Open Access Library Journal
2024, Volume 11, e12120
ISSN Online: 2333-9721
ISSN Print: 2333-9705

Output Gap and Inflation in Rwanda

Jean Claude Niyonsenga, Kabanda Richard

School of Economics, College of Business and Economics, University of Rwanda, Kigali, Rwanda
Email: niyorijeanclaude@gmail.com, richacha2000@gmail.com

How to cite this paper: Niyonsenga, J.C. and Richard, K. (2024) Output Gap and Inflation in Rwanda. *Open Access Library Journal*, **11**: e12120.
https://doi.org/10.4236/oalib.1112120

Received: August 16, 2024
Accepted: September 8, 2024
Published: September 11, 2024

Abstract

The assessment of potential output and the output gap holds significant importance for policymakers, as it serves as a cornerstone for maintaining macroeconomic stability encompassing aspects such as real GDP growth, price stability, and full employment. This study investigates various methodologies employed to estimate potential output and the output gap in Rwanda, utilizing seasonally adjusted quarterly data spanning from 2006Q1 to 2021Q4. Initially, we explore mechanical or statistical approaches including Hodrick-Prescott, linear time trend, Beveridge Nelson decomposition, and unobserved component model. Additionally, a multivariate approach, specifically the production function approach, is employed. Diagnostic evaluations, such as assessing Granger causality between the output gap and inflation, are conducted using Rwandan data from 2006 Q1 to 2021 Q4 to discern potential linkages. The findings across different methodologies suggest that the output gap fluctuates within a range of −6 to 6 during normal conditions; the primary implication underscores the necessity for fiscal and monetary policies to respond to positive and negative output gaps, respectively, thereby mitigating inflationary pressures and recessionary periods while fostering sustained economic growth. The study investigates the correlation between the output gap and inflation, revealing a robust causal relationship between the two factors in the Rwandan economy.

Subject Areas

Monetary Policy

Keywords

Output Gap, Macroeconomic Stability, Unobserved Component Model, Rwanda

1. Introduction

Estimates of potential output and the output gap hold significant importance within structural macroeconomic frameworks, particularly in the realm of monetary policy forecasting and analysis. When actual output surpasses potential output, resulting in a positive output gap, it typically signifies a potential source of inflationary pressures. In such instances, monetary policy responses often entail tightening measures aimed at reining in inflation and steering it back towards the target level. Policymakers rely on output gap estimates to guide their decisions in pursuit of desired economic outcomes, as highlighted by [1].

[2] argued that both potential output and the output gap represent latent variables, yet they can be inferred from observable indicators such as output, employment levels, capacity utilization, and inflation. Potential output refers to the enduring movement in output that aligns with maintaining stable inflation, while the output gap signifies the variance between actual output and potential output.

[3] revealed that when actual output surpasses potential output, it anticipates robust growth in aggregate demand, with employment levels exceeding full employment and capacity utilization surpassing its optimal level. This scenario denotes a positive output gap, typically leading to an upward trajectory in inflation. Conversely, a persistent negative output gap signals deflationary pressures, where actual output lags behind potential output. Such circumstances indicate an unhealthy economy.

Central banks require indicators of the domestic output gap to fine-tune short-term macroeconomic policies and strategize for long-term macroeconomic structural adjustments. Specifically, sluggish growth in potential output over the medium and long term serves as a signal to policymakers, prompting the necessity for implementing structural reforms [4].

The output gap serves as a proxy for gauging domestic inflationary pressures when forecasting inflation over the medium term, underscoring the necessity for monetary policy decisions to integrate insights from potential output and output gap estimations. The National Bank of Rwanda adopts inflation targeting as its monetary policy framework, with the output gap standing as a primary determinant of inflation dynamics [5]. Consequently, precise measurements are imperative to accurately capture potential output and the output gap, enabling policymakers to make informed decisions [6].

The core objective of the National Bank of Rwanda is to uphold price stability, foster a secure and stable financial system, and bolster government economic initiatives through effective employment of robust monetary policy instruments.

Earlier investigations into potential output and the output gap in Rwanda, conducted by [7], employed statistical filter methodologies such as linear trend, Hodrick-Prescott filter, and the unobserved component approach spanning from 1999 quarter one to 2012 quarter three. The findings highlighted the efficacy of the Hodrick-Prescott filter in delivering reliable estimates compared to other approaches. Considering the limitations of mechanical or statistical filters in adequately capturing pertinent information from other macroeconomic variables associated with actual GDP, this study opts for a multivariate approach, which offers greater efficacy in integrating relevant data from other macroeconomic indicators to derive potential output from actual GDP. For instance, the production function approach considers the contributions of labor, capital, and structural reforms in elucidating potential economic growth [8].

Previously, the multivariate approach has not been employed as an alternative method for estimating potential output in the case of Rwanda. The aim of this paper is to estimate potential output and the output gap in Rwanda by initially utilizing statistical filters as benchmark models, followed by the inclusion of the multivariate approach, which is expected to perform well in extracting trends from actual GDP data. Future research will delve into estimating potential output and the output gap in Rwanda using extended models grounded in economic theory.

The paper's structure is as follows: Section 2 reviews pertinent literature, while Section 3 provides a brief overview of the alternative methods utilized for estimating potential output. Section 4 presents empirical findings for each method. Section 5 synthesizes the main findings, and Section 6 offers concluding remarks.

2. Relevant Literature Review

In his study focusing on the United States, [9] employed both a production function and an unobserved component model to gauge output and the output gap. He indicated that unobserved component models exhibit superior robustness compared to other models. In the context of [10] underscored the efficacy of multivariate techniques in generating estimations. Similarly, [11] arrived at a similar conclusion for Canada where he revealed that output gap influences inflation.

During the Recession, [12] embarked on a study to explore the link between the output gap and inflation. Their findings indicate a diminished connection during this period, suggesting that inflation became less responsive to economic changes. Similarly, [13] investigated this relationship by employing a New Keynesian model in their research. Their results affirmed the Phillips Curve theory, revealing a positive correlation between inflation and the output gap.

In a study utilizing a structural time series approach, [14] delved into the relationship between inflation and the production gap. Their findings provided evidence supporting the predictions of the Phillips Curve, indicating a connection between these variables. Similarly, [15] conducted research in Europe and also identified a positive relationship between inflation and the output gap. This underscores how fluctuations in the output gap can influence inflationary pressures within countries.

In their study, [16] focused on developing nations and examined the relationship between the output gap and inflation. Their analysis revealed that elevated levels of inflation are associated with the output gap, demonstrating how resource constraints can lead to inflationary pressures.

More recently, [17] concluded that the output gap is a determining factor for inflation in the Eurozone. Supporting this, [18] observed that there is indeed an influence of the output gap on inflation. Expanding on this research, [19] used a

Markov regime-switching model to investigate the link between the output gap and inflation, finding that the output gap positively affects inflation.

Additionally, numerous studies have employed multivariate techniques to estimate output and assess the output gap.

3. Methodology

In this paragraph we will discuss approaches that statistical offices use to differentiate between actual output. We will demonstrate how the output series can be combined by one level. To achieve this objective, we will utilize unit root tests such as the Dickey Fuller and Phillips Peron tests, as the series comprises random permanent components. Forecasting output accurately poses a significant challenge for researchers ([20] [21]).

The National Institute of Statistics of Rwanda (NISR) recently published data on GDP, headline inflation, and core inflation for each quarter spanning from the first quarter of 2006 to the fourth quarter of 2021. World Development Indicators served as the primary source for gathering statistics on labor force participation, working-age population, unemployment rate, and employment rate for this study. To ensure comparability, the adjusted data underwent a logarithmic transformation (using the formula 100 * ln). Additionally, to align the frequency of variables, we applied the cubic spline method to convert the annual frequency of labor force participation rate, working-age population, employment, and unemployment rates.

3.1. Introduction to Statistical Methods

Two methods are commonly employed to estimate output: the univariate statistical approach and the multivariate approach. In this context, we have applied the Hodrick-Prescott filter (HP filter), developed by [22], along with the Beveridge-Nelson decomposition, introduced by Beveridge and Nelson in 1981. However, these techniques encounter difficulties when applied to series that are integrated or nearly integrated, as they struggle to differentiate transitory movements based solely on real GDP.

These methodologies have faced criticism in certain studies due to their potential limitations in providing accurate assessments of results. For instance, concerns raised by [23] and [24] question the ability of filters such as the HP filter and Band Pass filter to effectively capture fluctuations. Similarly, [25] found that these filters were inadequate in capturing nuanced elements within time series data. Despite their limitations, several researchers ([26]-[29]) have recognized filters as valuable tools for analyzing time series data with diverse growth patterns and cycles.

To tackle the endpoint issue encountered when employing the Hodrick-Prescott filter, [3] suggested a solution by advocating for projecting three years ahead to expand the sample size before applying the HP filter to the time series. In this study, we utilized various techniques including the Hodrick-Prescott filter, Beveridge-Nelson decomposition, unobserved component models, and linear trend analysis. These methods were selected due to their widespread acceptance among researchers and their accessibility when accessing data.

3.1.1. Linear Trend Method

A straightforward method for estimating potential production is the linear trend approach. This technique assumes that potential output will steadily rise over the study period. It involves fitting a regression line that incorporates real GDP along with constant and trend variables, assuming a consistent annual growth in output. Research conducted by [30] suggests that this method presupposes the absence of randomness in output over time, with the error term playing a significant role. The following econometric formula illustrates how to calculate potential output using the linear time trend:

$$y_t = \alpha + \beta t + \varepsilon_t \tag{1}$$

where: t stands for time and ε_t stands for error term.

The linear trend method is constrained by its assumption of a consistent rate of output increase. However, this assumption doesn't hold true in reality because various factors such as labor and capital exert influence on output and evolve over time, leading to fluctuations in output growth. Empirical studies indicate that economies like the United States and Japan experienced higher potential production growth rates in the 1950s and 1960s compared to the present era [31]. [32] contends that time series data frequently exhibit stochastic trends, suggesting that treating output as a function of time can yield regression results with limitations.

3.1.2. Hodrick-Prescott Filter

[22] distinguishes itself from the linear trend approach primarily by considering fluctuations in growth. To address this, the technique incorporates the use of the lambda smoothing parameter. In our study, we employed a lambda value of 1600 when analyzing seasonally adjusted quarterly data spanning from 2006 Q1 to 2021 Q4. This lambda value is widely endorsed by many experts in academia for quarterly data analysis. As a general guideline, a lambda value of 100 is recommended for annual frequency data, while a lambda value of 14,400 is suggested for monthly frequency data. By minimizing the objective function stated below, we obtained the desired results:

$$\min_{y_t^*} \sum_{i=1}^{\infty} \left(y_t - y_t^*\right)^2 + \lambda \sum_{i=2}^{\infty} \left[\left(y_{t+1}^* - y_t^*\right) - \left(y_t^* - y_{t-1}^*\right)\right]^2 \tag{2}$$

where y_t is the log of real GDP and y_t^* is the trend of output. $\left(y_t - y_t^*\right)^2$ the HP filter's initial stage, which determines the total squared deviations of the real output from its trend. The right-hand side part is $\left[\left(y_{t+1}^* - y_t^*\right) - \left(y_t^* - y_{t-1}^*\right)\right]^2$ to minimize the deviation of trend growth, it is important to consider the lambda weighting factor. This factor governs the smoothness of the trend line movement. When lambda assumes a higher value, the estimations resemble those obtained using the linear trend approach. Conversely, when lambda is set to a lower value, the pattern closely mirrors the actual GDP.

Applying an HP filter to the data offers the advantage of simplicity, allowing for the capture of variations in growth over time using a single observable variable. However, several factors warrant consideration. One such factor is the potential for bias in the sample. Another factor is the necessity of selecting the smoothing parameter (lambda). It is noteworthy that using filters to extract trends from cycles in non-stationary time series may not always yield effective results, as underscored by empirical studies conducted by ([11] [23] [33]). Therefore, it is prudent to exercise caution when relying on estimations derived from the Hodrick-Prescott (HP) filter approach in developing economies, where selecting an appropriate smoothing parameter can pose challenges.

3.1.3. Beveridge-Nelson Decomposition

[34] introduced a method aimed at distinguishing transitional movements within macroeconomic time series. They proposed employing a moving method to characterize these series, which takes into accounts both lag issues and the historical values of the series. According to Beveridge and Nelson, any non-stationary time series can be decomposed into movements and stationary series. The stationary series, with a mean of zero, correspond to components, whereas random movements with a drift signify changes in output. Their premise was that a time series exhibits a unit root at its level but becomes stationary after differencing, indicating that the series are integrated of order one. Hence, we can express the equation in the form of a moving representation.

$$(1-L)y_t = \Delta y_t = \mu + B(L)\varepsilon_t \tag{3}$$

First, define the polynomial lag, $B^*(L)=(1-L)^{-1}\left[B(L)-B(1)\right]$. Where, $B(1)=\sum_{j=0}^{\infty} B_j$, by rearranging the above equation, we can get:

$B(L)=B(1)+(1-L)B^*(L)$ and replace B(L) its value in the first equation:

$$\Delta y_t = \mu + B(L)\varepsilon_t = \mu + \left[B(1)+(1-L)B^*(L)\right]\varepsilon_t \tag{4}$$

Since $y_t = y_{\text{trend}} + y_{\text{gap}}$, it follows that $\Delta y_t = \Delta y_{\text{trend}} + \Delta y_{\text{gap}}$. Therefore, a change in the trend component of is equal to $\Delta y_{\text{trend}} = \mu + B(1)\varepsilon_t$. And a change in the cyclical component is equal to $\Delta y_{\text{gap}} = \mu + (1-L)B^*(L)\varepsilon_t$.

3.1.4. Univariate Unobserved Component Model

When conducting trend cycle analyses, incorporating unobserved component models is a feasible approach. Previous empirical studies, such as those conducted by researchers like [35]-[37] have utilized the state space form to address the modeling of unobserved components. These studies suggest that the trend follows a stochastic process, possibly resembling a random walk with drift, while proposing that the output gap exhibits characteristics of a second-order autoregressive model. In line with [36] research, the current study employs a second-order autoregressive model to depict the output gap, thereby reinforcing the notion that the trend follows a random walk with a constant.

$$y_t = y_t^* + \hat{y}_t \tag{5}$$

where, y_t is real GDP, y_t^* is a potential output or trend and $\hat{y}_t$ is an output gap or cycle.

$$y_t^* = \mu + y_{t-1}^* + \epsilon_t \tag{6}$$

$$\hat{y}_t = \hat{y}_{t-1} + \hat{y}_{t-2} + \eta_t \tag{7}$$

where $\epsilon_t^{y_t^*} \sim \mathcal{N}\left(0, \left(\delta_{y_t^*}\right)^2\right)$ represents the shocks to the trend and

$\eta_t^{\hat{y}_t} \sim \mathcal{N}\left(0, \left(\delta_{\hat{y}_t}\right)^2\right)$ represents the shocks to the output gap. The trajectory of an economy depends on two pivotal factors: the pace of its potential output growth and any transient disturbances it encounters. The drift parameter plays a significant role in illustrating an erratic path that evolves unpredictably. To accurately depict the characteristics of this parameter, we can utilize the following mathematical representation:

$$\mu_t = \mu_{t-1} + \epsilon_t^{\mu} \tag{8}$$

where $\epsilon_t^{\mu} \sim \mathcal{N}\left(0, \delta_{\mu}^2\right)$ These occurrences have a long-term effect because they provide a persistent shock to the rate of expansion of potential output. The model is formulated in state space form, and its parameters are determined according to the model specification. The measurement equation establishes a connection between observable variables and unobservable variables in the state space framework. Meanwhile, the transition equation elucidates the temporal evolution of unobserved variables [9].

To estimate the model's parameters, the Kalman filter approach is employed, and the log likelihood function is maximized. This function can be expressed mathematically as follows:

$$\log(\pi) = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{1}^{T}\log\left|F_t\right| - \frac{1}{2}\sum_{1}^{T} v_t^{\mathrm{T}} F_t^{-1} v_t \tag{9}$$

where T is the sample size, V is the prediction error matrix, and F is the mean square error matrix of the prediction errors.

3.2. Introduction to Multivariate Methods

The evaluation of structural relationships holds significant importance in multivariate procedures, drawing upon economic theory, and notably remains unaffected by the endpoint problem. In this study, we utilize two distinct techniques: bivariate unobserved component models and the production function approach.

3.2.1. Bivariate Unobserved Component

A study conducted by [37] utilized state space modeling to identify output and output gaps, employing both univariate and bivariate unobserved component models. The unemployment series data were integrated into the model. Subsequent investigations by [9] and [36] expanded on this research. Additionally, [11] utilized methods to establish a relationship between inflation and excessive demand using the Phillips curve approach. These advancements have facilitated the generation of forecasts concerning potential output growth and resulting output gaps. By incorporating the cycle component from the trend model as a variable, we can enhance our understanding of how inflation interacts with external factors.

$$\Delta\pi_t = \mu_t + \gamma\Delta\pi_{t-i} + \beta z_{t-i} + v_t \tag{10}$$

According to [38], the concept of potential output elucidates the relationship between fluctuations in inflation and the output gap. This suggests that when the output level remains steady, so does inflation. In their study, [39] presented a model illustrating a connection between demand and cyclical inflation, underscoring their interdependence. For further insights into unobserved component approaches, [40] book serves as a valuable resource.

3.2.2. Production Function Approach

An alternative approach, known as the production function technique, offers a unique method for estimating potential output by integrating economic theory. Through this approach, we can establish a clear relationship between potential output and production inputs such as labor and capital stock. This method entails calculating total factor productivity based on the residual value derived from the analysis. This technique has been prominently featured in studies conducted by reputable institutions such as the Congressional Budget Office [41] and OECD standards [42]. It is assumed that the capital stock operates at its maximum potential by fully utilizing all available resources. After a thorough examination of relevant literature in this field, we have adopted a labor share of 74% and an annual depreciation rate of 5% as our assumptions [43]. To express this concept mathematically:

$$Y(t) = AK^{\alpha}L^{1-\alpha} \tag{11}$$

In the above equation, A denotes productivity, encapsulating both structural reforms and technological progress. The variables Y represent real output, L represents labor input, and K signifies capital stock. Additionally, α indicates the share of output assigned to capital. Upon implementing a logarithm transformation on this equation

$$\log(y) = \log(A) + \alpha\cdot\log(K) + (1-\alpha)\cdot\log(L) \tag{12}$$

As per Dupasquier *et al.*, it has been suggested that potential employment should be adjusted for the non-accelerating inflation rate of unemployment (NAIRU) to achieve a more precise measurement.

$$E^* = (LF)^*(1-\text{NAIRU}) \tag{13}$$

where $\text{LF} = \text{LFPR}\times\text{WAP}$. To compute the labor force, we multiply the working-age population by their labor force participation rate. It's crucial to adhere to the guidelines outlined by [44] when estimating NAIRU. For further details, the results are included in our appendix.

We employ the HP filter technique to refine our labor force and total factor productivity measurements. This ensures data consistency and reliability, enabling us to express output as follows:

$$Y^* = A^* K^{*\alpha} L^{*(1-\alpha)} \tag{14}$$

In order to accurately determine employment numbers it is crucial to use the inventory method when calculating capital stock. Esteemed organizations, like the IMF, World Bank and OECD heavily rely on this approach to assess a country's capital stock. The formula commonly employed for implementing the perpetual inventory technique is as follows;

$$K_t = (1-\delta)K_{t-1} + I_t \tag{15}$$

where K_t represents the current level of capital stock, K_{t-1} represents the previous level of capital STOCK, I_t represents the current level of investment. To determine the condition of the capital stock, you can calculate it by multiplying the ratio of investment, to GDP by the real GDP in the reference year.

4. Empirical Results

4.1. Stationarity Tests

The raw values of GDP and core inflation series show non-stationarity. They become stationary when we consider their first differences. Various unit root tests, such as the Augmented Dickey Fuller and Phillips Perron tests confirm this. Thus it suggests that real GDP and inflation are both integrated of order one. In terms when we look at the changes, in their values over time, they become consistent.

Table 1. Unit root test results for variables.

Variables	Levels	1st Difference	Decision
GDP	2.31	-3.98^{***}	I (1)
CPI	−0.499	-4.849^{***}	I (1)

***1% level of significance, **5% level of significance, *10% level of significance. Source: Author's computations.

Based on the results of the stationarity test, the Augmented Dickey Fuller test, in Table 1, it is uncertain whether the series can be considered stable at their current levels. However, these series do exhibit stationarity after undergoing the first difference. In the following section, we will discuss the estimation outcomes obtained through various methodologies.

4.2. Linear Trend Estimation

The outcomes obtained using the linear trend technique, which assumes an expansion, in output, are provided below;

$$LGDP = 681.21 + 1.7 \times \text{Time Trend} - 7.21 \times \text{Dummy}$$

$$\begin{pmatrix} (0.6948) & (0.0195) & (1.26)(\text{standard errors}) \\ (980) & (86) & (-5.719)(\text{t-statistics}) \end{pmatrix}$$

$$R^2 = 0.99 \quad DW = 0.79$$

Source: Author's computations.

However, there are reasons to suspect serial correlation, as indicated by the low Durbin-Watson score of 0.79 observed in this study. Additionally, an autocorrelation test was conducted using the serial correlation LM test, resulting in a very small probability of 0.000, leading to the rejection of the null hypothesis. The regression findings reveal a high R-square value of exactly 0.99, indicating that our model fits accurately within this dataset context. However, in this specific case, the model specification process appears to be flawed. As suggested by the outcomes from linear trend analysis, the potential output (estimated as intercept plus slope multiplied by trend [681.21 + 1.7 * trend] and so forth) and potential economic growth remain consistently around approximately 1.7% for each quarter throughout the entire sampled period, without accounting for any potential data breakpoints. The concept of an output gap refers to the difference between actual output and potential output (or trend), as detailed in our methodology section. Given that the actual output in the fourth quarter of 2021 was 789.9 while the projected output was 794.3, the linear trend technique predicts a negative output gap of −4.4 for the next quarter.

From 2006 to 2022, Rwanda's growth rate has shown an upward trend based on this analysis. Examination of the trend indicates an output gap, signifying that actual output consistently lags behind potential output during this period. Despite challenges posed by COVID-19, as shown in Figure 1 and Figure 2, there was a decline in production in the 2020 quarter, which could be deemed somewhat acceptable. This implies that Rwanda experienced a slowdown during that period, prompting policymakers to respond with monetary and fiscal measures, such as investing government funds into infrastructure projects like schools.

The economy is currently undergoing a phase of recovery as indicated by the projections of output using the trend method. This becomes evident from the

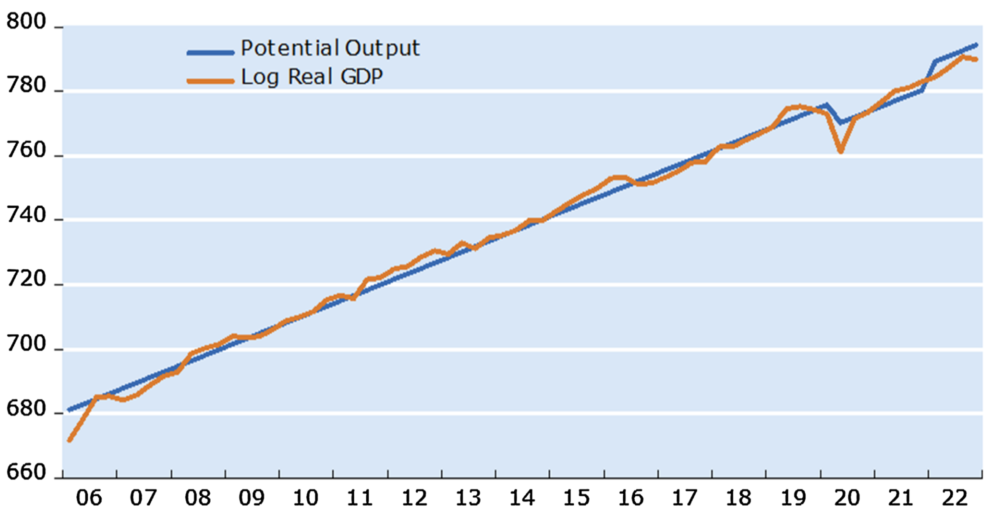

Figure 1. Linear trend actual and potential output (Source: Author).

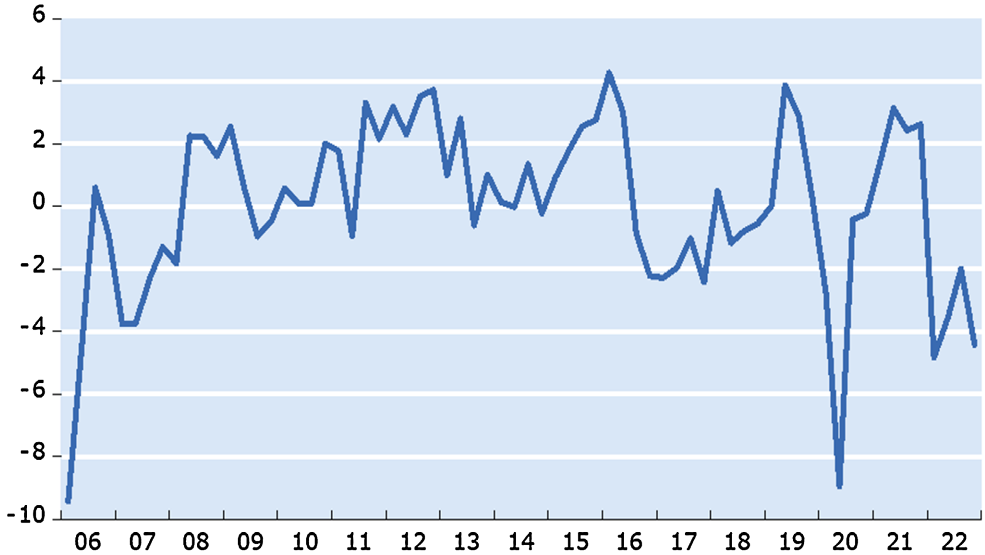

Figure 2. Linear trend output gap (Source: Author).

shift, in values, which have changed from negative to negative and has been observed.

In times, it has been observed that the estimates of output gaps have shown values. This suggests that the economy has been functioning below its output.

4.3. Hodrick-Prescott Filter

According to Hodrick-Prescott findings, the rate of trend growth has declined from around 1 percent recorded between 2006 to 2010 to 1.33 percent between 2020 to 2021. In Figure 3 and Figure 4, when considering the sample, the average output gap is around 0.01 percent. The HP filter analysis indicates an output gap during two periods; from Q1 2006 to Q4 2010 and from Q1 2020, to Q4 2021 highlighting that the Rwandan economy was not operating at its potential during those times.

In years according to Hodrick-Prescott trend estimates, it can be observed that the economy performed better, than its expected levels. Additionally, there were signs of recovery from the impact of the COVID-19, on activity.

Table 2. Actual and Potential output, 5 year's average growth (%).

Year	Actual	Linear Trend	HP filter	Univariate Beveridge-Nelson	Unobserved Component Model	Production Function
2006Q1-2010Q4	2.3	1.65	1.9	1.1	1.7	1.9
Q1-2015Q4	1.8	1.65	1.7	1.5	1.6	1.7
Q1-2019Q4	1.6	1.65	1.5	1.7	1.4	1.4
Q1-2021Q4	1.2	1.65	1.3	2.8	1.3	1.3
Q1-2021Q4	1.8	1.65	1.7	1.6	1.6	1.6

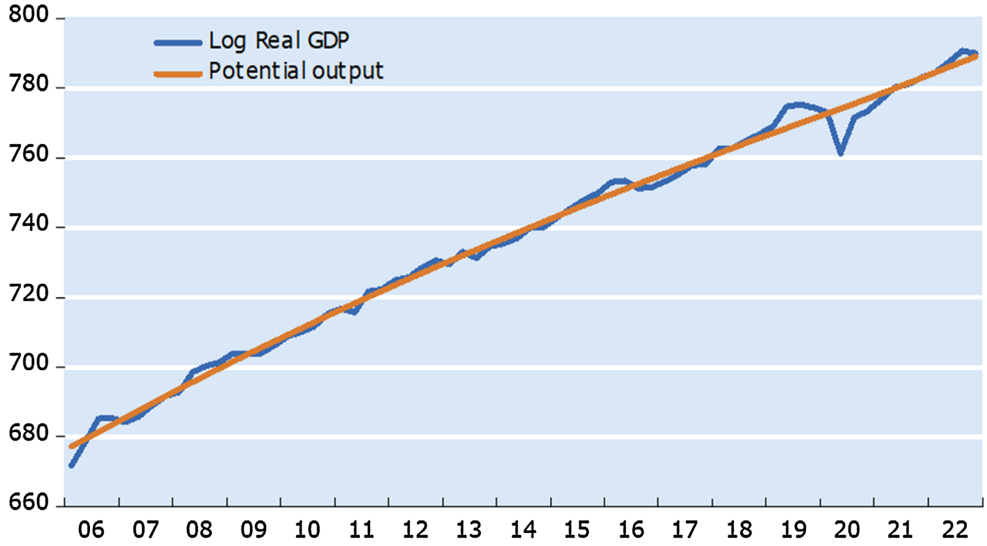

Figure 3. Hodrick-prescott filter actual and potential output (Source: Author).

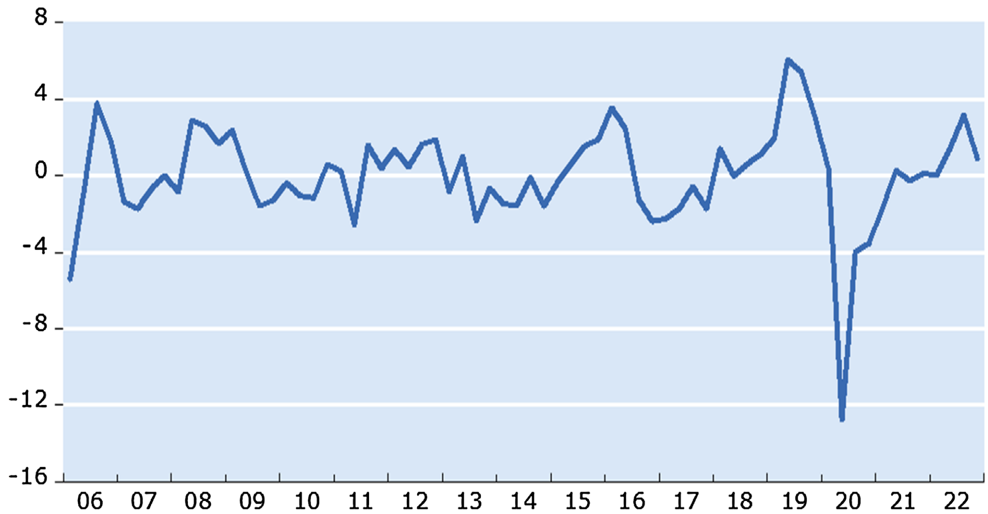

Figure 4. Hodrick-prescott filter output gap (Source: Author).

The Hodrick-Prescott estimated output gap has shown results in times indicating a promising path, for the economy starting from the second quarter of 2020.

4.4. Univariate Beveridge-Nelson Method

To determine the aspects of output and the output gap, we can analyze statistical publications such as output data. By applying the Beveridge Nelson approach to decompose a variable, we have determined that an ARIMA (1,1,1) model is the appropriate, for modeling Rwandas output. We conducted screening by evaluating the significance of coefficients and considering both the Akaike information criterion (AIC) and Schwartz information criterion (SC). The estimated model produces the following outcomes;

$$\Delta GDP_t = 1.68 + 0.58 \times \Delta GDP_{t-1} - 0.86 \times \text{error term}_{t-1}$$

$$\begin{pmatrix} (0.1620) & (0.2442) & (0.2055)(\text{standard errors}) \\ (10.39) & (2.37) & (-4.20)(\text{t-statistics}) \end{pmatrix}$$

Source: Author's computations.

In years, the Univariate Beveridge Nelson decomposition indicates a decrease, in output with a decline from 1.9 percent to 1.7 percent. Looking ahead, it is projected that the output gap will be 1.8, in the quarter of 2022.

The provided Figure 5 illustrates the outcomes of the Beveridge Nelson analysis demonstrating variations in output throughout the dataset.

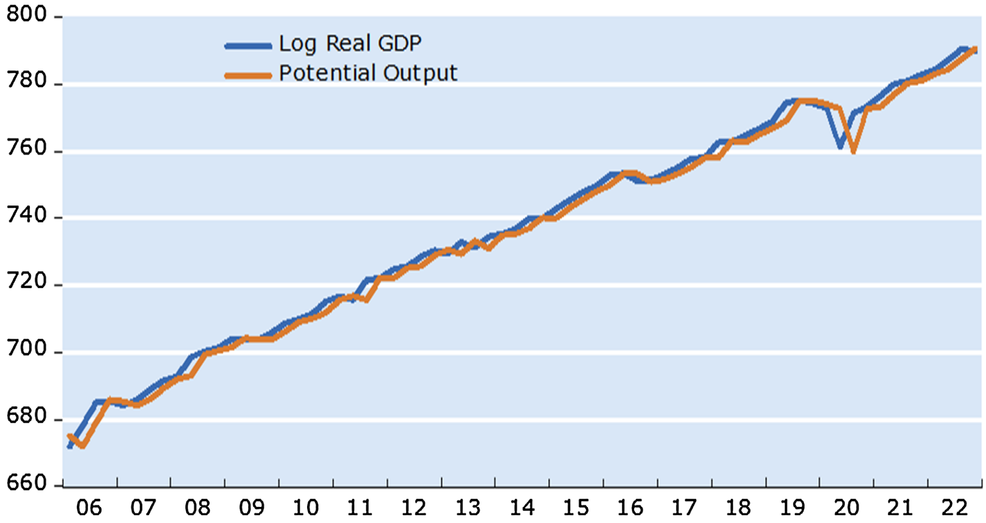

Figure 5. Univariate beveridge nelson actual GDP and potential GDP (Source: Author).

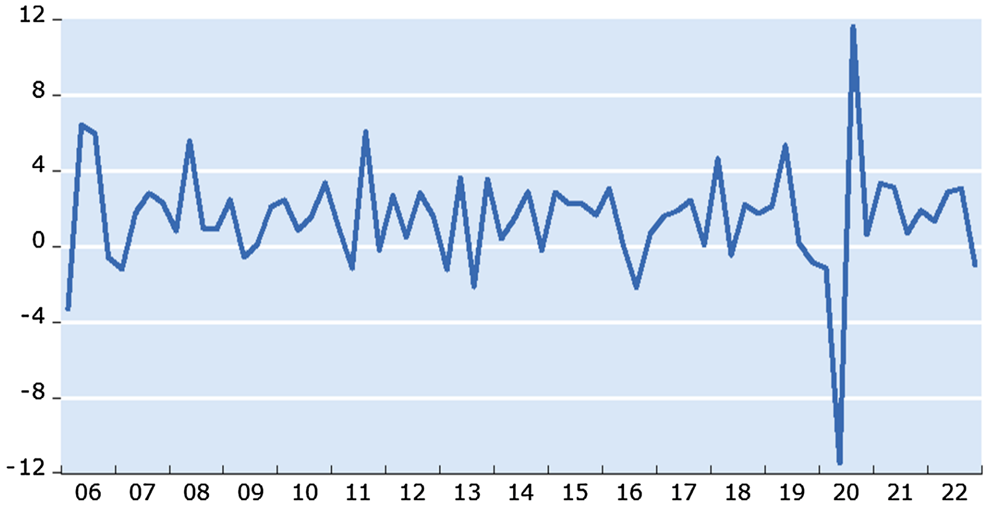

Figure 6. Univariate beveridge nelson output GAP (Source: Author).

Figure 6 indicates that except during downturns, like the 2020 quarter, which was impacted by the COVID-19 pandemic, the output gap resulting from Beveridge Nelson decomposition evolves between −4 and 4.

4.5. Unobserved Component Model

Following the work of [45], assumed that potential output could be modeled as a random walk with drift. We constructed the state space form and estimated the parameters in Eviews 11. Bivariate unobserved component method were also applied. Core inflation was included in the model after consulting the work done by [46] and [47]. According to [48] discussed how Federal Reserve does their forecasts about core inflation and mentioned that they include lagged values of core inflation, output gap and supply shocks plus some expert judgements to incorporate useful information not captured by the model. Results from the unobserved component model show that potential output is smoothed, as it is shown in **Figure 7**.

Figure 8 shows that in the last quarter of 2021, the output gap estimates were negative based on results from the bivariate unobserved component model due to

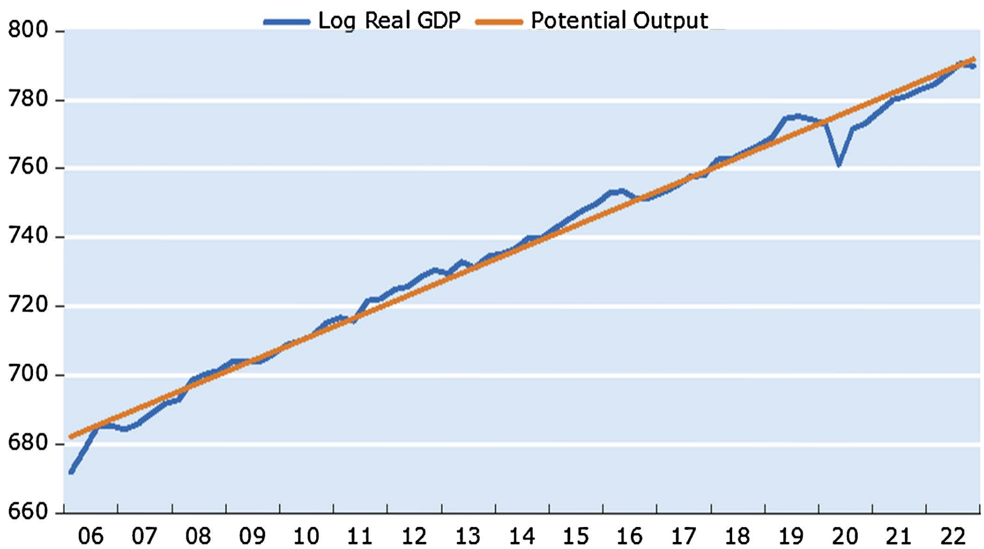

Figure 7. Univariate unobserved component actual GDP and potential GDP (Source: Author).

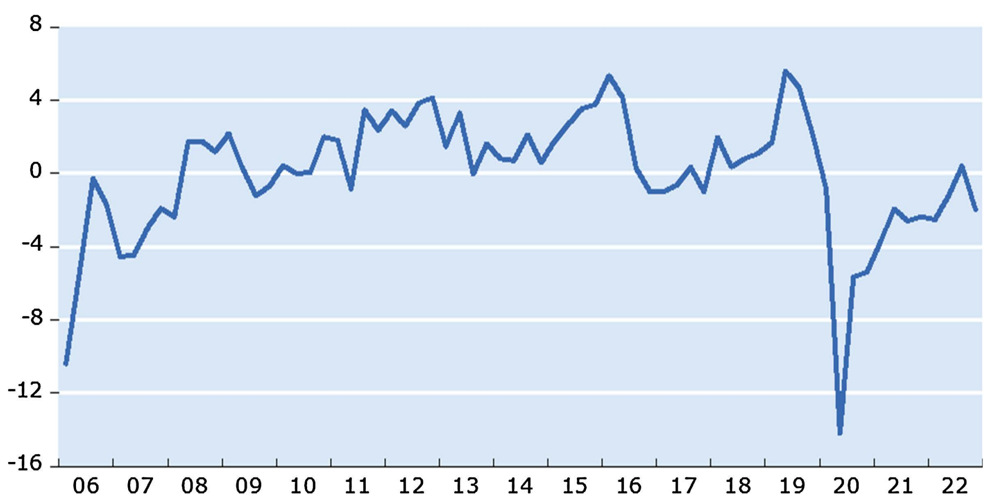

Figure 8. Univariate unobserved component output GAP (Source: Author).

the lingering COVID-19 pandemic that was negatively affecting the economy from performing to its potential level.

4.6. Production Function Model

According to the analysis conducted using the production function approach, the output gap has consistently averaged around zero during the period, under examination. It is worth mentioning that between the quarter of 2020 and the fourth quarter of 2021 this gap was observed to be negative, at a value of 1.8. Furthermore, when taking into accounts the sample, it is estimated that there is a trend growth rate of 1.7 as shown in Figure 9.

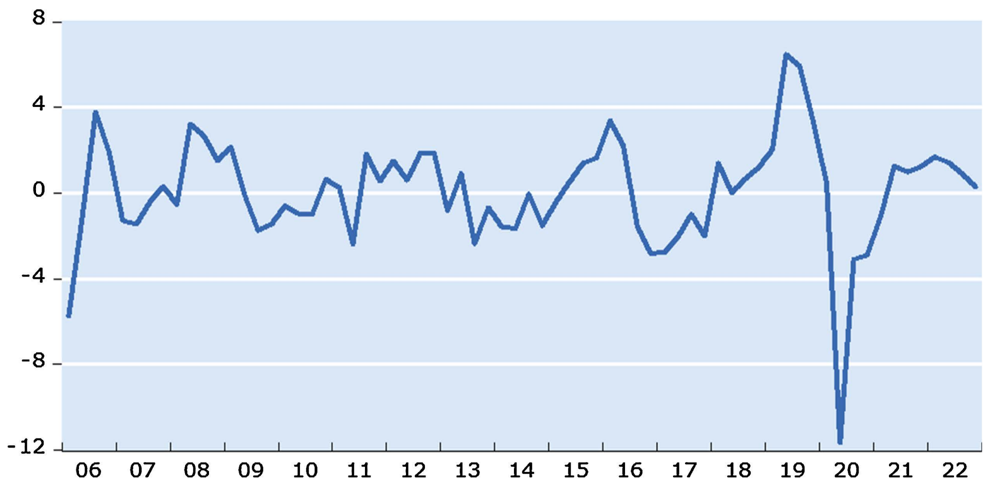

Figure 9. Production function output GAP (Source: Author).

5. Discussion of Results

Before we explore the relationship, between the production gap and core inflation lets first examine how different estimates, from models compare to the benchmark model.

5.1. Correlation Analysis for Output Gaps

Figure 10 illustrates the interconnections, among the output gaps generated by techniques.

Where: CYCLE_LINEAR_TREND represents the output gap from the linear trend regression model.

PD_GAP represents the output gap from the production function approach.

CYCLE_UNIV represents the output gap from the univariate unobserved component model.

CYCLE_BIVAR represents the output gap from the bivariate unobserved component model.

HP_GAP represents the output gap from the Hodrick-Prescott filter approach.

UBN_GAP represents the output gap from the univariate Beveridge-Nelson decomposition method.

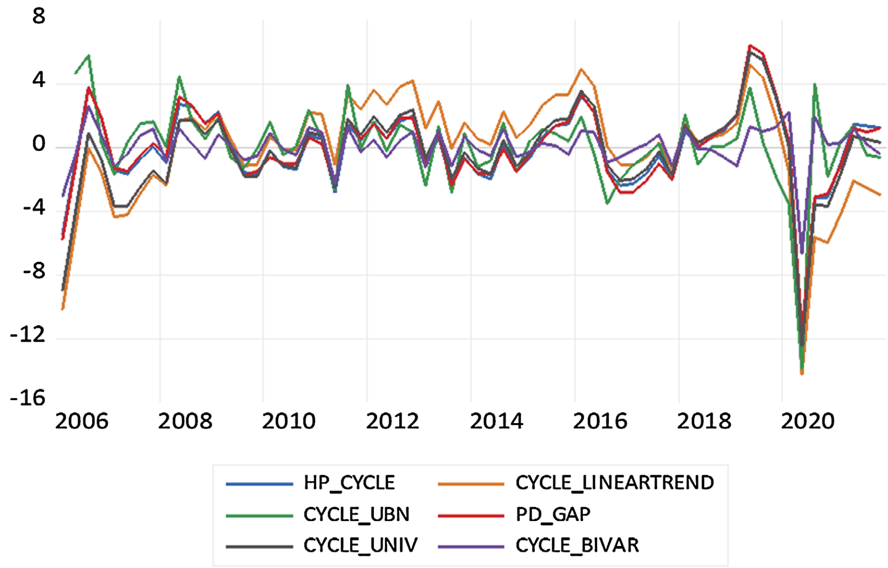

Figure 10. Output gap estimates from different models (Source: Author).

There is often an overestimation of the output gap, between 2010 and 2016 when using the linear trend approach. This is in contrast, to estimation methods that tend to show results throughout the entire sample period. To prevent excessive deviation from potential output, many researchers propose limiting such deviation to a maximum of 10%, with exceptions allowed only for unforeseen circumstances. As a consequence of challenges imposed by COVID-19, it was observed that all approaches predominantly revealed a negative output gap during the second quarter of 2020.

During the investigation, we compared all the procedures with the results obtained from the HP filter. It's worth mentioning that all the study methods used exhibited a correlation as depicted in Figure 11. This strongly indicates that the estimates of the output gap generated through approaches demonstrate a level of consistency. Furthermore, the OECD estimations of potential output and output gaps for member nations showed a similarity when using both the production function technique and Hodrick Prescott filter estimations [49]. This finding is further supported by [3] research on measuring output gaps in Sweden, where they concluded that all techniques produced patterns. Thus, it can be inferred that combining estimates from methodologies can provide outcomes for making well-informed judgments.

5.2. Output Gap and Inflation

After implementing an approach that considers both the output gap and prospective output, this study investigates how the projected output gap can provide insights into inflation trends in Rwanda. Additionally, the paper examines the Granger causation between inflation in Rwanda and the output gap derived from methodologies. From Table 3, the findings reveal a correlation between Rwanda's output gap and inflation from Q1 2006, to Q4 2022 as determined by Granger

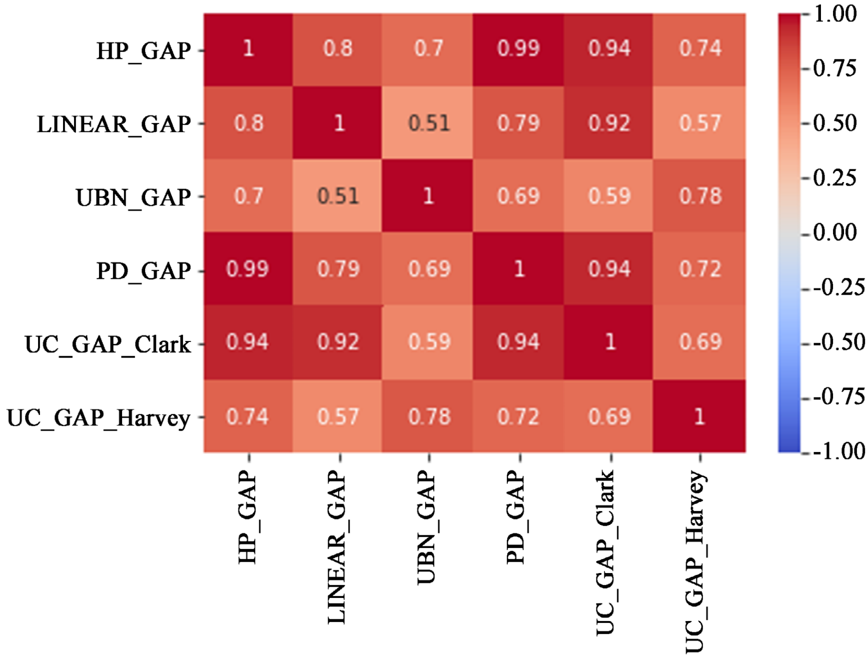

Figure 11. Heat-maps showing correlations for output gaps from different models.

Table 3. Granger causality test results.

Null Hypothesis	F-statistic	Probability
Core inflation does not Granger cause output gap	0.6	0.44
Output gap does not Granger cause core inflation	5.8	0.01

Source: Author's computations.

causality analyses. It is crucial to consider the data on Rwanda's output gap when modelling inflation. This is because there is a connection between the output gap and inflation as demonstrated by the Augmented Phillips curve. In a study conducted by [50] in Australia, it was found that incorporating the output gap improves the accuracy of inflation predictions. Similarly, [51] reached a conclusion when using a state space model to estimate the output gap and its impact on inflation in Canada. To determine the relationship between the output gap and inflation in Rwanda, regression analysis tests were performed.

Table 4. Relationship between output gap and inflation from regression results.

Variables	Coefficient	Standard errors	Test-statistic
Dependent variable: Core Inflation			
Constant	0.128	0.04	3
Output gap	-0.03	0.01	-2.17
Output gap (−1)	0.03	0.01	2.71
Core inflation (−1)	0.57	0.1	5.66

Source: Author's computations.

According to the data presented in Table 4, we conducted a regression analysis to examine the relationship between the output gap and core inflation. The results indicate a connection between these two variables. It is worth noting that all the test statistics in the table are considerably high surpassing 1.96 at a 95 percent significance level. This suggests that the output gap plays a role, in influencing core inflation in Rwanda.

6. Conclusions and Policy Implications

The Phillips curve illustrates the link between an economy's output gaps and inflation. When an economy exceeds its capacity (positive output gap), inflation pressures increase. Conversely, when the economy underperforms (negative output gap), inflation tends to rise.

A study assessed Rwanda's production capacity and output gaps from Q1 2006 to Q4 2021 using various analytical methods. Results showed varying output gaps, with significant impacts on core inflation from methods like the HP filter and the production method.

To manage inflation and economic performance, policymakers adjust fiscal and monetary policies based on the output gap. If the economy is overheating, they may raise taxes, cut spending, or increase interest rates to reduce demand. Conversely, if there's an output gap, they might lower interest rates, boost spending, or cut taxes to stimulate demand. These policies aim to balance economic activity and price stability, with effectiveness influenced by various factors and time lags. Central banks and policymakers monitor these dynamics closely to guide fiscal adjustments and support sustainable growth.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Osman, M., Louis, R. and Balli, F. (2008) Which Output Gap Measure Matters for the Arab Gulf Cooperation Council Countries (AGCC): The Overall GDP Out-Put Gap or the Non-Oil Sector Output Gap?

[2] Radovan, J. (2020) Estimating Potential Output and the Output Gap in Slovenia Using an Unobserved Components Model. Banka Slovenije.

[3] Cerra, V. and Saxena, S. (2000) Alternative Methods of Estimating Potential Output and Output Gap: An Application to Sweden. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3923379

[4] Ouliaris, S., Pagan, A. and Restrepo, J. (2016) Quantitative Macroeconomic Modeling with Structural Vector Autoregressions—An Reviews Implementation. IHS Global, 13.

[5] Michaelides, P. and Milios, J. (2009) TFP Change, Output Gap and Inflation in the Russian Federation (1994-2006). *Journal of Economics and Business*, **61**, 339-352. https://doi.org/10.1016/j.jeconbus.2008.10.001

[6] Hunt, B. and Conway, P. (1997) Estimating Potential Output: A Semi-Structural

Approach. Reserve Bank of New Zealand Discussion Paper, (G97/9).

[7] Kigabo, T. and Irankunda, J. (2014) Estimating Output Gap Model for Rwandan Economy. *BNR Economic Review*, **6**, 19-40.

[8] Fedderke, J.W. (2018) Exploring Unbalanced Growth: Understanding the Sectoral Structure of the South African Economy. *Economic Modelling*, **72**, 177-189. https://doi.org/10.1016/j.econmod.2018.01.012

[9] Kuttner, K.N. (1994) Estimating Potential Output as a Latent Variable. *Journal of Business & Economic Statistics*, **12**, 361-368. https://doi.org/10.1080/07350015.1994.10524551

[10] Slevin, G. (2001) Potential Output and the Output Gap in Ireland. Economic Analysis, Research and Publications Department, Central Bank of Ireland.

[11] Laxton, D. and Tetlow, R. (1992) A Simple Multivariate Filter for the Measurement of Potential Output, Volume 59. Bank of Canada Technical Report No. 59.

[12] Ball, L. and Mazumder, S. (2020) A Phillips Curve for the Euro Area. *International Finance*, **24**, 2-17. https://doi.org/10.1111/infi.12381

[13] Galí, J., Gertler, M. and David López-Salido, J. (2005) Robustness of the Estimates of the Hybrid New Keynesian Phillips Curve. *Journal of Monetary Economics*, **52**, 1107-1118. https://doi.org/10.1016/j.jmoneco.2005.08.005

[14] Stock, J.H. and Watson, M.W. (1999) Chapter 1. Business Cycle Fluctuations in Us Macroeconomic Time Series. In: *Handbook of Macroeconomics*, Elsevier, 3-64. https://doi.org/10.1016/s1574-0048(99)01004-6

[15] Staehr, K. (2004) Economic Transition in Estonia. Background, Reforms and Results. *Contemporary Change in Estonia*, *Baltic and East European Studies*, **4**, 37-67.

[16] Khan, M., Medeiros, C., Montiel, P., *et al.* (1991) Macroeconomic Models for Adjustment in Developing Countries.

[17] Budova, J., Sulikova, V. and Sinicakova, M. (2023) When Inflation Again Matters: Do Domestic and Global Output Gaps Determine Inflation in the EU? *Amfiteatru Economic*, **25**, 575. https://doi.org/10.24818/ea/2023/63/575

[18] Panovska, I. and Ramamurthy, S. (2022) Decomposing the Output Gap with Inflation Learning. *Journal of Economic Dynamics and Control*, **136**, Article ID: 104327. https://doi.org/10.1016/j.jedc.2022.104327

[19] Valadkhani, A. (2014) Switching Impacts of the Output Gap on Inflation: Evidence from Canada, the UK and the US. *International Review of Economics & Finance*, **33**, 270-285. https://doi.org/10.1016/j.iref.2014.06.001

[20] Dupasquier, C., Guay, A. and St-Amant, P. (1997) A Comparison of Alternative Methodologies for Estimating Potential Output and the Output Gap. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.48281

[21] Gerlach, S. and Smets, F. (1999) Output Gaps and Monetary Policy in the EMU Area. *European Economic Review*, **43**, 801-812. https://doi.org/10.1016/s0014-2921(98)00095-6

[22] Hodrick, R.J. and Prescott, E.C. (1997) Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money*, *Credit and Banking*, **29**, 1-16. https://doi.org/10.2307/2953682

[23] Harvey, A.C. and Jaeger, A. (1993) Detrending, Stylized Facts and the Business Cycle. *Journal of Applied Econometrics*, **8**, 231-247. https://doi.org/10.1002/jae.3950080302

[24] Cogley, T. and Nason, J.M. (1995) Output Dynamics in Real-Business-Cycle Models. *The American Economic Review*, **85**, 492-511.

[25] DeSerres, A., Guay, A. and St-Amant, P. (1995) Estimating and Projecting Potential Output Using Structural var Methodology: The Case of the Mexican Economy. Technical Report, Bank of Canada.

[26] Hodrick, R.J. (2020) An Exploration of Trend-Cycle Decomposition Methodologies in Simulated Data. Technical Report, National Bureau of Economic Research.

[27] Drehmann, M. and Yetman, J. (2018) Why You Should Use the Hodrick-Prescott Filter—At Least to Generate Credit Gaps.

[28] Kaiser, R. and Maravall, A. (1999) Estimation of the Business Cycle: A Modified Hodrick-Prescott Filter. *Spanish Economic Review*, **1**, 175-206. https://doi.org/10.1007/s101080050008

[29] Mise, E., Kim, T. and Newbold, P. (2005) On Suboptimality of the Hodrick-Prescott Filter at Time Series Endpoints. *Journal of Macroeconomics*, **27**, 53-67. https://doi.org/10.1016/j.jmacro.2003.09.003

[30] Njuguna, A.E., Karingi, S.N. and Kimenyi, M.S. (2005) Measuring Potential Output and Output Gap and Macroeconomic Policy: The Case of Kenya.

[31] Claus, I. (2000) Estimating Potential Output for New Zealand: A Structural var Approach. Reserve Bank of New Zealand Working Paper No. DP2000/03.

[32] Nelson, C.R. and Plosser, C.R. (1982) Trends and Random Walks in Macroeconmic Time Series: Some Evidence and Implications. *Journal of Monetary Economics*, **10**, 139-162. https://doi.org/10.1016/0304-3932(82)90012-5

[33] Hamilton, J.D. (2005) What's Real about the Business Cycle?

[34] Beveridge, S. and Nelson, C.R. (1981) A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'business Cycle'. *Journal of Monetary Economics*, **7**, 151-174. https://doi.org/10.1016/0304-3932(81)90040-4

[35] Harvey, A.C. and Koopman, S.J. (1992) Diagnostic Checking of Unobserved-Components Time Series Models. *Journal of Business & Economic Statistics*, **10**, 377-389. https://doi.org/10.1080/07350015.1992.10509913

[36] Watson, M.W. (1986) Univariate Detrending Methods with Stochastic Trends. *Journal of Monetary Economics*, **18**, 49-75. https://doi.org/10.1016/0304-3932(86)90054-1

[37] Clark, P.K. (1987) The Cyclical Component of U.S. Economic Activity. *The Quarterly Journal of Economics*, **102**, 797-814. https://doi.org/10.2307/1884282

[38] Gordon, R.J. (1990) What Is New-Keynesian Economics? *Journal of Economic Literature*, **28**, 1115-1171.

[39] Planas, C. and Rossi, A. (2004) Can Inflation Data Improve the Real-Time Reliability of Output Gap Estimates? *Journal of Applied Econometrics*, **19**, 121-133. https://doi.org/10.1002/jae.726

[40] Durbin, J. and Koopman, S.J. (2012). Time Series Analysis by State Space Methods. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199641178.001.0001

[41] Arnold, R.W. (2009) The Challenges of Estimating Potential Output in Real Time. *Federal Reserve Bank of St. Louis Review*, **91**, 271-290. https://doi.org/10.20955/r.91.271-290

[42] Chalaux, T. and Guillemette, Y. (2019) The OECD Potential Output Estimation Methodology.

[43] Barkema, J., Gudmundsson, T. and Mrkaic, M. (2020) What Do We Talk about When

We Talk about Output Gaps? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3758093

[44] Debelle, G. and Vickery, J. (1998) Is the Phillips Curve a Curve? Some Evidence and Implications for Australia. *Economic Record*, **74**, 384-398. https://doi.org/10.1111/j.1475-4932.1998.tb01933.x

[45] Clark, T.E. and McCracken, M.W. (2006) The Predictive Content of the Output Gap for Inflation: Resolving In-Sample and Out-of-Sample Evidence. *Journal of Money, Credit, and Banking*, **38**, 1127-1148. https://doi.org/10.1353/mcb.2006.0068

[46] Aastveit, K.A. and Trovik, T. (2014) Estimating the Output Gap in Real Time: A Factor Model Approach. *The Quarterly Review of Economics and Finance*, **54**, 180-193. https://doi.org/10.1016/j.qref.2013.09.003

[47] Rummel, O. (2015) Estimating the Output Gap for Kenya: A Practical Guide to Some Statespace and Kalman Filter Trend-Cycle Decompositions. Centre for Central Banking Studies, Bank of England.

[48] Furlanetto, F., Gelain, P. and Taheri Sanjani, M. (2021) Output Gap, Monetary Policy Trade-Offs, and Financial Frictions. *Review of Economic Dynamics*, **41**, 52-70. https://doi.org/10.1016/j.red.2020.07.004

[49] Cotis, J.-P., Elmeskov, J. and Mourougane, A. (2004) Estimates of Potential Output: Benefits and Pitfalls from a Policy Perspective. In: Reichlin, L., Ed., *Euro Area Business Cycle*: *Stylized Facts and Measurement Issues*, Centre for Economic Policy Research, 35-60.

[50] De Brouwer, G., *et al*. (1998) Methods of Estimating the Output Gap|RDP 9809: Estimating Output Gaps. Reserve Bank of Australia Research Discussion Papers.

[51] Kichian, M. (1999) Measuring Potential Output within a State-Space Framework. Technical Report, Bank of Canada.