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## **MEASURING BUSINESS CYCLE FLUCTUATIONS: AN ALTERNATIVE PRECURSOR TO ECONOMIC CRISES**

***Abstract.** This study constructs a factor-based model of business cycle identification for the Malaysian economy via the dynamic factor approach. Our central focus is to explore a factor-based business cycle indicator (BCI) that can serve as a good gauge for economic crises. The empirical finding is in harmony with the envisaged objective; the constructed BCI produces satisfactory identification of business cycle turning points and statistically outperforms the national-owned composite leading indicator (CLI) in terms of predictive accuracy and forecasting performance. Therefore, we reckon that the constructed BCI can serve to identify the business climate and foretell approaching economic crises in a timely manner.*

***Keywords:** Business cycle indicator, dynamic factor model, turning points, forecasting, Malaysia*

**JEL Classification: C38, C43, C61, E37**

### **Introduction**

Throughout history, getting a good grip on the current and future states of an economy has been a hard core issue for policymakers, investors, businesspeople and even political parties. Despite countries' best endeavours to presage recurring changes or phase shifts across fluctuating business cycles, business cycle identification is typically challenging as the "state of economy" is rather latent and unobservable. Nevertheless, the literature springing from theoretical and methodological developments in the study of business cycles has mounted since the legendary work on indicator construction in the spirit of [Burns and Mitchell](#)

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(1946) was carried out by the National Bureau of Economic Research (NBER). This growing interest manifested the need for an appropriate measure of business cycle forecasting, in which predictive ability can live up to its goal of characterizing the business cycle condition in a forward-looking manner.

Hitherto, measuring the business cycle and dating its turning points encompassed at least three prominent approaches, starting with the primitive non-parametric NBER methodology, followed [Stock and Watson's \(1989, 1991\)](#) methodology on the factor-based model and, more recently, [Hamilton's \(1989\)](#) approach using the Markov-based regime shifting model. Undeniably, each approach upholds its unique potency in what it is built to be, but the appropriateness of each approach in real-time applications rests with empirical discussion. As far as we are concerned, the extensive literature in this domain is well established across economically developed economies such as the US, European countries, and Organisation for Economic Co-operation and Development (OECD) member countries. Vast numbers of studies, for instance, [Bandholz and Funke \(2003\)](#), [Atabek, Coşar and Şahinöz \(2005\)](#), [Carriero and Marcellino \(2007\)](#), [Schirwitz \(2009\)](#), [Wang, et al. \(2009\)](#), [Poměnková \(2010\)](#) and [Caraiani \(2010\)](#), as well as others, have investigated various methodologies of indicator construction and diverse techniques for measuring and dating business cycle turning points and embraced continuous innovation in business cycle analysis.

Even though we believe that best practices diffusing across developed nations is a good reference for emerging economies, further exploration into the emerging society per se could be meaningful in describing the utility of indicator construction in business cycle forecasting for the emerging markets. At this point, we are motivated to construct a model-based business cycle indicator (BCI) for the Malaysian economy - one of the bright spots in the developing Asian countries which is also newly industrialized and rapidly emerging. It is obvious that economic transformations along with greater integration into the global market have significantly internationalized Malaysian businesses and impelled greater liberalization in the financial markets. Since risks are inherent in globalization and global interconnectedness plausibly magnifies risk contagion and external shocks, the prospective Malaysian economy presumably would be more prone to economic crises. In light of this concern, the search for a reliable forecasting tool for business cycle identification is crucial to support macroeconomics monitoring activity and risk management in the country.

Moreover, building a country-specific BCI is essential for country-wide economic policymaking and effective policy implementation. This is because policy lags can induce time lags in policy actions, making the full impact of a policy measure unachievable if the degree of foresight is not sufficient to tackle economic problems with instantaneous and correct timing. In this sense, the original policy

objective to stabilize an economy could result in destabilization, and therefore worsened economic condition. Thus, it makes great sense for a country's policymakers to be warned by some indicators of the current state and future roadmap of the economy.

The present study includes noteworthy aspects that make it unique and novel to the Malaysian economy; the study also contributes to the literature on business cycle analysis in developing economies. At the outset, we address the potential ability of the factor-based indicator to elicit the cyclical movement of the business cycle in a forward-looking manner. To the best of our knowledge, this is the first attempt to build a factor-based indicator for business cycle forecasting in Malaysia. Previous studies with this focus have relied heavily on the classical approach formulated by [Burns and Mitchell \(1946\)](#) while some studies, for instance, [Yap \(2009\)](#) and [Wong et al. \(2013\)](#), merely evaluated the forecasting performance of the publicly available indicator without adding to indicator construction. For the case of Malaysia, an important reference on indicator construction has been credited to [Zhang and Zhuang \(2004\)](#), who applied the sequential probability model (SPM) proposed by [Neftci \(1982\)](#) to construct a leading indicator for business cycle analysis.

Furthermore, the researchers also considered the potential weaknesses of several detrending procedures and opted for the band-pass filter proposed by [Christiano and Fitzgerald \(1999\)](#) for cycle extraction. This is in some way distinct from a handful of past studies that used the phase average trend (PAT) method or [Hodrick and Prescott's \(1997\)](#) filter<sup>1</sup>. Last but not least, we evaluated the forecasting performance of the constructed BCI against the publicly available composite leading indicator (CLI) based on the probability approach proposed by [Greer \(2003\)](#). On the whole, this paper aims to articulate the potential ability of the factor-based BCI to track the movement in business cycles in a well-timed manner and advocates the indicator as a sound gauge of future approaching crises.

The paper is organized as follows. Section 2 discusses the selection of business cycle reference series and the component variables. Then, Section 3 outlines the model specification and indicator construction and offers a discussion on empirical findings. The subsequent section details the robustness analysis and discusses corresponding findings, while the last section concludes.

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<sup>1</sup> Detailed discussion on the potential drawbacks of the Hodrick-Prescott (HP) filter can be obtained from [King and Rebelo \(1993\)](#), [Harvey and Jaeger \(1993\)](#), [Jaeger \(1994\)](#) and [Cogley and Nason \(1995\)](#).

### **Business Cycle and Component Series Selection**

Despite extensive development on business cycle analysis, what constitutes a business cycle remains unsettled. Most studies have used real gross domestic product (GDP) as a measure of the business cycle. To provide a more robust result, in addition to real GDP, we also used the Index of Industrial Production (IIP) to test the possibility of obtaining a better benchmark in measuring the business cycle. We ultimately decided on real GDP as it provides a better approximation of the real economic setting in Malaysia; real GDP provides the best representation that covers a broad range of economic activity and adequately reflects each of the real economic sectors in the country.

For component series selection, we considered macroeconomic and financial series, which by nature comprise leading features of the business cycle. In addition, we also accounted for the economic nature, characteristics and country-specific background of the Malaysian economy. At this stage, some of the well-known guidelines, such as those from the [Conference Board \(2000\)](#) and [OECD \(2001\)](#), served as important references for selecting a desirable and representative component series<sup>2</sup>. Correlation analysis and Granger causality tests were applied to support the selection of the component series. We ultimately decided on six component series that had an adequate correlation to the business cycle and a significant Granger cause for the development of the business cycle throughout the investigated period. The final selected variables included domestic stock prices, US stock prices, money supply, exportation, newly registered company and tourist arrivals. The sample period covered from 1995 through 2012.

All the variables of interest, in monthly basic, were adopted from various issues of the International Financial Statistics (IFS) Yearbook published by the International Monetary Fund (IMF). On the other hand, the CLI was compiled from various issues of Malaysian Economic Indicators published by the Department of Statistics Malaysia (DOSM). Since Malaysia does not maintain GDP series in monthly frequency, we performed an interpolation on the quarterly GDP series based on the technique proposed by [Gandolfo \(1981\)](#) and took the ratio of GDP to consumer price index (CPI) to obtain the monthly GDP in real terms. We then examined the stationary properties of the data series via the augmented Dickey-Fuller (ADF) unit root test developed by [Dickey and Fuller \(1979; 1981\)](#)<sup>3</sup>.

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<sup>2</sup> See, for example, [de Leeuw \(1991\)](#), [Yap \(2001\)](#) and [Jones and Ferris \(1993\)](#) for more economic and statistical criteria on component series selection.

<sup>3</sup> To conserve space, the ADF unit root test result is not presented in the text, but it is available upon request.

### Model Specification and Indicator Construction

Economists believe that development in economic activity occurs in a cycle in which an upswing marks the onset of an expansion phase and growth persists until it reaches the peak where downswing takes off, pointing to the period of contraction. The wave of economic activity, or more precisely the business cycle, is commonly accepted as the movement in GDP. However, the state of the business cycle is in fact a shared influence of various macroeconomic aspects. These aspects, when taken together, can concisely sum up the information content into a meaningful business cycle outlook. In this context, it is pertinent to postulate the cyclical movement in business condition as synchronized co-movement between a particular set of macroeconomic variables. Collectively, the shared influence makes up the so-called “state of business cycle”.

Intuitively, [Stock and Watson’s \(1989, 1991\)](#) parametric factor model is built on the assumption that macroeconomic variables that move together over time possess a common element that can be captured by a single underlying, unobserved component and the unobserved state can be dynamically extracted using a factor-based model. Following [Stock and Watson \(1991\)](#), we modified the specification to accommodate a six-variable dynamic factor model. We denoted the component series as  $Y_{1t}$ ,  $Y_{2t}$ ,  $Y_{3t}$ ,  $Y_{4t}$ ,  $Y_{5t}$  and  $Y_{6t}$  for domestic stock prices, US stock prices, money supply, exportation, newly registered company and tourist arrivals, respectively. We followed [Stock and Watson \(1991\)](#) so as to have the model specified under first difference because the unit root testing performed in the earlier stage points to the existence of a stationary state after differencing once. Thus, the first difference specification of the dynamic factor model can be written as follows:

$$\Delta Y_{it} = D_i + \gamma_i \Delta C_t + e_{it}, \quad i = 1, 2, 3, 4, 5, 6 \quad (1)$$

$$(\Delta C_t - \delta) = \phi_1 (\Delta C_{t-1} - \delta) + \phi_2 (\Delta C_{t-2} - \delta) + \omega_t, \quad \omega_t \sim i.i.d. N(0, \sigma_\omega^2) \quad (2)$$

$$e_{it} = \psi_{i1} e_{i,t-1} + \psi_{i2} e_{i,t-2} + \varepsilon_{it}, \quad \varepsilon_{it} \sim i.i.d. N(0, \sigma_\varepsilon^2), \quad i = 1, 2, 3, 4, 5, 6 \quad (3)$$

where  $\Delta C_t$  is the common component that enters Equation (1) with different weights and  $\sigma_\omega^2$  is set to 1 so as to normalize the common component. All the shocks are assumed to be independent.

Apart from this, Stock and Watson also recommended transforming the model into deviation from means to ensure that the maximum likelihood estimation can be performed without predicament. This is to account for a concern in which the

parameters  $D_i$  and  $\delta$  in the first population moment for the  $i$ -th variable,  $\Delta Y_{it}$ , represented in Equation (4) are not separately identified in the case of the sample first moment,  $\overline{\Delta Y}_i$ .

$$E(\Delta Y_{it}) = D_i + \gamma_i \delta \quad (4)$$

From the likelihood function, the model in deviation from means focuses on  $D_i + \gamma_i \delta$  terms, where  $i = 1, 2, 3, 4, 5, 6$ . We then can re-write the model as follows:

$$\Delta y_{it} = \gamma_i \Delta c_t + e_{it}, \quad i = 1, 2, 3, 4, 5, 6 \quad (5)$$

$$\Delta c_t = \phi_1 \Delta c_{t-1} + \phi_2 \Delta c_{t-2} + \omega_t, \quad \omega_t \sim i.i.d. N(0, 1) \quad (6)$$

$$e_{it} = \psi_{i1} e_{i,t-1} + \psi_{i2} e_{i,t-2} + \varepsilon_{it}, \quad \varepsilon_t \sim i.i.d. N(0, \sigma_\omega^2), \quad i = 1, 2, 3, 4, 5, 6 \quad (7)$$

where  $\Delta y_{it} = \Delta Y_{it} - \overline{\Delta Y}_i$  and  $\Delta c_t = \Delta C_t - \delta$ .

Subsequently, a state-space representation of the deviation from means model can be derived as follows:

**Measurement Equation:**

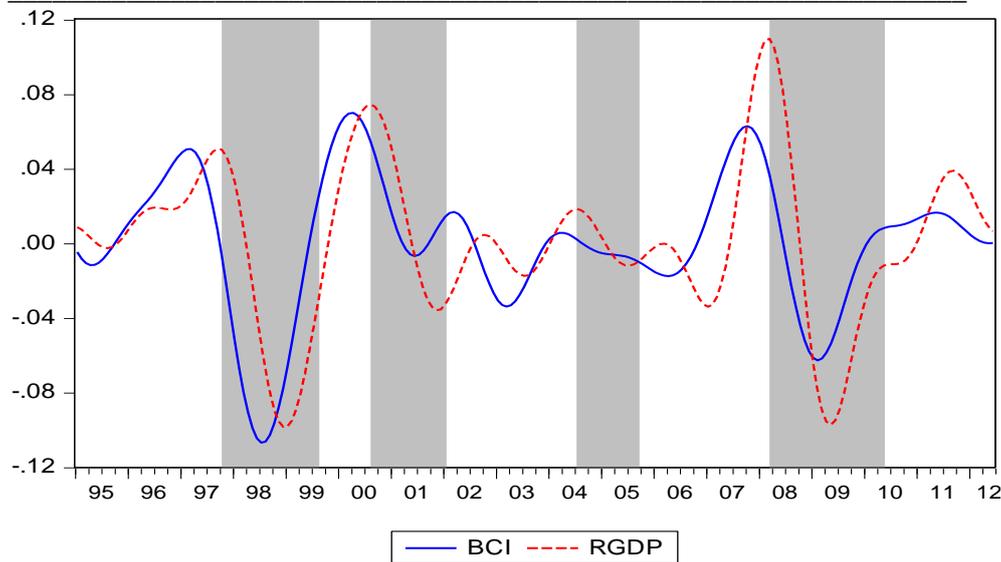
$$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \\ \Delta y_{4t} \\ \Delta y_{5t} \\ \Delta y_{6t} \end{bmatrix} = \begin{bmatrix} \gamma_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_3 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \gamma_5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \gamma_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{2t} \\ e_{2,t-1} \\ e_{3t} \\ e_{3,t-1} \\ e_{4t} \\ e_{4,t-1} \\ e_{5t} \\ e_{5,t-1} \\ e_{6t} \\ e_{6,t-1} \end{bmatrix} \quad (8)$$

**Transition Equation:**

$$\begin{bmatrix} \Delta c_t \\ \Delta c_{t-1} \\ e_{1t} \\ e_{1,t-1} \\ e_{2t} \\ e_{2,t-1} \\ e_{3t} \\ e_{3,t-1} \\ e_{4t} \\ e_{4,t-1} \\ e_{5t} \\ e_{5,t-1} \\ e_{6t} \\ e_{6,t-1} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 & \dots & 0 & 0 \\ 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \psi_{11} & \psi_{12} & \dots & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & \psi_{61} & \psi_{62} \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 \end{bmatrix} \begin{bmatrix} \Delta c_{t-1} \\ \Delta c_{t-2} \\ e_{1,t-1} \\ e_{1,t-2} \\ e_{2,t-1} \\ e_{2,t-2} \\ e_{3,t-1} \\ e_{3,t-2} \\ e_{4,t-1} \\ e_{4,t-2} \\ e_{5,t-1} \\ e_{5,t-2} \\ e_{6,t-1} \\ e_{6,t-2} \end{bmatrix} + \begin{bmatrix} \omega_t \\ 0 \\ \varepsilon_{1t} \\ 0 \\ \varepsilon_{2t} \\ 0 \\ \varepsilon_{3t} \\ 0 \\ \varepsilon_{4t} \\ 0 \\ \varepsilon_{5t} \\ 0 \\ \varepsilon_{6t} \\ 0 \end{bmatrix} \quad (9)$$

From Equations (8) and (9), we can estimate the model using the maximum likelihood estimation and extract the unobserved component through Kalman filtering. Kalman filtering is a recursive procedure that provides optimal estimates for the unobserved component and minimizes the forecast error via the maximum likelihood algorithm.

The extracted unobserved component forms the proxy of BCI index. The raw index is then transformed and normalized to facilitate the evaluation of forecasting performance in the later stage. To evaluate the performance of BCI in predicting the movement of real GDP, detrending and cycle extraction with the band-pass filter established by [Christiano and Fitzgerald \(1999\)](#) was then carried out. The resulting cyclical movement is represented in Figure 1, with the shaded area corresponding to major economic episodes that occurred across the period of 1995-2012. Our turning points analysis based on the [Bry-Boschan \(1971\)](#) dating algorithm gives rise to several important implications concerning the validity of BCI in anticipating the business cycle development and the evolution of crises incidents.



**Figure 1. BCI versus real GDP, 1995-2012**

We found that the movement in BCI synchronized well with the fluctuations in Malaysia's economic activity as proxied by real GDP. The recurring cycles across the investigated period are persistent but irregular. The average duration for expansion periods is relatively longer, ranging from 20 to 32 months while the length for contraction periods is consistently shorter in each cycle, about 12 to 15 months. The BCI detected four important episodes: the Asian financial crisis 1997/1998, US technology/dot-com bubble 2000/2001, oil price hike incident 2004/2005 and US sub-prime mortgage crisis 2008/2009.

More importantly, the constructed BCI marked the peaks and troughs at a relatively earlier point in time than the chronology of the real business cycle as reflected by real GDP. Of the eight turning points, the factor-based BCI only detected a false signal corresponding to the trough during the oil price hikes incident in 2004/2005. For this case, a slight transition in economic activity is observable, but no significant turning point was dated. We expected the shock from oil price hikes to permeate over the years, yet the real impact of the shock was not prompt. Therefore, the resulting trough reflected real output pass-off in late 2006, rather than mid-2005 as reported by DOSM. Our result is in line with Yap (2009), who also marked the real trough in oil price shocks at mid-2006.

**Table 1. Turning point dates for real GDP versus BCI**

<b>Incident</b>		<b>Real GDP</b>	<b>BCI</b>	<b>Type of Signal</b>	<b>Lead/Lag</b>
<b>Asian Financial Crisis</b>	Peak	1997M09	1997M03	Early Signal	+6
	Trough	1998M12	1998M07	Early Signal	+5
<b>US Dot-com Bubble</b>	Peak	2000M08	2000M04	Early Signal	+4
	Trough	2001M11	2001M06	Early Signal	+5
<b>Oil Price Hike Incident</b>	Peak	2004M07	2004M04	Early Signal	+3
	Trough	2005M07	-	False Signal	-
<b>US Sub-prime Mortgage Crisis</b>	Peak	2008M03	2007M10	Early Signal	+5
	Trough	2009M05	2009M02	Early Signal	+3

**Table 2. Turning point dates for real GDP versus CLI**

<b>Incident</b>		<b>Real GDP</b>	<b>CLI</b>	<b>Type of Signal</b>	<b>Lead/Lag</b>
<b>Asian Financial Crisis</b>	Peak	1997M09	1997M03	Early Signal	+6
	Trough	1998M12	1998M08	Early Signal	+4
<b>US Dot-com Bubble</b>	Peak	2000M08	2000M06	Early Signal	+2
	Trough	2001M11	2001M08	Early Signal	+3
<b>Oil Price Hike Incident</b>	Peak	2004M07	2004M04	Early Signal	+3
	Trough	2005M07	-	False Signal	-
<b>US Sub-prime Mortgage Crisis</b>	Peak	2008M03	2007M10	Early Signal	+5
	Trough	2009M05	2009M02	Early Signal	+3

On average, the length of the BCI's early signal is about 4.4 months (see Table 1). In contrast, the CLI, serving as a nationwide reference of economic activity in Malaysia, possesses relatively lower strength with regards to business cycle foresight with only 3.7 months of lead time on average (see Table 2). Despite the arbitrary signal for the oil price hike incident, the rest of the turning points were correctly dated and the duration of early signals was deemed to be sensibly sufficient for preventive measures and policy action. Therefore, the factor-based BCI produced a satisfactory outcome for business cycle forecasting and offered better predictive power for early signals of vulnerability to economic episodes.

### **Predictive Accuracy and Robustness Analyses**

With two competing indicators (BCI and CLI) at hand, a more formal statistical approach to analysing the predictive accuracy of the two indicators is particularly meaningful for a more credible study in the field of forecasting. From a forecasting

perspective, renewed interest in direction accuracy of macroeconomic forecasts clearly indicates that unreliable forecasts make no sense to users. Greer (2003) even argued that it is the large predicted change that in fact is useful to users. In other words, if a forecasting model comprises predicted changes that are not adequately significant to reveal the underlying impact of the real shock, the resulting forecasts will be susceptible.

Following Greer (2003), we subjected the two competing indicators to directional accuracy testing and complemented the finding with binomial testing. We broke the cyclical changes into three trichotomous scenarios; specifically, a large predicted increase, no significant changes and a large predicted decrease, and applied a threshold point of 5 percent to cut off the small predicted changes. Thus, the directional accuracy rate can be calculated based on the formula below:

$$\text{Directional Accuracy Rate (DAR)} = \frac{C_s}{N_s} \times 100 \quad (10)$$

where  $C_s$  is the number of correct predictions for significant large changes, and  $N_s$  refers to the total number of significant large changes in the business cycle as proxied by real GDP.

In addition, we harmonized the binomial testing with the direction accuracy result to verify the robustness of the factor-based BCI against the CLI. In particular, we were keen to know whether the success of the prediction is owing to the predictive power of the forecasting model (indicator) or to mere chance. This verification is crucial to portray that the indicator itself has compelling predictive power and is robust over time. The null hypothesis of binomial testing is: “The probability of correct prediction to direction of change in the forecasting model is 50 percent”. Rejection of the null hypothesis will lead to two distinct conclusions, depending on the outcome of direction accuracy testing (DAR). If DAR is over 50 percent, then the forecasting model is independent of wild guess. On the other hand, if DAR is below 50 percent, we can expect that wild guess possibly dominates the source for obtaining correct predictions. Failure in beating the wild guess again implies that the indicator is less likely to be a robust forecasting tool.

The comparative findings on DAR and binomial testing for the two competing indicators were tabulated and are shown in Table 3. The findings show that the factor-based BCI can predict the direction of change in the business cycle with an accuracy rate of up to 84 percent. On the other hand, the DAR of the publicly available CLI was at best 25 percent. With the binomial testing results pointing to a rejection of the null hypothesis in all cases, we can infer the robustness of BCI in business cycle forecasting; its compelling predictive ability and statistical

robustness in terms of forecasting as the source of the BCI's successful forecasts is attributable to the predictive power of the indicator, and not mere chance.

**Table 3. Directional accuracy and binomial testing results**

Lag (month)	Directional Accuracy Rate (DAR)		P(Binomial)	
	BCI	CLI	BCI	CLI
1	61.36%	18.18%	0.039	0.000
2	70.45%	20.45%	0.003	0.000
3	77.27%	22.73%	0.000	0.000
4	84.09%	25.00%	0.000	0.000
5	81.82%	25.00%	0.000	0.000
6	79.55%	22.73%	0.000	0.000

### Conclusion

To sum up, the factor-based BCI constructed in the present study has fulfilled our primary aim of building a reliable forecasting tool for business cycle identification in Malaysia. We observed that the reference chorology established on the basis of output growth has traced well the movement of economic activity in Malaysia while the constructed BCI tracked the fluctuations, especially the key turning points, at notably accurate and advanced timing. Essentially, with its capability to generate early signals for up to 4.4 months on average, the constructed BCI is fairly adequate to demonstrate a signalling mechanism that built upon the ideology of indicator construction on top of Stock and Watson's factor-based model.

Seeing that the early signal generated by the constructed BCI is contributory to macroeconomic policy building and crisis prevention, we expect BCI to perform sensibly well as an alternative precursor to economic crises. Besides, the BCI can complement other business cycle forecasting instruments and best practices of macroeconomic risk-monitoring activity. Apart for that, the robustness of the BCI, which statistically outperforms the publicly available CLI, suggests that the nationally owned composite indicator has significant room for further improvement. Thus, we perceive future innovation in indicator-based forecasting tools, especially the upgrading of composition and indicator construction, to be critical in sustaining the competency of the said indicator.

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