit rate, EXR as the Malaysian currency's exchange rate per U.S Dollar and CPI as the change in consumer price index or inflation.

3.2 Cointegration Test

At first, all variables were tested for stationary in log form and log differenced form. The unit root test was done using the commonly used Augmented Dickey Fuller (ADF) tests. A variable in a time series is said to be stationary if the distribution of the time series variable does not change over time. Stationarity implies that the future is like the past and is a reliable guide to the future.

Two noble laureates, Engle and Granger pioneered the cointegration technique and made significant contribution to testing Granger-causality. Two variables are said to be cointegrated if they share common trend and exhibits long run equilibrium. This means that the variables are not drifting away from each other arbitrarily. In the long run if a variable deviates, it will cause some other variable to adjust in order to come back to the long run path. The cointegration test states the long run relationship of the variables and indicates that the variables have an economic explanation and is not a spurious relationship.

Before proceeding further, we need to find the order of the VAR in order to find if the model is well specified. Order of VAR was decided based on two criteria, namely Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

However, the direction of the granger causality cannot be determined through cointegration and requires vector error correction model and variance decomposition analysis.

3.3 Long-Run Structural Modeling (LRSM)

Once we determine the number of lags and the cointegration relationships are found, we can proceed to Long- Run structural modeling to estimate the theoretical long run relationship among the variables.

3.4 Vector Error Correction Modeling (VECM)

The assumption in Vector Error Correction Model is that all variables are endogenous in the long run. Hence if the test shows that the coefficient is significant, it indicates that the corresponding variable is “endogenous”. And if the coefficient is insignificant, it means the corresponding variable is “exogenous”. By looking at the size of the coefficient of the error correction term, we will be able to identify the spread of a short term adjustment to bring about long term equilibrium and represents the proportion by which the disequilibrium in the dependent variable is being corrected in each short period.

3.5 Variance Decompositions (VDCs)

Variance Decomposition (VDC) tests the level of endogeneity and exogeneity by decomposing the variance of the forecast errors of a variable into proportions attributable to shocks in every variable including its own. The variable that is being explained mostly by its own past is deemed to be most exogenous compared to other variables. On the other hand, the variable that has most of decomposed proportions in other variables is said to be most endogenous.

3.6 Impulse Response Functions (IRFs)

Impulse response function shows the outcome in Variance Decomposition in graphical form. IRF maps out the dynamic response of one variable owing to one period standard deviation shock to another variable.

3.7 Persistence Profiles (PFs)

Persistence Profiles (PFs) maps out the dynamic response of the cointegrating vectors in the long run. The Persistent Profile shows the effects of a system wide shock on the long run relationship between the variables. The test reveals how many periods it takes for the equation to come back to equilibrium when there is a system wide shock.

4. Analysis and Findings

Step 1: Testing the non-stationarity/stationarity of each variable

All variables listed in the table below, was changed to log form and log differenced form. ADF test was run on the log form of the variables (LKLCI, LINP, LMS, LOIL, LINT, LEXR, LCPI) and on log differenced form (DKLCI, DINP, DMS, DOIL, DINT, DEXR, DCPI). Stationarity and non-stationarity of the variables are shown in the adjacent columns of the table 1.

Variable	Description	Stationarity	
		Log	Differenced Form
KLCI	Kuala Lumpur Composite Index	Non stationary	Stationary
INP	Industrial Production	Non stationary	Stationary
MS	Money Supply	Non stationary	Stationary
OIL	Global Crude Oil	Non stationary	Stationary
INT	Interest Rate	Non stationary	Stationary

EXR	Exchange Rate	Stationary	Stationary
CPI	Consumer Price Index	Non Stationary	Stationary

Unit root test shows that all variables in log form is non stationary except exchange rate but all variables in differenced form is stationary.

Step 2: Determination of the order (or lags) of the VAR model

Once the stationarity is tested, we need to determine the order of the VAR model. Based on the results, the order or lags of the VAR is 1, which has the highest SBC value of 1641.7. Formula used in Microfit in unrestricted multivariate VAR is as follows:

DKLCI DINP DMS DINT DEXR DCPI & C DOIL

Therefore, at this stage we choose VAR(1) model as our lag order model.

Step 3: Testing cointegration

Next is to determine the number of value of cointegrating relationships that exist in the model. The results in appendix 3 shows the results using multivariate cointegrating VAR, with unrestricted intercepts and restricted trends, and using a VAR of 2. Based on 'eigen values' and the 'trace statistics' the value of number of cointegration relationships (r) is less than or equal to 3 (Statistic of 27.0759 is less than 95% critical value of 31.7900).

Cointegration LR test based on Trace of the Stochastic Matrix, r is less than or equal to 4 since we rejected the alternative hypothesis of $r > 5$. (Statistic of 42.0525 which is less than the 95% critical value of 42.34). The Co-integration relations using Model Selection criteria shows that maximized LL prefers $r = 7$, AIC prefers $r = 7$, SBC prefers $r = 1$ and HQC prefers $r = 7$. Since the results based on different methods differ, we assume that there is at least one cointegration vector meaning $r=1$.

Step 4: Long Run Structural Modeling (LRSM)

Next step is to test the long run structural modeling to estimate the theoretically meaningful long-run relationships by imposing exact identifying and over-identifying restrictions based on theories. The following exact identifying restriction is imposed

$A=1$

Based on the results, at this stage the co-integration equation or linear combination can be defined as follows:

Vector 1 (Order of VAR=1, r=1)

$$\begin{aligned} &LKLCI_t + 2.630 LINP_t + 7.682 LMS_t - 1.425 LOIL_t - 1.204 LINT_t - 0.830 LEXR_t - 14.086 LCPI_t \sim I(0) \\ &\quad (2.315) \quad (5.450) \quad (0.965) \quad (0.857) \quad (1.858) \quad (9.208) \end{aligned}$$

where values in parentheses are standard errors.

Calculated t-ratios (by dividing coefficients of each variable by standard error) showed that none of the t-ratio is greater than 2. Therefore, order of VAR is increased to 2 and the equation can be written down as follows.

Vector 1 (Order of VAR=2, r=1)

$$\begin{aligned} &LKLCI_t + 0.039 LINP_t + 0.434 LMS_t - 0.343 LOIL_t - 0.357 LINT_t - 0.995 LEXR_t - 4.122 LCPI_t \sim I(0) \\ &\quad (0.814) \quad (1.132) \quad (0.343) \quad (0.263) \quad (1.344) \quad (2.964) \end{aligned}$$

where values in parenthesis are standard errors.

However, none of the t-values of the coefficients are greater than 2 making it insignificant. So we increased the order of the VAR to 3 and the equation at this stage can be written down as follows.

Vector 1 (Order of VAR=3, r=1)

$$\begin{aligned} &LKLCI_t - 0.282 LINP_t - 0.014 LMS_t - 0.214 LOIL_t - 0.355 LINT_t - 1.867 LEXR_t - 3.847 LCPI_t \sim I(0) \\ &\quad (0.471) \quad (0.635) \quad (0.202) \quad (0.179) \quad (1.114) \quad (1.7517) \end{aligned}$$

where values in parenthesis are standard errors.

Results showed that the calculated t value for LCPI is 2.1962 (greater than 2) and LINT is 1.9847 (close to 2), making the variables significant. T-value for LINP (0.5992), LMS (0.0213), LOIL (1.0622), LEXR(1.6766) is less than 2, therefore is not significant.

Based on the above conclusion, we further over identify the restrictions making value of A2=0 (INP), A3=0 (LMS), A4=0 (LOIL) A6=0 (LEXR). The over restriction parameters are

Order of VAR=3, r=1

A1=1; A2=0; A3=0; A4=0; A6=0

And the co-integration equation or linear combination equation with the over identifying restrictions at this stage can be as follows:

Vector 1

$$LKLCI_t - 0.230 LINT_t - 2.769 LCPI_t \sim I(0)$$

(0.080) (0.301)

where values in parenthesis are standard errors.

Step 5: Vector Error Correction Model (VECM)

As the 5th step, we test which variables are endogenous and which variables are exogenous. If the error correction coefficient stated as ECM(-1) is significant, it implies that the corresponding dependent variable is endogenous meaning that the variable depends on other variables. If the coefficient is insignificant, then the variable is said to be exogenous. The following table summarizes the results.

Variable	Description (Log)	Result
LKLCI	Kuala Lumpur Composite Index	Exogenous
LINP	Industrial Production	Endogenous
LMS	Money Supply	Endogenous
LOIL	Global Crude Oil	Exogenous

LINT	Interest Rate	Endogenous
LEXR	Exchange Rate	Exogenous
LCPI	Consumer Price Index	Endogenous

Step 6: Variance Decompositions (VDCs)

The sixth step in time series is the Variance Decomposition. This step involves the partition of the variance of the forecast errors into proportions attributable to shocks in each variable in the model equation which also includes the variable itself. The relative endogeneity and exogeneity can be determined from the table below. The first table shows Orthogonalized Variance Decomposition taking a horizon of 15 with the values normalized.

Orthogonalized (Normalized)		Taking Horizon =15						
Horizon	LKLCI	LINP	LMS	LOIL	LINT	LEXR	LINF	TOTAL
LKLCI	70.70%	17.01%	2.11%	0.26%	3.85%	1.47%	4.60%	100.00%
LINP	62.07%	14.26%	4.30%	0.51%	3.51%	3.17%	12.17%	100.00%
LMS	61.56%	7.23%	4.14%	0.52%	1.70%	6.60%	18.26%	100.00%
LOIL	22.64%	1.92%	1.44%	62.93%	2.88%	0.32%	7.86%	100.00%
LINT	5.91%	1.32%	2.94%	0.31%	84.95%	2.74%	1.84%	100.00%
LEXR	69.41%	0.65%	1.06%	1.83%	0.83%	24.77%	1.44%	100.00%
LINF	59.57%	25.01%	3.90%	0.40%	2.88%	3.02%	5.22%	100.00%

Variable LINT is significantly exogenous as around 85% of the decomposition comes from its past. LKLCI also shows that 70.7% of decomposition comes from its own past which indicates the relative exogeneity. Variable LOIL is also relatively exogenous as 62% of the decomposition comes from its past. Variable LMS and LINF are most endogenous as most of the decomposition comes from other variables. LKLCI affects LINF by 59.6%, and also effects LMS (61.6%), LEXR (69.4%), LINP (61.6%) and LMS(61.6%).

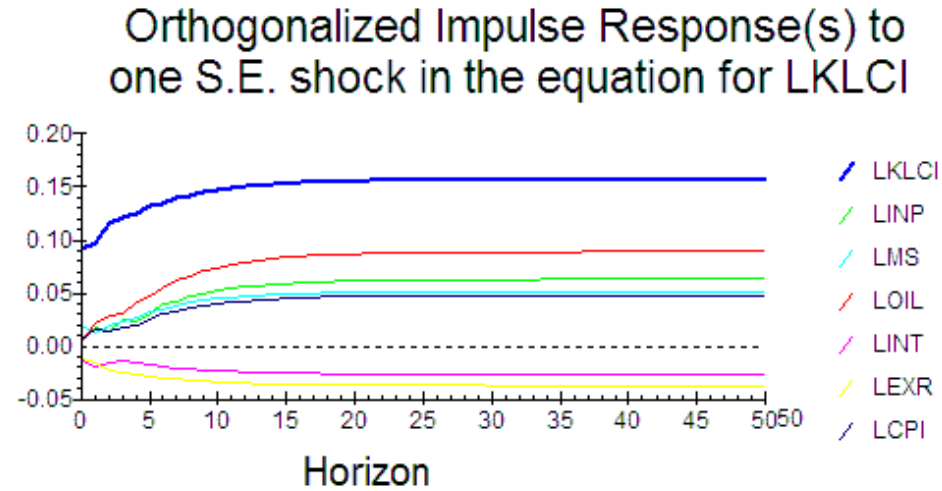
Generalized (Normalized)		Taking Horizon =15						
Horizon	LKLCI	LINP	LMS	LOIL	LINT	LEXR	LINF	TOTAL
LKLCI	71.55%	0.10%	11.28%	0.32%	12.28%	4.18%	0.29%	100.00%
LINP	49.96%	16.12%	11.55%	2.98%	10.80%	4.97%	3.62%	100.00%
LMS	55.86%	0.75%	24.80%	0.64%	12.81%	0.68%	4.46%	100.00%
LOIL	20.75%	3.05%	3.33%	59.79%	8.44%	4.11%	0.53%	100.00%
LINT	5.07%	1.81%	6.86%	0.70%	79.71%	3.64%	2.20%	100.00%
LEXR	40.02%	1.49%	9.58%	0.51%	3.55%	34.07%	10.78%	100.00%
LINF	62.37%	1.86%	15.72%	0.36%	10.33%	4.43%	4.93%	100.00%

Looking at the generalized Variance Decomposition, LINT is most exogenous as around 78% of decomposition comes from its past followed by KLCI which has around 71.5% decomposition coming from its past. LINF is the most endogenous as only around 5% comes from its past. Results show that KLCI affects LINF by 62%, and also effects LMS (55.9%), LEXR (40%), LINP (50%) and LOIL (20.7%). This shows that changes in KLCI affects many of the variables included in this model which contradicts with our initial assumption of KLCI being the target variable.

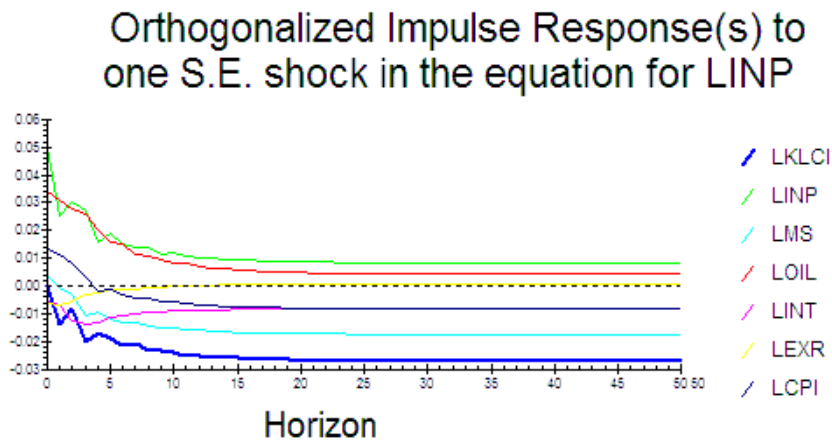
It is assumed in orthogonalized VDCs that when a variable is shocked, all other variables in the system are switched off however in the generalized VDCs no such restrictive assumptions are made. Hence, we expect to see significant differences in the two tables.

Step 7: Impulse Response Functions(IRFs)

IRFs maps out the dynamic response path of a variable owing to a one-period standard deviation shock to another variable. In the following graphs, IRFs are normalized such that zero represents the steady-state value of the response variable.

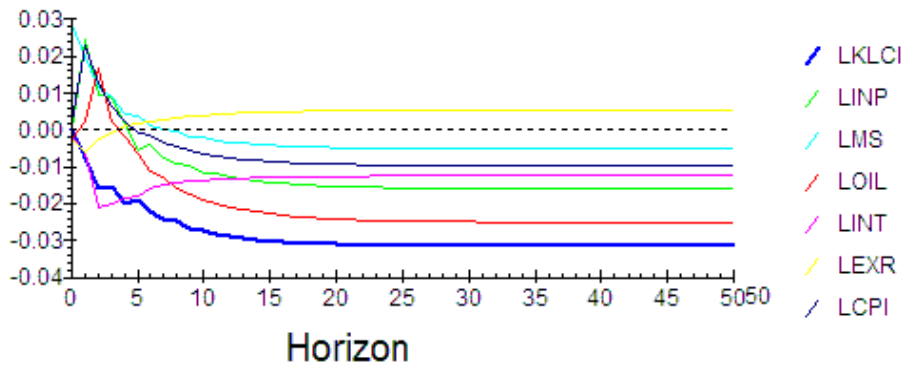


The above graph shows the orthogonalized impulse response to one standard error in the equation for LKLCI. It shows that variable LOIL, LINP, LCPI and LMS responded quite substantially showing the variables are highly correlated to KLCI. LEXR and LCPI responded negatively.



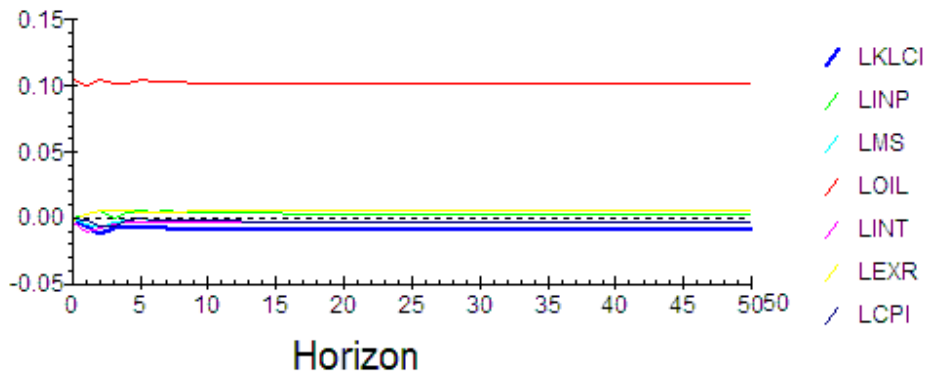
The above graph shows the orthogonalized impulse response to one standard error in the equation for LINP. It shows that all variables reacted negatively.

Orthogonalized Impulse Response(s) to one S.E. shock in the equation for LMS



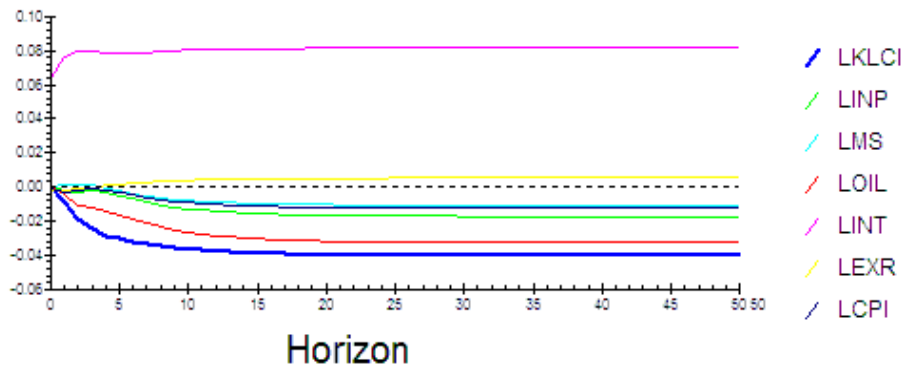
The above graph shows the orthogonalized impulse response to one standard error in the equation for LMS. It shows that LEXR reacted positively while the rest of the variables reacted negatively.

Orthogonalized Impulse Response(s) to one S.E. shock in the equation for LOIL



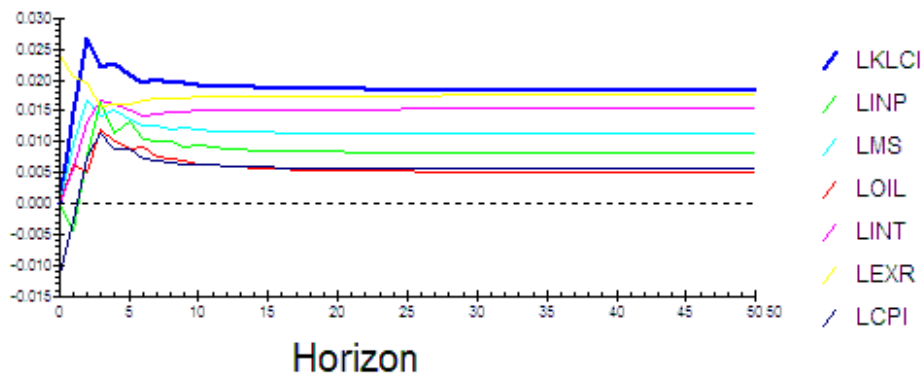
The above graph shows the orthogonalized impulse response to one standard error in the equation for LOIL. It shows that none of the variables reacted to the shock in LOIL indicating LOIL does not affect any variable to change.

Orthogonalized Impulse Response(s) to one S.E. shock in the equation for LINT



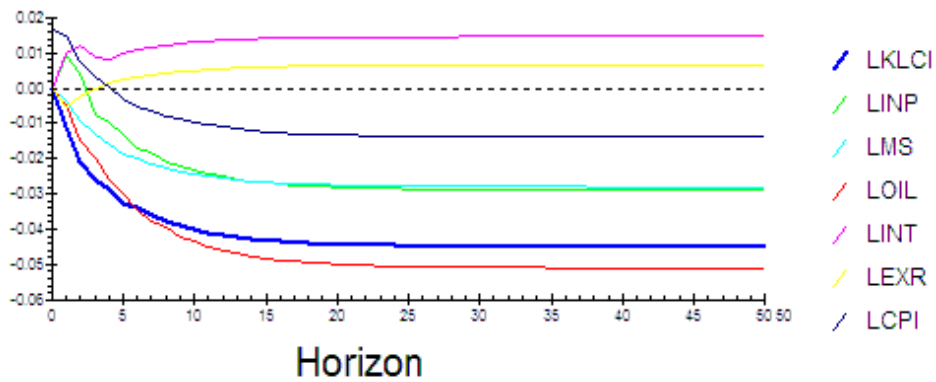
The above graph shows the orthogonalized impulse response to one standard error in the equation for LINT. It shows that all LEXR does not have any effect from the shock while all other variables reacted negatively.

Orthogonalized Impulse Response(s) to one S.E. shock in the equation for LEXR



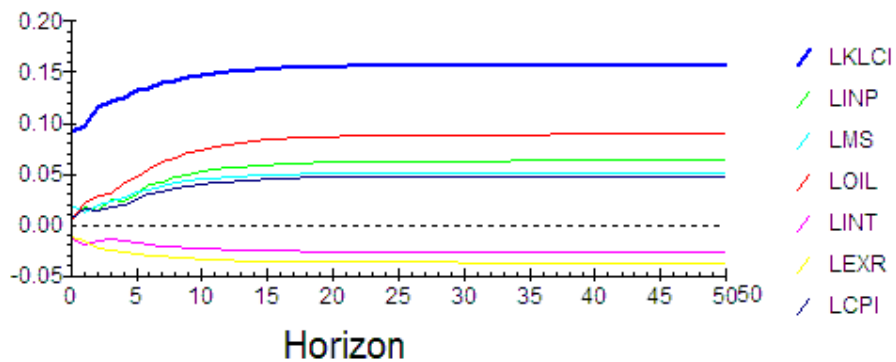
The above graph shows the orthogonalized impulse response to one standard error in the equation for LEXR. It shows that all variables react significantly to the shock suggesting that LEXR has a major impact on all the variables.

Orthogonalized Impulse Response(s) to one S.E. shock in the equation for LCPI



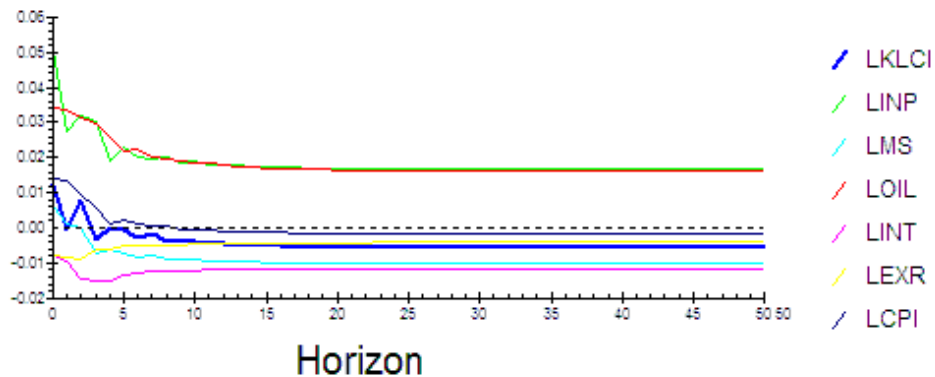
The above graph shows the orthogonalized impulse response to one standard error in the equation for LCPI. It shows that LEXR and LINT reacted somewhat positive while rest of the variables responded negatively.

Generalized Impulse Response(s) to one S.E. shock in the equation for LKLCI



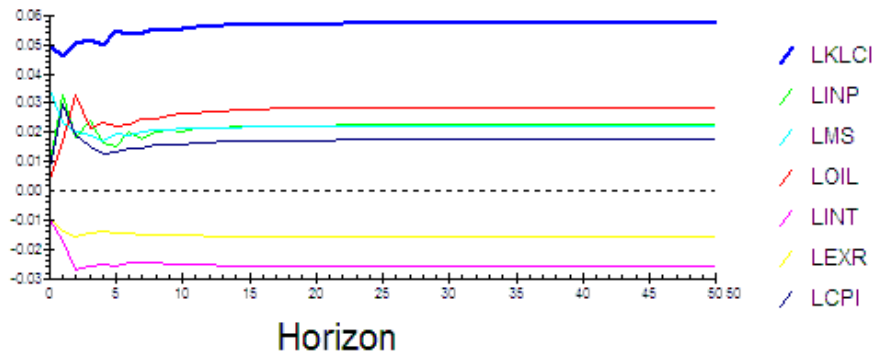
The above graph shows the generalized impulse response to one standard error in the equation for LKLCI. It shows that LOIL, LINP, LMS, and LCPI react positively while LEXR and LINT reacted negatively to the shock.

Generalized Impulse Response(s) to one S.E. shock in the equation for LINP



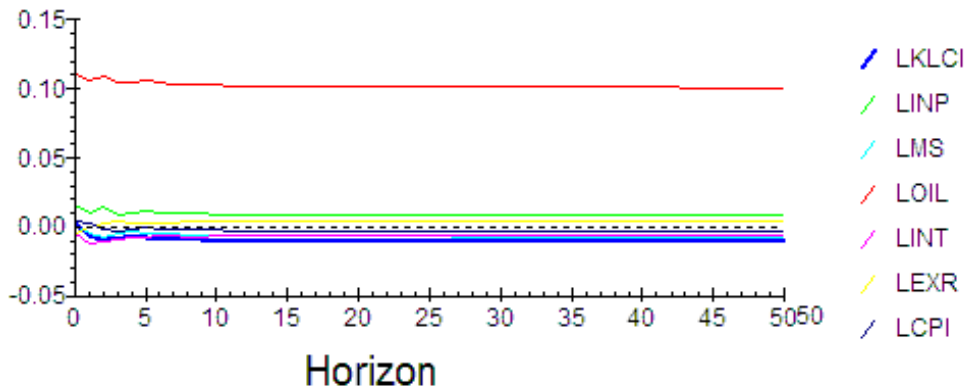
The above graph shows the generalized impulse response to one standard error in the equation for LINP. It shows that all variables react negatively to the shock except for LEXR and LINT, which had not much effect from the shock.

Generalized Impulse Response(s) to one S.E. shock in the equation for LMS



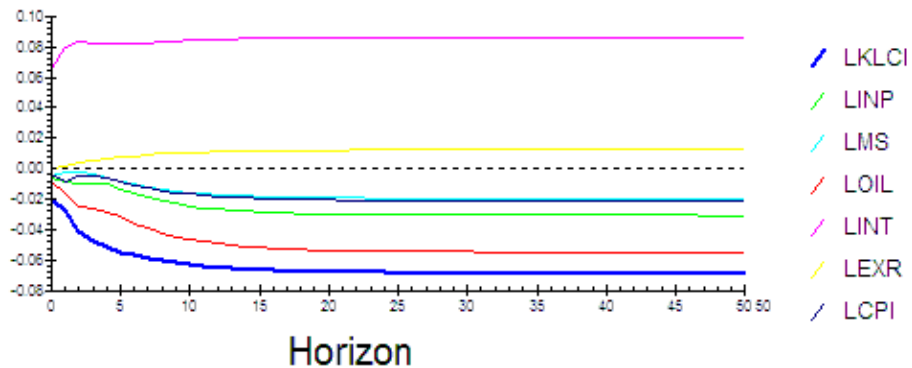
The above graph shows the generalized impulse response to one standard error in the equation for LMS. It shows that LOIL, LINP, LCPI and LKLCI reacted significantly while LINT and LEXR reacted negatively..

Generalized Impulse Response(s) to one S.E. shock in the equation for LOIL



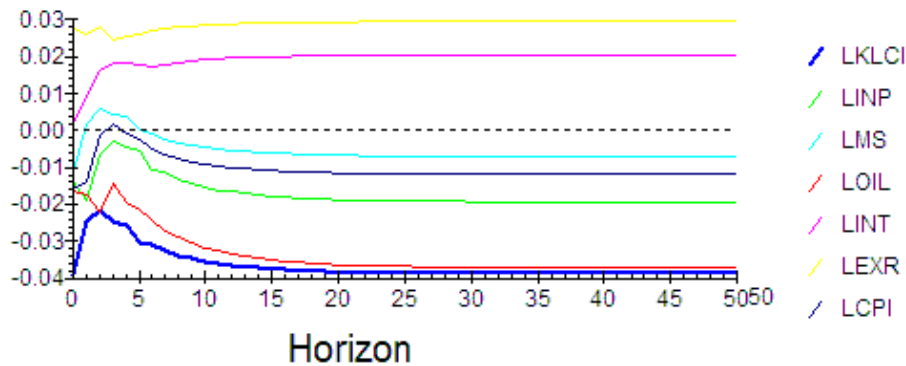
The above graph shows the generalized impulse response to one standard error in the equation for LOIL. It shows that none of the variables reacted to the shock in LOIL indicating LOIL does not affect any variable to change.

Generalized Impulse Response(s) to one S.E. shock in the equation for LINT



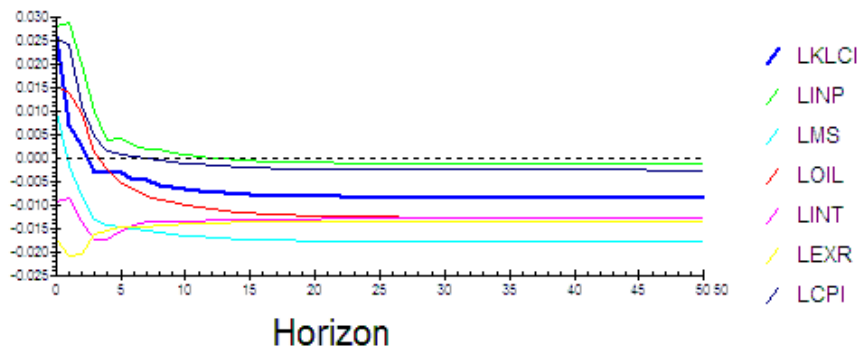
The above graph shows the generalized impulse response to one standard error in the equation for LINT. It shows that LEXR responded slightly while LMS, LCPI, LINP, LOIM and LKLCl reacted negatively..

Generalized Impulse Response(s) to one S.E. shock in the equation for LEXR



The above graph shows the generalized impulse response to one standard error in the equation for LEXR. It shows that LINT reacted very significantly but LMS, LCPI, LINP, LOIL and LKLCI responded negatively.

Generalized Impulse Response(s) to one S.E. shock in the equation for LCPI



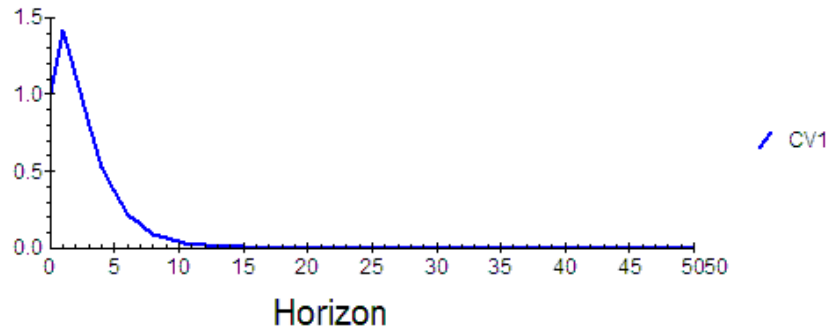
The above graph shows the generalized impulse response to one standard error in the equation for LCPI. It shows that all variables responded negatively.

Step 8: Persistence Profiles (PF)

The Persistent Profile trace out the effects of a system wide shock on the long run relations among the variables and how long it takes to return back to equilibrium. From the graph below

it shows that once the whole system equation is being shocked, it takes roughly 13 periods to return back to equilibrium.

Persistence Profile of the effect of a system-wide shock to CV'(s)



5. Conclusion

The purpose of this study is to examine the relationship between stock returns and macroeconomic variables in the Malaysian economy. The cointegration results indicate that there is at least one cointegrating equation indicating a long run relationship among the variables. From the equation derived from LRSM, only interest rate (LINT) and consumer price index (LCPI) show a significant long run relationship to stock returns which is in line with the study by Islam (2003) Islam and Watanapalachaikul (2003). Interest rate shows a negative relationship with the target dependent variable KLCI This confirms with the economic theory that when interest rates rises, funds are moved to fixed income instruments and stock prices are expected to fall. The same relationship is found in Mukherjee and Naka (1995), Dritsaki & Dritsaki (2004) and, Islam (2003). Inflation measured by consumer price index also had a negative relationship with stock returns which is also the relationship found in Wongbangpo and Sharma (2002).

Vector error correction model (VECM) suggests that Stock Returns (LKLCI), Oil price (LOIL) and Exchange rate (LEXR) are exogenous while Industrial Production (LINP), Money Supply (LMS), Interest Rate (LINT) and Consumer Price Index (LCPI) are endogenous. Further looking at the relative endogeneity and exogeneity, Variance Decomposition VDCs shows that interest rate (LINT) is most exogenous while consumer price index has been most endogenous. It also reveals that all endogenous variables are highly affected by stock returns (KLCI). Impulse Response Function to one standard error shock in the equation for Stock Return (LKLCI) and Exchange rate (LEXR) received significant responses from other variables. However, none of the variables reacted to a shock on Oil price (LOIL).

Although at 5% level of significance, stock returns are shown to be exogenous; with a 10 % level of significance the variable is considered endogenous. It also shows that interest rates are most exogenous even though stock returns are mostly affected by its own past. On the other hand, other economic variables are expected to change when there is a change in stock returns. This

opposite causal effect could be the reason why many previous studies has a different conclusion for Malaysia compared to other countries under study.

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