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Determination of Period on Baxter King Filter for Indonesian Business Cycle

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Abstract

This study investigates the appropriate period range for the Baxter-King filter in the context of the Indonesian business cycle. The standard parameter of 6 to 32 quarters commonly used in the Baxter-King filter was originally derived from the United States postwar business cycle, and is therefore considered inappropriate when applied directly to Indonesian economic data. To address this issue, Singular Spectrum Analysis (SSA) is employed to empirically identify the cyclical components of Indonesian real GDP, using seasonally adjusted quarterly data spanning from 1983 Q1 to 2016 Q2. The SSA decomposition yields ten principal components, of which nine exhibit sinusoidal patterns with periodicities exceeding four quarters, confirming their classification as genuine business cycle components rather than seasonal fluctuations. These components reveal multiple cyclical frequencies occurring in conjugate pairs as well as distinct shorter periodicities, collectively spanning from 13.40 to 67.00 quarters substantially wider than the conventional range assumed in the standard Baxter-King framework. This empirically derived interval is therefore recommended as a more suitable period range for the Baxter-King filter when analyzing the Indonesian business cycle.

Keywords: *Business cycle, singular spectrum analysis, baxter-king filter, GDP, indonesia*

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1. INTRODUCTION

According to Burns and Mitchell [1] the business cycle is a form of aggregate economic activity fluctuation. The business cycle could be measured using an economic term that reflects the aggregation of various economic activities, namely Gross Domestic Product (GDP). It reflects the aggregation of a variety of economic activities, including consumption, government expenditure, investment, and export-import. According to Jacobs [2], the business cycle cannot be directly observed, but it may be extracted from time-series economic data. Therefore, in business cycle research, the cyclical components contained in the GDP data series are proxy.

Classical methods could be used to extract cycles from time-series data since the data contains trend, cyclical, seasonal, and random irregular components. In addition, cycles could be extracted from time-series data using filters, such as the Hodrick-Prescott filter [3], Baxter-King filter [4], and the Christiano-Fitzgerald filter [5] (the first time-series data is a seasonal adjustment). This study focuses on the Baxter-King filter, which requires the determination of two parameters: lag $\mathcal{K}$ and cycle period range. There is a rule of thumb for filling up these parameters, which states that if the data series is quarterly level, the lag $\mathcal{K}$ should be set to 12 and the period range should be between 6 and 32 [4].

The determination of the period range in the Baxter–King filter is based on the length of the US business cycle, which has a period of 6 to 32 quarters [4]. However, according to the authors, this range is inappropriate for extracting the Indonesian business cycle. Therefore, we investigate a suitable period range for the Baxter–King filter that aligns with the economic conditions in Indonesia. To achieve this, we adopt Singular Spectrum Analysis (SSA) to identify cycle components, as SSA can decompose time series into more specific constituent elements [6], [7].

The novelty of this study lies in employing SSA to empirically calibrate the period range of the Baxter–King filter specifically for the Indonesian context, rather than relying on the conventional US-derived parameters. This data-driven approach provides a methodological contribution that can be replicated for business cycle analysis in other emerging economies.

2. METHOD

2.1 Data and Variables

The data used in this study is real GDP data that has been seasonally adjusted. The data are sourced from Fajar [8] and cover the period from 1983:Q1 to 2016:Q2. Moreover, this period encompasses various economic phenomena reflected in GDP fluctuations (see Table 3.1, pp. 75 in [8]).

2.2 Singular Spectrum Analysis (SSA)

Step 1. Embedding

Suppose a time series $x_1, x_2, \ldots, x_T$, choose an integer number L called *window length* with L in $2 \le L \le {}^{T}\!/_{2}$, and set $K = T - L + 1$. Defined trajectory matrix:

$$\boldsymbol{X} = (X_1, \ldots, X_T) = \begin{pmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_T \end{pmatrix}.$$

$\boldsymbol{X}$ is a Hankel matrix, which means that all elements on the main antidiagonal are equal. On that basis, it can be considered $\boldsymbol{X}$ as multivariate data with L characteristics and K observations so that the covariance matrix is $\boldsymbol{S} = \boldsymbol{XX}'$ with $L \times L$ dimension. In this study, the authors set $L = {}^{T}/_{2}$ based on Ref. [6], [7].

Step 2. Singular Value Decomposition (SVD)

$\boldsymbol{S}$ has eigenvalues and eigenvectors are $\lambda_1, \dots, \lambda_L$, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$ and $U_1, \dots, U_L$. The SVD of $\boldsymbol{X}$ obtained as follows:

$$\boldsymbol{X} = E_1 + E_2 + \cdots + E_d$$

where $E_i = \sqrt{\lambda_i} U_i V_i'$, $i = 1,2, \dots, d$. E_i is called the principal component, d is the number of eigenvalues λ_i and $V_i = \boldsymbol{X}' \, U_i / \sqrt{\lambda_i}$.

Step 3. Grouping

The grouping step is the stage of grouping $\boldsymbol{X}$ into subgroups based on the pattern forming the time series, namely the trend, periodic, quasi-periodic and noise components additively. Partition the set of indexes $\{1,2, \dots, d\}$into groups $I_1, I_2, \dots, I_n$, then the $\boldsymbol{X}_I$ corresponding on $I = \{i_1, i_2, \dots, i_b\}$ that defined with:

$$\boldsymbol{X}_I = E_{i_1} + E_{i_2} + \cdots + E_{i_b}.$$

So that the decomposition is represented by:

$$\boldsymbol{X} = \boldsymbol{X}_{I_1} + \boldsymbol{X}_{I_2} + \cdots + \boldsymbol{X}_{I_n} \,, \tag{1}$$

where $\boldsymbol{X}_{I_j} (j = 1,2, \dots, n)$ called the reconstruction component. The contribution of the $\boldsymbol{X}_I$ components is measured by the share of the corresponding eigenvalues $\sum_{i \in I} \lambda_i / \sum_{i=1}^{d} \lambda_i$. The grouping stage follows the automatic grouping method reported in [8], which groups the extracted main components according to the proximity of their frequency values. When multiple main components have closely spaced frequency magnitudes, they are merged into a single reconstruction component. This process is repeated iteratively until a set of reconstruction components is obtained.

Step 4. Reconstruction

In this last step, transformation is carried out $\boldsymbol{X}_I$ into a new time series with a number of T observations obtained by diagonal averaging or Hankelization. Let's say $\boldsymbol{Y}$ is a matrix with $L \times K$ dimension with elements $y_{ij}, 1 \leq i \leq L, 1 \leq j \leq K$. Then $L^* = \min(L, K)$, $K^* = \max(L, K)$ and $T = L + K - 1$. So that, $y_{ij}^* = y_{ij}$ if $L < K$ and $y_{ij}^* = y_{ji}$ if $L > K$. The matrix is $\boldsymbol{Y}$ transferred to a series $y_1, y_2, \dots, y_T$ using the Equation (2).

This corresponds to averaging the matrix elements along antidiagonal $i + j = k + 1$, for the example, suppose $k = 1$ stated $y_1 = y_{1,1}$, for $k = 2$ mean that $y_2 = (y_{1,2} + y_{2,1})/2$. Note that if the $\boldsymbol{Y}$ matrix is the path matrix of some series $(z_1, \dots, z_T)$ then $y_i = z_i$ for all i.

$$y_k = \begin{cases} \dfrac{1}{k} \displaystyle\sum_{m=1}^{k} y_{m,k-m+1}^* \,, 1 \leq k \leq L^* \\ \dfrac{1}{L^*} \displaystyle\sum_{m=1}^{L^*} y_{m,k-m+1}^* \,, L^* \leq k \leq K^* \\ \dfrac{1}{T-k+1} \displaystyle\sum_{m=k-K^*+1}^{T-K^*+1} y_{m,k-m+1}^* \,, K^* \leq k \leq T \,. \end{cases} \tag{2}$$

The diagonal averaging in **Equation (2)** is applied to all components of the $\boldsymbol{X}_{I_j}$ matrix in **Equation (1)** to produce a series $\widetilde{\boldsymbol{X}}^{(k)} = \left(\breve{x}_1^{(k)}, \breve{x}_2^{(k)}, \dots, \breve{x}_T^{(k)}\right)$, so that the series is $x_1, x_2, \dots, x_T$ decomposed into a sum of m series reconstructions:

$$x_t = \sum_{k=1}^{m} \breve{x}_t^{(k)}, t = 1,2, \dots, T .$$

In this study, SSA was applied only up to the reconstruction stage. Cyclical components were then identified as those exhibiting a sinusoidal pattern with a period exceeding one year (four quarters); more than one such sinusoidal component may be present.

2.3 Sample Spectrum

The sample spectrum is formulated [9]:

$$\hat{s}_x(\omega_v) = \frac{1}{2\pi} \sum_{\mathbb{m}=-(T-1)}^{T-1} \hat{\gamma}_m e^{-\mathrm{i}\omega_v \mathbb{m}}$$

$$\hat{s}_x(\omega_v) = \frac{1}{2\pi}\left(\hat{\gamma}_0 + 2\sum_{\mathbb{m}=1}^{T-1} \hat{\gamma}_{\mathbb{m}}(\cos(\omega_v \mathbb{m}))\right)$$

$$\hat{s}_x(\omega_v) = \frac{T}{8\pi}\left(\hat{U}_j^2 + \hat{V}_j^2\right),$$

where $\mathrm{i} = \sqrt{-1}, \omega_v = 2\pi f_v = 2\pi j/T$, $v = 1, \dots, q$ called the Fourier frequency or the fundamental frequency. If the number of observation data is odd, then $T = 2q + 1$, but if the number of observation data is even, then $T = 2q$.

$$\hat{\gamma}_{\mathbb{m}} = \begin{cases} \dfrac{1}{T} \displaystyle\sum_{t=\mathbb{m}+1}^{T} (x_t - \bar{x})(x_{t-m} - \bar{x}) & \text{for } \mathbb{m} = 0,1,2, \dots, T-1 \\ \hat{\gamma}_{-\mathbb{m}} & \text{for } \mathbb{m} = -1,-2,-3, \dots, -(T-1) \end{cases}$$

$$\hat{U}_v = \frac{2}{T}\sum_{t=1}^{T} x_t \cos(\omega_v t)$$

$$\hat{V}_v = \frac{2}{T}\sum_{t=1}^{T} x_t \sin(\omega_v t)$$

$$A_v = \sqrt{U_v^2 + V_v^2}, \text{the } v-\text{th amplitude} .$$

Periodogram is an analytical tool used to detect periodicity in time series data (in certain cases, periodicity cannot be detected, but with a smoothed spectrum plot). The periodogram is formulated as follows:

$$\hat{s}_x(\omega_v) = \frac{1}{2} I(\omega_v) . \tag{3}$$

Plot the sample spectrum $\left(\hat{s}_x(\omega_v)\right)$ according to the equivalent frequency with the periodogram plot $\left(I(\omega_v)\right)$ according to the frequency equivalent due to the functional relationship in **Equation (3)**. So that the sample spectrum plot has the same function as the periodogram. Peaks in the spectrum plot correspond to specific periods. These periods are recorded as the periodicities of the sinusoidal components. The periodicities of the significant sinusoidal components of a time series are what determine the cycle duration.

2.4 Smoothed Spectrum

The $\hat{s}_x(\omega_j)$ estimator is asymptotically unbiased but has inconsistent variance (variance does not decrease even though the sample is enlarged), the solution to this problem is to construct a smoothed spectrum which is formulated as:

$$\tilde{s}_x(\omega_v) = \frac{1}{2\pi}\left(W_H(0)\hat{\gamma}_0 + 2\sum_{m=1}^{H} W_H(\mathbb{m})\hat{\gamma}_m(\cos(\omega_v \mathbb{m}))\right) \quad (4)$$

$$W_H(\mathbb{m}) = W\left(\frac{\mathbb{m}}{H}\right).$$

The $W(.)$ function must meet the following conditions:

$$|W(z)| \leq 1$$
$$W(0) = 1$$
$$W(z) = W(-z)$$
$$W(z) = 0, \quad |z| > 1.$$

The Bartlett Window, Tukey-Hamming Window, Tukey Hanning Window, and Parzen Window are a few window lags that are often implemented in the smoothed spectrum in **Equation (4)**.

The researcher is free to select which Window to apply, although consideration must be given to choosing the right H. It depends on the kernel function or window lag employed, but the determination of truncation lag H must be taken into account, according to the authors, who claims that window lag is similar to bandwidth in nonparametric statistics and truncation lag H is similar to bandwidth in kernel functions. The author selects a truncation lag of $2\sqrt{T}$ and a spectrum that has been smoothed using a Bartlett window in **Equation (5)**.

$$W_H(\mathbb{m}) = \begin{cases} 1 - \frac{|\mathbb{m}|}{H}, & |\mathbb{m}| \leq H \\ 0, & |\mathbb{m}| > H \end{cases}. \quad (5)$$

3. RESULTS AND DISCUSSION

The first stage of implementing Singular Spectrum Analysis (SSA) is the decomposition of adjusted real GDP—real GDP that has been corrected for seasonal effects—and the parameter L plays a crucial role. In this study, L = 67 (based on Section 2.2 in the Step 1), obtained by dividing the number of observations (134) by two, which yields an appropriate window length. From the 67 components generated by Singular Value Decomposition (SVD), only the top 10 components were retained for further analysis because they explain 99.96% of the variance in adjusted real GDP (see **Figure 1 and 2**).

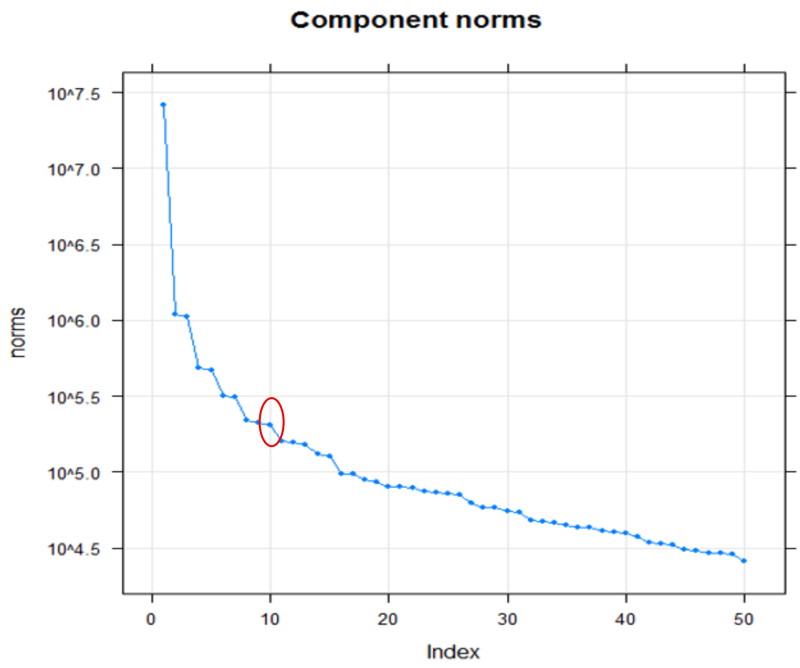

Figure 1. Plot of Eigen Vectors

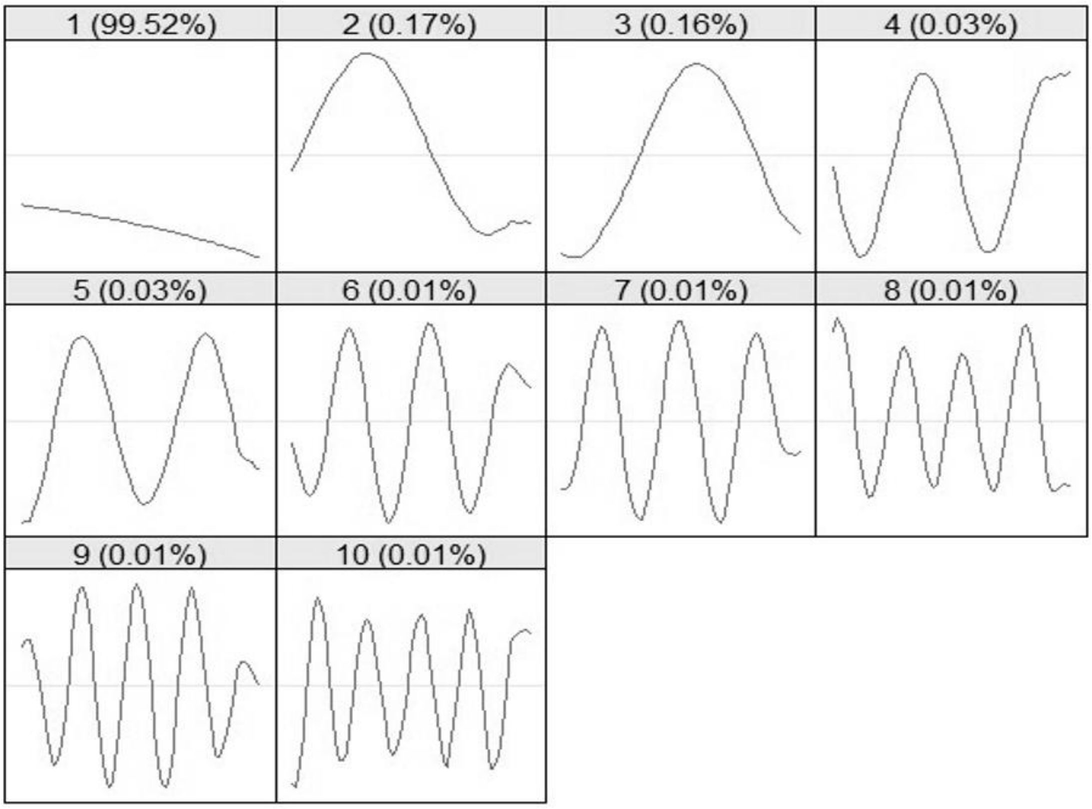

Figure 2. Plot of Eigen Vectors

As shown in **Figure 2**, the first eigenvector is the only one whose pattern is not undulating; it follows a trend line, whereas the next nine eigenvectors exhibit a wave-like (sinusoidal) pattern. The reconstruction procedure produces ten components. Plots of these components and their spectra are provided in the appendix. The first component displays an upward trend instead of a sinusoidal pattern. The second through tenth components are sinusoidal. In other words, the business cycle consists of the second component (the first sinusoidal component) through the tenth component (the ninth sinusoidal component).

The spectrum plot of each component from the second to the tenth contains a single highest peak (see **Appendix 1**), which corresponds to the period of that component. **Table 1** presents the maximum spectrum value (in the time domain, the spectrum is autocovariance, and in the frequency domain, autocovariance is the spectrum) and the corresponding period for each component. According to **Table 1**, it can be obtained that: (1) each sinusoidal component has a distinct periodicity, and all periodicities exceed four quarters; and (2) the sinusoidal components form conjugate pairs with identical periods. The first and second sinusoidal components share a periodicity of 67 quarters, the third and fourth 33.50 quarters, the fifth and sixth 22.33 quarters, while the seventh, eighth, and ninth components have periodicities of 16.75, 14.89, and 13.40 quarters, respectively. On this basis, the length (periodicity) of the business cycle ranges from 13.40 to 67.00 quarters, because the periodicity is derived from the periodicities of the 9 strongest sinusoidal components among the many others that explain the fluctuations in the time series under study (see **Table 1**). Therefore, this time interval can then be used in the Baxter–King filtering procedure. These findings align with earlier work indicating that the Indonesian economic cycle is erratic and ranges from 13 to 67 quarters [8].

Table 1. Maximum Value and Point Period for Each Sinusoidal Components

The n^{th} component	Maximum Value of log-Spectrum	Point Period at The Maximum Value of log-Spectrum
2 (1^{st} sinusoidal component)	20.98	67.00
3 (2^{nd} sinusoidal component)	21.16	67.00
4 (3^{rd} sinusoidal component)	19.05	33.50
5 (4^{th} sinusoidal component)	19.56	33.50
6 (5^{th} sinusoidal component)	18.11	22.33
7 (6^{th} sinusoidal component)	18.18	22.33
8 (7^{th} sinusoidal component)	17.41	16.75
9 (8^{th} sinusoidal component)	17.02	14.89
10 (9^{th} sinusoidal component)	17.03	13.40

The results in **Table 1** are methodologically supported by the parameter choices made in the SSA implementation. The selection of window length $L = 67$, equivalent to half the total number of observations ($T = 134$), follows the general recommendation in the SSA literature that L should be set to approximately $T/_2$ to allow sufficient embedding of long-period oscillations [6], [7]. This choice is particularly important because the Indonesian business cycle contains very long periodicities, as evidenced by the 67-quarter peak identified in the first and second sinusoidal components. Moreover, the components were grouped and reconstructed based on their dominant frequency, retaining only those that reflect periodicities consistent with the business-cycle frequency range [10]. Retaining only the top nine sinusoidal components, which collectively account for 99.96% of the variance, ensures that the reconstructed cyclical components are free from overfitting and noise contamination, thereby lending credibility to the identified period range of 13.40 to 67.00 quarters.

One of the principal strengths of Singular Spectrum Analysis (SSA) lies in its capacity to decompose a time series into trend and oscillatory components. Its multivariate extension, Multivariate Singular Spectrum Analysis (M-SSA), provides a robust framework for identifying oscillatory modes and reconstructing the common cyclical dynamics of macroeconomic indicators, even when business-cycle fluctuations display considerable irregularity [11]. This capability is particularly pertinent in the Indonesian context, which has historically been shaped by a range of domestic structural challenges and external disturbances, most notably the 1997–1998 Asian Financial Crisis.

The first component represents the trend, while the second through tenth components exhibit sinusoidal patterns that constitute the cyclical structure of Indonesian GDP. The business cycle indicator produced by SSA resembles band-pass filtered output and is in line with established business cycle chronologies [12]. This corroborates the validity of using SSA as an alternative to conventional filters—such as the Hodrick–Prescott or Baxter–King filters—for cycle extraction.

The spectrum plots of the second through tenth components each reveal a single dominant peak, the frequency of which corresponds to the period of the respective sinusoidal component, as summarized in **Table 1**. The identification of period points via the spectrum is methodologically grounded, as computing the periodogram is recommended for assessing the dominant periodicity of each principal component in SSA-based cycle identification [10]. This study adopts an analogous approach through smoothed spectrum estimation using a Bartlett window with a truncation lag of $2\sqrt{T}$, enabling clearer identification of peak periods even when raw periodogram estimates are noisy.

Two important findings emerge from Table 1. First, all nine sinusoidal components have periodicities exceeding four quarters (one year), indicating that they represent genuine cyclical rather than seasonal components. Second, the cyclical components appear in conjugate pairs, each sharing a common periodicity: the first and second sinusoidal components have a periodicity of 67 quarters; the third and fourth, 33.50 quarters; and the fifth and sixth, 22.33 quarters. SSA exhibits this pairing behavior when decomposing time series that contain quasi-periodic oscillations, because pairs of eigenvectors with nearby eigenvalues generally correspond to the same oscillatory mode. SSA is well suited for short and noisy time series such as macroeconomic data. It also allows a time series to be decomposed into trend, cyclical, seasonal, and noise components, and it can reveal strong features that differ from those produced by conventional macroeconomic filters [13].

The seventh, eighth, and ninth sinusoidal components display somewhat shorter and distinct periodicities of 16.75, 14.89, and 13.40 quarters, respectively, suggesting that the Indonesian GDP series contains multiple cyclical frequencies that overlap and interact. Taken together, the periodicity range of the Indonesian business cycle ranges from 13.40 to 67.00 quarters. This range is substantially wider than the conventional 6-to-32-quarter band assumed in the Baxter–King filter. The original Baxter–King filter was designed to isolate fluctuations persisting for periods of two to eight years (i.e., 8 to 32 quarters), based on the characteristics of the U.S. postwar business cycle [4]. Applying this parameter directly to Indonesian data would therefore risk excluding long-wave cyclical components that are empirically present and economically significant.

This finding supports the central argument of the study: the period-range parameter of the Baxter–King filter should not be mechanically adopted from the U.S. context when applied to emerging economies such as Indonesia. Indonesia's business cycle is shaped by a distinct combination of external and domestic factors (see Table 3.1, p. 75, in [8]), and dominant external factors such as global economic activity, particularly that originating from the Chinese economy [14]. These structural characteristics naturally produce longer and more irregular cycles than those of advanced economies.

Studies on Indonesia's sectoral economic cycles further confirm that deceleration phases are primarily caused by external shocks, contributing to the erratic and elongated nature of the aggregate cycle [15].

On this basis, the period range of 13 to 67 quarters identified through SSA provides an empirically grounded calibration for the Baxter-King filter when applied to Indonesian GDP data. This range aligns with the conclusion in the referenced work [8], which similarly identified the Indonesian economic cycle as ranging from 13 to 67 quarters in an irregular fashion. The use of SSA to inform the parameter setting of a conventional band-pass filter represents a methodological contribution of this study combining the interpretive precision of spectral decomposition with the filtering utility of the Baxter-King approach for country-specific business cycle analysis.

4. CONCLUSION

According to the preceding discussion, the range of Indonesia's business cycle duration is between 13.40 and 67 quarters, which may be used as a more suitable calibration for the Baxter-King filter in the Indonesian business cycle, replacing the standard parameter of 6 to 32 quarters that was originally derived from the United States postwar business cycle and is therefore inappropriate when applied directly to the Indonesian business cycle. Compared to conventional filters such as the Hodrick-Prescott and Baxter-King filters, the SSA approach offers several advantages: it is data-adaptive and requires no prior assumption about the frequency range, capable of simultaneously uncovering multiple cyclical frequencies, and does not impose stationarity or normality assumptions that are often problematic for macroeconomic data from developing countries. Nevertheless, this study has several limitations. The selection of the window length parameter (L) in SSA still involves a degree of subjectivity that may influence the decomposition results. Furthermore, the analysis relies solely on a single variable (real GDP) and is ex-post in nature, thus not capturing more recent Indonesian economic dynamics nor other relevant macroeconomic variables. It is also required for forthcoming research to determine whether economic growth is a more appropriate proxy for the business cycle, and to further explore the Multivariate SSA (M-SSA) approach with more up-to-date data in order to strengthen the robustness of these findings.

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Conflict of Interest Statement

Authors state no conflict of interest.

Data Availability

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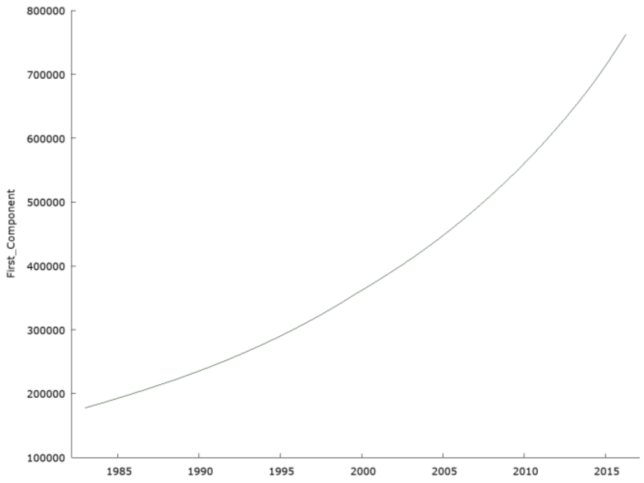
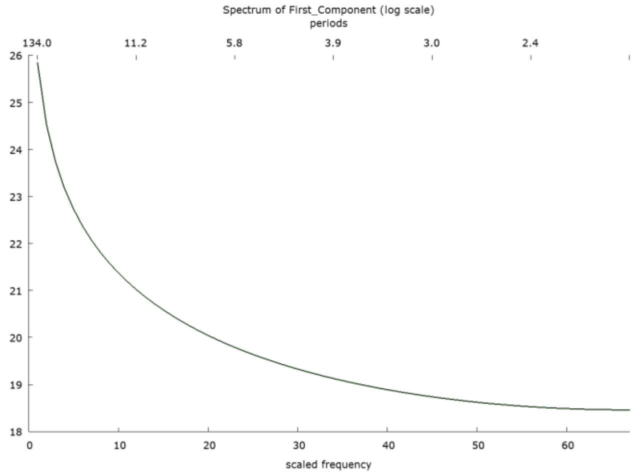
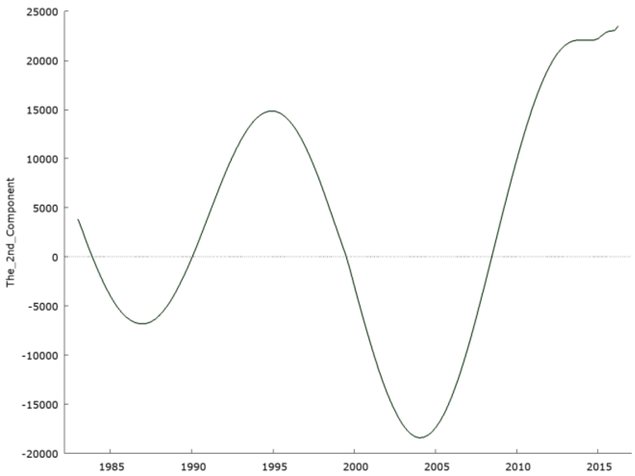
Appendix 1



Plot of The First Component



Plot of Spectrum of Natural Logarithm The First Component



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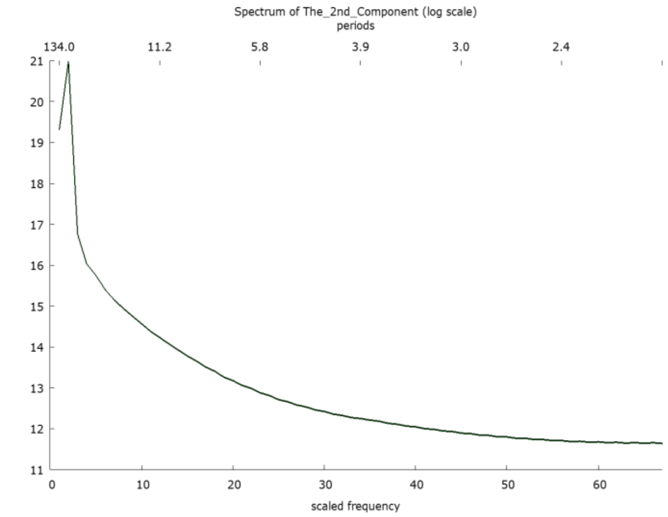
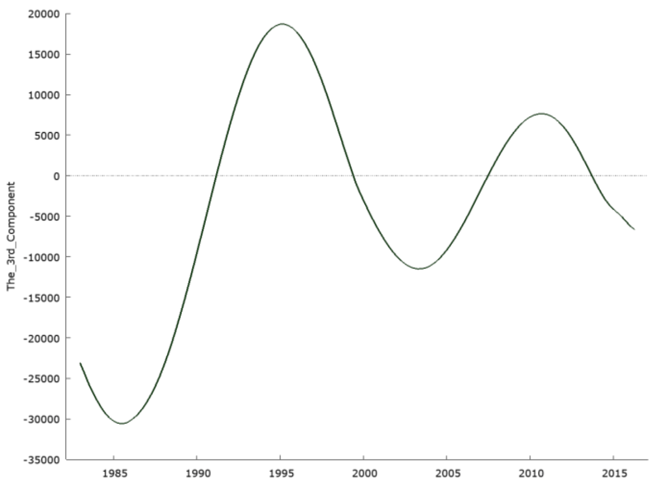
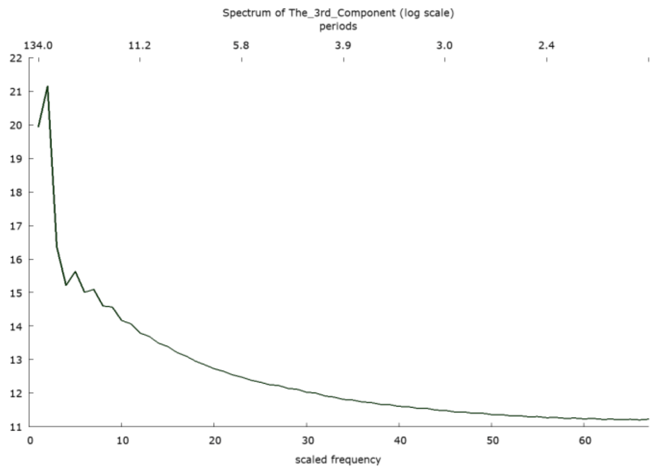


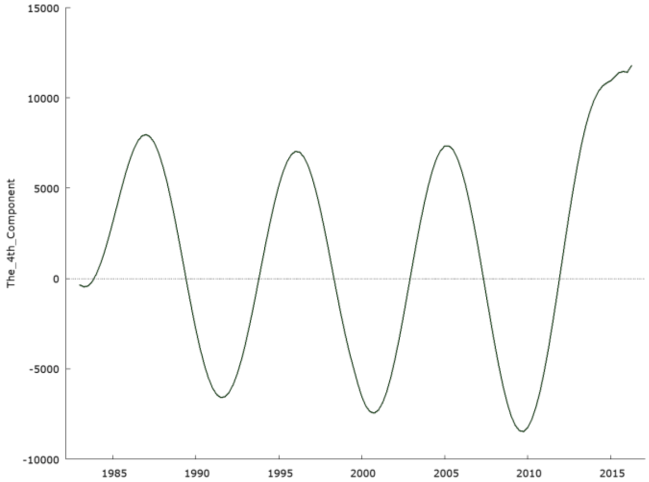
Plot of Spectrum of Natural Logarithm The Second Component



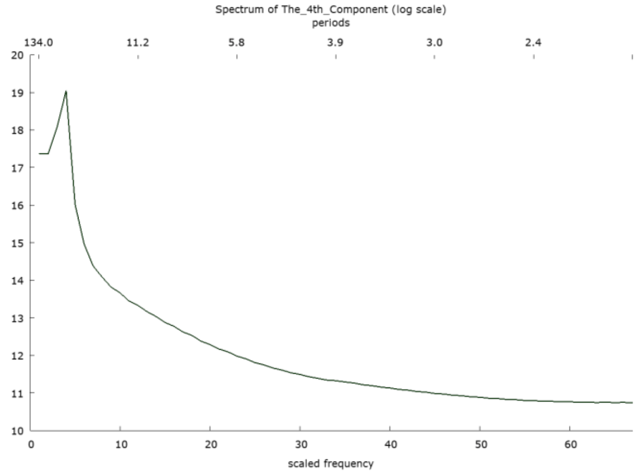
Plot of The Third Component



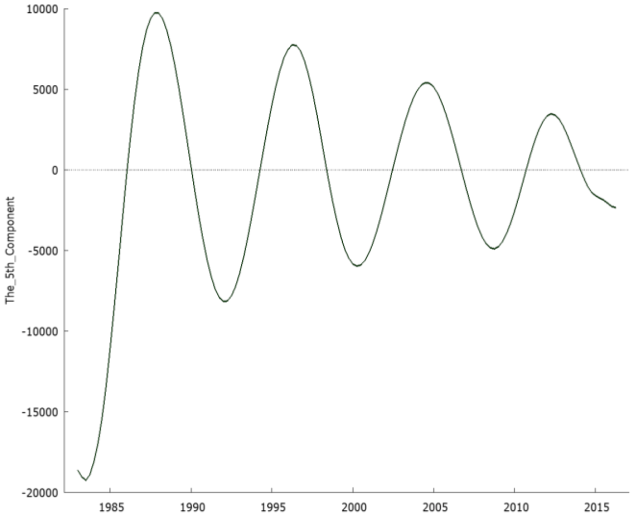
Plot of Spectrum of Natural Logarithm The Third Component



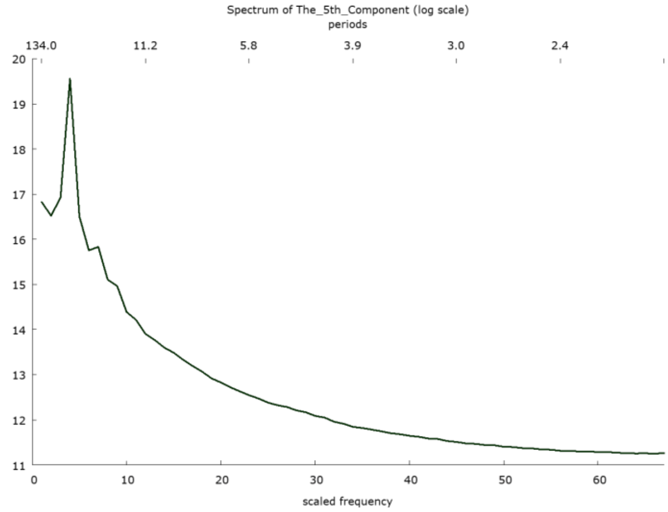
Plot of The Fourth Component



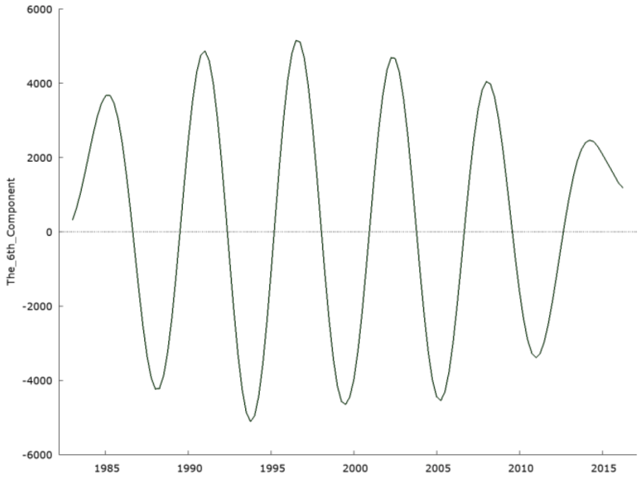
Plot of Spectrum of Natural Logarithm The Fourth Component



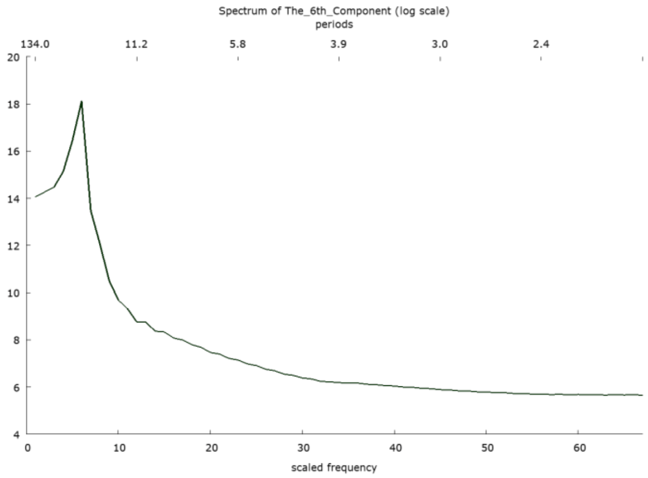
Plot of The Fifth Component



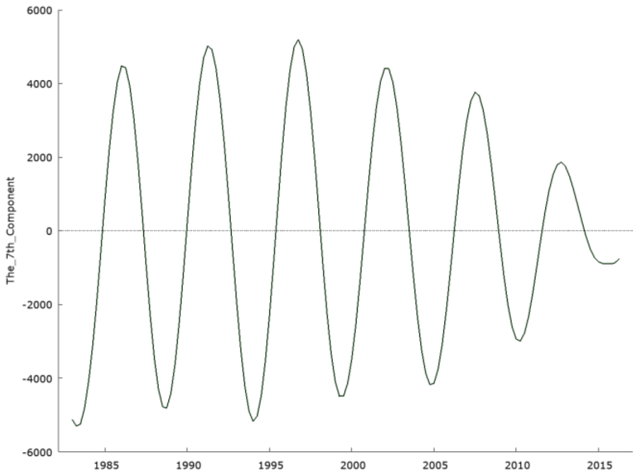
Plot of Spectrum of Natural Logarithm The Sixth Component



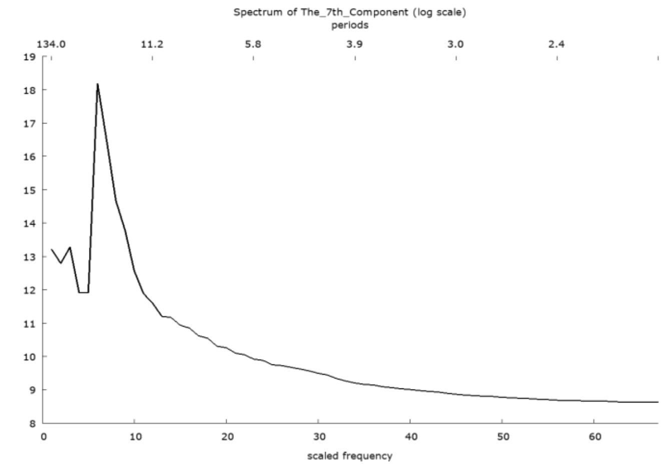
Plot of The Sixth Component



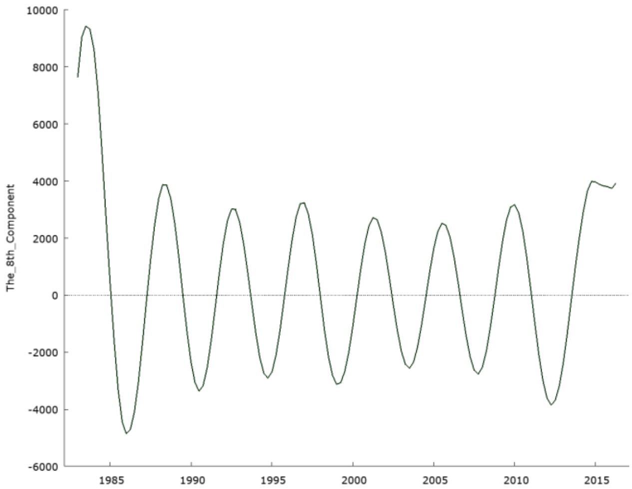
Plot of Spectrum of Natural Logarithm The Fifth Component



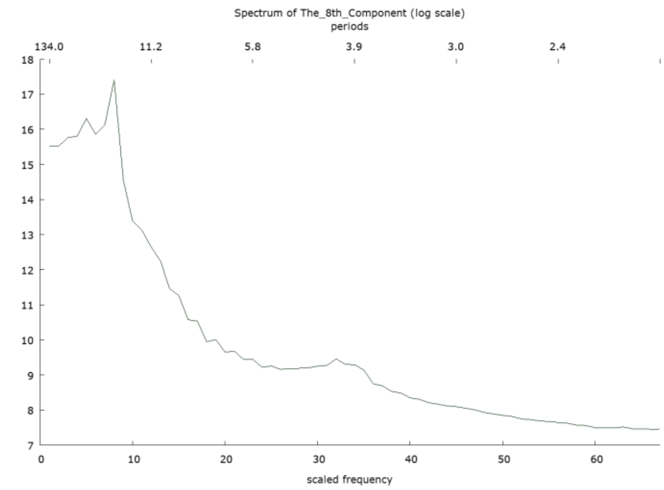
Plot of The Seventh Component



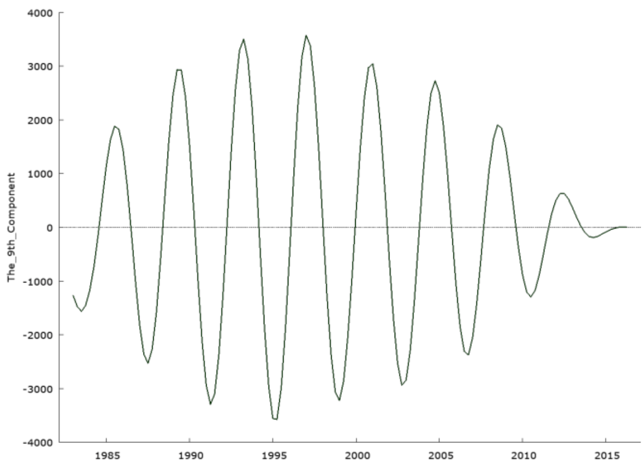
Plot of Spectrum of Natural Logarithm The Seventh Component



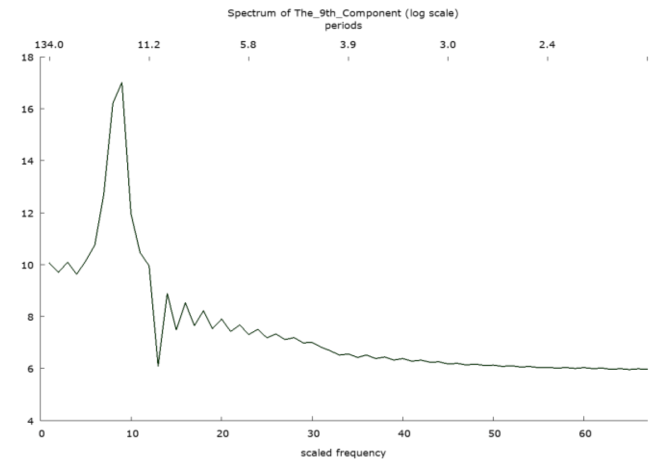
Plot of The Eighth Component



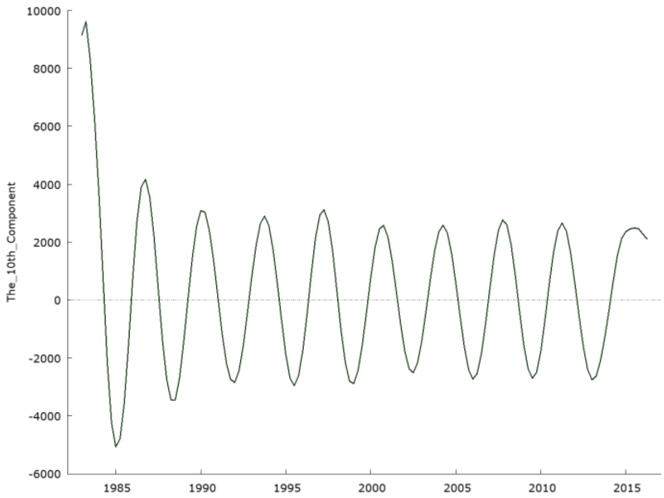
Plot of Spectrum of Natural Logarithm The Eighth Component



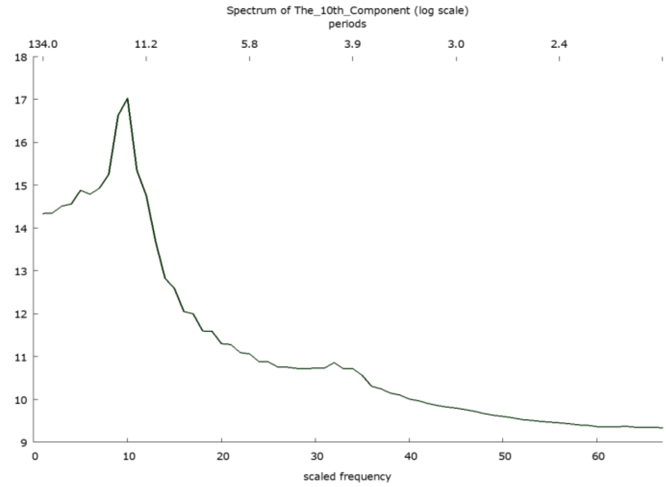
Plot of The Ninth Component



Plot of Spectrum of Natural Logarithm The Ninth Component



Plot of The Tenth Component



Plot of Spectrum of Natural Logarithm The Tenth Component