“The Lead-Lag Pattern of Leading, Coincident and Lagging Indicators in Malaysia”

The Lead-Lag Pattern of Leading, Coincident and Lagging Indicators in Malaysia

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Abstract

This paper attempts to study the structure of the relationships between leading, coincident and lagging indicators of Malaysian economy. The use of cross-autocorrelation between those indicators indicates the usefulness of those indicators in using them for forecasting. The results suggest that the leading indicator leads the coincident indicator by three months and the lagging indicator by about twelve months. The presence of the positive cross-autocorrelation between the leading indicator and excess returns provides another channel for information regarding the future Kuala Lumpur Composite Index (KLCI) movement in the Kuala Lumpur Stock Exchange. It is found that the leading economic indicator leads the market excess return by one month. The relationship is not found subject to Lucas critique, thus usage of this relationship can be applied without much concern regarding the exogeneity of the leading economic indicator.

Key words: Lead-Lag pattern, Leading, coincident and lagging indicators, Kuala Lumpur Composite Index (KLCI), Kuala Lumpur Stock Exchange (KLSE).

1. Introduction

The importance of predicting future economic events is undisputed. From a political standpoint, heading off future weakness may be the difference between staying in office or joining the ranks of the unemployed. In these attempts to anticipate general business conditions, people look for signals about the economy cyclical. Economic indicators are usually used to forecast changing business cycle in an economy as they are descriptive and ex-ante time series data for forecasting economic or business conditions. They are useful for the study of cyclical expansions and contractions in business activities and have been grouped into 3 categories, namely leading, coincident and lagging indicators. The essential feature of the indicators system is the reference cycle, which is used to classify the categories of indicators.

The origins of the current leading indices for the nation go back to the late 1930s. Since the time of Mitchell (1913), economists have constructed leading economic indicators as forecast for economic or business barometer for changing economy. Further, Mitchell and Burns (1946) drew up a list of 71 statistical series that they considered to be reliable indicators of economic recoveries. The list was later extended to include leading indicators of recessions. Lists of coincident and lagging indicators were developed as well. These lists were periodically revised, and over time, the individual indicators were combined to construct composite indices intended to summarize the information on the individual indicators and give an overall assessment of the economy.

Further development of composite indices was based on the notion that there is a set of indicators that reflects the current state of the economy, a set that reflects the future state of the economy, and a set that reflects past economic activity. Once researchers identified and categorized individual cyclical indicators as coincident, leading, or lagging, the next step was to combine at least some of those indicators into single composite indices. Since business cycles are defined as broad-based contractions and expansions, combinations of indicators or composite indices are generally better at tracking the cycles than any single indicator. Then, Moore and Shiskin (1950) had developed the method used to calculate the index based on the standard composite index methodology. They try to answer the questions of, which indicators should be included in each composite index? Should they all be given the same weight in forming the composite index? As an answer to these questions, Moore and Shiskin (1950) developed an explicit scoring system to gauge the value of the individual

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series as indicators of the business cycle. They considered such factors as how large a portion of the economy is reflected in the series, how much the series fluctuates with the cycle, how large and how frequent revisions to the series are, and how promptly the data for the series are available. They used their scores not only to draw up short and long lists of indicators but also to weight the indicators in constructing composite indices.

Stock and Watson (1989) provide a particularly strong challenge to the traditional leading index approach by applying modern time series techniques to the selection and weighting of the leading index components. Their research was convincing, in the first out-of-sample experiment. But, the Stock and Watson Leading Index failed to predict, or even acknowledge, the recession that occurred from July 1990 to March 1991.

However, the record of the traditional leading index has not been perfect, but it has been helpful in predicting recessions. Questions are frequently raised, about how the index is constructed. A major issue is how the weights for the components are determined (Martin, 1990). While the current weights adjust for the volatility of the various components, they do not reflect differences in how broadly the indicators represent the economy or how consistent they have been in leading recessions or recoveries. Also, as their names suggest, the index of leading indicators ought to lead the index of coincident indicators. However, no statistical technique is employed to ensure that the leading index actually "leads" the coincident index (Green and Beckman, 1993).

The composite indices are calculated by using the method developed by Moore and Shiskin (1950), which consists of averaging the month-to-month growth rates of the index components, after standardizing them to the same units, and then cumulating this average growth rate into an index. This index is then adjusted to have (1) the same average absolute percent changes as the cyclical component of industrial production; and (2) the same average trend rate of growth as real GDP.

In this study, we examine the behavior of the Economic Indicators of Malaysia as in Table 1 and the forecasting effectiveness of the leading economic indicators (LEI). The leading indicator can be as an input to a transfer function model of coincident economic indicator (CEI). By definition, the LEI leads the economy and the CEI coincides with the economy. Thus, the LEI should lead CEI. According to Mincer and Zarnowitz (1969) and Granger and Newbold (1977), no change forecast for GDP and random walk with drift models may be a useful benchmark for forecasting. In this paper, we extend our model to include volatility in search for the above relationship. We further looked at the possibility of using the LEI as an indicator for excess return.

Table 1

The components of each Malaysian economic indicators

Coincident indicators	Leading indicators	Lagging indicators
1. Index of industrial production	1. Real M1 money supply	1. Rate for 7-day call money
2. Real gross imports	2. KLSE Industrial Index	2. Real excess lending to private
3. Real manufacturing salaries and wages	3. Real total traded (8 major trading partners)	3. Number of investment projects approved
4. Total manufacturing employment	4. Growth rate of Consumer Price Index for services (inverted)	4. Number of Employees Provident Funds defaulters (inverted)
5. Real manufacturing sales	5. Growth rate for industrial material price index	5. New vehicles registered
6. Real Employees Provident Funds contributions	6. Ratio of price to unit labor cost for manufacturing	6. Trend adjustment factor
7. Trend adjustment factor	7. Approved housing permits	
	8. New companies registered	
	9. Trend adjustment factor	

Source: Malaysian Economic Indicators, Department of Statistics, Malaysia, August 2001.

The graphs of Malaysian economic indicators are plotted in Figures 1 and 2. These are constructed by using the data from the Department of Statistic, Malaysia (2001). The recession, contraction and business cycle are also extracted from the same source.

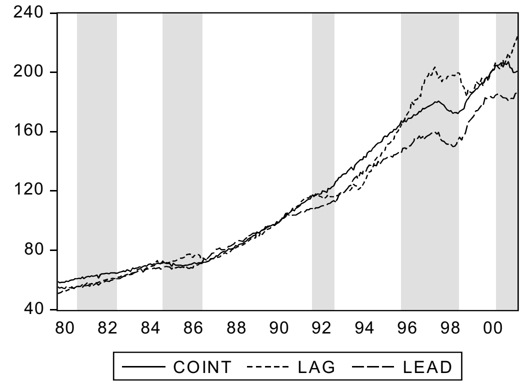

Fig. 1. Six-month smoothed leading, coincident and leading indices

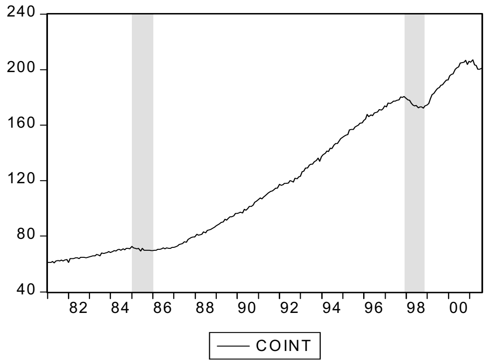

Fig. 2. The coincident index and Malaysian Business cycle turns

2. Theory

In our first step to study the lead-lag relationship or the economic indicators, we use the cross-autocorrelations method. Cross-autocorrelation is nothing new in econometrics, however the decomposition of the autocorrelation can produce important insight regarding the behavior of the time-series data (Campbell, Lo and Mackinlay, 1997). According to them, cross-autocorrelation can be decomposed in cross-autocovariances and own-autocovariances. To see the decomposition, they make assumption below:

$\boldsymbol{R}_t$ is a jointly covariances-stationary stochastic process with expectation $E(\boldsymbol{R}_t) = \boldsymbol{\mu} \equiv [\mu_1 \ \mu_2 \ \ldots\ldots \ \mu_N]'$ and autocovariance matrices $E[(\boldsymbol{R}_{t-k} - \boldsymbol{\mu})(\boldsymbol{R}_t - \boldsymbol{\mu})' = \Gamma(k)$ where, with no loss of generality, we take $k \geq 0$ since $\Gamma(k) = \Gamma'(-k)$.

If $\boldsymbol{\iota}$ is defined as $[1 \ \ldots \ 1]'$, then the equal weighted market index can be expressed as $R_{mt} = \boldsymbol{\iota}'\boldsymbol{R}_t/N$.

Thus, $$Cov[R_{mt-1}, R_{mt}] = \mathrm{Cov}\left[\frac{\iota' R_{t-1}}{\mathrm{N}}, \frac{\iota' R_t}{\mathrm{N}}\right] = \frac{\iota'\Gamma(1)\iota}{\mathrm{N}^2}$$

and $$\frac{Cov[R_{mt-1}, R_{mt}]}{Var[R_{mt}]} = \frac{\iota'\Gamma(1)\iota}{\iota'\Gamma(0)\iota} = \frac{\iota'\Gamma(1)\iota - \mathrm{tr}(\Gamma(1))}{\iota'\Gamma(0)\iota} + \frac{\mathrm{tr}(\Gamma(1))}{\iota'\Gamma(0)\iota}$$

where *tr*(·) is the *trace* operator which sums the diagonal entries of its square-matrix argument. Thus first term of the right-hand side of (1) contains only the cross-autocovariances and second term only the own-autocovariances. If the own-autocovariances are negative then the autocovariance must be positive. Moreover, the cross-autocovariances must be large, so large as to exceed the sum of the negative own-autocovariances.

In identifying the length of the lead-lag effect, we will choose the length where the cross-autocorrelation is largest. Besides using the cross-autocorrelations, we also test the relationship using Granger causality test to statistically test the strength of the cross-autocorrelations and using the GARCH(1,1) model to take volatility into considerations. Long-run relationship is also tested by using the cointegration test. This will further strengthen the hypotheses of lead-lag relationship. A preliminary analysis is done to test the form of exogeneity of exogenous variables. This is done to see if the hypothesized relationship is subject to Lucas critique. We further test for any lead-lag relationship between excess return and leading economic indicator to see for leads in excess return.

3. Data and empirical results

All data were obtained from the Department of Statistics, Malaysia. Data include the Malaysia Leading, Coincident and Lagging Economic Indicators and their growth rates. These are monthly time-series data from 1972:01 to 2001:08. The data are seasonally adjusted and the growth rates are expressed as compound annual rates based on the ratio of the current month's index to the average index during the preceding 12 months.

Our first step in exploring the lead-lag relationship is to use the cross-autocorrelation results in Table 2. We use the growth rates for the 3 economic indicators. The first column in Table 2 shows the cross-autocorrelation between coincident indicator and the respective lag of leading indicator. Thus the figures denote how strong in terms of cross-autocorrelation coefficients, the leading economic indicator (LEI) leads the coincident economic indicator (CEI) for the respective periods. The rest of the column gives similar interpretation. From Table 2, we see that the LEI optimally leads the CEI by 3 months, and it leads the lagging economic indicator by 12 months. Of possible interest is the negative cross-autocorrelation in the third column for the leading effect of lagging indicator for LEI. However in this paper we only concentrate on the LEI and CEI. We also provide the Granger causality test for rate of change of the three indicators and level data. The results are shown in Table 3 and it confirms the findings in Table 2 for the leading effect of LEI at lag 3 on CEI.

We use regression analysis to test the significance of the relationship of LEI(-3) and CEI. All the 3 indicators are found to be nonstationary at level data and only stationary at the first difference. Thus the regression equation below is used:

$$GCEI_t = c_0 + \alpha_0 GLEI_t + \alpha_1 GLEI_{t-1} + \alpha_2 GLEI_{t-2} + \alpha_2 GLEI_{t-3} + \varepsilon_t. \quad (1)$$

Tests for hypotheses of no autocorrelation, no heteroscedasticity and no ARCH effect are carried out. It is found that for equation (1), we reject all the 3 hypotheses. To correct this we run the GARCH(1, 1) model and the result is given in Table 4.

The results in Table 4 show the strong significance of GLEAD(-3) (at 1%). However, GLEAD(-2) is also significant (at 5%). Of interest is the variance equation. In this equation, the GARCH term which can be interpreted as the forecast error is insignificant while the ARCH term which is last period volatility is significant at 5% level with coefficient of 0.513. This can be interpreted as the CEI only make adjustment to the volatility of last month. This may indicate that last periods forecast error is not important, perhaps due to the accuracy of LEI that leads CEI.

To see if the LEI is of any lead for investors, we do similar analysis as previously done for the LEI and CEI. However, we do the analysis for LEI and excess return. Excess return is used here following the work of Chauvet and Potter (2000) where it is used in studying the leading indicators for stock market. They defined excess return as;

$$\text{Excess return} = \log[(P_t + D_t)/P_{t\text{-}1}] - \log(1+R_f),$$

where P is the market index and R_f is the 3-month T-bill.

Table 2

Cross-auto correlation between leading, coincident and lagging indicators

	GCOINT		GLAG		GLEAD		GLAG
GLEAD	0.66108	GCOINT	0.295434	GLAG	-0.046538	GLEAD	-0.046538
GLEAD(-1)	0.669085	GCOINT(-1)	0.326078	GLAG(-1)	-0.122897	GLEAD(-1)	0.001877
GLEAD(-2)	0.706447	GCOINT(-2)	0.374325	GLAG(-2)	-0.171943	GLEAD(-2)	0.065618
GLEAD(-3)	0.716961	GCOINT(-3)	0.419214	GLAG(-3)	-0.229661	GLEAD(-3)	0.136762
GLEAD(-4)	0.700547	GCOINT(-4)	0.448024	GLAG(-4)	-0.265947	GLEAD(-4)	0.20436
GLEAD(-5)	0.68389	GCOINT(-5)	0.474582	GLAG(-5)	-0.295725	GLEAD(-5)	0.281221
GLEAD(-6)	0.643759	GCOINT(-6)	0.502026	GLAG(-6)	-0.343107	GLEAD(-6)	0.350247
GLEAD(-7)	0.585275	GCOINT(-7)	0.516435	GLAG(-7)	-0.367619	GLEAD(-7)	0.419126
GLEAD(-8)	0.529495	GCOINT(-8)	0.535063	GLAG(-8)	-0.397744	GLEAD(-8)	0.47481
GLEAD(-9)	0.490925	GCOINT(-9)	0.542919	GLAG(-9)	-0.401849	GLEAD(-9)	0.519402
GLEAD(-10)	0.412154	GCOINT(-10)	0.541636	GLAG(-10)	-0.434389	GLEAD(-10)	0.560047
GLEAD(-11)	0.358226	GCOINT(-11)	0.535766	GLAG(-11)	-0.431194	GLEAD(-11)	0.580818
GLEAD(-12)	0.293841	GCOINT(-12)	0.547888	GLAG(-12)	-0.437464	GLEAD(-12)	0.604367
						GLEAD(-13)	0.584753
						GLEAD(-14)	0.578416
						GLEAD(-15)	0.55499
						GLEAD(-16)	0.530784
						GLEAD(-17)	0.515677
						GLEAD(-18)	0.478089
						GLEAD(-19)	0.452747
						GLEAD(-20)	0.423256
						GLEAD(-21)	0.40073
						GLEAD(-22)	0.362608
						GLEAD(-23)	0.346948
						GLEAD(-24)	0.309735

Tables 5 and 6 give the Granger causality and the GARCH(1, 1) results for relationship between LEI and excess returns. The results support LEI as leading excess return by 1 month. However at lag 2 months excess returns granger caused LEI. Thus, in our next equation we use equation (2) to test the leading effect of LEI on excess return.

$$\text{EXSRPCt} = c_0 + \alpha_1 \text{GLEI}(-1) + \varepsilon_t. \tag{2}$$

After testing for autocorrelation, heteroscedasticity and ARCH effect, we reject the null hypotheses of no heteroscedasticity and no ARCH effect. Table 6 shows the result for the GARCH(1, 1) model, where the LEI significantly leads the excess return by 1 month at 10% level.

Table 3

Granger causality tests for indicator at lag 3

Null Hypothesis:	Obs	F-Statistic	Probability
GLAG does not Granger Cause GCOINT	231	1.84654	0.13958
GCOINT does not Granger Cause GLAG		2.33883	0.07435
GLEAD does not Granger Cause GCOINT	231	8.59973	2.0E-05
GCOINT does not Granger Cause GLEAD		0.50329	0.68039
GLEAD does not Granger Cause GLAG	231	3.92245	0.00933
GLAG does not Granger Cause GLEAD		2.65591	0.04929
LAG does not Granger Cause COINT	259	3.57460	0.01461
COINT does not Granger Cause LAG		8.47685	2.2E-05
LEAD does not Granger Cause COINT	259	9.26031	7.8E-06
COINT does not Granger Cause LEAD		0.67807	0.56619
LEAD does not Granger Cause LAG	259	9.51127	5.7E-06
LAG does not Granger Cause LEAD		5.03035	0.00211

Table 4

ARCH regression for equation (1)

	Coefficient	Std. Error	z-Statistic	Prob.
GLEAD(-1)	0.069660	0.087980	0.791768	0.4285
GLEAD(-2)	0.225923	0.102707	2.199673	0.0278
GLEAD(-3)	0.276505	0.076400	3.619161	0.0003
C	2.692376	0.331854	8.113132	0.0000
	Variance Equation			
C	2.545476	0.938151	2.713291	0.0067
ARCH(1)	0.513073	0.187567	2.735411	0.0062
GARCH(1)	0.200183	0.224103	0.893261	0.3717
R-squared	0.522097	Mean dependent var		6.179151
Adjusted R-squared	0.510718	S.D. dependent var		4.118924
S.E. of regression	2.881132	Akaike info criterion		4.828232
Sum squared resid	2091.833	Schwarz criterion		4.924362
Log likelihood	-618.2560	F-statistic		45.88394
Durbin-Watson stat	0.491098	Prob(F-statistic)		0.000000

Table 5

Granger causality for LEI and Excess Returns

Null Hypothesis at Lags: 1	Obs	F-Statistic	Probability
EXSRPC does not Granger Cause GLEAD	256	1.02820	0.31155
GLEAD does not Granger Cause EXSRPC		3.02473	0.08322
Null Hypothesis at Lags: 2			
EXSRPC does not Granger Cause GLEAD	255	3.24851	0.04048
GLEAD does not Granger Cause EXSRPC		1.40659	0.24691

At higher lags no more significant.

Following the methodology used by Alogoskoufis and Smith (1991) in testing if an exogenous variable is subject to Lucas critique, we run a 30-month rolling regression on equation (2) and GLEI = c_0 + a_1GLEI(-1) and plot the graph of the rolling coefficients for $GLEI_{t-1}$ in Table 4. From the graph we can see some similarity in the pattern of the coefficient of $GLEI_{t-1}$, thus this can be interpreted as the relationship in equation (2) is not subject to Lucas critique (1976). This would mean that equation (2) can be used without much concern regarding the invariance of the coefficient of $GLEI_{t-1}$.

4. Conclusions

In this paper, we test the lead-lag effect of Malaysian leading, coincident and lagging economic indicators. It is observed that the leading indicator leads the coincident indicator by 3 months and it leads the lagging indicator by 12 months. Further it is shown that, even though the Kuala Lumpur Composite Index (KLCI) is a component of the leading indicator, it still provides important information on the direction the KLCI. This may provide important information to investors as the leading indicator also incorporates other economic variables including money supply, price and industrial index, that may influence the Kuala Lumpur Stock Exchange. Further it is also observed that the leading effect of leading economic indicator for the KLCI is not subject to Lucas critique (1976), thus giving us more confident to use the leading indicators as it is invariant to changes of other variables.

Table 6

GARCH(1, 1) analysis for LEI and Excess Returns

	Coefficient	Std. Error	z-Statistic	Prob.
GLEAD(-1)	0.371412	0.108018	3.438412	0.0006
C	-7.269284	0.627890	-11.57732	0.0000
	Variance Equation			
C	17.35254	6.129484	2.830995	0.0046
ARCH(1)	0.338151	0.093671	3.609963	0.0003
GARCH(1)	0.515094	0.114385	4.503145	0.0000
R-squared	-0.002017	Mean dependent var		-4.522663
Adjusted R-squared	-0.017922	S.D. dependent var		9.905374
S.E. of regression	9.993740	Akaike info criterion		7.197310
Sum squared resid	25168.46	Schwarz criterion		7.266359
Log likelihood	-919.8544	Durbin-Watson stat		2.196886

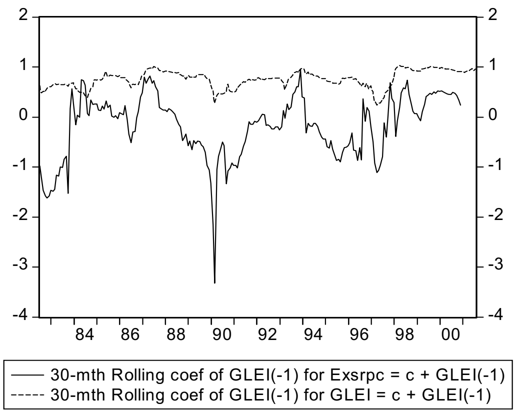

Fig. 3. Rolling coefficient of LEI(-1)

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