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Analyzing Business Cycles in Azerbaijan: Application of Various Filters and Spectral Analysis

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Abstract

This study investigates the cyclical behavior of Azerbaijan's economy and its non-oil-gas sector through the application of various filtering techniques, including the Hodrick-Prescott (HP), Baxter-King (BK), and Christiano-Fitzgerald (CF) filters. Utilizing quarterly GDP data from Q1 2001 to Q4 2023, we analyze the volatility, cycle duration, and significant periods of economic growth and contractions. Our analysis reveals that the HP filter shows more pronounced and volatile cyclical components, while the BK and CF filters provide smoother and more moderated views. Spectral analysis, employing periodograms smoothed with Bartlett, Hamming, Hann, and Parzen kernel windows, identifies cycle durations ranging from 4.1 to 19.4 quarters for total GDP and 4.3 to 19.4 quarters for non-oil-gas GDP. We find that Azerbaijan's economy exhibits higher volatility compared to advanced economies, likely due to its dependence on oil exports and susceptibility to external shocks. Key periods such as the 2008 financial crisis and the COVID-19 pandemic significantly impacted economic performance, with notable declines identified across all filtering methods. The HP filter indicates a sharp and more prolonged downturn during these crises, whereas the BK and CF filters capture less prolonged and less severe impacts. This research provides a comprehensive understanding of Azerbaijan's business cycles, highlighting the importance of robust methodologies in economic analysis. Our findings contribute to the limited literature on Azerbaijan's economy and offer valuable insights for policymakers aiming to enhance economic stability and growth.

Keywords: Baxter-King filter, Christiano-Fitzgerald filter, economic fluctuations, Hodrick-Prescott filter, periodogram

1. Introduction

The study of business cycles is integral to understanding the fluctuations in economic activity over time, characterized by periods of expansion and contraction. These cycles are essential for policymakers, economists, and businesses as they provide insights into the underlying economic trends and potential future economic conditions. Azerbaijan's economy has undergone significant transformations, particularly since the mid-2000s, driven largely by the exploitation of its vast oil and gas reserves. These developments have led to periods of rapid economic growth, followed by phases of volatility due to fluctuating global oil prices.

The literature examining business cycles in Azerbaijan is rather limited. Mammadov and Adigozalov (2014), who made an attempt to build a leading indicator system for Azerbaijan, found that between January 2000 and May 2014, the Azerbaijan non-oil economy experienced six turning points, including three peaks and three troughs, corresponding to three expansion and four contraction periods. The average duration of these phases was 43 months (≈ 4 years) for expansions and 10 months (≈ 1 year) for contractions. In the other study, Ahmadova (2020) conducts a singular spectrum analysis to analyze Azerbaijan's GDP using monthly data from 1997 to 2019. The author finds that for the periods of 1997-2004, 2005-2014, and 2015-2018, the trend-only models explained 68-80% of the variability (R^2). Adding a seasonal component improves these models, increasing R^2 to 78-84%. The singular spectrum analysis identified a 43-44 month (≈ 4 years) cyclic component and incorporating this into the models further increased R^2 by 1-3%.

This paper aims to extend the current literature by providing a comprehensive analysis of the cyclical behavior of Azerbaijan's economy and its non-oil-gas sector. In particular, this study uses several filtering techniques, including the two-sided Hodrick-Prescott (HP), the Baxter-King (BK), and the Christiano-Fitzgerald (CF) filters to estimate the business cycles. We conducted the spectral analysis to determine the low and high-frequency bands for the BK and CF filters. This allowed us to identify cycle periods ranging from 4.1 to 19.4 quarters for total GDP and 4.3 to 19.4 quarters for non-oil-gas GDP. Our analysis reveals notable differences in the output gap estimates generated by the HP, BK, and CF filters applied to Azerbaijan's GDP and non-oil-gas output data from 2001 to 2023. The HP filter shows more pronounced and volatile cyclical components, particularly evident during periods of economic change, such as the early 2000s and the 2008 financial crisis. In contrast, the BK and CF filters provide smoother and more moderated views of the economic cycles, highlighting their ability to capture medium-term fluctuations with less sensitivity to short-term variations. The discrepancies among these filters underscore the importance of using multiple methods for a comprehensive analysis of economic performance. For instance, during the 2008 financial crisis, the HP filter indicated a sharp but brief downturn, while the BK and CF filters reflected a more prolonged and severe impact. Similarly, during the COVID-19 pandemic, all filters showed significant declines, but the HP filter captured an earlier start in the case of the non-oil-gas sector and more pronounced negative effects. These findings emphasize the varying sensitivities of different filters to economic shocks and the need for careful selection and interpretation of filtering methods in business cycle research.

The paper is structured as follows: first, we provide an overview of Azerbaijan's economic background and the significance of GDP analysis. Next, we delve into the methodology of spectral analysis, outlining the techniques and tools employed. This is followed by the application of spectral analysis to Azerbaijan's GDP data, presenting the results and their interpretations. Finally, the last section concludes the paper.

2. Methodology

Business cycles research has been a central theme in macroeconomics, with various methods developed to analyze and interpret these cycles. The HP filter, introduced by Hodrick and Prescott (1997), is widely used for separating the cyclical component of economic time series from the trend. It identifies the cyclical $(y_t - \tau_t)$ and trend (τ_t) components by minimizing the following objective function:

$$minimize\ \sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2 \quad (1)$$

where T is the sample size and λ is a smoothing parameter. The first term minimizes the deviation of the trend component from the overall series data, in other words, the cyclical component. The second term, which is a second derivative of τ_t, penalizes rapid changes in the slope of the trend and λ determines the magnitude of the penalty. This filter is two-sided as the derivative is centered at time t, considering the past and future values.

Despite its straightforwardness, the HP filter has been criticized for its end-point bias and arbitrary choice of smoothing parameter. The end-point problem arises because the HP filter uses a symmetric moving average to smooth the data, which means that the filter cannot account for future data points when it smoothes the endpoints of the time series. This can lead to distorted estimates of both the trend and cyclical components, especially near the end of the series. The choice of λ is often arbitrary because there is no universally accepted theoretical basis for selecting its value. Hodrick and Prescott recommend a smoothing parameter of λ = 100 for annual data, λ = 1600 for quarterly, and λ = 14400 for monthly data. Different values of λ can significantly change the resulting trend and cyclical components, which can lead to different interpretations of the data. This lack of a standard criterion makes the selection process somewhat subjective. This sensitivity poses a problem for robust analysis, as the conclusions drawn from the filtered data can vary depending on the chosen smoothing parameter.

The BK filter, a band-pass filter, offers an alternative approach by focusing on the frequency domain (Baxter & King, 1999). The BK filter explicitly controls the frequency range of the cycles it extracts, but it requires the specification of low and high-frequency cut-offs. This allows researchers to target specific periodicities of interest. Unlike the HP filter, the BK filter does not suffer from the end-point problem. The BK filter uses a symmetrical moving average means that it does not rely on end-point data as heavily, avoiding the need for ad-hoc adjustments or extensions of the data series. The BK filter can be simply represented as (StataCorp, 2023):

$$c_t = \sum_{j=-q}^{+q}(b_j - \bar{b}_q)\, y_{t-j} \quad (2)$$

where c_t is the cyclical component of the series y_t, b_j are the weight coefficients, $\bar{b}_q$ is the mean of the weight coefficients cut at ±q. The weights b_j and their mean $\bar{b}_q$ are calculated as follows:

$$b_j = \begin{cases} \frac{\omega_h - \omega_l}{\pi}, & j = 0 \\ \frac{\sin(j\omega_h) - \sin(j\omega_l)}{\pi j}, & j \neq 0 \end{cases} \quad (3)$$

$$\bar{b}_q = \frac{\sum_{j=-q}^{+q} b_j}{2q+1} \quad (4)$$

The CF filter, also a band-pass filter, has a strong theoretical basis in frequency domain analysis, like the BK filter, but it also incorporates statistical estimation techniques that can provide more reliable results (Christiano and Fitzgerald, 2003). The CF filter does not rely on a fixed lag length for its moving average. Instead, it adjusts the filter weights dynamically, allowing for more accurate extraction of the cyclical component even when the underlying data structure changes. It can be represented as follows (StataCorp, 2023):

$$c_t = b_0 y_t + \sum_{j=1}^{T-t-1} b_j y_{t+j} + \tilde{b}_{T-t} y_T + \sum_{j=1}^{t-2} b_j y_{t-j} + \tilde{b}_{t-1} y_1 \tag{5}$$

where b_0, b_j are the weights of the ideal band-pass filter. $\tilde{b}_{T-t}$ and $\tilde{b}_{t-1}$ are linear functions of the ideal band-pass filter. For the non-stationary case with $1 < t < T$, they are set as:

$$\tilde{b}_{T-t} = -\frac{1}{2} b_0 - \sum_{j=1}^{T-t-1} b_j \text{ and } \tilde{b}_{t-1} = -\frac{1}{2} b_0 - \sum_{j=1}^{t-2} b_j \tag{6}$$

Therefore, the CF filter deals better with endpoint issues. It can provide estimates for the beginning and end of the sample without losing as many observations. This is a significant advantage over the BK filter, which loses data at the endpoints due to its symmetrical moving average approach.

Although the BK and CF filters have certain advantages over the HP filter, their results are sensitive to the choice of the frequency bands. İdentification of the relevant frequency bands demands the implementation of the spectral analysis of the time series. Spectral analysis is a technique used in time series analysis to decompose a complex signal into its constituent frequencies. This method provides insight into the periodic components of the data, making it particularly useful for identifying and understanding cycles and oscillatory behavior within the series. One common tool for spectral analysis is the periodogram, which estimates the power spectral density (PSD) of a time series. The periodogram transforms the time domain data into the frequency domain using the Fourier transform, revealing the strength of different frequency components present in the original signal. It works by computing the squared magnitude of the discrete Fourier transform (DFT) of the time series data (StataCorp, 2023):

$$C_k^2 = \frac{1}{n^2} \left| \sum_{t=1}^{n} x(t) e^{2\pi i (t-1)\omega_k} \right|^2 \tag{7}$$

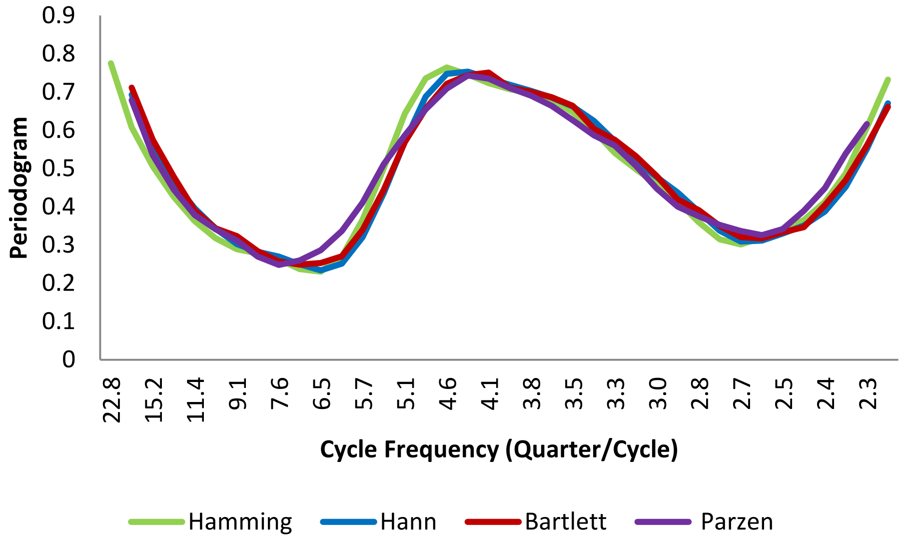
This results in a plot where the x-axis represents frequency (ω_k) and the y-axis represents the power or amplitude of the corresponding frequency components (C_k^2). Peaks in the periodogram indicate dominant frequencies, which correspond to cycles or repeating patterns in the time series. However, raw periodograms can be noisy and may require smoothing techniques, such as Bartlett, Hamming, Hann, and Parzen kernel windows, to produce more reliable estimates of the spectral density.

3. Data description and preprocessing

The dataset for this study consists of quarterly total GDP and non-oil-gas GDP data for Azerbaijan, spanning from Q1 2001 to Q4 2023 expressed in the constant prices. This data is sourced from the State Statistical Committee of the Republic of Azerbaijan. Both series are seasonally adjusted using the X11 method. Before the application of filters, the series is converted into a logarithmic form and multiplied by 100 hundred to have the trend and cyclical components in percentage terms. Before spectral analysis, the series is transformed into the log-difference form to achieve stationarity.

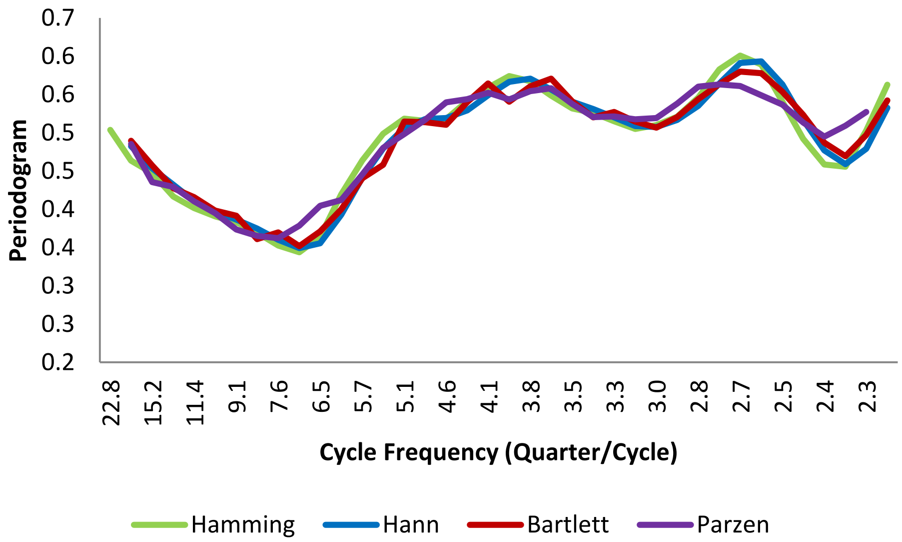
The application of the BK and CF filters requires the specification of the cycle periods. To provide reasonable estimates of the cycle periods, we conducted a spectral analysis. However, given raw periodograms can be noisy and require the use of kernel windows, such as Bartlett, Hamming, Hann, and Parzen to produce more reliable estimates of the spectral density. The other important issue is the selection of the bandwidth for the kernels because a high value can result in bias, while a low value cannot be sufficient to reduce the variance. Hamilton (1994) suggests a selection procedure that involves creating spectrum estimates using different bandwidths and then using personal judgment to select the bandwidth that provides the most believable estimate. This strategy allows for exploring various representations of the signal and choosing the one that seems most accurate.

Figure 1. Spectral density of total GDP



Source: Authors' calculations

Figure 2. Spectral density of non-oil-gas GDP



Source: Authors' calculations

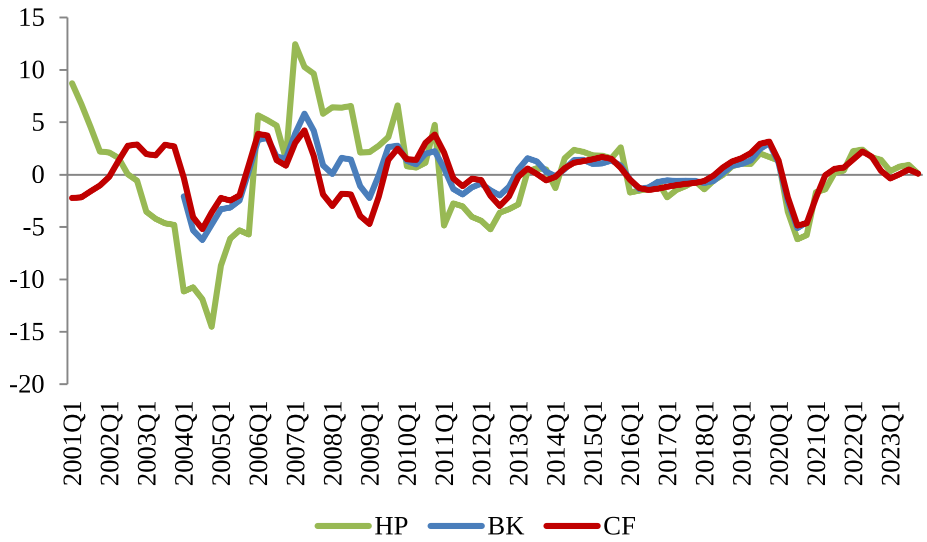
While not offering an objectively perfect solution, this approach can be useful in dealing with very noisy periodograms such as those of Azerbaijan's total and non-oil-gas GDP. This approach leads us to conclude that for our periodograms the optimal bandwidth is 5. The spectral densities of the total and non-oil-gas GDP for Bartlett, Hamming, Hann, and Parzen kernels are reported in Figures 1-2. Taking the average of cycle frequencies across four kernels suggests that the cycle period ranges from 4.1 to 19.4 quarters for total GDP and from

4.3 to 19.4 quarters for non-oil-gas GDP (≈ 1-5 years). For comparison, in advanced countries, the cycle period is usually assumed to range from 6 to 32 quarters (1.5 to 8 years). The shorter cycle periods in Azerbaijan might reflect higher volatility due to various factors such as dependence on oil exports, limited diversification, and vulnerability to external shocks. Advanced economies, on the other hand, often have more stable economic structures and policy frameworks that help to smooth out fluctuations over longer periods.

4. Results

Figure 3 presents the total output gap series generated by the HP, BK, and CF filters. The visual inspection shows that the HP filter shows more pronounced and volatile cyclical components, reflecting short-term economic changes more sensitively. In contrast, the BK and CF filters provide a smoother and more moderated view of the economic cycles. The discrepancies among the filters highlight the importance of using multiple methods to capture a comprehensive picture of economic performance, considering the varying sensitivities to different types of economic fluctuations and shocks.

Figure 3. Total output gap (%)



Source: Authors' calculations

From 2001 to 2003, the HP filter indicated substantial positive cyclical components, with a peak of 8.7% in 2001Q1, which contrasts starkly with the negative values captured by the CF filter during the same period. For instance, the CF filter shows a negative value of -2.22% in 2001Q1. These discrepancies can suggest the end-point bias of the HP filter. As mentioned before, the bias arises because the HP filter relies on symmetric moving averages, which are not available at the boundaries of the series.

From 2004 to 2008, the filters exhibit similar trajectories but with varying magnitudes. The HP filter demonstrates a pronounced downturn in 2004, reaching a trough of -14.5% in Q4, followed by a significant recovery peaking at 12.5% in Q1 of 2007. The BK filter captures a smoother cycle with less extreme fluctuations, identifying a trough at -6.2% in Q3 of 2004 and a peak at 5.8% in Q2 of 2007. The CF filter also indicates a downturn, albeit to a lesser extent, with a trough at -5.2% in Q3 of 2004 and a recovery peaking at 4.2% in Q2 of 2007. The substantial recovery, marked by a positive output gap from 2006 to 2008, was primarily driven by rapid growth in oil production in this period.

During the 2008 financial crisis, all filters show a downturn, though the extents vary. The HP filter indicates a sharp decline to 2.1% in 2008Q4 but the gap remains positive throughout the crisis. The frequency filters show more severe declines with the gaps entering the negative zone. The BK filter shows a decline to -2.22% in the same quarter. The CF filter records a decline to -4.71% in 2009Q1. This period underscores the differing sensitivities of the filters, with the CF filter reflecting an earlier start of recession and more pronounced negative impacts during economic downturns.

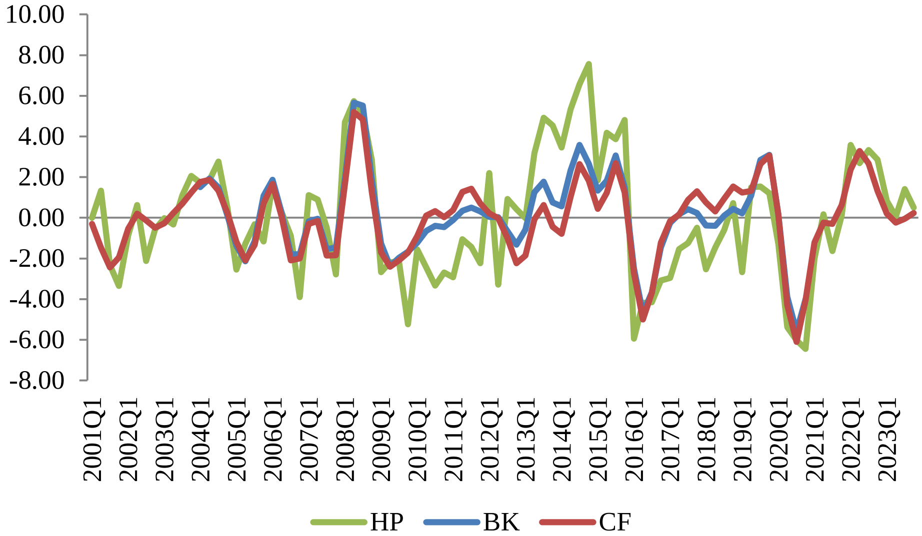
Following the anti-records in 2009Q1, the economy displayed positive trends that persisted until 2010Q4. The HP filter indicated its output gap peaked at 6.6% by the end of 2009Q4. Similarly, the BK filter showed a peak output gap of 2.8% by the same period. The CF filter also demonstrated recovery, reaching its maximum value of 3.8% in 2010Q4, suggesting a gradual economic improvement over time. However, positive developments did not last long, and in 2011Q1, due to exhaustion of sources of oil production growth, the output gap abruptly entered the negative zone and stayed there by the end of 2012. The HP filter reported a sharp decline to -4.9% in 2011Q1, remaining negative at -4.0% by 2011Q4. The BK and CF filters also reflected downturns with negative gaps throughout the year. By 2012, the output gaps remained negative across all filters, with the HP filter showing a slight recovery towards the end of the year from -4.4% in 2012Q1 to -3.3% in 2014Q4. The BK and CF filters had opposite trends. The BK filter showed a deterioration from -0.9% in 2012Q1 to -2.0% in 2012Q3, while the CF filter declined further from -0.5% in 2012Q1 to -3.0% in 2021Q3.

From 2013 to 2015, the filters generally showed signs of recovery, oscillating around zero, indicating periods of relative economic stability, though the HP filter shows more volatile swings. The BK and CF present a more stable trend, with values generally oscillating around zero, indicating moderate economic fluctuations. The 2016-2018 period, marked by the currency devaluation, sees negative values across all filters, with the HP filter showing a trough of -2.2% in 2017Q1, while the BK filter registers a low of -1.7% in 2016Q1 and the CF filter bottoms out at -1.5% in 2016Q4. The recovery is reflected in the subsequent quarters, with the HP filter showing a return to positive values by 2018, while the other filters indicate a slower recovery trajectory.

From 2019 to the COVID-19 pandemic, the filters capture robust economic performance, particularly in 2019, where the HP filter peaks at 3.0% in 2019Q4, the CF filter at 3.2% in the same quarter, and the BK filter at 2.5% in 2019Q3. The COVID-19 pandemic's impact is starkly evident, with all filters showing a significant decline reflecting the severe economic contraction and the impact on both global oil demand and local economic activity in 2020. The HP filter shows a sharp decline to -6.2% in 2020Q3, the BK filter to -5.1%, and the CF filter to -4.9%, reflecting the severe economic downturn. Post-pandemic recovery is evident from 2021Q3 onwards, with the HP filter peaking at 2.4% and the CF filter peaking at 2.2% in 2022Q2. By 2023Q4, both filters stabilized around zero.

Figure 5 presents the non-oil-gas output gap series generated by the HP, BK, and CF filters. The comparison of Azerbaijan's total and non-oil-gas GDP gap reveals two significant differences. First, the non-oil-gas sector appears to be less volatile than the total GDP, which is especially evident in the case of the HP filter. Second, often the total GDP and non-oil-gas GDP cycles demonstrated different patterns and the correlation coefficient between these series does not exceed 0.3.

Figure 4. Non-oil-gas output gap (%)



Source: Authors' calculations

During the early 2000s, Azerbaijan's non-oil-gas output experienced significant volatility. The HP filter starts with positive values such as 1.0% in 2001Q1, but shows volatility and dips, reaching the bottom of -3.3% in 2001Q4. The CF filter shows a slightly different picture, it starts with negative values, indicating periods of economic contraction. For instance, in 2001Q1, the output was -0.3%, and it further declined to -2.4% by 2001Q3. From 2003Q2-Q3, the data start to show signs of recovery, indicating the beginning of economic stabilization and growth.

The mid-2000s marked a period of volatility in Azerbaijan's non-oil-gas sector. For instance, the HP filter shows a peak of 2.8% in 2004Q3, the BK filter shows a peak of 1.9% in 2004Q2, and the CF filter aligns with this trend, recording 1.9% in the same quarter. However, in 2005, the non-oil-gas sector faced some setbacks, as reflected in negative values for the first 3-4 quarters across all filters. The HP filter declined to -2.6% in 2005Q1, the BK and CF filters dropped to -2.1% in 2005Q2. These declines could be attributed to economic adjustments or external shocks. However, by 2005Q4, there was a recovery, with the BK and CF filters rising correspondingly to 1.1% and 0.7%, indicating a rebound in economic activities. The HP filter remained in the negative zone.

In 2006-2007, the non-oil-gas sector experienced both growth and fluctuations. The year started strong with the HP filter at 1.7%, but the gap declined to -3.9% in 2006Q4. In 2007Q1-Q2, it returned to the positive zone, and in 2007Q3-Q4, it again became negative. The BK filter also has a positive gap at 1.9% in Q1, but the values declined in the latter half, with the lowest being -1.8% in 2006Q3 and 2006Q4 and remained negative by 2007Q4. The CF filter mirrored this trend, showing a significant drop to -2.1% in 2006Q3 and remaining in the negative zone by 2007Q4. These fluctuations indicate challenges in maintaining growth amidst varying economic conditions. In 2007, the non-oil-gas sector demonstrated resilience despite fluctuations. The BK filter showed minor negative values throughout the year, with the lowest being -1.5% in 2007Q3. The CF filter also showed a significant negative trend in 2007Q3 at -1.9%.

In 2008, the non-oil-gas sector reached its peak, with the highest values recorded in Q2: 5.7% (HP), 5.7% (BK), and 5.2% (CF). However, this peak was followed by a decline in 2008Q4, signaling the initial impact of the global financial crisis. In 2009, the output continued to decline. The HP filter reached its lowest point at -5.2% in 2009Q4 and both the

BK filter and the CF filter dropped to -2.4% in 2009Q2. This downturn was characterized by reduced economic activity and lower investment levels.

The period from 2010 to 2012 continued this trend of economic struggles, with predominantly negative cyclical components indicating ongoing underperformance. The post-crisis period was challenging, with the non-oil-gas economy showing predominantly negative cyclical components. The non-oil-gas GDP saw a gradual recovery and subsequent growth from 2013 to 2015. The HP filter indicates strong growth, particularly in 2014, with a peak of 7.6% in 2014Q4. The BK filter moves back into positive territory by 2013, with a peak of 3.6% in 2014Q3. The CF filter similarly shows positive trends, peaking at 2.7% in 2015Q3.

The year 2016 was a challenging period for Azerbaijan's non-oil-gas sector, characterized by a significant economic slowdown triggered by the devaluation of the domestic currency. The HP filter values were notably negative throughout the year, with the lowest value at -6.0% in 2016Q1, indicating a substantial decline in economic activity. The BK and CF filter values were negative throughout the year as well, both hitting a low of -4.7% and -5.0% respectively in 2016Q2. The HP filter suggests that the non-oil-gas sector started recovering only in 2019Q1 and by 2019Q4 reached 1.2%. However, according to the BK and CF filters, there is a notable recovery from 2017Q2 to 2019Q4. By 2019, both filters recorded values like 3.1% in 2019Q4, indicating a return to growth. This period of recovery and growth can be attributed to improved economic policies and stabilization efforts.

The COVID-19 pandemic had a significant adverse impact on Azerbaijan's non-oil-gas output. The data for 2020 shows sharp declines across all filters. The HP filter values turned sharply negative, with the lowest point at -6.4% in 2020Q4, reflecting the economic disruptions caused by lockdowns and reduced global economic activity. The BK and CF filters similarly indicated significant declines, with the lowest value of -5.6% and -6.1% in 2020Q3, respectively. The pandemic led to widespread economic challenges, including decreased consumer spending, disrupted supply chains, and a contraction in sectors such as tourism and services. Government efforts to mitigate the impact included stimulus packages, support for small and medium-sized enterprises, and public health measures to control the spread of the virus.

The data from 2021 to 2023 indicates a recovery phase, with positive cyclical components suggesting that the non-oil-gas sector of Azerbaijan's economy is bouncing back post-pandemic. This recovery was driven by the easing of lockdown measures, a rebound in global economic activity, and government support initiatives. Investments in healthcare infrastructure, vaccination campaigns, and measures to boost economic resilience played pivotal roles in the post-pandemic recovery. The HP filter turned positive from 2021Q4 onwards, peaking at 3.6% in 2022Q1. The CF filter showed a similar recovery pattern, but peaking at 3.3% in 2022Q2.

5. Conclusion

Understanding the dynamics of business cycles is crucial for developing effective economic policies and fostering sustainable economic growth. Business cycles, characterized by fluctuations in economic activity, encompass periods of expansion and contraction in an economy. Analyzing these cycles provides insights into the underlying mechanisms that drive economic performance and stability. This study provides a comprehensive analysis of Azerbaijan's business cycles, employing various filtering techniques to estimate cyclical components and gain deeper insights into the economic fluctuations of this resource-dependent economy. Our analysis reveals significant differences in the volatility and cyclical behavior of total GDP versus non-oil-gas GDP, reflecting the economy's sensitivity to oil price fluctuations and external shocks.

The application of the HP, BK, and CF filters demonstrates varying sensitivities to economic fluctuations, highlighting the necessity of using multiple methods to obtain a nuanced understanding of the business cycles. The spectral analysis and periodogram further aid in identifying relevant frequency bands, ensuring a more precise application of these filters to Azerbaijan's economic data. Thus, the conducted spectral analysis shows that the cycle periods range approximately from 1 to 5 years for total GDP and non-oil-gas GDP. These results are generally in line with the previous studies of Mammadov and Adigozalov (2014) and Ahmadova (2020) who conclude that cycles can last up to 4 years.

Our findings indicate that while the HP filter tends to show more pronounced cyclical components, the BK and CF filters provide a smoother view, particularly advantageous in capturing long-term trends without significant endpoint bias. This comparative analysis underscores the importance of selecting appropriate filtering techniques based on the specific characteristics of the data and the research objectives.

The results highlight several key periods of economic activity, including rapid growth phases driven by oil production, significant downturns during the global financial crisis and COVID-19 pandemic, and the more stable but still volatile non-oil-gas sector. These insights are crucial for policymakers in Azerbaijan, as they navigate the challenges of economic diversification and strive to develop more resilient economic strategies.

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