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Vulnerability Analysis of Macroeconomic Indicators for Early Detection of Currency Crisis: Case Study of Indonesian Economy on 1991–2019

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The purpose of this study is to detect the currency crisis in Indonesia by exploring the vulnerability of macroeconomic variables. The Exchange Market Pressure Index was used to determine the crisis period by modeling the threshold value. Early indicators were determined using the signal analysis approach; therefore, the vulnerability level of each macroeconomic variable is known and used to determine the leading indicators. The result showed that the Signal Analysis and Herrera–Garcia approaches are the best detection models. Furthermore, it was concluded that the Signal Analysis approach was better in detecting crises compared to the Herrera–Garcia approach.

Keywords: Exchange market pressure index; leading indicator; signal analysis; Herrera–Garcia model.

JEL Classifications: F31, F41

1. Introduction

The exchange rate is one of the essential factors in a country's economy, used to determine its stability (Zehirun *et al.*, 2014; Nelson, 2018). In 1998, Indonesia and some Southeast Asian countries experienced economic crisis due to external shocks. However, in 2008, the United States also encountered a similar effect, and in 2011, Europe experienced a debt crisis (Hill, 2012).

The vulnerability of macroeconomic variables is the genesis of a currency crisis, which led to the issue's lesser susceptibility. Macroeconomic variables also have varying degrees of vulnerability, irrespective of the fact that the economy is in good condition. However, some variables are in poor condition; therefore, it is important to conduct early detection to determine variables vulnerable to crises (Ramasamy and Karimi, 2015).

This research is based on the early detection of the currency crisis in Indonesia. The Signal Approach developed by Goldstein, Kaminsky, and Reinhardt in 2000 (abbreviated as GKR, 2000) was specifically used to accurately detect 29 banking and 89 currency crises in 25 countries in Asia, including Philippines, Korea, and Thailand. In terms of probability signal, Indonesia was ranked the top 8, while Malaysia ranked 10th. Conversely, Indonesia is ranked 25th with a relatively low probability signal.

This is because the real effective exchange rate of Rupiah is far below the minimum threshold. However, the reverse is the case in other Southeast Asian countries affected by the crisis. The Real Effective Exchange Rate is considered a leading indicator and used to obtain the highest probability. Therefore it is necessary to carry out in-depth studies on the various methods used to determine these indicators, and compare it with similar researches to produce a detection signal with a relatively high probability.

The Early Warning System Currency Crisis approach developed by Kaminsky and Reinhart (1999) utilized nine indicators, namely: Real Effective Exchange Rate, export growth, stock prices, M2/reserve, economic growth, foreign exchange reserve growth, M2 multiplier, credit/GDP, and real interest rates. This study showed that before the crisis occurred, there were overheated symptoms of poor economic growth in the Asian region. However, the research did not identify the crisis in Indonesia, as well as numerous poor signals' in several unaffected countries, such as Hong Kong and Singapore. It was further reported that the slightest shock on a country's currency has a significant impact on market participants. Subsequently, the Contagion Effect plays an essential role in triggering the financial crisis in Asia.

A simpler model referred to as the Herrera and Garcia (1999) approach was developed by Adiningsih *et al.* (2002). It is inexpensive and updated monthly because the model aggregates utilize existing variables to produce signals dependent on the composite index's behavior to obtain a set of key indicators in the same direction over a certain period. Furthermore, it is aggregated by standardization, thereby determining the Macroeconomic Vulnerability Index (IMV). Subsequently, the IMV is filtered to produce a signal, which is carried out in two ways, namely GARCH (simple or level) and ARIMA residual models (Bollerslev, 1986).

Generally, this model is used to detect crisis with four economic fundamentals. Contagion effects contribute to speculative attacks. Detection using GARCH (simple) and ARIMA residual models significantly produces a lot of signals. However, most of them are false. The ratio of false to good signals (Noise-to-Signal Ratio (NSR)) is relatively large; therefore, the greater the value of the NSR, the smaller its signal probability in predicting crisis and vice versa (Adiningsih *et al.*, 2002; Sussangkarn and Tinakorn, 2002).

The Signal Analysis and Herrera–Garcia approaches have their advantages and disadvantages; therefore, an in-depth study is needed to enable the existing methods to produce effective signals.

2. Methods

2.1. *Approach to identifying crisis periods*

A currency crisis is a sudden and steep decline in the value of a nation's currency, thereby leading to a significant decrease in foreign reserves (Kaminsky *et al.*, 1998). The decline in value negatively affects the economy by creating instabilities in the exchange rate, thereby forcing the central bank to raise interest rates in an attempt to prevent further depreciation. A currency experiences crisis when its deviation exceeds its standard average threshold value of +1.5 deviations.

The Exchange Market Pressure Index (EMPI) is commonly used to determine the crisis period (Eichengreen *et al.*, 1995; Girton and Roper, 1977; Nitithanprapas and Willet, 2000; Bordo *et al.*, 2001; Bussiere and Fratzscher, 2002; Siregar and Pontines, 2007). Kaminsky *et al.* (1998) and Kaminsky and Reinhart (1999) defined EMPI as follows:

$$\mathrm{EMPI}_{i,t} = \frac{\Delta e_{i,t}}{e_{i,t}} - \frac{\sigma_e}{\sigma_r}\frac{\Delta r_{i,t}}{r_{i,t}} + \frac{\sigma_e}{\sigma_i}\Delta i_{i,t}, \tag{1}$$

where $\mathrm{EMPI}_{i,t}$ is the Exchange Market Pressure Index for i country at t period, $e_{i,t}$ is the exchange rate of currency in i country against the US Dollar in t period, $r_{i,t}$ is the gross foreign reserves of i country in t period, i_{it} is the nominal interest rate of i country in t period, σ_e is the standard deviation of changes in the exchange rate ($\frac{\Delta e_{i,t}}{e_{i,t}}$), while σ_r is the standard deviation of the rate of change in foreign reserves ($\frac{\Delta r_{i,t}}{r_{i,t}}$), and σ_i is the standard deviation of changes in the nominal interest rate $\Delta i_{i,t}$.

The implementation of the EMPI is used in detecting early warning signals by estimating its critical value, which shows a financial crisis whenever the 3-sigma rule is applied. Therefore, the financial crisis occurs when the EMPI value is greater than the mean, standard deviation of the sample δ (Knedlik, 2006), which is stated as follows:

$$\text{Crisis} = \begin{pmatrix} 1, & \text{if} \quad \mathrm{EMP}_{i,t} > \mu_{\mathrm{EMP}} + \delta.\sigma_{\mathrm{EMP}} \\ 0, & \text{otherwise} \end{pmatrix}, \tag{2}$$

where μ_{EMP} and σ_{EMP} are the mean values and the standard deviation of an EMPI sample, respectively.

The use of critical values derived from EMPI shows that the standard deviation of a crisis generally ranges from 1 to 3. The greater the critical value, the lesser the filtered signals detected, and vice versa.

2.2. *Early indicator selection*

Studies carried out by Kaminsky (1999), Goldstein *et al.* (2000), Zhuang (2005), and Lestano and Kuper (2003) stated that early indicators are empirically used to predict currency crises.

In principle, when the indicators used are relatively few, it makes data provision easier and more practical. However, more detailed information from the economic sector is not absorbed when extracted from the data. Conversely, when the indicator is relatively large, it produces richer information used to detect certain sectors that provide signals, thereby preventing a crisis from occurring. However, this needs a relatively large amount of data, which can be represented by other indicators.

Furthermore, based on economic theory and data availability, indicators were selected based on Kaminsky *et al.*'s (1998) research as shown in Table 1.

All data are in the form of year-on-year changes, to avoid seasonal influences and deviations from trends. "Level" is used when data is not affected by seasonality.

Table 1. Early indicators macroeconomic.

No.	Indicators	Transformation	Data frequency	References
1.	Real output	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
2.	Stock price	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
3.	Foreign exchange reserves	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999); Eddison (2003)
4.	Domestic-foreign interest difference	Level	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003), Demirguc-Kunt *et al.* (2000)
5.	The excess of M1 real balance	Level	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
6.	M2/foreign exchange reserves	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003), Demirguc-Kunt *et al.* (2000)
7.	Bank deposits	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
8.	M2 multiplier	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
9.	Domestic credit/ GDP	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003), Demirguc-Kunt *et al.* (2000)

Table 1. (*Continued*)

No.	Indicators	Transformation	Data frequency	References
10.	Real deposit interest rate	Level	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003), Demirguc-Kunt *et al.* (2000)
11.	Loan/deposit interest rate ratio	Level	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
12.	Real effective exchange rate	Deviation from trend	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003), Demirguc-Kunt *et al.* (2000)
13.	Export	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
14.	Import	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999), Eddison (2003)
	Trade exchange rates	Growth *y-o-y*	Monthly	Kaminsky *et al.* (1998), Berg and Pattillo (1999)

This indicator was selected based on the studies carried out by Adiningsih *et al.* (2002) and Goldstein *et al.* (2000). According to them, Indonesia experiences a low signal probability of detecting a currency crisis, which is different from other Asian countries because the Rupiah's real effective exchange rate is far below the minimum threshold.

2.3. *Estimation of trends and deviations with the Hodrick–Prescott filter*

The trend estimation of the real and effective exchange rate is usually not a linear model. Therefore, the Hodrick–Prescott (HP) filter approach is appropriate to estimate real and effective trends and deviations from an exchange in order to produce a relatively high probability of detecting crisis signals. The HP filter was used to estimate the trends and deviations of the data, as stated in the following equation: y_t for $t = 1, 2, 3, \ldots$, where t denotes the logarithm of the time-series variable (Hodrick and Prescott, 1997). The y_t series consists of the trend component τ_t, the seasonal component e_t, and the error component e_t, therefore $y_t = \tau_t + e_t + \in_t$. The existence of λ positive value (adjusting the sensitivity of trend to short-term fluctuations is achieved by modifying the multiplier λ), shows that the component trend is solvable

$$\min_{\tau}\left(\sum_{t=1}^{t}(y_t - \tau_t)^2 + \lambda\sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2\right). \tag{3}$$

2.4. *Signal detection mechanism*

2.4.1. *Signal analysis*

A 24-month "signaling horizon" was utilized, and the indicator is located in an abnormal area and observed monthly. When a signal is received, a crisis occurs within the stipulated number of months (included in category A). Conversely, the signal is considered inappropriate assuming there was no crisis within the stated period (in category B). Supposing the indicator does not show any signal, then no crisis was detected within 24 months (category D), and assuming it occurs, then it is included in category C (Table 2).

To calculate the performance of each indicator, Goldstein *et al.* (2000) stated that the unconditional probability of a crisis is shown as $P(\text{Crisis}) = (A + C)/(A + B + C + D)$, while the conditional probability is shown as $P(\text{Crisis}|S) = A/(A + B)$. Furthermore, the marginal predictive power is shown as $P(\text{Crisis}|S) - P(\text{Crisis})$. Category B is called noise because it produces a bad signal. Therefore, the proportion of months that issued bad and good signals were $B/(B + D)$ and $A/(A + C)$. Furthermore, the comparison between these two ratios is known as "Adjusted Noise-to-Signal Ratio," (NSR), and stated as follows:

$$\text{Noise-to-Signal Ratio} = \frac{\frac{B}{B+D}}{\frac{A}{A+C}}. \tag{4}$$

A smaller NSR value illustrates a better indicator. Therefore, an NSR value of 0 indicates that the signal generated by the indicator is perfect.

The probability measurement of early indicators showed that the greater the number of signals, the higher the composite (Boonman *et al.*, 2019). The method used to combine signals is by counting the number of individual indicators that cross the threshold in a particular month, as stated in the following equations:

$$I_t^{(1)} = \sum_{j=1}^{n} S_t^j, \tag{5}$$

where S_t^j= 1 assuming the j variable pass the threshold at t period, and S_t^j =0 for others.

The weighting of the composite indicator based on the NSR adjustment of each variable is required. Assuming each early indicator of S_{it} has an average weight of 0

Table 2. Indicator signal matrix.

	Crisis in "signaling horizon"	There is no crisis in "signaling horizon"
Signal	A	B
There is no signal	C	D

Source: Kaminsky *et al.* (1998).

and 1, therefore:

$$I_t^{(1)} = \sum_{t=1}^{n} S_t^j \cdot \frac{1}{W^j}, \tag{6}$$

where $W^j =$ Noise-to-Signal Ratio of j variable (Berg and Pattillo, 1999).

The Signal Analysis approach does not have a test tool to determine the level of significance in predicting the probability of a crisis. However, it is carried out based on the level of accuracy and calibration. The performance is determined in accordance with the mean square error using the Quadratic Probability Score (QPS), while the Global Bias Square (GBS) is used to measure the accuracy of the forecast calibration.

The accuracy of composite indicators was conducted using a QPS. T probability forecast is $\{P_t\}_{t=1}^{T}$, where P_t is the probability of crisis $[t, t+h]$ on the information conveyed by the composite indicator I in period t. Meanwhile, $\{R_t\}_{t=1}^{T}$ is the realization time series, where $R_t = 1$ supposing a crisis occurs within the range of t and $t+h$, and $R_t = 1$ assuming a crisis does not occur. QPS is stated as follows:

$$\mathrm{QPS} = \frac{1}{T} \sum_{t=1}^{T} 2(P_t - R_t)^2, \tag{7}$$

where QPS is within the range of 0 and 2, where $0 =$ perfect accuracy.

The application of calibration on probability forecasting is in accordance with its accuracy and the relative frequency observed. Forecasting calibration is measured by GBS as follows:

$$\mathrm{GBS} = 2(\bar{P} - \bar{R})^2, \tag{8}$$

where $\bar{P} = \frac{1}{T} \sum_{t=1}^{T} P_t$, and $\bar{R} = \frac{1}{T} \sum_{t=1}^{T} R_t$. GBS is within the range of 0 and 2, where 0 is the perfect global calibration, which occurs when the average probability forecasting is equal to its realization (Abimanyu and Imansyah, 2008).

2.4.2. *Herrera–Garcia approach*

The Herrera and Garcia (1999) approach in terms of detecting signals is obtained by transforming or filtering the index of macroeconomic vulnerability (IMV) as well as aggregating it; additionally, its components are the leading indicators of crisis.

Transforming or filtering the IMV to produce a signal is carried out based on the following steps: First, determine the temporary ARIMA Model (Box and Jenkins, 1976) which analyzes the p and q values in the process to be installed by calculating the ACF and PACF stationary time series. Time series are differentiated as much as d times to make it stationary before implementing the model; it is therefore referred to as ARIMA (p, d, q), and is estimated. Second, choose the best model. Goodness of fit is used for diagnostic review. Model selection considers the least number of parameters and Smallest Root Mean Square of Error (RMSE).

Subsequently, smaller RMSE is better than all suitable models, and it leads to more accurate future forecasts.

3. Data Description

Data were obtained from the International Financial Statistics (IFS), while those related to the "Indonesia-IDX-Composite" were collected from the Indonesian Economic and Financial Statistics (SEKI) Bank from 1991 (1)–2019 (12). Appendix A shows a monthly observation for 348 months. According to Mankiw (2019), Real Output is a measure of the output of a certain period based on constant prices. This is obtained by converting Nominal GDP to constant price GDP, as shown in line 16 of a 2010 study. Furthermore, Indonesia's foreign exchange reserves are shown in line 3 with the difference between domestic and foreign interest rates with the United States obtained from lines 4 to 2. The excess of the real M1 balance is the residual regression with GDP, in accordance with inflation and predetermined trends (Kaminsky *et al.*, 1998). Real M1 and GDP are obtained from lines 8 and 16, while inflation is from the Consumer Price Index growth rate found in line 10. M2/Foreign exchange reserves obtained from line 7 are divided by row 3, while bank deposits are obtained from line 13. Kaminsky *et al.* (1998) stated that Multiplier M2 shows significant changes in reserve equity, obtained from line 9. Domestic credit/GDP was obtained from line 17. Meanwhile, the Real Saving Interest Rate is obtained by subtracting the nominal interest from the inflation rate reflected in the growth rate of the Consumer Price Index (İskenderoğlu Ö, 2011). This was obtained from row 2 minus the growth rate of row 10 Loan/deposit interest rate ratio i.e., row 14 divided by row 13. The nominal exchange rate × domestic CPI/US CPI (Kaminsky *et al.*, 1998) is obtained from multiplying rows 1 and 10, further divided by row 5. Exports and imports are obtained from lines 11 and 12. The Trade Exchange Rate is the ratio between the exported and imported quality of goods (Kaminsky *et al.*, 1998), obtained from line 11 and divided by line 12.

4. Results

4.1. *Determination of currency crisis period*

The results from the EMPI calculations based on Eqs. (1) and (2) in accordance with critical values are the basis for determining the crisis period. The threshold is equal to Mean + 1.5 Standard Deviation, where EMPI values that exceed it are identified as "Crisis," and vice versa, therefore the exchange rate crisis period in Indonesia is shown in Table 3.

4.2. *Vulnerability estimation results in macroeconomic variables*

Transformations are conducted on all modified data in the form of year-on-year changes to avoid seasonal influences, while the "levels" are applied, supposing it is

Table 3. Crisis period in Indonesia (1991–2019).

Year	Month of crisis	Frequency
1991	February	1
1994	March	1
1997	July, November, December	3
1998	January, May	2
2000	August	1
2001	January	1
2006	May	1
2008	September	1

unaffected. This is carried out by observing the deviation of the trend on the "Real Exchange Rates" indicator using the HP filter as shown in Eq. (3). The results from the calculation illustrate the early indicators of the exchange rate crisis, as shown in Table 4.

The main indicators are obtained by analyzing the results from the ranks shown in Table 4. Conversely, the main or leading indicators are shown in Table 5.

Table 4. Early indicators of exchange rate crisis in Indonesia (1991–2019).

No.	Early indicator	$A/(A+C)$ (%)	NSR	$A/(A+B)$ %	$(A+D)/(A+B+C+D)$ %	Ranking
1	Real output	7042	1092	41,667	54,938	9
2	Stock price	5634	1365	36,364	54,321	13
3	Foreign exchange reserves	7299	1319	35,714	55,247	12
4	The difference in domestic-foreign interest	13,380	0.082	90,476	61,420	2
5	Excess on M1 real balance	8451	1300	37,500	53,704	11
6	M2/foreign reserves	9155	0.180	81,250	59,259	3
7	Bank deposits	10,563	0.260	75,000	59,259	5
8	M2 multiplier	8451	1040	42,857	54,938	8
9	Domestic credit/GDP	8451	0.780	50,000	56,173	7
10	Real savings interest rate	11,972	0.184	80,952	60,185	4
11	Loan/deposit interest rates	4930	1449	35,000	54,321	15
12	Real exchange rates	15,493	0.071	91,667	62,346	1
13	Export	5634	1365	36,364	54,321	14
14	Import	7042	1092	41,667	54,938	10
15	Trade exchange rates	11,972	0.413	65,385	58,642	6

Notes: $(A/A+C)(\%)$ = Pre crisis that can be predicted accurately,
NSR = Noise-to-Signal Ratio,
$(A/A+B)(\%)$ = Crisis Conditional Probability,
$(A+D)/(A+B+C+D)(\%)$ = Accuracy of Prediction.

Table 5. Main early indicators of exchange rate crisis in Indonesia (1991–2019).

No.	Early indicator	$A/A+C$ (%)	NSR	$A/A+B$ (%)	$(A+D)/(A+B+C+D)$ (%)	Ranking
4	The difference in domestic-foreign interest	13,380	0.082	90,476	61,420	2
6	M2/foreign reserves	9155	0.180	81,250	59,259	3
10	Real savings interest rate	11,972	0.184	80,952	60,185	4
12	Real exchange rates	15,493	0.071	91,667	62,346	1

Table 5 shows that the "Real Exchange Rate" indicator is at the highest level. The use of the HP filter turned out to be able to produce a reasonable estimate, and it is the smallest NSR (rank 1) used to determine the leading indicator. Subsequently, when compared with the research conducted by GKR (2000), the real exchange rate indicator is far below the threshold limit and does not generate any signal.

4.3. *Estimation results from composite index and crisis probability*

The greater the early indicators that detect signals, the higher the value of the composite index and the crisis probability. Generally, the composite index is more reliable than the use of a single indicator in predicting crises. Furthermore, it is determined by the threshold value, and in this study, it is equal to mean + 1.5 standard deviations. This method was applied to obtain a signal detection, where the results are compared either by using 15 early indicators or 4 leading indicators, as shown in Table 6.

Table 6 shows that the composite index formed from several indicators produces more signals (32 signals) than those obtained from the main or leading indicator (29 signals). However, Table 7 shows whether these signals are predicted accurately.

Table 7 shows that the formation of a composite index using 15 early indicators and 4 leading indicators is relatively the same. The NSR values in both cases are zero, meaning that there are no signal disturbances. The relatively small difference is in the number of months accurately predicted with composite indexes of 15 and 4 indicators,

Table 6. Comparison of signal detection at the composite index of 15 early indicator with 4 main early indicators (leading).

Year	Composite index signal (15) (month)	Total	Composite index signal (4) (month)	Total
1996	7,8,9,10,11,12	6	7,8,9,10,11,12	6
1997	1,2,3,4,5,6,7,8,9,10,11,12	12	1,2,3,4,5,6,7,8,9,10,11	11
1998	1,2,3,4,5,8,9,10,11,12	10	1,4,5,8,9,10,11,12	8
1999	1,2,3,4	4	1,2,3,4	4
	Total	32	Total	29

Table 7. Comparison of composite index signal accuracy of 15 early indicators with 4 leading indicators.

Signal generation with threshold = mean + 1.5 standard deviations	Composite index (15)	Composite index (4)
Noise-to-signal ratio (NSR)	0	0
The number of pre-crisis months which precisely predicted	32	29
% pre-crisis period that gives signals ($A/(A+C)$)	22,535	20,422
% incorrect signal ($B/B+D$)	0	0
QPS	0.204	0.197
GBS	0.008	0.006
% accuracy of prediction $(A+D)/(A+B+C+D)$	66,050	65,123

at 22.535% and 20.422%, respectively. Likewise, the prediction accuracy has a relatively small difference of 66.050% in the composite index of 15 early indicators and 65.123% in the 4 leading indicators.

The performance measurement utilized the QPS, and both values are relatively the same, 0.204 for the composite index with 15 indicators, and 0.197 for the 4 leading indicators. It is interpreted that they both have accurate performance because their values are approximately zero.

The results from the forecasting calibration were carried out with the GBS. Both values are also approximately zero, 0.008, and 0.006, which means that they are almost perfect.

Based on these results, signal detection of the composite index using either the 15 early or 4 leading indicators has relatively no significant difference. Therefore, it is reasonable to predict a crisis by simply using 4 early leading indicators as the composite index.

4.4. *Estimation results with the Herrera–Garcia approach*

Signal detection using the Herrera–Garcia approach is based on 4 leading indicators, known as the Index of Macroeconomics Vulnerability (IMV). The IMV is standardized to obtain a zero mean and unit variance. Furthermore, filtering was carried out using the ARIMA residual model.

The initial step is to apply the ARIMA Models. This modeling was applied to produce the best Least Number of Parameters and Smallest RMSE. A smaller RMSE means better than all existing models, therefore, future forecasts are more accurate. Furthermore, it is also based on the residuals estimated from the model that need to be white noise, which is a form of stochastic error with zero mean, constant variance, and non-auto correlated. It is usually very difficult to determine economic and financial data that are very large with high volatility. Therefore, in this study, these two requirements were met by dividing the data into six groups, each consisting of 56 data series, as shown in Table 8.

Table 8. IMV estimation results with ARIMA models.

	Group 1	Group 2	Group 3
Model	ARIMA(1,0,0)(1,0,0)^{12}	ARIMA(1,1,0)(1,0,1)^{25}	ARIMA(1,1,1)(1,0,1)^{15}
	Group 4	Group 5	Group 6
Model	ARIMA(1,1,0)	ARIMA(1,1,0)	ARIMA(1,0,0)

Table 9. The estimation results of ARIMA residual model.

	Group 1	Group 2	Group 3
Model	ARIMA (0,0,1)	ARIMA(0,1,1)	ARIMA(0,1,1)
	Group 4	Group 5	Group 6
Model	ARIMA(0,0,1)	ARIMA(0,1,1)	ARIMA(0,1,1)

The results from the residual are normally distributed (zero mean and unit variance) in accordance with the six ARIMA models and are initially used to detect the signal by modeling. The signals are detected when the model shows deviations from normal behavior as well as when the statistics are greater than zero. The estimation from the ARIMA Residual Model is shown in Table 9.

The estimated results from the modeling produced residuals from each group, which was aggregated and its total used to detect signals as shown in Table 10.

Table 10. Signal detection results from the ARIMA residual model.

Year	The signal of ARIMA residual models	Total	Year	The signal of ARIMA residual models	Total
1991	2,3,8,11	4	2005	2,4,5,7,8,11	6
1992	1,4,5,6,7,10	6	2006	1,3,4,5,7,11	6
1993	1,3,5,9	3	2007	5,7,8,9,12	5
1994	1,2,4,6,7,8,9,10,12	9	2008	3,4,7,10,11,12	6
1995	2,4,5,9,10,11	6	2009	3,5,7,9,10	5
1996	2,4,8,9,11	5	2010	1,2,4,7,8,9,12	7
1997	1,3,4,5,6,7	6	2011	1,2,3,6,8	5
1998	1,2,4,6,7,8,11	7	2012	1,4,6,7,8,10,12	7
1999	9,10	2	2013	1,2,3,4,8,9,10,11	8
2000	4,8,10,11	4	2014	1,3,5,7,8,12	6
2001	1,2,5,7,9,10,11	7	2015	7,8,9,12	4
2002	1,5,11	3	2016	3,7,9	3
2003	1,2,3,6,9,10	6	2017	1,2,6,7,9,12	6
2004	1,4,5,6,10	5	2018	1,3,5,11	4

Table 11. Comparison of signal accuracy from signal analysis with ARIMA residual model.

Signal accuracy	Signal analysis	ARIMA residual model
Noise-to-signal ratio (NSR)	0	1144
The number of pre-crisis months that precisely predicted	29	60
% pre-crisis period that give signals $(A/(A+C))$	20,422	42,253
% incorrect signal $(B/B+D)$	0	48,352
QPS	0.197	0.907
GBS	0.006	0.358
% accuracy of prediction $(A+D)/(A+B+C+D)$	65,123	47,531

According to Table 10, signals detected by the ARIMA residual model are numerous than those obtained by using the Signal Analysis approach. However, it is necessary to determine the accuracy of the signal in predicting crises, as well as compare it with the signal analysis approach, as shown in Table 11.

Table 11 shows that the number of pre-crisis months predicted correctly by the ARIMA Residual Model is numerous (60), compared to the signal analysis approach (29), with 42.253% and 20.422%, respectively. However, the ARIMA Residual Model has a high NSR of 1.144, which means that several false signals were detected. Meanwhile, the signal analysis with NSR equal to zero means that no false signals were detected, or the crisis was predicted correctly. This result is reinforced by the wrong/incorrect signal $(B/B+D)$ of 0%, while the ARIMA Residual Model obtained 48.352%. The outcome of the accuracy and calibration of the model was also strengthened as shown by QPS (0.197) and GBS (0.006) on signal analysis that was approximately zero, it means that the results are relatively perfect. Meanwhile, the ARIMA Residual Model with QPS (0.907) and GPS (0.358) is relatively inaccurate. The percentage of prediction accuracy further strengthens this result $((A+D)/(A+B+C+D))$ of 65.123% in signal analysis, which is better than 47.531% of the ARIMA Residual Model.

5. Conclusion

The HP filter is capable of producing a reasonable estimation of a trend deviation. In this case, the transformation of the "Real Exchange Rate" indicator is able to produce the smallest NSR value from the macroeconomic variables. However, according to previous studies concerning similar cases conducted in Indonesia, no crisis signal was generated. This model's use is effective because there are non-linear trends, while the linear aspects are inefficient.

The comparison of the results from the Signal Analysis, the Herrera–Garcia method, and the ARIMA Residual Model approach, shows that the ARIMA Residual Model is used to detect several crisis signals with less accuracy. In contrast, the Signal

Analysis approach produces relatively fewer signals with higher accuracy. This is observed in the value of NSR = 0.

Appendix A. Data (Fragment) of Macroeconomic Indicator (1991.01–2019.12)

	Concept	Unit	Code	Scale	1991M01	1991M02
1	Indonesia-Domestic Currency per U.S. Dollar, End of Period	Rate	ENDE_XDC_USD_RATE	Units	1.912,00	1.920,00
2	Indonesia-Interest-Money Market Rate	Percent per Annum	FIMM_PA	Units	17,61	20,38
3	Indonesia-International Liquidity, Total Reserves excluding Gold, US Dollars	RAXG_USD	Millions		7.332,08	8.493,26
4	USA-Interest-Money Market Rate	Percent per Annum	FIMM_PA	Units	6,91	6,25
5	USA-Prices, Consumer Price Index, All items, Index	PCPI_IX	2010 = 100	Units	61,73	61,82
6	Indo-Bank Deposite		Billions of Rp	Units	38.965	35.782
7	Indonesia-Money Supply (M2)		Billions of Rp	Units	84,344	84,392
8	Indonesia-Money Supply (M1)		Billions of Rp	Units	23,017	26,258
9	Indonesia-Reserve		Billions of Rp	Units	2.244	3.642
10	Indonesia-Prices, Consumer Price Index, All items, Index	PCPI_IX	2010=100	Units	13,26	13,30
11	Indonesia-Goods, Value of Exports, US Dollars	TXG_FOB_USD	Millions		2.554,00	2.361,00
12	Indonesia-Goods, Value of Imports, CIF, US Dollars	TMG_CIF_USD	Millions		1.942,00	2.097,30
13	Indonesia-Deposit Rate	Percent per Annum	FIDR_PA	Units	21,35	22,09
14	Indonesia-Lending Rate	Percent per Annum	FILR_PA	Units	25,00	24,90
15	Indonesia-IDX-Composite	Index			383.02	391.33
16	Indonesia-Real GDP		2010 = Base Year(billion)		208.191,78	208.191,78
17	Indonesia-Domestic credit provided by financial sector (% of GDP)				4.2469	4.2469

Appendix B

Figure B.1. Graph of Indonesia EMPI.

Figure B.2. Graph of Indonesia currency crisis periods.

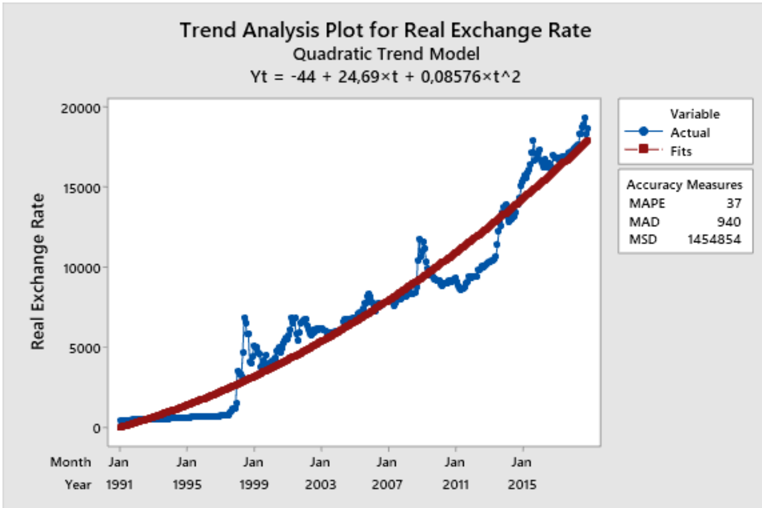


Figure B.3. Trend analysis plot for real exchange rate.

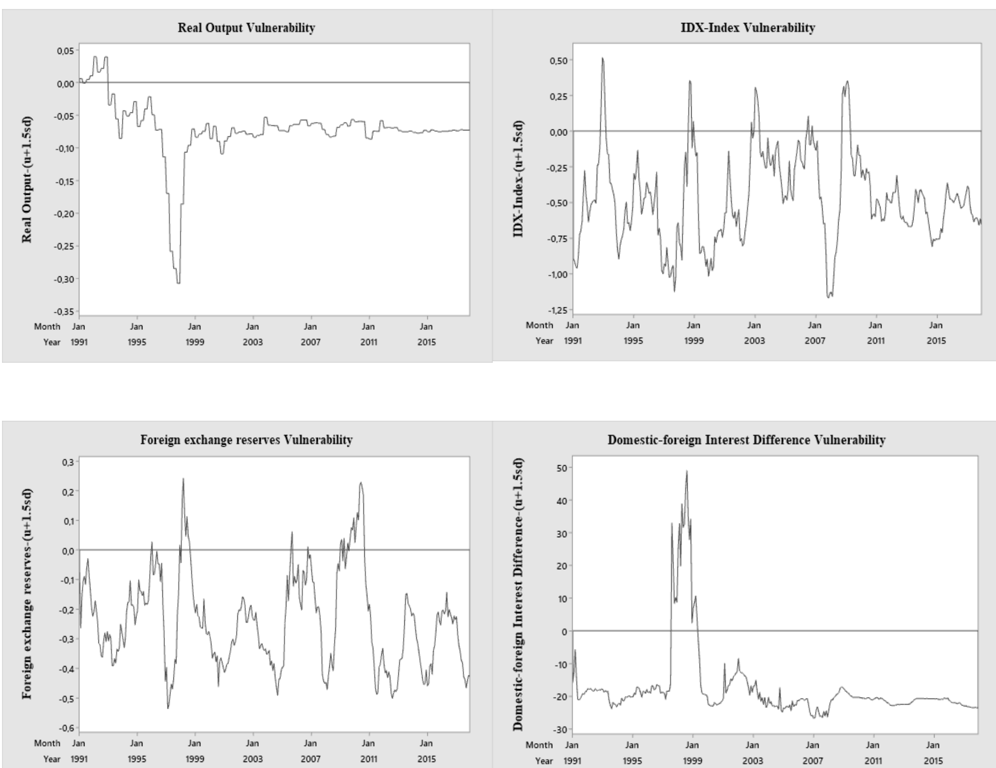


Figure B.4. Graph of vulnerability indicator.

Figure B.4. (*Continued*)

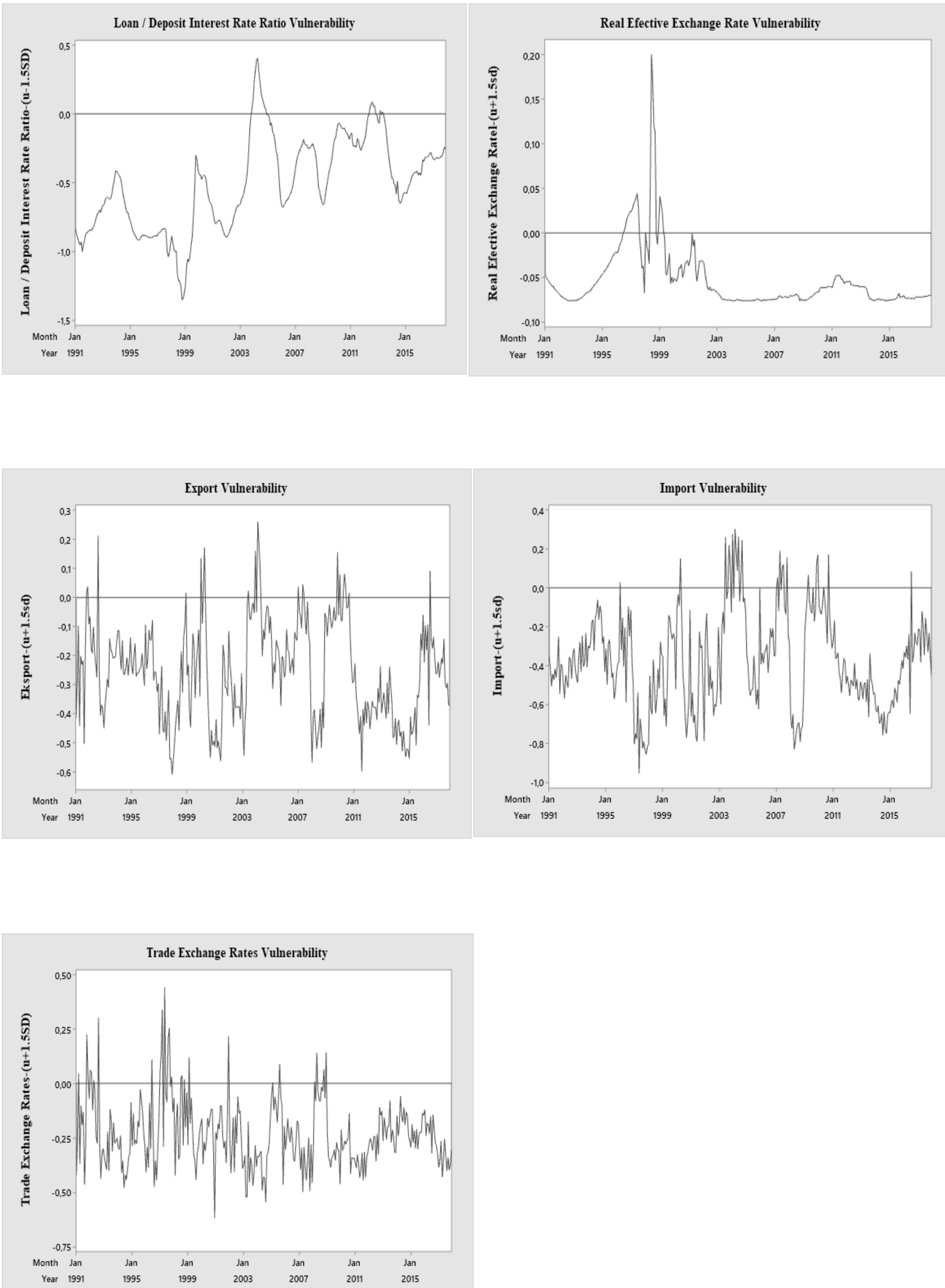
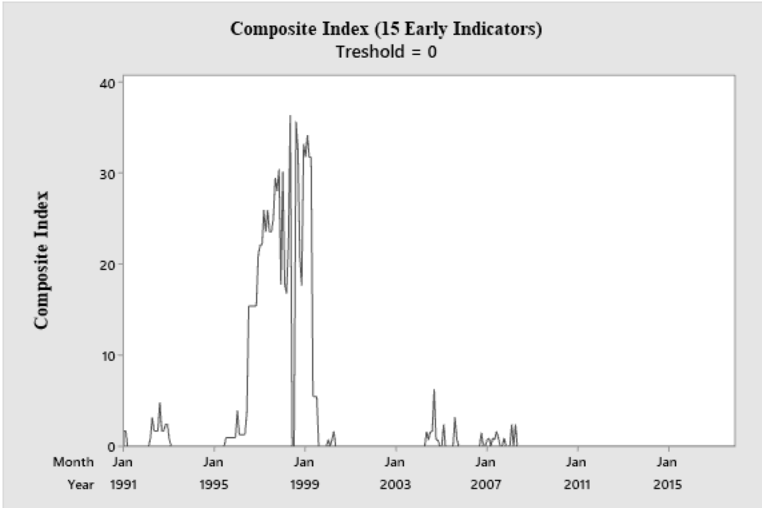


Figure B.4. (*Continued*)



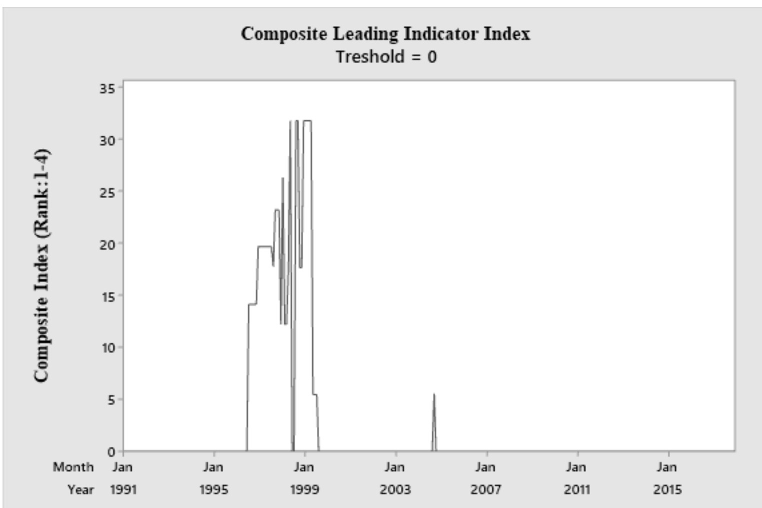
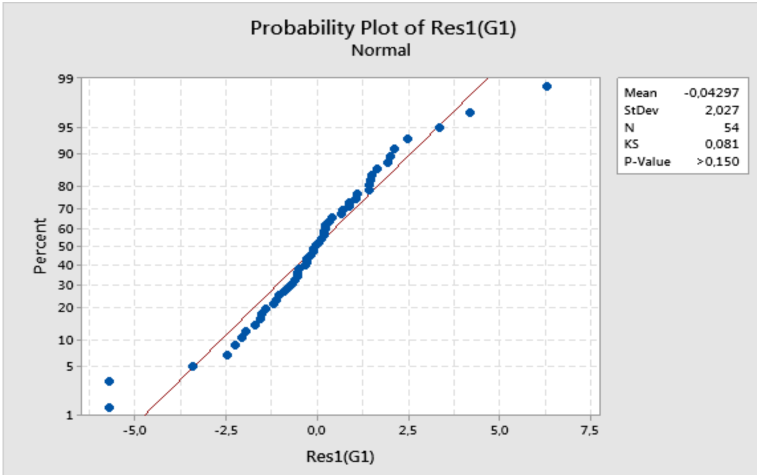


Figure B.5. Graph of composite index (15 early indicators) and composite leading indicator index.

Probability Plot of Residual (Group 1)



Probability Plot of Residual (Group 2)

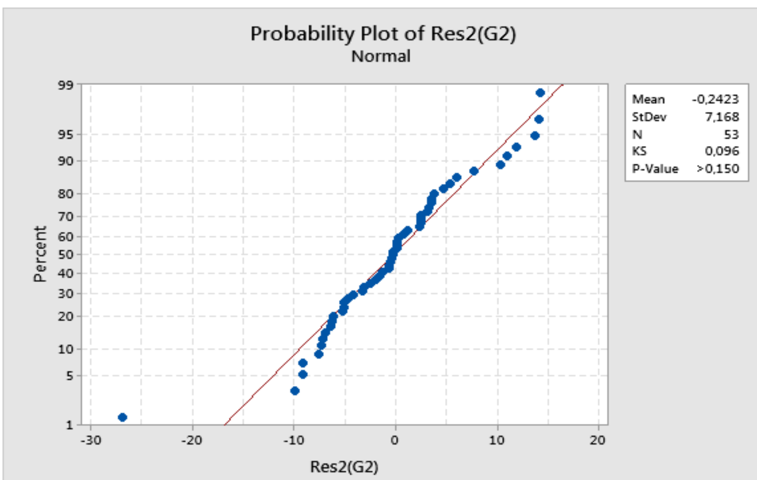
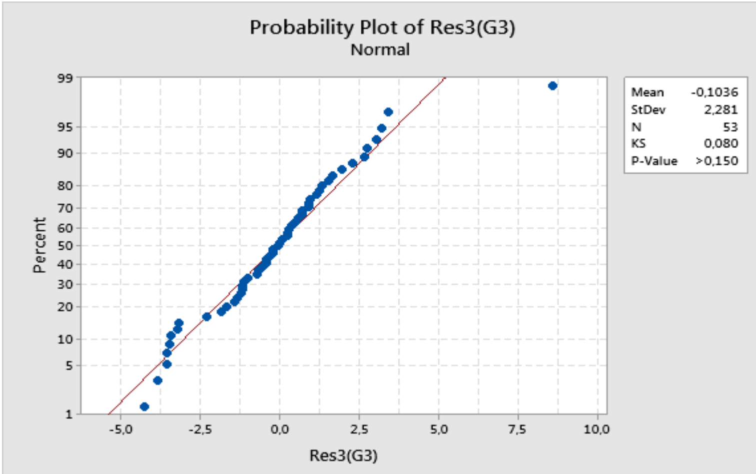


Figure B.6. Residual normality test results of the ARIMA residual model.

Probability Plot of Residual (Group 3)



Probability Plot of Residual (Group 4)

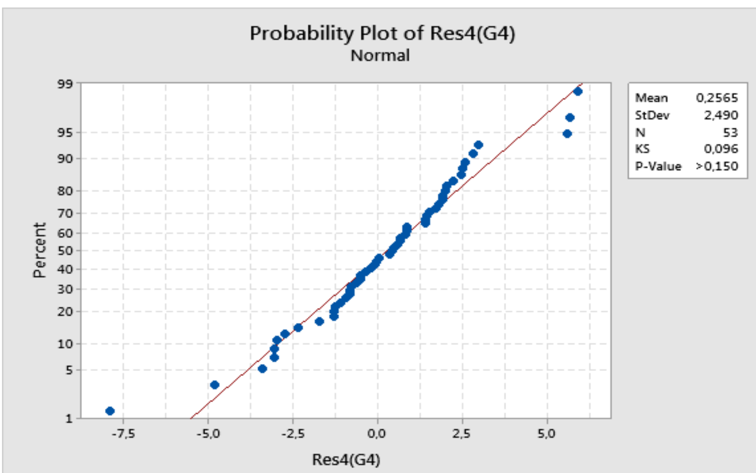
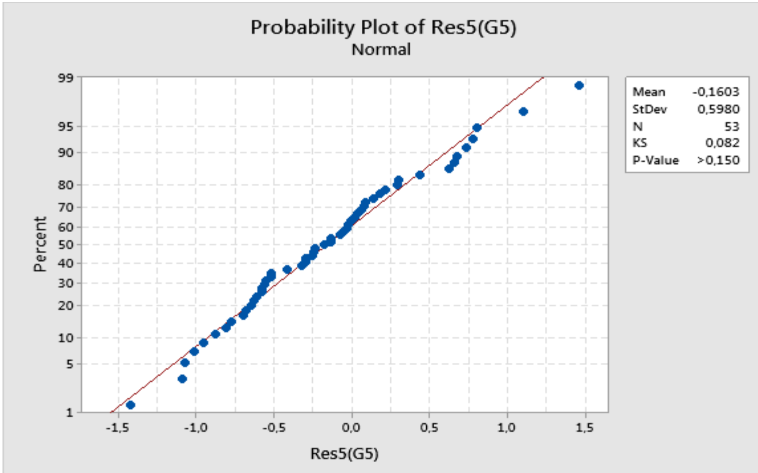


Figure B.6. (*Continued*)

Probability Plot of Residual (Group 5)



Probability Plot of Residual (Group 6)

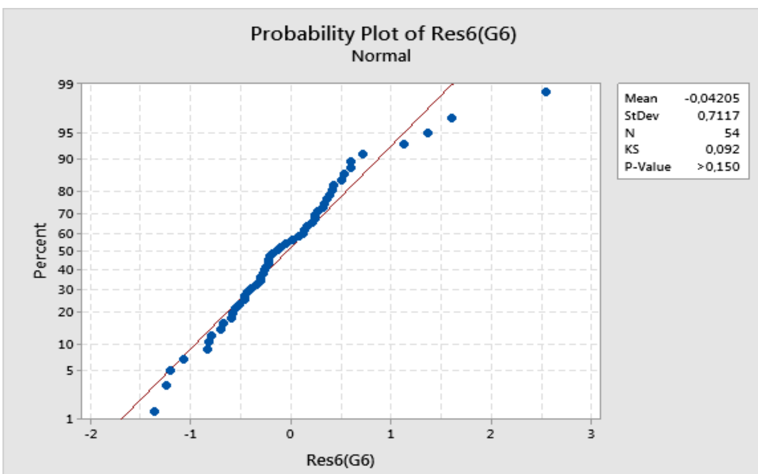
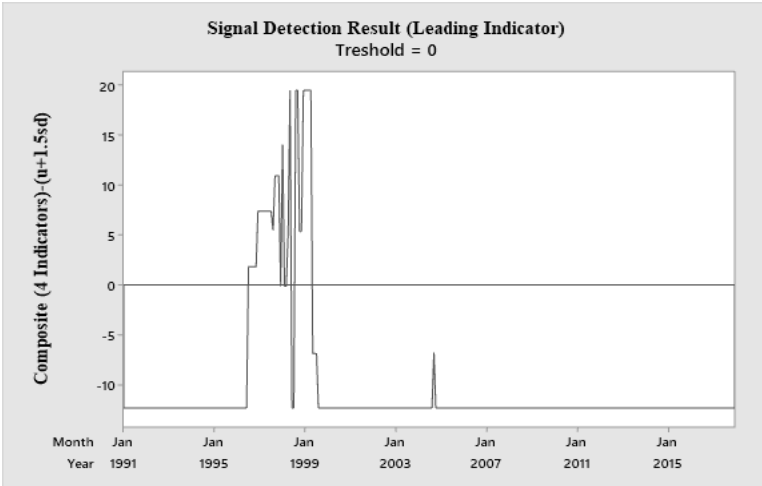


Figure B.6. (*Continued*)

Signal Detection Results by Signal Analysis



Signal Detection Results by ARIMA Residual Model

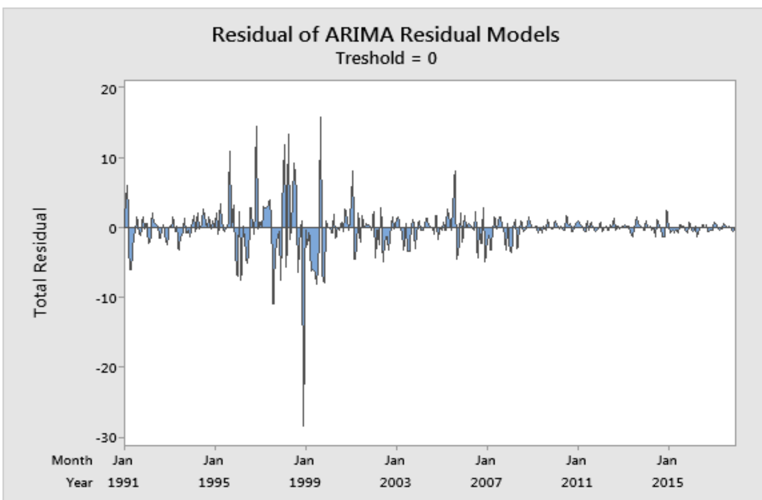


Figure B.7. Graph of leading indicator signal detection (using signal analysis approach and ARIMA residual model).

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