Causality between Stock Market Index and Macroeconomic Variables: A Case Study for Malaysia

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A Case Study for Malaysia

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***Abstract**:*

The causal relations and dynamic interactions among macroeconomic variables and stock market index are important in the formulation of a country's macroeconomic policy. In this study, to investigate the lead-lag relationship between stock market index and macroeconomic variables, we employ several conventional time-series techniques and a recently introduced method – wavelet analysis - to economics and finance. The data used in this paper is the monthly data of the selected macroeconomic variables such as (1) Kuala Lumpur Composite Index, (2) exchange rate, (3) inflation, (4) government bond yield, (5) short-term interest rate and (6) export over the period of January 1996 to September 2013. Our findings tend to suggest that a cointegrating relationship does exist between KLCI and selected macroeconomic variables. The results of the error correction model, the generalized variance decompositions as well as the wavelet cross-correlation analysis suggest that the short-term interest rate, KLCI and government bond yields are exogenous variables; especially, the short-term interest rate is the most leading variable. Policy makers may concentrate on the adjustment and control of the short-term interest rate in order to achieve the desired results for the target economic variables.

Key Words: Stock Market, Causality, Macroeconomic variables, Time-series techniques, Wavelet Analysis

1. Introduction

An efficient capital market hypothesis (EMH) insists that security prices adjust accordingly to new market information and the current prices of securities reflect all information about the security including publicly available information. Investors are assumed to be unable to utilize available information to predict stock price movement in order to make profit through shares trading (Malkiel and Fama 1970). According to EMH, policy makers should feel free to adjust or introduce new national macroeconomic policies without the fear of influencing capital market and the stock market. It also suggests that stock market should reflect expectations about future performance of public listed companies, thereby, the stock market should be utilized as leading indicators of future economic activities, and not the other way around. Therefore, the direction of macroeconomic policy are depending on the causal relations and vigorous interactions among macroeconomic variables and stock market index.

EMH also suggests that all relevant information in the market are fully reflected in current stock prices due to stiff competition among companies. Therefore, no investor will be able to earn abnormal returns through prediction of the future stock market movements (Chong and Goh 2003). Since investment advisors would be unable to assist investors to earn profit greater than the market according to EMH, there should be no advisory business if one were to agree with the conclusions of EMH (Maysami, Lee et al. 2005).

Many contradiction evidence against EMH that has been found in the past 30 years which indicate that macroeconomic variables help to predict stock returns. Among the research which is contradicting with EMH conclusion are Miller, Jeffrey et al. (1976), Nelson (1976) and Fama and Schwert (1977) whose affirming that macroeconomic variables influence stock returns (Miller, Jeffrey et al. 1976; Nelson 1976; Fama and Schwert 1977).

Granger (1986) and Johansen and Juselius (1990) introduced cointegration analysis as a way to determine the existence of long-term equilibrium among selected variables. This cointegration analysis is the preferred approach to examine the relationship between economic variables with stock markets. A set of time-series variables are cointegrated if they are integrated of the same order and a linear combination of them are stationary. The linear combinations would point to the existence of a long-term relationship between the variables. An advantage of cointegration analysis is that through building an error-correction model (ECM), the dynamic co-movement among variables and the adjustment process toward long-term equilibrium can be examined. (Granger 1986; Johansen and Juselius 1990).

There has been a growing literature showing strong influence of macroeconomic variables and stock markets by using cointegration analysis and ECM methodology, especially for developed countries (Hondroyiannis and Papapetrou 2001; Lu, Metin IV et al. 2001). Researchers have turn their attention to examine similar relationships in developing countries, particularly countries in the growth engines of Asia such as Korea and Japan (Maysami and Koh 2000; Maysami and Sim 2001). However, the study on Malaysia is limited. We would like to give small contribution to the academic literature by performing our study on Malaysian macroeconomic variables and Kuala Lumpur Composite Index (KLCI).

Therefore, the objectives of this paper were to evaluate does the stock market led to economic growth in Malaysia case or vice versa by testing with Johansen's vector error correction model (VECM) test. Additionally, we are going to employ wavelet techniques to check robustness of our results. This paper will explore (a) does the stock market "Johansen-cause" the real economy, in which past values of stock prices able to improve the prediction of future economic growths? (b) Does the real economy "Johansen-cause" the stock market, in the sense that the lagged values of economic activities advances the prediction of the stock market?

By applying Johansen's (1990) VECM and wavelet techniques, our study examines the short and long-term equilibrium relationships between (1) Kuala Lumpur Composite Index, (2) exchange rate of MYRUSD, (3) inflation (represented by Consumer Price Index – CPI), (4) government bond yield, (5) short-term interest rate and (6) export. The paper begins with a brief introduction to the literature and establishes the theoretical and empirical justification for modeling the stock market composite index with macroeconomic variables. We applied Johansen's (1990) vector error correction model (VECM), variance decompositions, long-run structural modeling (LRSM) and as well as wavelet analysis. The advantage of LRSM is that it has improve a major limitation of the conventional cointegrating estimates by imposing exactly identifying and overidentifying restrictions on the cointegrating vector (Masih, Al-Elg et al. 2009).

2. Literature Review

Research on growth engine of Asian countries have been done by several researchers such as Mukherjee and Naka (1995), and Maysami and Koh (2000). Mukherjee and Naka (1995) apply Johansen's VECM to analyze the relationship between the Japanese Stock Market and exchange rate, inflation, money supply, real economic activity, long-term government bond rate and call money rate. They concluded that a cointegration relation existed and stock prices play a role in this relation

(Mukherjee and Naka 1995). Meanwhile Maysami and Koh (2000) examined similar relationships in Singapore and they find that inflation, money supply growth, changes in short and long-term interest rate and variations in exchange rate formed a cointegration relation with changes in Singapore's stock market (Maysami and Koh 2000).

Similar study by Bhattacharya and Mukherjee (2003) whom investigate the nature of the causal relationship between stock prices and macroeconomic aggregates in the foreign sector in India. They test the causal relationship between the Bombay Stock Exchange (BSE) Sensitive Index and the three macroeconomic variables, which are exchange rate, foreign exchange reserves and value of trade balance. They find that there is no causal linkage between stock prices and the three variables under investigation due to the financial sector in India has remained dominated by the banking sector and stock market in India is still in a transitory phase (Bhattacharya and Mukherjee 2003).

Study on causality of Malaysia stock index with macroeconomic variable has been done by Azman-Saini, Habibullah et al. (2006), Har, Ee et al. (2008) and Asmy, Rohilina et al. (2009). Azman-Saini, Habibullah et al. (2006) in their study through Granger non-causality method find that Malaysia stock prices are led by the exchange rate during the crisis period. Malaysian Ringgit depreciated against US dollar during the crisis and it significantly influences the Malaysian stock prices (Azman-Saini, Habibullah et al. 2006). Har, Ee et al (2008) investigate causal relationships between Malaysia stock market and the economy using formal tests of causality developed by C.J. Granger on yearly Malaysia data for the period of 1977 until 2006. Results show that stock market Granger caused economic activity with no reverse causality observed (Har, Ee et al. 2008). Asmy, Rohilina et al. (2009) studies the effects of macroeconomic variables on stock prices for Malaysia in the pre-crisis (1987 – 1995) and post crisis period (1999 – 2007). The macroeconomic variables in their studies are inflation, money supply and exchange rate. The findings indicate that these variables share a long-run relationship in both periods, indicating that deviations in the short-run stock prices will be adjusted towards the long-run value. The long-run equilibrium indicates that there is a positive relationship between inflation rate (CPI) and stock prices (Asmy, Rohilina et al. 2009).

Even though lead-lag relationships have been analyzed between many financial markets in previous studies, the analysis should distinguish between the short and long-run investor (see, for example, Candelon et al., 2008, Gallegati, 2008). From a portfolio diversification perspective, the first type of investor is generally more interested in knowing the co-movement of stock returns at higher frequencies, that is, short-run fluctuations, while the latter concentrates on the relationship at lower frequencies, that is, long-run fluctuations. Hence, one has to rely on frequency domain analysis to achieve insights about the co-movement at the frequency level (see, for example, A'Hearn and Woitek, 2001 and Pakko, 2004). One should remember that, notwithstanding its recognized interest, analysis of the frequency domain is much less found in financial empirical literature (see, for example, Rua & Nunes, 2009).

3. Econometrics Concepts and Methodology

Firstly, we want to apply the standard cointegration, vector error correction and variance decomposition techniques to address the issue of this paper. Then, we are going to employ wavelet analysis to check the robustness of results. The techniques other than wavelet method are well-known time-series techniques in economics and finance (for more details, refer to Masih and Masih (1997, 1999 and 2001). Therefore, we are not going to discuss in detail these conventional techniques. For wavelet analysis, we only describe the fundamental methods which are useful for our research purposes. For a more complete and comprehensive development of the theory and use of wavelets, see Percival and Walden (2000), Gencay et al., (2002) and (Gallegati, 2010).

3.1 Wavelet cross-correlation

According to literature, both Discrete Wavelet Transform (DWT) and Maximal Overlap Discrete Wavelet Transform (MODWT) can decompose the sample variance of a time series on a scale-by-scale basis via its squared wavelet coefficients. However, the MODWT-based estimator has been shown to be superior to the DWT-based estimator (Percival, 1995 and Gallegati, 2008). Therefore, we are going to apply Maximal Overlap Discrete Wavelet Transform (MODWT) in our study.

Whitcher et al. (1999, 2000) extended the notion of wavelet variance for the maximal overlap DWT (MODWT) and introduced the definition of wavelet covariance and wavelet correlation between the two processes, along with their estimators and approximate confidence intervals. To determine the magnitude of the association between two series of observations X and Y on a scale-by-scale basis the notion of wavelet covariance has to be used. Following Gençay et al. (2001) and Gallegati (2008) the wavelet covariance at wavelet scale j may be defined as the covariance between scale j wavelet coefficients of X and Y, that is $\gamma_{XY,j} = \mathrm{Cov}[\tilde{\omega}^{X}_{j,t}\tilde{\omega}^{Y}_{j,t}]$.

An unbiased estimator of the wavelet covariance using maximal overlap discrete wavelet transform (MODWT) may be given by in the following equation after removing all wavelet coefficients affected by boundary conditions (Gallagati, 2008),

$$\tilde{\gamma}_{XY,j} = \frac{1}{\tilde{N}_j} \mathrm{N} - 1 \sum_{t=L_{J-1}}^{N-1} \tilde{\omega}^{X}_{j,t}\tilde{\omega}^{Y}_{j,t}$$

Then, the MODWT estimator of the wavelet cross-correlation coefficients for scale j and lag τ may be achieved by making use of the wavelet cross-covariance, $\tilde{\gamma}_{\tau,XY,j}$, and the square root of their wavelet variances $\tilde{\sigma}_{X,j}$and $\tilde{\sigma}_{Y,j}$ as follows:

$$\tilde{\rho}_{\tau,XY,j} = \frac{\tilde{\gamma}_{\tau,XY,j}}{\tilde{\sigma}_{X,j}\tilde{\sigma}_{Y,j}}$$

The wavelet cross-correlation coefficients $\tilde{\rho}_{\tau,XY,j}$, similar to other usual unconditional cross-correlation coefficients, are between 0 and 1 and offers the lead/lag relationships between the two processes on a scale-by-scale basis.

Starting from spectrum $S_{\omega\,X,j}$ of scale j wavelet coefficients, it is possible to determine the asymptotic variance Vj of the MODWT-based estimator of the wavelet variance (covariance). After that, we construct a random interval which forms a 100(1 − 2p)% confidence interval. The formulas for an approximate 100(1 − 2p)% confidence intervals MODWT estimator robust to non-Gaussianity for $\tilde{\upsilon}^2_{X,j}$ are provided in Gençay et al. (2002) and Gallegati (2008). According to empirical evidence from the wavelet variance, it suggests that Nj = 128 is a large enough number of wavelet coefficients for the large sample theory to be a good approximation (Whitcher et al., 2000 and Gallegati, 2008).

4. Data, Empirical Results and Discussions

4.1 Data

The data used in this paper is the monthly data of the selected macroeconomic variables such as (1) Kuala Lumpur Composite Index, (2) exchange rate of MYRUSD, (3) inflation (represented by Consumer Price Index – CPI), (4) government bond yield, (5) short-term interest rate and (6) export in the period of January 1996 to September 2013. All data obtained from Datastream at INCEIF (International Centre for Education in Islamic Finance).

4.2 Empirical Results and Discussion

We have conducted unit root tests in level and difference form. Results indicate that while all variables contain a deterministic trend, we cannot reject the presence of a unit root for any of the variables. All variables were found non-stationary at the 'level' form but stationary after at the 'differences' form. We also applied Philips-Perron test and found the variables under investigation is non-stationary at level form and stationary at difference form. In the beginning, we also include import variable but it has to be dropped since unit root tests result indicate that import variable is stationary at level form.

We proceed with testing of vector auto regression (VAR) to find the optimal order or the number of lags to be used. The optimal lag structure for each of the VAR models was selected by maximizing the information criteria. In the final analysis, we use a lag of 2. We did not report results here due to space constrain, the full details of tests can be requested from the authors.

The results based on Johansen's (Johansen, 1988; Johansen and Juselius 1990) multivariate cointegration test (Table 1) tend to suggest that these six variables are bound together by long-run equilibrium relationship.

Table 1. Johansen ML results for multiple cointegrating vectors

H_O	H_1	Statistic	95% Crit.	90% Crit.
Maximum Eigenvalue Statistics				
$r = 0$	$r = 1$	82.73	43.61	40.76
$r \leq 1$	$r = 2$	34.74	37.86	35.04
Trace Statistic				
$r = 0$	$r \geq 1$	183.91	115.85	110.60
$r \leq 1$	$r \geq 2$	101.18	87.17	82.88
$r \leq 2$	$r \geq 3$	66.44	63.00	59.16
$r \leq 3$	$r \geq 4$	40.71	42.34	39.34

We applied the standard Johansen cointegration test to find the presence of multiple cointegrating vectors as in Table 1 above. A study by Gonzalo (1994) provides empirical evidence to support the Johansen Procedure's relatively superior performance over other methods for testing the order of cointegration rank. As illustrated in Table 1, we found that the six variables under investigation have one cointegrating vector at 95% significance level on the basis of maximal Eigenvalue and three cointegrating vector under Trace statistics. Beside Johansen cointegration test, we also applied Engle-Granger cointegration test and came into the same conclusion as Johansen test which inform us that there is cointegration for these variables. An evidence of cointegration implies that the relationship is not spurious. i.e. there is a theoretical relationship among the variables and that they are in equilibrium in the long run.

Statistically, the above results indicate that the variables we have chosen result in a stationary error term. In economic interpretation, the six variables are theoretically related and they tend to move together in the long term. However, we tend to believe that there is one cointegrating vector based on intuition as well as previous finding that indicate macroeconomic variables and stock market continues to become increasingly integrated nationally. Based on the above statistical result, we shall assume that there is one cointegrating vector, or relationship.

To sum up, the stock market and the economic variables are cointegrated where their relations to one another is not merely spurious or by chance. This conclusion has an important implication for investors or policy makers. Given that these variables are cointegrated, the opportunity to gain abnormal returns via portfolio diversification is limited. In short term, an investor can improve returns (relative to risk) by diversifying his equity investment. However, in long term, his strategy would not yield that investor consistently abnormal returns. This is because these cointegrated macroeconomic variables and stock market would eventually realign themselves into a long-term relationship with one another.

Table 2. Long Run Structural Modeling

Variable	Coefficient	Standard Error	*t*-ratio	Implication
LMYRUSD	1.9869	0.1877	10.5849	Variable is significant
LKLCI	-	-	-	-
LCPI	-0.0825	1.5444	0.0535	Variable is not significant
LEXPORT	-0.8599	0.2099	4.0962	Variable is significant
LINTEREST	-0.1204	0.0810	1.4868	Variable is not significant
LGBONDY	-0.2677	0.1593	1.6803	Variable is not significant

Next, we try to test the coefficients of this cointegrating vector against the theoretically expected coefficients. By doing this, we are able to compare our statistical findings with the theoretical (or intuitive) expectations. We normalize on our focused variable (index), the KLCI, by relying on the Long Run Structural Modelling (LRSM). Calculating the t-ratios manually, we found two variables to be significant – MYRUSD and EXPORT. The results are presented in Table 2. From the above analysis, we arrive at the following cointegrating equation:

$$\text{KLCI} + 1.9869\text{MYRUSD} - 0.8599\text{EXPORT} \rightarrow I(0)$$

From our findings, we conclude that three variables (KLCI, MYRUSD and export) are cointegrated to a significant degree. However, the cointegration equation will not reveal to us which variable is the leading or lagging variable. Information on the direction of Granger-causation is very useful for investors and policy makers. By knowing which variable is exogenous and endogenous, investors and policy makers can make a better forecasting of their investment or new policy to be taken. Typically, an investor and policy maker would be interested to know which variable is the exogenous variable because they can closely monitor the performance of that variable as it would have significant effect on the expected movement of other variables.

In order to identify the exogenous and endogenous of variables, we use Vector Error Correction Model (VECM) in addition to decomposing the change in each variable. By examining the error correction term, e_{t-1}, for each variable, and checking whether it is significant, we found that there are three exogenous variables, KLCI, short-term interest rate (INTEREST) and government bond yield (GBONDY). The other variables were found to be endogenous as described in the Table 3.

Table 3. Error correction model for six economic variables

Dependent Variable	DMYRUSD	DKLCI	DCPI	DEXPORT	DINTEREST	DGBONDY
DMYRUSD(1)	0.07 (0.06)	0.04 (0.14)	0.00 (0.01)	0.01 (0.14)	0.22 (0.10)	-0.11 (0.09)
DKLCI(1)	0.16 (0.03)	0.14 (0.08)	0.01 (0.00)	-0.18 (0.08)	0.09 (0.05)	-0.02 (0.05)
DCPI(1)	-0.77 (0.63)	1.79 (1.43)	0.24 (0.07)	0.75 (1.48)	0.59 (0.99)	0.76 (0.89)
DEXPORT(1)	-0.04 (0.03)	0.02 (0.06)	0.00 (0.00)	-0.46 (0.06)	0.04 (0.04)	-0.02 (0.04)
DINTEREST(1)	-0.05 (0.04)	-0.25 (0.09)	0.00 (0.00)	-0.01 (0.10)	0.29 (0.07)	0.00 (0.06)
DGBONDY(1)	0.08 (0.05)	-0.15 (0.11)	0.01 (0.01)	0.33 (0.12)	0.05 (0.08)	0.25 (0.07)
ECM(-1)	-0.12 (0.01)	0.00 (0.03)*	-0.00 (0.00)	0.10 (0.03)	0.01 (0.02)*	0.03 (0.02)
Chi-square SC (1)	26.56 (0.01)	36.61 (0.00)	22.12 (0.04)	70.00 (0.00)	23.37 (0.03)	24.71 (0.02)

Chi-square FF (1)	43.35 (0.00)	42897 (0.51)	0.21 (0.65)	2.07 (0.15)	35.74 (0.00)	10.00 (0.00)
Chi-square N (1)	1093 (0.00)	405.1 (0.00)	10672 (0.00)	8.98 (0.01)	4567 (0.00)	396.9 (0.00)
Chi-square Het (1)	129.61 (0.00)	0.13 (0.72)	2.94 (0.09)	5.21 (0.02)	17.21 (0.00)	1.12 (0.29)

Notes: SEs are given in parenthesis. The diagnostics are chi-squared statistics for: serial correlation (SC), functional form (FF), normality (N) and heteroskedasticity (Het). The equations, therefore, are well specified.
* Indicate significance at the 5% level.

The implication of this result is that the variable of interest to investors would be the KLCI, short-term interest rate and government bond yield. These exogenous variables would receive market shocks and transmit the effects of those shocks to other variables. A policy maker in government department or an investor would be interested to monitor movements in the KLCI, interest rate and government bond yield as changes to these variables is likely to affect government policy or investment in a significant way.

Even though we have identified that the KLCI, short-term interest rate and government bond yield are the exogenous variable, we are unable to identify the relative exogeneity of those variable and endogeneity of the remaining variable. We have to apply variance decomposition (VDC) because VECM unable to assist us in this matter. VDC decomposes the variance of forecast error of each variable into proportions attributable to shocks from each variable in the system, including its own. The least endogenous variable and most exogenous variable is thus the variable whose variation is explained mostly by its own past variations.

Table 4: Percentage of forecast variance explained by innovations in: Generalized variance decompositions.

Months		∆MYRUSD	∆KLCI	∆CPI	∆EXPORT	∆INTEREST	∆GBONDY
24	**∆MYRUSD**	22.1%	45.9%	1%	16.8%	7.9%	6%
60		19%	48%	0%	17%	9%	7%
	∆ KLCI						
24		5.2%	82.7%	0.007%	0.0004%	11.1%	0.003%
60		5%	82%	1%	0.00%	11%	0%
	∆CPI						
24		0.4%	0.4%	78.2%	2%	2.9%	16%
60		0%	1%	77%	2%	3%	16%
	∆ EXPORT						
24		10%	6%	2%	74%	3%	6%
60		10%	7%	2%	71%	3%	6%
	∆ INTEREST						
24		2%	1%	3%	1%	93%	0%
60		2%	1%	3%	1%	93%	1%
	∆ GBONDY						
24		0.00%	8%	10%	0%	2%	79%
60		0.00%	9%	10%	0%	2%	78%

We rely on Generalized VDCs, which are invariant to the ordering of variables and more reliable than Orthogonolised VDC to identify the most lead variable and most laggard variable. The Results are presented in Table 4.

We can rank the variable by relative exogeneity, as depicted in the Table 5.

Table 5: Relative exogeneity based on Generalized Variance Decomposition Analysis

No.	**Variable Relative Exogeneity** **At Horizon = 24 & 60**
1	INTEREST
2	KLCI
3	GBONDY
4	CPI
5	EXPORT
6	MYRUSD

From the above results, we can make the following key observations:

- The Generalised VDCs confirm the results of the VECM in that INTEREST, KLCI and GBONDY is the most exogenous variables.
- The relative rank in exogeneity is somewhat stable as time passes. Between 24 months and 60 months, there are no changes in the ranking.
- The difference in exogeneity between the variable is substantial. For example, in the horizon 24 months, 71% separate the most exogenous variable and the least exogenous (or most endogenous) variable.

The above result would have the following plausible implications for policy makers and investors. Among the variables, it appears that short-term interest rate is the most exogenous variable followed by KLCI and government bond yield. It is surprising to see that MYRUSD is the least endogenous variable since it is the variable that has been shocked by the government in 1998 during the financial turmoil.

4.3 Wavelet analysis

We arrive the point that short-term interest rate, KLCI and government bond yield are most exogenous variables. However, we want to observe their relationship in different time scales and to employ wavelet analysis in order to check the robustness of the results.

4.3.1 Wavelet Cross-Correlation Analysis (Lead - lag or Causality analysis)

Simple correlations cannot capture the basic fact that lags often exist between variables, whatever their timescales. In order to grasp the lead-lag relationship between two variables, we have applied wavelet-cross-correlation. In Figures 2, 3 and 4, we report the MODWT-based wavelet cross-correlation between the KLCI, interest rate and government bond yield, with the corresponding approximate confidence intervals, against time leads and lags for all scales, where each scale is associated with a particular time period. The individual cross-correlation functions correspond to – from bottom to top - wavelet scales $\lambda_1, \ldots, \lambda_4$ which are associated with changes of 1-2, 2-4, 4-8, 8-16 months. The red lines bound approximately 95% confidence interval for the wavelet cross-correlation.

If the curve is significant on the right side of the graph, it means that the second time series is leading the first time series; for example, in the case of KLCI – short-term interest rate, if the curve is significant on the right side of the graph, it means that the short-term interest rate is leading the KLCI; If the curve is significant on the left side of the graph, it is the opposite. In other words, the wavelet cross-correlation skewed to the right means the second time series is leading the first time series; skewed to the left, it is the opposite. If both the 95% confidence levels are above the horizontal axes, it is considered as significant positive wavelet cross-correlation; if the both 95% confidence levels are below the horizontal axes, it is considered as significant negative wavelet cross-correlation.

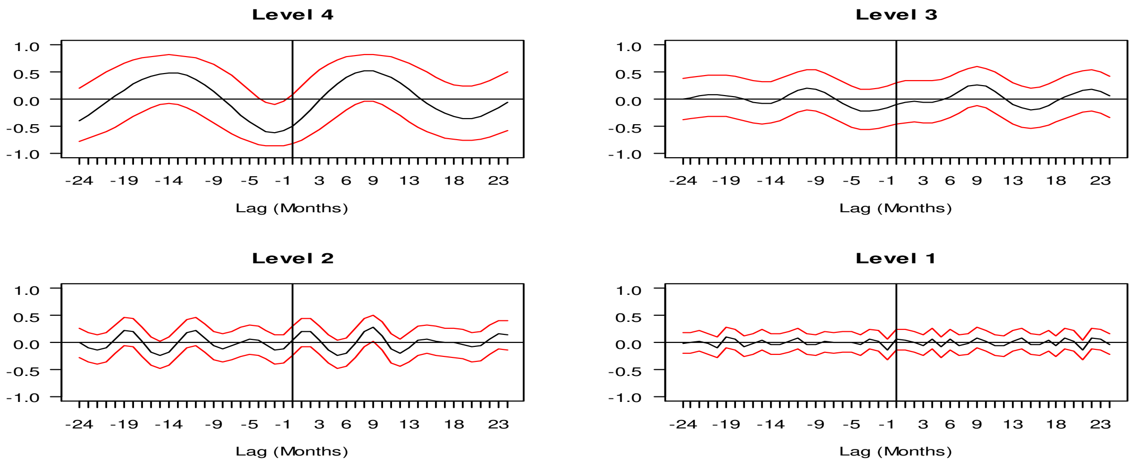

Figure 2: Wavelet cross-correlation between government bond yield and short-term interest rate at first four levels, with 95% confidence interval

Figure 2 presents the wavelet cross-correlations of the government bond yield and short-term interest rate at first four levels. From this figure, we can observe the following:

At the 1, 2 and 3 wavelet levels, we can observe there is no significant lead-lag relationship between government bond yield and interest rate. At the wavelet level 4, the curve skewed to left hand side with negative value. This implies that there is significant negative wavelet cross-correlation between these two variables in the long run (longer than 16 months). Put differently, the government bond yield is leading the short-term interest rate in the long-term with inverse relationship.

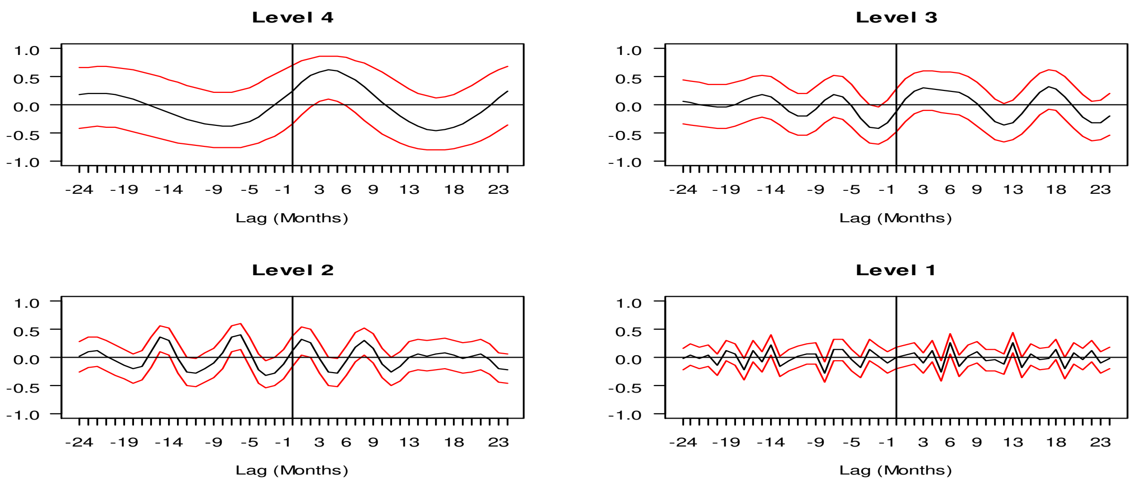

Figure 3: Wavelet cross-correlation between KLCI and short-term interest rate at first four levels, with 95% confidence interval

Figure 3 presents the wavelet cross-correlations of the KLCI and short-term interest rate at first four levels. From this figure, we can observe the following:

At the wavelet level 1 which associated with 1-2 months, there is no clear wavelet cross-correlation between KLCI and short-term interest rate. However, at levels 2 and 4, the curve skewed to right hand side with positive values. In other words, the short-term interest rate is leading the KLCI with positive relationship.

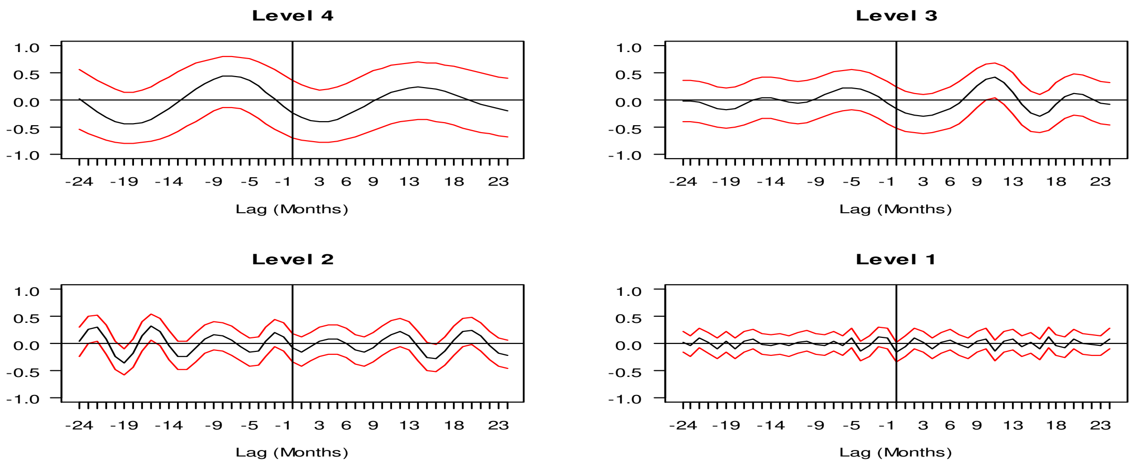

Figure 4: Wavelet cross-correlation between government bond yield and KLCI at first four levels, with 95% confidence interval

Figure 3 presents the wavelet cross-correlations of the government bond yield and the KLCI at first four levels. From this figure, we can observe the following:

At levels 1, 2 and 4 do not display any significant relationship between the government bond yield and the KLCI. However, there is a significant relationship between these two variables at level 3 which associated with 4-8 months with positive value. It means that the KLCI is leading the government bond only at level 3.

Our results are consistent with findings by Har, Ee et al (2008) and Asmy, Rohilina et al. (2009). Har, Ee et al (2008) explored causal relationships between stock market and the economy activity. Results show that stock market Granger caused economic activity with no reverse causality observed. The longest significant lag length observed from the results was two years (Har, Ee et al. 2008). Asmy, Rohilina et al. (2009) studies the effects of macroeconomic variables on stock prices for Malaysia in the pre-crisis (1987 – 1995) and post crisis period (1999 – 2007). The findings indicate that these variables share a long-run relationship in both periods, indicating that deviations in the short-run stock prices will be adjusted towards the long-run value.

We conclude that our findings in this Section are consistent with findings by conventional time-series techniques. Our results may confirm that among these three different variables, the short-term interest rate is the most exogenous variable the government bond yield is the least one. On top of that, we documented some additional findings at different time scales.

5. Concluding Remarks

The focus of this article was an attempt to test the possible directions of causality between stock market index and macroeconomic variables that were labeled by Ross (1976) as Arbitrage

Pricing Theory. We applied the time-series techniques such as the Johansen's VECM and generalized variance decompositions which are an improvement on and an extension to the standard cointegrating techniques. Additionally, we have applied wavelet techniques to check the robustness of our results. We concluded that the cointegration does exist between KLCI and exchange rate, inflation, government bond yields, export and short-term interest rate. The analysis of the error correction model, the generalized variance decompositions and wavelet analysis suggest that the short-term interest rate, KLCI and government bond yields are exogenous variables.

Our findings are in line with the previous researchers such as Mukherjee and Naka (1995), Maysami and Koh (2000), Islam and Watanapalachaikul, Mysami, Howe and Hamzah (2004). The major policy implication of the findings, based on our rigorous econometric analysis, is that a pro-active policy of economic growth through adjusting and controlling the short-term interest rate, KLCI and government bond yields will help enhance economic growth in an open developing country like Malaysia. Through VDC and wavelet technique, we find that the short-term interest rate is the most exogenous variable. Policy makers can concentrate on the adjustment and controlling of short-term interest rate in order to get the desired results on their economic target variables.

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