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DISCUSSION PAPER SERIES
EU-ERA DP 2/2021

Development of Labour Market Leading Indicators for Unemployment Rates in Malaysia

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PERKESO Social Security Organization
EMPLOYMENT INSURANCE SYSTEM Employment Insurance System
EU ERA EIS-UPMCS Centre for Future Labour Market Studies
ISSN 2785-9096
9 772785 909007

ISSN 2785-9096

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July 2021

Abstract

Motivation and Aim: The unemployment rate is one of the key indicators used to monitor the health of the economy at any point in time. Nevertheless, the unemployment rate in Malaysia is usually provided with a two-month lag. This paper develops a methodology to determine reasonably accurate, reliable and timely signals relating to the set of leading indicators for the unemployment rate in Malaysia.

Methods and Materials: Following the system developed by the Organisation for Economic Co-operation and Development (OECD) that outlined the composite leading indicators methodology, 17 publicly available variables for the leading indicator candidates are investigated empirically. The potential leading indicators were chosen from diverse aspects of economic activity, which were then filtered and evaluated based on pairwise correlation and Granger causality analyses. Once selected, the leading indicators were aggregated into a composite leading index and their forecast performance of the unemployment rates for in-sample and out-of-sample were measured.

Key Finding: The results show that the Kuala Lumpur composite index (KLCI), total loans (LOAN) and money supply (M2) satisfy all the informativeness criteria to be considered the leading indicators for the unemployment rates in Malaysia. Hence, the composite leading index constructed from these variables provides accurate tracking of the unemployment rate in Malaysia.

Policy Implications: Leading indicators can be a useful short-term tool that helps a government build a more responsive labour market policy, particularly in phases of economic recovery. Economic fluctuations due to various movement control restrictions have directly and indirectly affected employment, so leading indicators for unemployment rates are required for monitoring purposes. Furthermore, the leading indicators can provide an early signal system to the Active Labour Market Policy (ALMP) for attenuating cyclical and structural unemployment.

Keywords: Leading indicators, unemployment rate, labour market, Malaysia

Development of Labour Market Leading Indicators for Unemployment Rates in Malaysia

1. Introduction

A leading indicator is economic data that corresponds with a future movement or change in some phenomenon of interest. The indicator was initially used as an early signal for turning points in business cycles, but due to its significant influence, it is now applied in predicting aggregate economic activity. An indicator helps by detecting the direction of the economy earlier, enabling the government to make and launch policies at the right time. Given that output and unemployment are inter-related—the higher the growth in output, the greater the demand for labour and vice-versa—the development of timely, reasonably accurate and reliable leading indicators to predict the labour market movements are necessary.

This paper seeks to identify the potential leading indicators for the labour market in Malaysia with specific application to the unemployment rate. Managing labour market conditions during crisis and post-crisis periods is challenging because of dynamic economic movements. It has been observed that economic activities and the labour market have been responsive to the various movement control restrictions implemented by the government to prevent the COVID-19 infection. For example, unemployment rates reduced from 5.3% in May 2020 to 4.9% in June 2020 when the government relaxed the movement control restrictions. Policy monitoring is restricted as the unemployment rate data is reported with a two-month lag in relation to the current real-time. With the unprecedented global pandemic and world economic downturn, it is crucial to conduct a timely assessment of the labour market conditions in Malaysia by utilising the leading indicators.

In identifying the potential leading indicators for unemployment in Malaysia, this paper evaluates diverse sets of data, including financial and monetary policies, international trade, the Kuala Lumpur Composite Index (KLCI) and credit conditions to provide a total of 17 potential indicators. The potential leading indicators selected significantly affect the movement of the unemployment rate and are reliable sources of data. Following the OECD approach (Gyomai & Guidetti, 2012), the selection of indicators was determined according to three major steps: (i) the choice of the target and candidate leading variable, (ii) data filtering and (iii) data evaluation.

Next, the leading indicators were aggregated into a composite leading index and their forecast performance of the unemployment rate was measured.

The major contribution of this study is its development of leading indicators for the labour market in Malaysia with specific application to the unemployment rate. Research related to the development of leading indicators for the labour market in Malaysia has been the subject of long-standing debate. However, to the best of the authors' knowledge, studies solely focusing on developing leading indicators for the unemployment rate in Malaysia remain scarce. In this regard, the development of the leading indicators would assist policy-makers in determining effective policy responses to labour market issues. This study contributes to the labour market literature by offering empirical evidence on developing the leading indicators for the unemployment rate in Malaysia.

Although this paper determines the leading indicators for the unemployment rate, the methodologies developed in this paper can deal with various candidates for the leading indicators and different targeted variables, such as loss of employment (LOE) and employment generation. The unemployment rate was applied as the targeted variable and the 17 candidates for the potential leading indicators were chosen because of the data availability that would enable sufficiently robust observations. It is extremely important to measure fiscal policy variables, in particular, public expenditure and disbursement, as they directly and indirectly influence employment, but they were not available for inclusion in this assessment model.

This paper is structured into five sections. Section 2 provides a review of the related literature, with specific attention given to the leading indicators for the labour market. Section 3 explains the research methodology along with the data sources applied in this study. Section 4 provides the estimation results and Section 5 concludes by providing several policy implications of the study.

2. Review of Related Studies

In this section, the literature review summarises the importance of developing leading indicators and the research gaps in determining these indicators for the labour market in Malaysia.

Leading indicators studies in economics

Leading indicators have been considered an informative set of tools that reflect future economic conditions since the pioneering work of Mitchell and Burns (1938) and Burns and Mitchell (1946). Their studies combined several selected variables into a composite index to give an overall assessment of the economy. Afterwards, Koopmans (1947) revised the Burns-Mitchell study, focusing on different features of the components and the evaluation and methods needed to find the best indicators. The field has attracted many researchers and practitioners to apply leading indicators in predicting economic directions (Puah, Shazali, & Wong, 2016; Handoko, 2017; Plakandaras, Cunado, Gupta, & Wohar, 2017; Stundziene, Barkaukas, & Giziene, 2017; Iyetomi, et al., 2020).

Puah et al. (2016) constructed a composite leading index based on a non-parametric approach to track the macroeconomic environment in Cambodia. The study displays two notable leading variables with an average lead time of several months, namely money supply (M1) and total exportation. Handoko (2017) analysed 24 variables with monthly data from 2010 to 2016 to compile a composite leading index for the Gross Regional Domestic Product of Eastern Indonesia. Plakandaras (2017) utilised dynamic probit and Support Vector Machine (SVM) models to analyse how accurately the leading indicators can forecast United States recessions. Stundziene et al. (2017) examined various candidate leading indicators taken from different categories, such as economics, industry, finance, the real estate market and business expectations, to predict the economic cycles of Lithuania. Iyetomi et al. (2020) studied 62 time series to determine the best-performing leading indicators for analysing business cycles of the United States.

In the Malaysian context, the Department of Statistics Malaysia (DOSM) computes and reports periodically the leading indicators to reflect the economic conditions of the country (Department of Statistics Malaysia, 2020). The DOSM currently suggests seven indicators for constructing a composite leading index: real money supply (M1), the Bursa Malaysia industrial index, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, the number of housing units approved, the expected manufacturing sales value and the number of new companies registered.

Various studies in the Malaysian literature apply leading economic indicators in their research. For example, Izani and Raflis (2004) examined the behaviour of nine leading economic indicators of Malaysia and showed that the indicators provide important information about the economic conditions at state levels. Wong et al. (2012) demonstrated that the performance of the composite leading index in forecasting the real Gross Domestic Product (GDP) is relatively adequate. Lau and Lee (2015) compared the ability of the equity style index and stock market index to predict the future movement of the composite leading economic index in a multivariate Granger causality framework. They found that the equity style index is more sensitive and performs better in detecting turning points of business cycles.

Recently, several studies have examined the indicator-based forecasting tool from different perspectives in Malaysia. For example, Abu Mansor et al. (2015) developed an early warning indicator to forecast economic vulnerability and monitor macroeconomic risk. Wong et al. (2016) constructed a factor-based business cycle indicator capable of generating the early signals of economic crises, on average up to 4.4 months in advance. Recently, Voon et al. (2020) examined monthly data from 2000 to 2015 to build a composite leading indicator for housing affordability. The study also employed a time-varying Markov switching model to assess the indicator and found that it has a leading period of 9.5 months on average.

Significance of leading indicators in the labour market

The aforementioned leading indicator studies only focus on forecasting economic activity, but recent literature has emphasised the use of the leading index approach in assessing future labour market conditions. This is possible because production output and unemployment are inter-related—the higher the growth in output, the greater the demand for labour and vice-versa. For instance, Atabek, Cosar and Sahinoz (2015) included variables related to the labour market in constructing a composite leading index for economic activity. Among the variables are the number of employees, payments to workers in the manufacturing industry and business tendency survey results regarding expected employment. Guerard, Thomakos and Kyriazi (2020) used several leading economic indicators to forecast the unemployment rate of the United States. Given the linkages between the labour market and economic activity indicators, a composite leading index for unemployment can be developed to reveal early signal changes that can be used as a reference resource for policy-making.

The literature survey found that studies of leading indicators for the unemployment rate in Malaysia are scarce, although similar studies in other countries are abundant. One recent study applied leading indicators to predict the state of the labour market in Turkey (Yunculer, Sengul and Yavuz, 2014). The authors analysed 72 series related to the Turkish non-agricultural unemployment rate, searching for composite leading indicators that would reflect future labour market conditions. Later, Tule, Ajilore and Ebuh (2016) computed a composite leading index for the unemployment rate in Nigeria. The study investigated 16 variables from six categories of indicators: aggregate economic activity, foreign trade, financial and monetary policies, foreign activity, consumer and business confidence and credit. Moreover, Claus (2011) examined 95 variables to construct seven leading indexes for quarterly employment in New Zealand. The study revealed no leading index model that dominates at all forecast horizons, although the indexes show a smaller root mean square error.

Over recent years, several attempts have been made to use internet search data as a leading indicator in predicting the unemployment rate. Chadwick and Sengul (2012) applied Google Trends data to nowcast the monthly non-agricultural unemployment rate for Turkey. D'Amuri and Marcucci (2017) revealed that the Google-based model outperforms other models, improving the forecast horizon in predicting the monthly United States unemployment rate. Nagao, Takeda and Tanaka (2019) also showed that Google search data performs better in nowcasting the unemployment rate.

Although research on composite leading indicators for the labour market has been undertaken, it is limited to only certain countries. This gap motivated the authors to identify the leading indicators for predicting the unemployment rate in Malaysia and, furthermore, to evaluate the composite leading index performance.

3. Methodology and Data Sources

In identifying the leading indicators for the unemployment rate, this study applied the approach of the OECD (see Gyomai et al., 2012) that was widely adopted for selecting empirical leading indicators (see, for example, Yunculer et al., 2014; Tule et al., 2016; Handoko, 2017). Methodologically, it involved three major steps: (i) the choice of the target and candidate leading variables, (ii) data filtering and (iii) data evaluation. The first step was to select the target variables and choose the appropriate indicators that could serve the target series. The second step was to filter all the targeted variables with proper filtering methods, such as TRAMO/SEATS and Hodrick-Prescott. The third step assessed each candidate leading series against the target variables using both pairwise correlation and Granger causality techniques, as suggested by Gyomai et al. (2012) and Marcellino (2006), respectively. After the leading indicators had been identified, the indicators were aggregated into a composite index and the forecast performance of the index was measured.

3.1 Candidates for leading variable

The first step involved the identification of the target variables and potential leading indicators. In general, the potential leading indicators comprised various short-term indicators that could be informative in inferring the movements of the unemployment rate in Malaysia. **Table 1** presents a description of the leading indicator candidates for the unemployment rate in Malaysia. All the listed variables used monthly frequency data, spanning January 2014 to December 2020 (84 observations).

Choice of targeted variable

The targeted variable is the goal variable that the authors wanted to observe and consider as a lagging component. In this study, the focus is on the unemployment rate as the targeted variable. By definition, the unemployment rate is the proportion of the unemployed population compared to the total population of the labour force. Essentially, it includes the unemployed workers in all employment categories and includes employees, employers, the self-employed and unpaid family workers.

Conventionally, the unemployment rate is often used as a key indicator to explain the inter-linkages between labour market outcomes and economic conditions at any point in time. This is due to the high sensitivity between unemployment rates and economic fluctuations. For example, a downturn in the economy would trigger a reduction in job demand, leading to an increase in unemployment. Hence, unemployed people cannot pay taxes and less money would be spent on the economy, resulting in negative economic consequences.

It is important to note that the choice of the targeted variable for the labour market is not limited to the unemployment rate. Other indicators such as loss of employment (LOE), the size of the informal sector, employment generation and the participation rate could also be utilised as variables for monitoring labour market conditions. Nevertheless, these variables could not be considered in this paper because insufficient data observations were available to allow effective modelling.

LOE is a unique variable that can be considered in the future development of leading indicators for the labour market. From the labour market perspective, LOE is a sub-set of the unemployment rate. These indicators are distinct as they are compiled based on different methodologies and coverage. LOE is real-time administrative data maintained by the Office of Employment Insurance System (EIS) and the Social Security Organisation (SOCSO). It captures information about insured people from among the private-sector employees in the formal sector who had lost their jobs (excluding voluntary resignation, expiry of a fixed-term contract and retrenchment due to misconduct). Meanwhile, the unemployment rate is estimated based on survey-based data (i.e., a Labour Force Survey) by the Department of Statistics Malaysia (DOSM) and captures data on the labour force, including employers, employees, own-account workers and unpaid family worker who did not work during the reference week, regardless of whether they are actively or inactively unemployed. Although LOE is a sub-set of unemployment, it provides a good approximation for labour market monitoring purposes.

Candidates for leading indicator variables

A leading indicator is a series of economic data that corresponds to a future movement or change in the targeted variable. It helps to build a broad understanding of the future performance and forecast any change in the targeted variable before it occurs; in this case, the variable is the unemployment rate. The candidate leading variables were selected from a wide range of indicators that can intuitively allow the movement of the unemployment rate to be inferred. As shown in **Table 1**, the authors identified 17 different candidate leading series that can be grouped under the following six categories:

(1) Macroeconomic indicators
Indications of future unemployment trends could be observed through fluctuations in aggregate demand or its components, where employment growth is often expected to precede output growth. This study uses the industrial production index (IPI) as a proxy of aggregate demand conditions.

(2) Foreign trade indicators
In an open economy, foreign trade measures the production growth from the perspective of the exchange of goods, services and capital across countries. Foreign trade in Malaysia is strongly developed due to globalisation and economic liberalisation and comprises a significant proportion of total output and employer growth. The real effective exchange rate (REER), exports (X), imports (M), total trade (XM), real imports of semiconductors (RMSC) and real imports of other basic precious and other non-ferrous metals (RMPM) are among the established indicators employed. REER influences the competitive position of countries, while imports and exports indicate the effects of trade activities on unemployment.

(3) Monetary and financial variables
Monetary and fiscal policies are essential in shaping the direction of economic activity, which accelerates the labour absorption in the economy. Candidate variables that could capture the effects of monetary policy on economic activities are the Kuala Lumpur composite index (KLCI) and money supply (M1[1], M2[2], M3[3]).

(4) Consumer and business confidence indicators
Consumer and business confidence indicators are valuable sources of information that influence the magnitude of the production of

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[1] M1, or narrow money, is money supply that is composed of currency in circulation (notes and coins), demand deposits, traveller's cheques and other checkable deposits, which can be immediately converted into currency.
[2] M2, or intermediate money, includes M1 plus savings deposits, short-term time deposits, 24-hour money market funds, certificates of deposit and other time deposits.
[3] M3, or broad money, is defined as M2 plus large time deposits in banks.

output and labour demand. The study uses the consumer price index (CPI) to reflect the expenditure information of individuals, households and businesses. The sales value of manufacturing (MAN) is also employed as another potential indicator.

(5) Credit conditions
The availability and cost of credit are drivers of the growth in domestic demand. An increase in domestic demand will ultimately be reflected in a rise in employment, particularly in the labour-intensive small and medium enterprises sub-sector. For example, total loans (LOAN) and the number of housing units approved (HA) could be considered variables that illustrate credit conditions.

(6) Labour market indicators
The labour market indicator is directly related to the supply and demand of labour in the job market. In this regard, the study uses average salaries and wages per employee in the manufacturing sector (SW) and companies on the register at the end of the period (NCR).

3.2 Filtering

The second step in finding the most significant empirical leading indicators was filtering the data. Data filtering is needed to eliminate seasonal patterns, outliers and trends that could potentially hinder the true underlying cyclical patterns in the candidate series. The filter process involved the following procedures: seasonal adjustment, outlier detection, de-trending and smoothening and normalisation.

The seasonality of a time series can be considered stochastic or deterministic, depending on how seasonal patterns evolve through times. Stochastic seasonality assumes that seasonality can be represented by a stochastic process, while deterministic seasonality assumes that the seasonal pattern is constant. In this stochastic analysis, constant seasonality is removed because fixed seasonal patterns might obscure the underlying trend of the series.

As mentioned in sub-section 3.1, this study applied monthly data series, so seasonal adjustment had to be performed. Seasonal adjustment is a procedure that removes the seasonal and calendar variations from a time series that may harm its cyclical movements. This process is essential to standardise the time series as seasonality affects them with different timing and levels of intensity. Hence, the seasonally adjusted data highlighted the remaining components: the irregular, trend and cyclical components.

Table 1: List of target variables and candidates for leading indicators

No	Description	Variable	Type	Unit	Period (monthly)	Source
1	Unemployment rate	UR	Target	%	2014-2020	DOSM
2	Industrial production index	IPI	Candidate	Index	2014-2020	DOSM
3	Consumer price index	CPI	Candidate	Index	2014-2020	DOSM
4	Total export	X	Candidate	RM million	2014-2020	DOSM
5	Total import	M	Candidate	RM million	2014-2020	DOSM
6	Total trade (X+M)	XM	Candidate	RM million	2014-2020	DOSM
7	Real imports of semiconductors	RMSC	Candidate	RM million	2014-2020	DOSM
8	Real imports of other basic precious & other non-ferrous metals	RMPM	Candidate	RM million	2014-2020	DOSM
9	Sales value of manufacturing	MAN	Candidate	RM million	2014-2020	DOSM
10	Companies on register at end of period	NCR	Candidate	In number	2014-2020	DOSM
11	Total loans	LOAN	Candidate	RM million	2014-2020	BNM
12	No. of housing units approved	HA	Candidate	In number	2014-2020	BNM
13	Average salaries and wages per employee in manufacturing sector	SW	Candidate	RM	2014-2020	DOSM
14	Kuala Lumpur composite index	KLCI	Candidate	Index	2014-2020	DOSM
15	Money supply, M1	M1	Candidate	RM million	2014-2020	BNM
16	Money supply, M2	M2	Candidate	RM million	2014-2020	BNM
17	Money supply, M3	M3	Candidate	RM million	2014-2020	BNM
18	Real effective exchange rates	REER	Candidate	Index	2014-2020	IMF

Note: DOSM, BNM and IMF refer to the Department of Statistics Malaysia, Bank Negara Malaysia and International Monetary Fund, respectively.

This study utilised TRAMO/SEAT methods via EViews10 software as the programme is a fully automatic procedure that is flexible yet robust and can handle routine applications to a large number of series. TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) are linked programmes initially developed by Gómez and Maravall (1997) at the Bank of Spain. This method is divided into two main parts, which TRAMO and SEATS will run, respectively. The first part is the pre-adjustment and removal of deterministic effects (i.e., outlier and calendar variations) from the series through a regression model with ARIMA noise. The second part is the decomposition of the time series to estimate and remove seasonal components from the time series. Hence, TRAMO pre-adjusts the series, which is then adjusted by SEATS.

Outlier detection

Outliers are observations in the component series that lie outside the normal range of observations. It is important to identify and remove outliers from the series because they potentially skew statistical measurements and data distributions, leading to a misleading representation of the underlying data. Thus, removing the outliers gives results with a better fit of data and, in turn, more skilful predictions. Through the TRAMO/SEATS seasonal adjustment method, the TRAMO programme incorporates algorithms to automatically detect the location and nature of potential outliers in each series and then correct them.

De-trending and smoothening

De-trending involves removing long-term trends in the data while smoothening keeps the cyclical pattern of the series. For this purpose, the Hodrick-Prescott filter (1997) was applied, which remains one of the most widely used de-trending methods to obtain a smooth estimate of the long-term trend component of a series. For monthly data, the smoothing parameter, $\lambda = 14{,}400$ was used in order to obtain the optimal results.

Normalisation

Data normalisation is the process of rescaling the data to a specific range when the series is associated with large differences in units and scales. This process is essential in comparing phenomena of different size but with the same origin. Hence, all the potential leading indicators must be normalised as they differ in size. The normalisation method developed by Gyomai et al. (2012) was used in this study, where the filtered observation (x) is subtracted from the mean of the filtered series (μ), then divided by the standard deviation (σ) of the filtered series; a value of 100 is added to each observation. Data normalisation (x'), based on the Gyomai and Guidetti method, can be written as follows:

$$x' = \frac{x-\mu}{\sigma} + 100 \quad (1)$$

3.3 Evaluation of the conformity of selected indicators with the targeted variable

The last step involved evaluating the candidate leading series for their behaviour related to the targeted variable using a set of statistical methods. Two analyses were adopted in this study, the pairwise correlation and Granger causality approaches. Pairwise correlation estimates the cross-correlation structure and correlation coefficient between the candidate variable and the targeted variable, while Granger causality identifies the series that Granger-cause the targeted variable. Then, the candidate series that passed both evaluations were considered the leading indicators for the unemployment rate.

Pairwise correlation

Leading indicators can be determined by investigating the leads and lags of the candidate variables and the correlation between the candidate and targeted variables. This pairwise correlation provides valuable information on the cyclical relationship between the candidate series and the targeted variable. The goal is to find candidate variables that lead the targeted variable and have a highly significant correlation.

Cross-correlation, or lead-lag correlation structure, is an analysis that determines whether there is a causal relationship between two data series (i.e., the targeted variable and the leading indicator). Given two time series: X_t and Y_t, the cross-correlation function can be defined as:

$$Corr(\tau) = Corr(X_t, Y_{t-\tau}),\ \tau = 0, \pm 1, \pm 2, \dots, \pm \ell \quad (2)$$

where Y_t shifted by the time τ, and ℓ is the number of lags included in the estimation. Asymmetry of the cross-correlation function around the zero lag suggests that one time series (X_t) predicts or leads the other time series (Y_t). If $Corr(\tau) > Corr(-\tau)$, this means X_t leads Y_t; $Corr(\tau) < Corr(-\tau)$, means Y_t leads X_t.

Furthermore, a correlation coefficient is used to measure the direction and strength of the linear relationship between two data series. It is a measure related to covariance and can be expressed as:

$$Corr\ (X, Y) = \frac{Cov(X,Y)}{Std(X)Std(Y)} \tag{3}$$

where the covariance of two variables is divided by their standard deviations. In addition, the result coefficients must range between -1 and $+1$. A coefficient of -1 implies a perfect negative relationship or weak correlation, while $+1$ indicates a perfect positive relationship or strong correlation.

Granger causality

The next step in the evaluation process was to evaluate the causality between the targeted variable and the leading variable. Causality is the relationship between cause and effect, whereby independent (candidate) variables are the factors that cause changes in the dependent (target) variable but not the other way around.

Granger causality is a statistical concept of causality or influence in terms of predictability (Granger, 1969). If X_t Granger-causes Y_t, then past values of X_t contain information that helps in the prediction of Y_t. A simple Granger causality test involving two stationary series (X_t and Y_t) can be written as:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \tag{4}$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \mu_t \tag{5}$$

where ε_t and μ_t are the uncorrelated white-noise series. m can equal infinity but, in practice, it is assumed to be finite due to the limited length of the available data.

By assuming that only stationary series are involved, the definition of the simple Granger causality test above indicates that X_t do not Granger-cause Y_t if b_j is zero, as shown in Equation (4); similarly, Y_t do not Granger-cause X_t if c_j is zero, as shown in Equation (5). This means that each variable is independent of the other. If both events occur or b_j and c_j is not zero, this means that there is a feedback or bi-directional causality between

X_t and Y_t. Otherwise, there would be one-way or unidirectional Granger causality running from X_t to Y_t or Y_t to X_t.

3.4 Aggregation of leading series into a composite index

Once the leading indicators had been empirically determined, the series was aggregated into a composite leading index and the forecast performance of the index was measured. The leading indicators were aggregated using a simple averaging technique due to its simplicity and practicability. Aggregation of the leading indicators was performed to improve the predictive capacity of the overall index.

4. Results and discussion

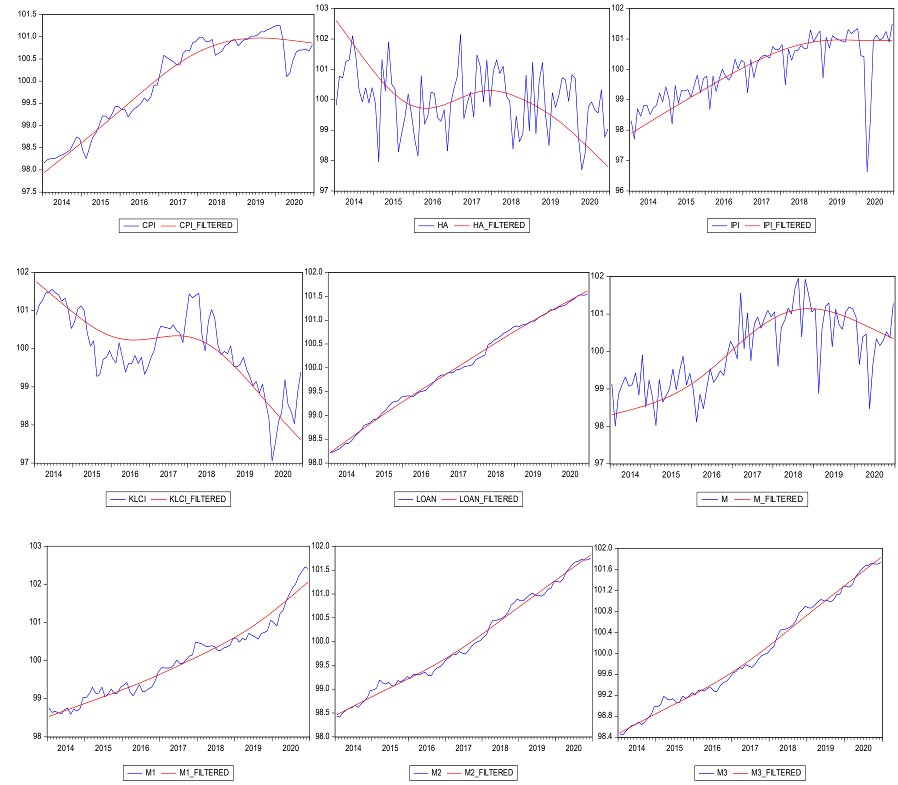
This section discusses the result of each stage of developing the leading indicators for the unemployment rate in Malaysia. The authors used the autoregressive integrated moving average (ARIMA) method for benchmark model regression and the ordinary least square (OLS) method for the composite leading index model regression to compare both forecast performances.

4.1 Data filtering

To identify the leading indicators, each pre-selected component series was filtered by sequence—seasonally adjusted, outliers corrected, de-trended, smoothed, turning points detected and normalisation—to reveal the true underlying cyclical pattern of the series.

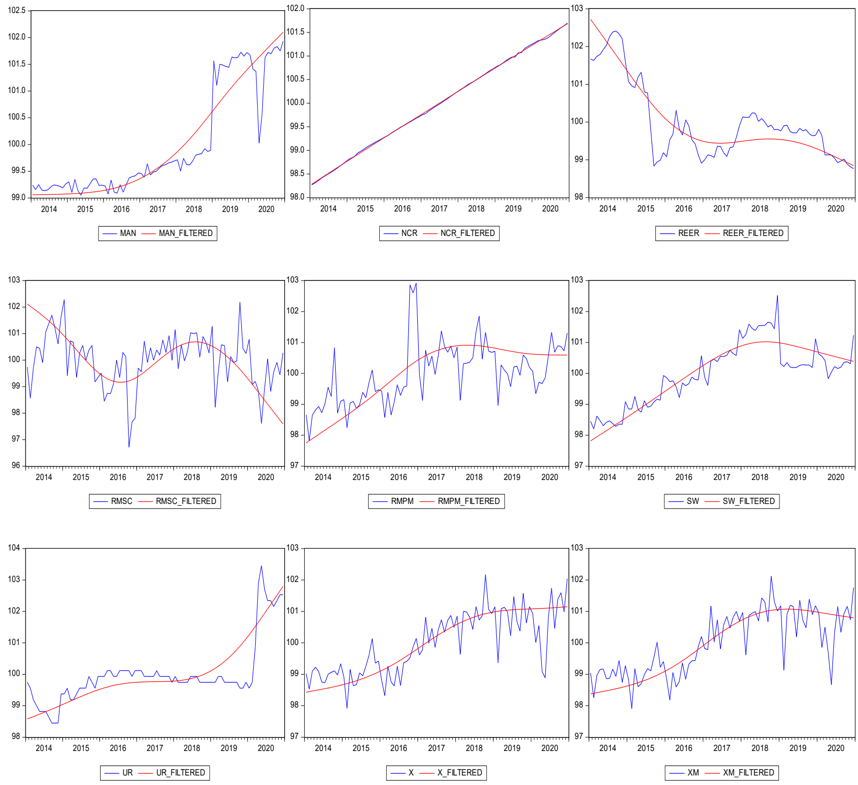
Any seasonal patterns of the target and each candidate series were removed and the presence of outliers was corrected by performing the TRAMO/SEATS method in EViews10. Afterwards, an internal trend of the series was extracted via the Hodrick-Prescott filter technique and each series was finally normalised, as explained in section 3.2. The results of data filtering are displayed in Figure 1, in which the filtered series provides a seasonally smoother version of the original series. The blue line in **Figure 1** represents raw variables; meanwhile, the red line represents filtered variables.

Figure 1: Plots of raw and filtered variables



Note: Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

Figure 1: Plots of raw and filtered variables (continued)



Note: Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

4.2 Data evaluation

Next, the candidate component series was evaluated for its cyclical performance using two statistical analyses, as described in section 3.3. The first evaluation was based on pairwise correlation analyses, which was used to determine the relationship between the candidate leading indicator and the target variable. Secondly, Granger causality was used, which identifies potential leading series that Granger-cause the unemployment rate.

Pairwise correlation analyses

A cross-correlation function was utilised to check whether the pre-selected component series leads or lags the unemployment rate, which follows the condition of $Corr\ (\beta) < Corr(-\beta)$. As monthly data frequency was available, the cross-correlation between the series analysed up to 12 lag lengths. In addition, the candidate series was also expected to have a correlation value of not less than 0.55 with the unemployment rate and positive intervals in terms of the correlation structure. **Table 2** presents the results of the pairwise correlation between the candidate leading series and the unemployment rate.

Among the given indicators in Table 2, the variables that have significant correlation values and lead the unemployment rate include the sales value of manufacturing (MAN), companies on the register at the end of the period (NCR), total loans (LOAN), the Kuala Lumpur composite index (KLCI), the money supply (M1, M2, M3) and real effective exchange rate (REER). The negative correlation value of the KLCI and REER shows a negative relationship with the unemployment rate.

Table 2 also shows that the consumer price index (CPI), real imports of semiconductors (RMSC), number of housing units approved (HA), and average salaries and wages per employee in the manufacturing sector (SW) lead the unemployment rate. However, due to weak correlation (less than 0.55), these variables could not be considered leading indicators.

Table 2: Pairwise correlation between the unemployment rate and candidate leading indicators

No	Candidate Leading Indicators	Correlation Value	Correlation Structure
1	IPI	0.3946***	Lag (-7)
2	CPI	0.4887***	Lead (+12)
3	X	0.4112***	Lag (-12)
4	M	0.1874	Lag (-7)
5	XM	0.3243**	Lag (-12)
6	RMSC	-0.4231***	Lead (+7)
7	RMPM	0.3893***	Lag (-12)
8	MAN	0.5546***	Lead (+12)
9	NCR	0.6847***	Lead (+12)
10	LOAN	0.6730***	Lead (+12)
11	HA	-0.3885***	Lead (+8)
12	SW	0.4473***	Lead (+10)
13	KLCI	-0.7387***	Lead (+12)
14	M1	0.7681***	Lead (+12)
15	M2	0.6857***	Lead (+12)
16	M3	0.6809***	Lead (+12)
17	REER	-0.7463***	Lead (+12)

Notes: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.
Source: Authors' computations.

Granger causality analysis

Before executing the Granger causality analysis, two important steps were undertaken: (1) stationarity and (2) selection of optimal lags. Stationarity is required in a series to remove the risk of spurious regression. Thus, each series was first tested using the Augmented Dickey-Fuller, ADF (Dickey & Fuller, 1981) and Phillips-Perron, PP (Phillips & Perron, 1988) unit root tests, where the presence of the unit root is rejected at a 5% significance level (see ***Appendix A***). The selection of optimal lags for the series was also essential as excessive long lags would decrease the degree of freedom and over-parametrisation; meanwhile, short lags would lead to omitted variables and produce serially correlated errors. In this study, the lag length was selected using the Akaike Information Criterion (AIC), considering 1 to 12 lags for each specification.

The results, as presented in **Table 3**, show three causalities. The first was a unidirectional causality to the unemployment rate from the total loans (LOAN), Kuala Lumpur composite index (KLCI) and money supply (M1, M2, M3). As these variables were also confirmed as leading the unemployment rate, as shown in Table 3, these candidate series were chosen as the final choice of leading indicators for the unemployment rate in Malaysia. Second, bi-directional causal nexus relationships were found between the unemployment rate and the sales value of manufacturing (MAN), real imports of other basic precious and other non-ferrous metals (RMPM) and companies on the register at the end of the period (NCR). Third, a unidirectional causality was identified from the unemployment rate to the industrial price index (IPI), consumer price index (CPI), total exports (X), total imports (M), total trade (XM), total loans (LOAN) and number of housing units approved (HA). The second and third causalities were exempted from the selection of final leading indicators as they were irrelevant.

Only a causality that runs from the candidate leading series to the unemployment rate was considered a leading indicator. Variables with bi-directional and unidirectional causality from the unemployment rate were excluded because they were unsuitable as leading indicators. The existence of bi-directional causality results in a biased composite leading index, while causality running from the unemployment rate indicates the leading indicator is a lag variable.

Table 3: Granger causality between the target unemployment rate and candidate leading indicators

No	Granger Causal Relations	Optimal Lag (Criteria: AIC)	Chi-Sq. Stat	P-values
1	IPI does not Granger cause UR	12	9.724	0.6402
	UR does not Granger cause IPI		40.6397	0.0001
2	CPI does not Granger cause UR	2	3.849	0.1460
	UR does not Granger cause CPI		7.5682	0.0227
3	X does not Granger cause UR	3	1.1196	0.7723
	UR does not Granger cause X		22.6703	0.000
4	M does not Granger cause UR	3	2.8873	0.4093
	UR does not Granger cause M		16.4694	0.0009
5	XM does not Granger cause UR	3	1.6285	0.6529
	UR does not Granger cause XM		21.8706	0.0001
6	RMSC does not Granger cause UR	2	0.2941	0.8633
	UR does not Granger cause RMSC		3.6447	0.1616
7	RMPM does not Granger cause UR	2	4.7158	0.0946
	UR does not Granger cause RMPM		6.6618	0.0358
8	MAN does not Granger cause UR	2	5.6415	0.0596
	UR does not Granger cause MAN		5.3126	0.0702
9	NCR does not Granger cause UR	2	6.0793	0.0479
	UR does not Granger cause NCR		13.4612	0.0012
10	LOAN does not Granger cause UR	2	5.7991	0.055
	UR does not Granger cause LOAN		1.4673	0.4802
11	HA does not Granger cause UR	3	3.0002	0.3916
	UR does not Granger cause HA		15.3353	0.0016
12	SW does not Granger cause UR	3	2.2871	0.515
	UR does not Granger cause SW		2.3971	0.4942
13	KLCI does not Granger cause UR	2	28.3369	0.000
	UR does not Granger cause KLCI		3.1788	0.2041
14	M1 does not Granger cause UR	2	6.647	0.036
	UR does not Granger cause M1		1.5449	0.4619
15	M2 does not Granger cause UR	2	6.8405	0.0327
	UR does not Granger cause M2		0.3033	0.8593
16	M3 does not Granger cause UR	2	7.1844	0.0275
	UR does not Granger cause M3		0.251	0.8820
17	REER does not Granger cause UR	2	4.1273	0.1270
	UR does not Granger cause REER		1.8127	0.4040

Note: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.
Source: Authors' computations.

4.3 Measuring the forecast performance of composite leading indicators

Finally, the study investigated the forecast performance of the leading indicators, KLCI, LOAN and M2[4], by constructing a composite leading index. These leading variables were aggregated into the index using simple averaging following the OECD approach (Gyomai et al., 2012). However, simple average aggregation implicitly implies that an index is weighted by its standard deviations since the series are normalised by their standard deviations (see section 3.2).

Table 4 summarises the estimation results from the benchmark and composite leading index model of the unemployment rate for in-sample and out-of-sample forecasting. The unemployment rate was modelled as an AR(3) autoregressive process and a constant term as a benchmark, while for the leading index model, a 1-period lag of the UR and CLI was included. In forecasting the unemployment rate, both in-sample and out-of-sample forecasting was implemented, based on the parameters estimated over 2014:1 to 2020:12 and 2014:1 to 2020:6, respectively.

Table 4: Benchmark and composite leading index model estimation for in-sample and out-of-sample forecasting

Sample	**In-sample forecasting**			**Out-of-sample forecasting**		
	2014:1 to 2020:12			**2014:1 to 2020:6**		
Variable	**Coefficient**	**t-Statistic**	**P-value**	**Coefficient**	**t-Statistic**	**P-value**
Panel A. Benchmark Model.						
C	100.5917	89.4056	0.0000	100.1779	109.7297	0.0000
AR(3)	0.9946	25.0930	0.0000	0.9937	21.7457	0.0000
R-squared	0.9595			0.9497		
Adjusted R-squared	0.9585			0.9484		
Panel B. Composite Leading Index Model.						
C	-0.7873	-0.5775	0.5653	-0.4476	-0.3334	0.7398
NUR(-1)	1.0503	178.6978	0.0000	1.0600	115.4983	0.0000
CLI	-0.0419	-2.5529	0.0126	-0.0550	-3.1708	0.0022
R-squared	0.9994			0.9989		
Adjusted R-squared	0.9994			0.9989		

Note: AR, NUR and CLI refer to the autoregressive, normalised unemployment rate and composite leading index, respectively.
Source: Authors' computations.

[4] M2 can be replaced by M1 and M3 as the variables also included as leading indicators.

The forecast performance can be measured by the root mean square (RMSE), mean absolute error (MAE), mean absolute per cent error (MAPE) and Theil inequality (Theil) of the forecasts relative to the unemployment rate. Comparing the forecast performance measurements for the in-sample and out-of-sample, the forecasting model results, as shown in **Table 5**, reveals that the composite leading index forecasting model performed better than the benchmark forecasting model. This shows that the CLI is reliable in predicting future cycles of the unemployment rate. The evaluation graphs of the benchmark forecasting model and composite leading index forecasting model for the in-sample and out-of-sample scores can be referred to in **Appendix B**.

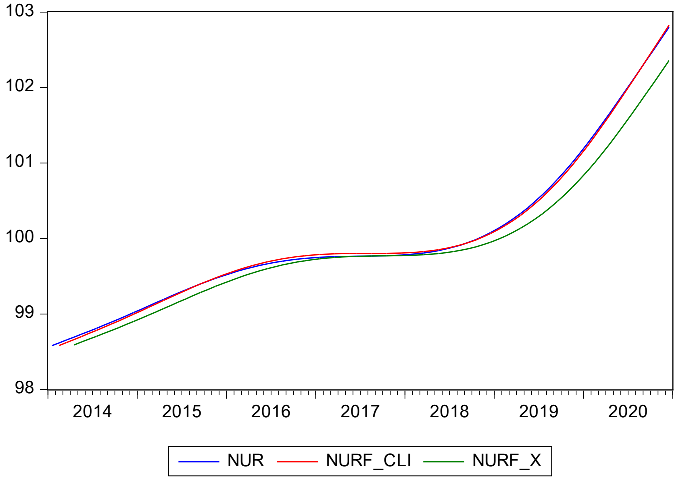
Table 5: Evaluation of in-sample and out-of-sample forecasting

Models	In-Sample forecasting				Out-of-sample forecasting			
	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil
UR_X	0.1998	0.1458	0.1447	0.0010	0.2106	0.1478	0.1466	0.0010
UR_CLI	0.0246	0.0220	0.0220	0.0001	0.0256	0.0227	0.0227	0.0001

Note: RMSE, MAE, MAPE and Theil refer to the root mean square error, mean absolute error, mean absolute per cent error and Theil inequality, respectively.
Source: Authors' computations.

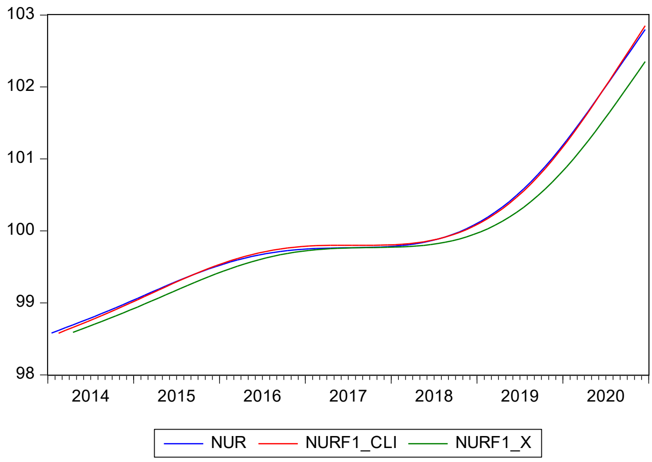
Figure 2 and **Figure 3** compare the track of the normalised actual unemployment rate with the normalised benchmark forecasted unemployment rate, as well as the normalised forecasted unemployment rate with the composite leading index for the in-sample and out-of-sample forecasts. The blue, red and green lines represent the normalised actual unemployment rate, normalised benchmark forecasted unemployment rate and normalised forecasted unemployment rate with composite leading index, respectively. In **Figure 2**, it can be observed that the cyclical of NURF_CLI tracks the NUR more closely and accurately compared to the NURF_X. Similarly, **Figure 3** also shows that NURF1_CLI tracks the NUR better than NURF1_X. Both results indicate that the leading indicators contain adequate information with which to anticipate the turning points of the unemployment rate cycles in Malaysia. The collected normalised and forecasted data are given in **Appendix *C***.

Figure 2: Evolution of the actual unemployment rate (NUR), in-sample normalised forecasted unemployment rate with composite leading index (NURF_CLI) and in-sample normalised benchmark forecasted unemployment rate (NURF_X)



Source: Authors' computations.

Figure 3: Evolution of the actual unemployment rate (NUR), out-of-sample normalised forecasted unemployment rate with composite leading index (NURF1_CLI) and out-of-sample normalised benchmark forecasted unemployment rate (NURF1_X)



Source: Authors' computations.

5. Conclusion and policy implications

This study aimed to develop reasonable accurate, reliable and timely signals related to the set of leading indicators for the unemployment rate in Malaysia. By following the standard methodology in the literature, the identification of leading indicators involved three main phases, namely the choice of target and candidate leading variable, data filtering and data evaluation. Among the 17 leading indicator candidates, the study findings indicate that the Kuala Lumpur composite index (KLCI), total loans (LOAN) and money supply (M1, M2, M3) are the leading indicators for the unemployment rate in Malaysia. It was also found that the composite leading index significantly outperformed the benchmark forecasting model for both in-sample and out-of-sample forecasting.

In relation to the labour market, this paper offers three policy implications. Firstly, leading indicators are a convenient and quick set of tools that can help develop responsive policy-making. The existence of leading indicators can remove at least one month of lag in the unemployment rate due to its lead nature, as it provides faster information about the labour market movement. Hence, the timely signal offers valuable input for the government to allocate resources and funding at the right time to mitigate labour market issues.

Secondly, the leading indicators can provide an early signal system to the Active Labour Market Policy (ALMP) for attenuating unemployment. ALMP approaches can be described as public interventions in the labour market that aim to facilitate its efficient functioning and correct disequilibria, and which can be distinguished from other general employment policy interventions in that they act selectively to favour particular groups in the labour market. Interventions are divided into *measures*, *services* and *supports*. Leading indicators support the information that is useful for the *measures* approach to combating cyclical and structural unemployment and promoting employment.

Thirdly, monetary policy is highly sensitive to labour market movements. The monetary leading indicators provide valuable inputs for the authorities to use in making policy interventions. They influence the commodities and alleviate financial pressures that affect businesses. Monetary policy instruments, such as the overnight policy rate (OPR), can influence the liquidity in the market. A reduction in the OPR means lower borrowing costs and greater money to spend, hence more investment and aggregate domestic demand. This can help in attenuating unemployment and thus boosting economic growth in Malaysia.

Although the findings on leading indicators are most relevant to monetary-policy variables, this does not imply that fiscal-policy variables are insensitive to the movement of unemployment rates. The fact that this study was unable to include fiscal-policy variables in the models was due to data unavailability. It is extremely important to measure fiscal-policy variables, in particular, public expenditure and disbursement, as they directly and indirectly influence employment. The methodologies and approaches provided in this paper can easily be updated once monthly fiscal data is available.

Acknowledgments

The authors are grateful of Prof. Dr. Muzafar Shah Habibullah for guidance and assistance in development of the leading indicator. We thank Assoc. Prof. Dr. Mohd Yusof Saari, Dr. Muhammad Daaniyall Abd Rahman and Mr. Abdul Rahim bin Abdul Razak for motivation and support for this research. We also thank the anonymous referees for their useful suggestions and feedbacks.

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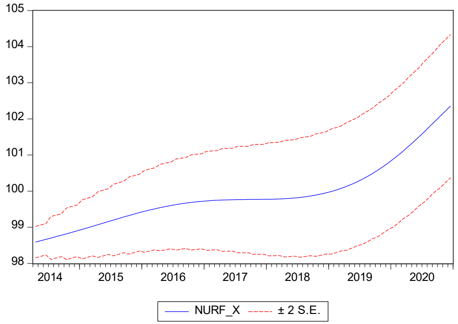
Appendix A: Unit Root Test Results.

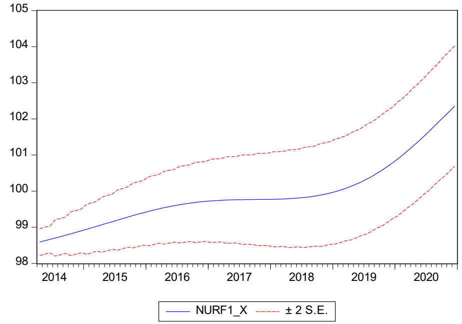
Variable	Level		First Difference	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Panel A. Augmented-Dickey Fuller Test.				
UR	-1.0451	-2.7696	-6.3104***	-6.3272***
IPI	-2.3007	1.0943	-3.3268**	-4.0025**
CPI	-1.7256	-1.2725	-7.0705***	-7.2199***
X	-0.7121	-3.1992*	-2.9994**	-2.9689
M	-1.9631	-2.5122	-2.9118**	-3.1079
XM	-0.9423	-2.7442	-3.0128**	-3.0767
RMSC	-5.3747***	-5.3880***	-5.9597***	-5.9133***
RMPM	-1.4395	-5.1343***	-3.4782**	-3.4797**
MAN	-0.4175	-3.0415	-11.4346***	-11.4273***
NCR	-2.9151**	-2.2118	-4.9809***	-12.2876***
LOAN	-2.6971*	-1.2622	-8.1242***	-8.7779***
HA	-6.7177***	-6.8962***	-6.8242***	-6.7897***
SW	-1.4792	-1.7344	-1.9562	-2.1228
KLCI	-1.89	-2.4511	-6.6902***	-6.6241***
M1	0.8416	-1.9327	-1.3287	-1.6137
M2	0.0129	-1.944	-5.3497***	-5.3201***
M3	0.1331	-1.8384	-5.4244***	-5.4036***
REER	-1.7596	-2.1527	-6.9406***	-6.9024***
Panel B. Phillips-Perron Test.				
UR	-0.8772	-2.2862	-6.1145***	-6.1429***
IPI	-3.7874***	-5.7417***	-20.2493***	-21.1733***
CPI	-1.7583	-1.3314	-6.4371***	-6.5161***
X	-2.9691**	-6.3380***	-14.846***	-16.0327***
M	-3.8565***	-6.1535***	-19.1851***	-19.142***
XM	-3.1343**	-6.1655***	-15.9559***	-15.8543***
RMSC	-5.5066***	-5.5113***	-15.0027***	-14.9202***
RMPM	-3.9107***	-5.1009***	-17.709***	-18.838***
MAN	-0.4176	-2.8316	-11.7151***	-11.9418***
NCR	-3.3783**	-1.888	-10.6492***	-12.0148***
LOAN	-2.5309	-1.3835	-8.2647***	-8.7857***
HA	-6.7131***	-6.9137***	-35.1396***	-35.0081***
SW	-1.6359	-2.5686	-13.2005***	-13.1961***
KLCI	-1.8322	-2.3981	-8.4186***	-8.3358***
M1	1.0766	-2.1726	-9.8428***	-9.9717***
M2	-0.2518	-2.3459	-8.9867***	-8.9322***
M3	-0.1684	-2.2583	-9.0676***	-9.0091***
REER	-1.6412	-1.9986	-6.9483***	-6.9101***

Note: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total export, total import, total trade, real imports on semi-conductor, real imports of other basic precious & other non-ferrous metals, sales value of manufacturing, companies on register at end of period, total loans, no. of housing units approved, average salaries and wages per employee in manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3, and real effective exchange rates, respectively.
Source: Authors' computations.

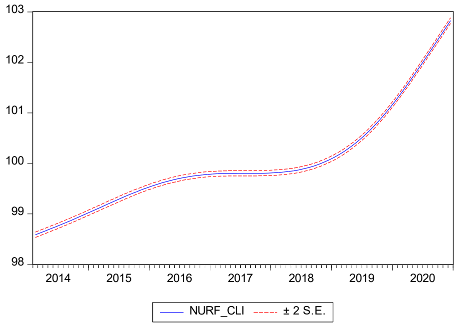
Appendix B: Evaluation graphs of in-sample and out-of-sample benchmark forecasting model and composite leading index forecasting model



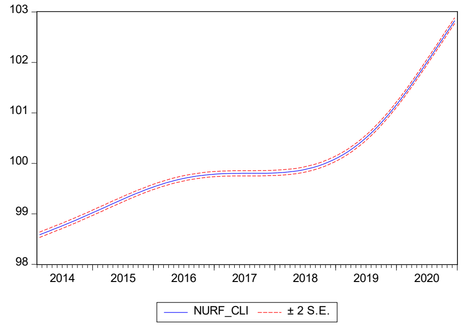
Forecast: NURF_X	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M04 2020M12	
Included observations: 81	
Root Mean Squared Error	0.199767
Mean Absolute Error	0.145830
Mean Abs. Percent Error	0.144663
Theil Inequality Coefficient	0.000999
Bias Proportion	0.532801
Variance Proportion	0.314540
Covariance Proportion	0.152659
Theil U2 Coefficient	2.915531
Symmetric MAPE	0.144857



Forecast: NURF1_X	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M04 2020M12	
Included observations: 81	
Root Mean Squared Error	0.201637
Mean Absolute Error	0.147798
Mean Abs. Percent Error	0.146623
Theil Inequality Coefficient	0.001008
Bias Proportion	0.537277
Variance Proportion	0.313017
Covariance Proportion	0.149704
Theil U2 Coefficient	2.942910
Symmetric MAPE	0.146821



Forecast: NURF_CLI	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M02 2020M12	
Included observations: 83	
Root Mean Squared Error	0.024642
Mean Absolute Error	0.022036
Mean Abs. Percent Error	0.022042
Theil Inequality Coefficient	0.000123
Bias Proportion	0.000000
Variance Proportion	0.000156
Covariance Proportion	0.999917
Theil U2 Coefficient	0.363759
Symmetric MAPE	0.022042



Forecast: NURF_CLI	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M02 2020M12	
Included observations: 83	
Root Mean Squared Error	0.024642
Mean Absolute Error	0.022036
Mean Abs. Percent Error	0.022042
Theil Inequality Coefficient	0.000123
Bias Proportion	0.000000
Variance Proportion	0.000156
Covariance Proportion	0.999917
Theil U2 Coefficient	0.363759
Symmetric MAPE	0.022042

Note: Variables NURF_X, NURF_CLI, NURF1_X, and NURF1_CLI denote in-sample normalised benchmark forecasted unemployment rate, in-sample normalised forecasted unemployment rate with composite leading index, out-of-sample normalised benchmark forecasted unemployment rate, and out-of-sample normalised forecasted unemployment rate with composite leading index, respectively.
Source: Authors' computations.

Appendix C: Normalised and Forecasted Data, January 2014 - December 2020.

Year	Month	Normalised Data					Forecasted Data			
		NUR	NKLCI	NLOAN	NM2	CLI	NURF_X	NURF_CLI	NURF1_X	NURF1_CLI
2014	January	98.58	101.76	98.21	98.46	99.48	-	-	-	-
2014	February	98.62	101.69	98.26	98.49	99.48	-	98.58	-	98.58
2014	March	98.66	101.62	98.31	98.53	99.48	-	98.62	-	98.62
2014	April	98.69	101.55	98.35	98.56	99.49	98.59	98.66	98.59	98.66
2014	May	98.73	101.48	98.40	98.59	99.49	98.63	98.70	98.63	98.70
2014	Jun	98.77	101.41	98.45	98.63	99.49	98.67	98.74	98.67	98.74
2014	July	98.81	101.34	98.49	98.66	99.50	98.70	98.78	98.70	98.78
2014	August	98.85	101.27	98.54	98.69	99.50	98.74	98.82	98.74	98.82
2014	September	98.89	101.20	98.59	98.73	99.50	98.78	98.87	98.78	98.86
2014	October	98.93	101.13	98.64	98.76	99.51	98.82	98.91	98.82	98.91
2014	November	98.98	101.06	98.68	98.79	99.51	98.86	98.95	98.86	98.95
2014	December	99.02	100.99	98.73	98.82	99.52	98.90	99.00	98.90	99.00
2015	January	99.06	100.93	98.78	98.86	99.52	98.94	99.04	98.94	99.04
2015	February	99.11	100.86	98.82	98.89	99.52	98.98	99.09	98.98	99.09
2015	March	99.15	100.80	98.87	98.92	99.53	99.03	99.13	99.03	99.13
2015	April	99.19	100.73	98.91	98.95	99.53	99.07	99.18	99.07	99.18
2015	May	99.24	100.67	98.96	98.98	99.54	99.11	99.22	99.11	99.22
2015	Jun	99.28	100.62	99.00	99.02	99.55	99.16	99.27	99.16	99.27
2015	July	99.32	100.56	99.05	99.05	99.55	99.20	99.31	99.20	99.31
2015	August	99.36	100.51	99.09	99.08	99.56	99.24	99.36	99.24	99.36
2015	September	99.40	100.46	99.14	99.11	99.57	99.28	99.40	99.28	99.40
2015	October	99.44	100.42	99.18	99.14	99.58	99.33	99.44	99.32	99.44
2015	November	99.47	100.38	99.23	99.17	99.59	99.37	99.48	99.36	99.48
2015	December	99.51	100.35	99.27	99.21	99.61	99.40	99.51	99.40	99.52
2016	January	99.54	100.32	99.31	99.24	99.62	99.44	99.55	99.44	99.55
2016	February	99.57	100.29	99.35	99.27	99.64	99.48	99.58	99.48	99.58
2016	March	99.60	100.27	99.40	99.30	99.66	99.51	99.61	99.51	99.62
2016	April	99.62	100.26	99.44	99.34	99.68	99.54	99.64	99.54	99.64
2016	May	99.64	100.24	99.48	99.37	99.70	99.57	99.67	99.57	99.67
2016	Jun	99.67	100.23	99.52	99.40	99.72	99.60	99.69	99.60	99.69
2016	July	99.68	100.23	99.56	99.44	99.74	99.63	99.71	99.62	99.71
2016	August	99.70	100.23	99.60	99.47	99.77	99.65	99.73	99.65	99.73
2016	September	99.71	100.23	99.64	99.51	99.79	99.67	99.75	99.67	99.75
2016	October	99.73	100.24	99.68	99.55	99.82	99.69	99.76	99.69	99.76
2016	November	99.74	100.24	99.72	99.58	99.85	99.70	99.77	99.70	99.77
2016	December	99.74	100.25	99.77	99.62	99.88	99.72	99.78	99.72	99.78
2017	January	99.75	100.26	99.81	99.66	99.91	99.73	99.79	99.73	99.79
2017	February	99.76	100.28	99.85	99.70	99.94	99.74	99.79	99.74	99.79
2017	March	99.76	100.29	99.89	99.74	99.97	99.75	99.80	99.75	99.80
2017	April	99.76	100.30	99.93	99.78	100.00	99.76	99.80	99.75	99.80
2017	May	99.76	100.31	99.97	99.82	100.04	99.76	99.80	99.76	99.80
2017	Jun	99.77	100.32	100.01	99.86	100.07	99.76	99.80	99.76	99.80
2017	July	99.77	100.33	100.05	99.91	100.10	99.77	99.80	99.76	99.80
2017	August	99.77	100.34	100.09	99.95	100.13	99.77	99.80	99.77	99.80
2017	September	99.77	100.34	100.13	100.00	100.16	99.77	99.80	99.77	99.80
2017	October	99.77	100.34	100.17	100.04	100.18	99.77	99.80	99.77	99.80
2017	November	99.78	100.33	100.21	100.09	100.21	99.77	99.80	99.77	99.80

Note: Variables NUR, NKLCI, NLOAN, NM2, CLI, NURF_X, NURF_CLI, NURF1_X, and NURF1_CLI denote normalised unemployment rate, normalised Kuala Lumpur composite index, normalised total loans, normalised money supply M2, composite leading index, in-sample normalised benchmark forecasted unemployment rate, in-sample normalised forecasted unemployment rate with composite leading index, out-of-sample normalised benchmark forecasted unemployment rate, and out-of-sample normalised forecasted unemployment rate with composite leading index, respectively.

Appendix C: Normalised and Forecasted Data, January 2014 - December 2020 (continued).

Year	Month	Normalised Data					Forecasted Data			
		NUR	NKLCI	NLOAN	NM2	CLI	NURF_X	NURF_CLI	NURF1_X	NURF1_CLI
2017	December	99.78	100.33	100.26	100.13	100.24	99.77	99.81	99.77	99.80
2018	January	99.79	100.31	100.30	100.18	100.26	99.78	99.81	99.77	99.81
2018	February	99.80	100.29	100.34	100.22	100.28	99.78	99.82	99.78	99.81
2018	March	99.81	100.27	100.38	100.27	100.31	99.79	99.83	99.78	99.82
2018	April	99.82	100.24	100.42	100.32	100.33	99.79	99.84	99.79	99.83
2018	May	99.84	100.20	100.46	100.37	100.34	99.80	99.85	99.80	99.85
2018	Jun	99.86	100.16	100.50	100.41	100.36	99.81	99.87	99.81	99.87
2018	July	99.89	100.11	100.54	100.46	100.37	99.83	99.89	99.82	99.89
2018	August	99.91	100.06	100.58	100.51	100.38	99.84	99.92	99.84	99.91
2018	September	99.95	100.00	100.62	100.56	100.39	99.86	99.95	99.86	99.94
2018	October	99.99	99.94	100.66	100.61	100.40	99.89	99.98	99.89	99.98
2018	November	100.03	99.87	100.70	100.65	100.41	99.92	100.02	99.92	100.02
2018	December	100.08	99.80	100.74	100.70	100.41	99.95	100.07	99.95	100.06
2019	January	100.13	99.72	100.78	100.75	100.42	99.99	100.12	99.99	100.11
2019	February	100.19	99.64	100.82	100.80	100.42	100.03	100.17	100.03	100.17
2019	March	100.26	99.56	100.86	100.84	100.42	100.08	100.24	100.08	100.24
2019	April	100.33	99.47	100.90	100.89	100.42	100.13	100.31	100.13	100.31
2019	May	100.41	99.38	100.93	100.94	100.42	100.19	100.38	100.19	100.38
2019	Jun	100.49	99.29	100.97	100.98	100.42	100.26	100.46	100.26	100.46
2019	July	100.58	99.20	101.01	101.03	100.41	100.33	100.55	100.33	100.55
2019	August	100.68	99.11	101.05	101.08	100.41	100.41	100.65	100.41	100.65
2019	September	100.78	99.01	101.08	101.12	100.41	100.49	100.75	100.49	100.75
2019	October	100.89	98.91	101.12	101.17	100.40	100.58	100.86	100.58	100.86
2019	November	101.01	98.82	101.16	101.22	100.40	100.68	100.97	100.68	100.98
2019	December	101.13	98.72	101.19	101.26	100.39	100.78	101.10	100.78	101.10
2020	January	101.26	98.62	101.23	101.31	100.39	100.89	101.22	100.89	101.23
2020	February	101.39	98.53	101.26	101.36	100.38	101.01	101.36	101.00	101.37
2020	March	101.52	98.43	101.30	101.40	100.38	101.13	101.49	101.12	101.50
2020	April	101.66	98.34	101.33	101.45	100.37	101.25	101.63	101.25	101.65
2020	May	101.80	98.24	101.37	101.50	100.37	101.38	101.78	101.38	101.79
2020	Jun	101.94	98.15	101.40	101.54	100.37	101.52	101.93	101.51	101.94
2020	July	102.08	98.06	101.44	101.59	100.36	101.65	102.07	101.65	102.09
2020	August	102.22	97.97	101.48	101.64	100.36	101.79	102.22	101.79	102.24
2020	September	102.37	97.88	101.51	101.68	100.36	101.93	102.37	101.93	102.39
2020	October	102.51	97.79	101.55	101.73	100.35	102.07	102.52	102.07	102.55
2020	November	102.66	97.70	101.58	101.78	100.35	102.22	102.68	102.21	102.70
2020	December	102.80	97.61	101.62	101.82	100.35	102.36	102.83	102.35	102.85

Note: Variables NUR, NKLCI, NLOAN, NM2, CLI, NURF_X, NURF_CLI, NURF1_X, and NURF1_CLI denote normalised unemployment rate, normalised Kuala Lumpur composite index, normalised total loans, normalised money supply M2, composite leading index, in-sample normalised benchmark forecasted unemployment rate, in-sample normalised forecasted unemployment rate with composite leading index, out-of-sample normalised benchmark forecasted unemployment rate, and out-of-sample normalised forecasted unemployment rate with composite leading index, respectively.

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