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Assessing the ability of output gap estimates to forecast inflation in emerging countries

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Abstract

We find that, while different models used to estimate the output gap in five major emerging economies show similar trends over time, they lead to different conclusions about how well the output gap can predict inflation. This suggests that the choice of model can significantly impact the conclusions drawn about the relationship between the output gap and inflation. The multivariate Hodrick–Prescott filter and the structural vector autoregressive model produce the smallest forecast errors in most cases among the four output gap models considered. We further find some indications of a better inflation forecasting ability of the output gap in countries with inflation targeting, suggesting that the improved transparency related to inflation targeting might support the inflation forecasting process.

Keywords: Phillips curve, output gap, inflation forecasts, emerging economies.
JEL classification: C1, C32, C53, C61, E37.

1. Introduction

The output gap is a phenomenon that plays a crucial role in the formulation and implementation of macroeconomic policies. For example, a positive output gap reflects excess demand, leading to increased inflation pressures. In such circumstances, monetary policymakers increase interest rates to cool down the economy. A negative output gap would have the opposite effect. Low demand would translate to downward pressure on inflation, leading to interest rate cuts.

Central banks often use complex general equilibrium models to estimate the output gap and utilize these estimates to forecast inflation. However, academic researchers studying multiple countries mostly use simpler and smaller models. Dua and Gaur (2009) found that for developed Asian economies (Japan, Korea, Hong Kong, and Singapore), the output gap might be a sufficient variable

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to control inflation. In contrast, for developing Asian economies (Philippines, Thailand, China, and India), the aggregate demand alone is insufficient to determine inflation, as the agricultural supply shocks are vital factors that influence domestic inflation. These findings suggest that the extent to which the output gap helps explain inflation may depend on the structure and development level of the economy.

The output gap is not directly observable, and its estimates are surrounded by considerable uncertainty (Bjørnland et al., 2005; Cuerpo et al., 2018; Biru, 2013). This element of uncertainty is even more challenging in cases of estimates in real-time, which are often crucial to policymakers. In this regard, the literature has proposed several methods for optimal choice to estimate the output gap. These methods can be grouped into non-structural univariate methods and structural methods. The commonly used non-structural methods include the Hodrick–Prescott filter (HPF), the band-pass filter (BPF), and the unobserved components model. The main drawback of the pure statistical methods approach is the lack of economic theory foundations. Hence, structural methods, which incorporate economic theory, have grown popular. One such method is the structural vector autoregressive model (SVAR). More recently, there is a growing literature that uses a mixed approach (called multivariate methods) by combining the advantages of both statistical and structural methods (Alichi, 2015).

The majority of studies on output gap estimates have been conducted for developed economies, with the literature remaining inconclusive regarding the best method for these estimates (Chagny and Döpke, 2001; Menashe and Yakhim, 2004; Bjørnland et al., 2005; Darvas and Vadas, 2005; Orphanides and van Norden, 2005; Konuki, 2008; Cuerpo et al., 2018; Lemone et al., 2008; Darvas and Simon, 2015). In contrast, output gap studies for emerging economies often report the superior performance of multivariate models over univariate methodologies (Sarikaya et al., 2005; Kara et al., 2007; Federeke and Mengisteab, 2016; Saulo et al., 2010; Zhang et al., 2013; Kemp, 2014; Felipe, 2015; Grigoli, 2015; Pham, 2020; de Oliveira et al., 2021). However, there is a notable caveat in this body of literature: most studies primarily focus on using output gap estimates to forecast inflation, neglecting to examine the ability of the output gap itself as a tool for forecasting inflation.

This caveat is particularly evident given that, in the context of developed economies, the literature often finds that the output gap contains limited information about inflation (Orphanides and van Norden, 2005; Cuerpo et al., 2018; Lemone et al., 2008). Therefore, this paper aims to address this gap by focusing on the role of the output gap as a tool for forecasting inflation in the BRICS countries — Brazil, Russia, India, China, and South Africa. These nations represent a growingly important economic group, and understanding the predictive power of the output gap in these economies is crucial for effective economic policy and planning.

We examine the ability of the output gap to forecast inflation, focusing on whether different measures of the output gap lead to varying conclusions about its predictive power. Our analysis centers on four specific gap models, which are popular in the literature: HPF, BPF, the multivariate Hodrick–Prescott filter (MVHPF), and SVAR. These alternative measures of the output gap are compared with a simple autoregressive model for inflation as a benchmark. This approach allows us to assess the usefulness of the output gap as a forecasting tool for inflation within these significant emerging economies.

The rest of the paper is organized as follows: Section 2 offers a brief overview of the economic structure of each BRICS member. Section 3 describes the methods employed to estimate the output gap. Section 4 discusses the association between the output gap and inflation forecasting. Section 5 presents the data and the results of the analysis. Section 6 concludes the paper with final remarks and implications.

2. Brief overview of BRICS economic structures

An overview of business cycles in BRICS countries will help us understand our empirical results. The BRICS countries have diverse economic structures. Amongst the group, China has the strongest industrial base, contributing more than 30% of GDP in 2022. The Chinese economy largely relies on the industrial sector, mainly the manufacturing industries. China is one of the global leaders in electronic production. For the longest time, the agricultural sector has been the largest contributing sector to India's GDP, at rates topping 40% in 1960. In the last two decades, however, the rapid growth in the services sector resulted in the agricultural sector trailing behind. In 2022, the services sector contributed to almost 50% of GDP, much higher compared to 38% in 2000. Over the same period, the agricultural sector has declined to 16.7% of GDP.

Compared to other emerging markets, Brazil is also known for its strong agriculture and food production, with its main products including soybeans, beef, and coffee. The sector contributed to about 7% of GDP in 2022. The services and manufacturing industries are also making a significant contribution. In the last decade, the services sector has accounted for about 60% of GDP. Additionally, the country has an estimated 21.8 trillion U.S. dollars of natural resource commodities, including gold, iron, oil, and timber. Russia and South Africa, however, are the natural and commodity powerhouses in the BRICS group.

Russia is known for its oil and gas, which contributed close to 20% of GDP in 2022. The mining sector, including gold and platinum, and commodities like precious metals, ore, and coal are the cornerstones of South Africa's economy. South Africa also has a well-developed financial and services sector. The services sector contributed more than 60% of GDP in 2022. Overall, the BRICS countries are characterized by strong agricultural, natural resources and commodities, steady manufacturing, and rapidly growing service sectors.

In terms of consumption and investment: since 2010/11 we have seen China's economy switching from being an investment-led economy to a consumption-led economy, after becoming the world's second-largest economy. Domestic investment peaked at 47% of GDP in 2010 and 2011 and dropped to 43% in 2022. Domestic consumption stood at 48.9% of GDP in 2010 and has since surpassed 50% of GDP (Appendix A).

For all other BRICS countries, economic growth has always relied heavily on domestic demand, much of that being consumption (Appendix B). In Brazil and South Africa, consumption accounts for more than 80% of GDP, on average. Moreover, these two countries have the lowest domestic investment rates, 18.1 and 16.5% of GDP, on average, respectively. Possible reasons for low investment include labor market structural issues, high public debt, the slow pace of structural reforms, corruption, elevated levels of real interest rates, fees, and investment costs.

The BRICS countries have diverse and dynamic labor markets, thereby reflecting the diverse economic structures of these economies. China's rapid industrialization has led to a massive shift in the workforce from agriculture to manufacturing and services (Beletskaya, 2022). The development of small and medium enterprises has remained the main channel to absorb employment. China has a large total labor force (781,8 million in 2022), relatively cheap labor and a single-digit unemployment rate (4.9% of total labor force). Similarly, India also has a massive and diverse workforce, which is gradually shifting to the services sector from agriculture. For the first time, the country's unemployment rate rose to two digits (10.2%) in 2020, reflecting the impact of COVID-19. Brazil and South Africa have suffered a high unemployment rate in the last decade, 13% and 30%, respectively. South Africa, however, has made great strides in opening job opportunities for female workers, increasing from 50.3% to 54.3% in the last decade (Statistics South Africa, 2023). The country's labor market has been long characterised by structural unemployment. Russia's labor market is influenced by its transition from a centrally planned economy to a market-oriented one. The country has a skilled labor force, particularly in science and technology. However, Russia's labor market is highly exposed to oil and gas market swings.

Each member country has its unique characteristics, but their challenges in the labor market tend to be common. These challenges include skills shortages (all countries, except Russia), high informal unemployment (India) and high unemployment (Brazil and South Africa). In response, BRICS countries have developed and implemented various labor market reforms. For instance, in 2017 Brazil implemented a labor reform that granted greater autonomy to employers and employees in determining work relations. The concern is that the Brazilian labor programs focus on income support with little attention to the re-skilling of youth. China implemented a National Vocational Skill Development Action Plan aimed at increasing its skilled labor to a minimum of forty million people by 2025. Similarly, South Africa has continued its use of Sector Education and Training Authorities (SETAs) to improve coordination and governance of training in key sectors of the economy. The effectiveness of these reforms is critical during times of economic slowdown when the economy requires extra effort to ensure labor market sustainability and increase productivity and competitiveness.

Moreover, the BRICS group is highly globalized. Therefore, its economic cycles and labor markets are susceptible to global economic developments, technological changes, and increased international competition (Radulescua et al., 2014; Beletskaya, 2022). For instance, during the global financial crisis in 2008–2009, the BRICS countries, except for China, experienced a significant slowdown in economic growth (Appendix B). This was followed by uneven recovery due to differences in economic structures and policy response. Similarly, during the COVID-19 pandemic, BRICS countries experienced an economic downturn and uneven recovery. These past experiences indicate that BRICS business cycles are not synchronized. Overall, the trajectory of each country's business cycle has been shaped by its unique set of economic conditions and policies.

3. Methods to estimate output gaps

This paper focuses on four gap models, HPF, BPF, MVHPF, and SVAR.

3.1. Hodrick–Prescott filter (HPF)

HPF is one of the most used methods and one of the most controversial. HPF minimizes the following objective function:

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

where: y_t is the observed time series (real GDP); y_t^* is the long-term unobserved component (HP trend or potential GDP), which is assumed to follow a smooth trajectory; λ is the smoothing parameter, which influences HPF results. When $\lambda \to 0$, the HP trend, y_t^*, will be the original observed series, y_t. A considerable value for λ results in a smooth trend component, while in the extreme case of $\lambda \to \infty$, the trend component will be a linear trend.

One of the major criticisms of HPF is its *ad hoc* choice for the value of the smoothing parameter. Following Hodrick and Prescott (1997), the smoothing parameter is set at 1,600 for quarterly data in this paper. Despite all the shortcomings, HPF remains the most straightforward method and is still primarily used in economics to estimate the potential GDP.

3.2. Band-pass filter (BPF)

The idea behind BPF is that all stationary time series can be converted to frequency domain based on the spectral representation theorem. One can define a business cycle as fluctuations at certain frequencies. In the frequency domain, it is possible to analyze which cycles of different lengths contribute to the dynamics of the time series. Typically, researchers define business cycles between six quarters and thirty-two quarters of frequency. Therefore, business cycles can be estimated by eliminating cycles outside this range.

The version of the BPF developed by Baxter and King (1995) is calculated by moving averages. Thus, missing observations are generated at the beginning and the end of the sample period. We use the Christiano and Fitzgerald (2003) version to avoid the loss of observations. This is an asymmetric filter where the weights on the leads and lags can differ. The asymmetric filter is time-varying, with the weights depending on the data and changing for each observation. Thus, it avoids observation losses at the sample period's beginning and end.

3.3. Multivariate Hodrick–Prescott filter (MVHPF)

MVHPF is developed by Laxton and Tetlow (1992). This method adds equations derived from known economic relationships to HPF. Chagny and Döpke (2001) provide the following example:

$$\pi_t = \pi_t^e + A(L)(y_t - y_t^*) + \varepsilon_{\pi,t}. \tag{2}$$

Equation (2) is an augmented Philips-curve relationship, where the actual inflation rate π depends on inflation expectations (π^e) and the current and lagged output gap. The squared residuals from the Philips-curve expression are added to the objective function of HPF, leading to the following minimization problem:

$$\min \sum_{t=1}^{T}(y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T}[(y_t^* - y_{t-1}^*) - (y_{t-1}^* - y_{t-2}^*)]^2 + \sum_{t=1}^{T}\beta_t \varepsilon_{\pi,t}^2, \tag{3}$$

where, when we assume that $A(L) = \alpha_2 + \alpha_3 L$, so that only the contemporaneous and the one-period lagged values of the output gap is included in equation (2):

$$\sum_{t=1}^{T}\beta_t \varepsilon_{\pi,t}^2 = \sum_{t=1}^{T}\beta_t[\pi_t - (\vartheta_1 + \alpha_1\pi^e + \alpha_2(y_t - y_t^*) + \alpha_3(y_{t-1} - y_{t-1}^*))]^2. \tag{4}$$

An important objective of the multivariate filter is to reduce the uncertainty associated with estimates of the potential output (y_t^*). Thus, the smaller the variance of the residuals, the more valuable the information added by the economic relationship will be. Following Laxton and Tetlow (1992), we set $\beta_t = 1$ and $\lambda = 1{,}600$. The initial values for the parameters ϑ_1, α_1, α_2, and α_3 are estimated by a multivariate regression for inflation.

3.4. Structural vector autoregressive method (SVAR)

A classic example of a SVAR is presented in the seminal paper of Blanchard and Quah (1989). Building from Blanchard and Quah (1989) and following Funke (1997), we applied a bivariate VAR model including real GDP growth rate and inflation rate:

$$y_t = \begin{bmatrix} \Delta\log(q_t) \\ \Delta\log(p_t) \end{bmatrix} \sim I(0), \tag{5}$$

where y_t is a two-variable vector with real GDP growth rate ($\Delta\log(q_t)$) and inflation rate ($\Delta\log(p_t)$).

Both variables are assumed to be stationary. The moving average representation of the underlying SVAR model can be written as follows:

$$\begin{bmatrix} \Delta\log(q_t) \\ \Delta\log(p_t) \end{bmatrix} = \sum_{i=0}^{\infty} L^i A_i \varepsilon_t, \tag{6}$$

where: A_i is a matrix; L is the lag operator; ε_t is white noise residuals capturing supply and demand shocks.

To identify the type of structural shocks driving the system, a long-run neutrality restriction is imposed, whereby the matrix of long-run multipliers $A(1)$ is forced to be upper triangular:

$$\sum_{i=0}^{\infty} A_{11,i} = 0. \tag{7}$$

This is the case when the cumulative amount of (temporary) effects of demand shocks on changes in income is zero, and thus demand shocks do not have long-run effects on the income level. The output gap within this framework is given by the fraction of GDP movements explained by demand shocks. The potential GDP is given by the deterministic component of the model and the impact of supply shocks.

4. The role of the output gap in inflation forecasting

A principal issue is an analysis of the ability of the output gap to forecast inflation. To this end, we will examine a backward-looking Philips curve (see Fisher et al., 2014) both for an in-sample analysis and an out-of-sample forecasting:

$$\pi_t = \alpha + \sum_{i=1}^{a} + \alpha_{1i}\pi_{t-1} + \sum_{j=0}^{b} \alpha_{2j}\, gap_{t-j} + u_t, \tag{8}$$

where $\pi_t = \log(p_t) - \log(p_{t-1})$, and p_t denotes the price level.

We assume that inflation is affected by past inflation values and the current and past values of the output gap. We estimate the coefficients $\{\alpha, \alpha_{1i}$, and $\alpha_{2j}\}$ by ordinary least squares. The lags are represented by a and b, and determined using the Akaike Information Criterion. We test the null hypothesis $\alpha_{2j} = 0$ in the in-sample analysis. If this null hypothesis cannot be rejected, then there is no information content concerning inflation in the gap series.

4.1. Out-of-sample inflation forecasts

The recursive estimation method is used to construct the out-of-sample forecasts. For the out-of-sample forecast, the model parameters are estimated only up to the start date of the forecast. We consider the period 2000Q1 to 2022Q4, in which the countries had more stable prices following the pre-2000 introduction of inflation targeting (Brazil, India, and South Africa) and a tolerance band for China and Russia. Hence, the first date of the estimation sample is 2000Q1. We make forecasts up to 12 quarters ahead and evaluate these forecasts in the 2010Q1–2022Q4 period. According to the recursive estimation method, the first observation of the estimation period is unchanged, but we keep lengthening the estimation sample period. We first estimate the model for 2000Q1–2009Q4 and forecast for 2010Q1–2012Q4. The second estimation period is the 2000Q1–2010Q1 period, and forecasts for 2010Q2–2013Q1 are made, and so on. We re-estimate the coefficients $\{\alpha, \alpha_{1j}, \alpha_{2j}$, and $\rho_{1j}\}$ at each forecast round by ordinary least squares. We compare our forecasts with the realized inflation values to calculate forecast errors.

We have four gap models for inflation forecasting (equation 8), corresponding to the number of alternative output gap estimates used in this paper. Since we forecast multi-periods-ahead using a model that includes the output gap, we also must forecast the output gap. For example, for the out-of-sample inflation forecast we make from 2012Q4 to 2013Q1 using data up to 2012Q4, we need to know the 2013Q1 forecast value of the output gap. The following univariate autoregressive model is used to forecast the output gap:

$$gap_t = \alpha + \sum_{j=1}^{m} \rho_{1j}\, gap_{t-j} + u_t. \tag{9}$$

We first calculate one-period ahead forecasts from equations (8) and (9) and then iterate these forecasts using the two equations over the forecast horizon (h) to obtain multi-period ahead forecasts (this is the so-called iterated forecast method, see, for example, Pincheira and West, 2016).

To compare the forecasting performance of the output gap models with a benchmark model, we use a simple autoregressive forecasting model of inflation, henceforth "*Inflation AR-benchmark model*".

$$\pi_t = \alpha + \sum_{i=1}^{a} \omega_{1i} \pi_{t-i} + u_t. \tag{10}$$

4.2. Forecast evaluation

We employ well-known loss functions to evaluate the forecasts: mean error (ME), mean absolute error (MAE), root mean squared error (RMSE), and mean squared forecast error (MSFE), for which we calculate the forecast error in percentages. That is, since inflation is defined as the difference in the logarithm of the price level, $\pi_t = \Delta\log(p_t)$, we calculate price level forecasts and express the forecast error as a percent of the price level:

$$\varepsilon_{t+h|t} = \frac{p_{t+h} - p_{t+h|t}}{p_{t+h}}, \tag{11}$$

where: $\varepsilon_{t+h|t}$ is the h-period ahead forecast error expressed as the percent of the h-period head price level; $p_{t+h|t}$ is the h-period ahead forecast of the price level using information up to time t; p_{t+h} is the actual price level at time $t+h$.

Our out-of-sample evaluation period, 2010Q1–2022Q4, is sufficiently long and includes critical economic developments for emerging markets, such as the recovery from the global financial crisis, the impact of the 2013 taper tantrum, and the sharp decline in economic growth due to COVID-19 pandemic.

We compare the forecast accuracy of the output gap model to the Inflation AR-benchmark model. This is done by testing the null hypothesis that the difference between the output gap model's MSFEs and that of the AR model is zero. The alternative hypothesis is that the output gap models forecast better than the Inflation AR-benchmark model. The Clark and West (2007) approach is used for the test.

We also test for the unbiasedness of the forecasts. We estimated the following equation for the forecast unbiasedness test, Clements et al. (2007):

$$\log(p_{t+h}) - \log(p_{t+h}) = \beta + \varepsilon_t, \tag{12}$$

where β is a parameter to estimate; ε_t is the regression error. The null hypothesis of unbiasedness corresponds to the test of $\beta = 0$. We regress forecast error on a constant using ordinary least squares.

5. Data and results

5.1. Data

Data covers the period from 2000Q1 to 2022Q4. The data collected for each country includes the following variables: real GDP, inflation, and inflation expectations. The data is sourced from the central banks of the respective countries,

Table 1
Descriptive statistics for GDP and inflation.

Countries	Period	Real GDP growth		Inflation rate	
		Mean	Std. dev.	Mean	Std. dev.
Brazil	Pre-GFC	0.84	0.89	7.82	3.31
	Post-GFC	0.16	0.95	5.91	2.10
China	Pre-GFC	1.22	1.54	1.25	1.48
	Post-GFC	0.49	0.93	2.53	1.28
India	Pre-GFC	1.69	1.00	4.24	0.98
	Post-GFC	1.55	0.58	6.81	2.66
South Africa	Pre-GFC	1.75	0.32	4.43	3.84
	Post-GFC	0.36	0.43	5.29	0.93
Russia	Pre-GFC	1.04	0.42	15.04	4.65
	Post-GFC	0.37	0.69	6.86	3.72

Note: The pre-GFC = 2000Q1–2006Q4; post-GFC = 2011Q1–2019Q4 (excluding the COVID-19 period).
Source: Author's calculations.

the World Bank Database, the OECD, IMF International Financial Statistics, and BIS databases. The quarterly GDP data is seasonally adjusted. The average growth rate declined drastically post the global financial crisis, except for India. The inflation rate has remained relatively stable in four countries, except Russia, where it fell to less than half post-GFC compared to pre-GFC (see Table 1). The variability over the sample period suggests there could have been changes in the size of shocks to trend and cyclical components of these economies, particularly in South Africa.

5.2. Comparison of the estimated output gaps from different methods

For all five countries, output gap estimates from the different methods show remarkably similar dynamics over time, with a sharp decline during the onset of the COVID-19 pandemic in 2020 (see Fig. 1). In addition, we observe a V-shaped recovery post-COVID-19 pandemic, but the growth rates remain below pre-pandemic levels.

The methods were also able to capture the significant recession periods. For Brazil, 2001, 2003, and 2008 show negative output gaps. The energy crisis can explain the 2001 recession, the high interest rates, and the substantial external economic slowdown (Considera et al., 2019). The recession from 2003 to early 2004 can be explained by the low-risk appetite of foreign investors following the election of the new president at the end of 2002. The other year with negative output gaps is 2008 due to a well-known shock of the global financial crisis.

For China, all methods captured large negatives in the output gap in 2003Q1, which can be explained by the economic impact of the Severe Acute Respiratory Syndrome (SARS) outbreak.

In the case of India, the notable negative output gap from 2002 to 2003 can be explained by a large drop in agricultural production following the worst drought to hit the country at the time (Nagaraj, 2013). The economy rebounded strongly until the global financial crisis and growth was well above its potential before the pandemic in 2020.

Fig. 1. Output gap estimates.

Note: BCB — Bank of Brazil; SARB — South African Reserve Bank; RHS — right-hand scale. The attempts to obtain central bank output gap estimates for India, China and Russia were unsuccessful.
Source: Author's calculations.

The models, except the SVAR, suggest that the Russian economy was overheating before the global financial crisis (GFC) in 2008. The SVAR model, however, shows a divergence from the other models during the GFC. Notably, the SVAR model captures the underperformance of the economy already in the 2008Q1, whereas other models start capturing economic slowdown in 2008Q3. The SVAR model is designed to capture structural shocks in the economy such as external shocks and the structural interactions between multiple economic variables. In the absence of a unique structural shift in the Russian economy in 2008, the SVAR model's capture of the 2008 recession early on can be attributed to the model's sensitivity to structural shocks, and the ability to model dynamic interactions among multiple variables. We observe similar results during the COVID-19 in 2020.

The univariate models suggest that post the 2008 GFC, the economy performed well around its potential. In stark contrast, the MVHPF model suggests overwhelming growth, to levels above those seen pre-GFC. This discrepancy could indicate that either the MVHPF is overestimating the output gap or the HPF and BPF are underestimating it.

The underperformance of the South African economy is not surprising as the country's economy has been constrained by multiple factors such as skilled labor shortages, structurally low domestic savings and investment, lack of fiscal discipline, previous unproductive investments, and rising import of consumption goods (Binatli and Sorjahbji, 2012, Matthee, 2016, Purifield et al., 2014). Fedderke and Mengisteab (2016) find similar results.

The output gap estimates reported by the central banks of Brazil and South Africa are similar to our results. The alignment of our estimates with those of central banks implies that our simpler models can approximate the result from the more complex models used by central banks. Policymakers and researchers can use our results with greater confidence, knowing they are consistent with the central banks' assessments.

Therefore, contrary to the widespread view that using various models is crucial for estimating the output gap, our results suggest that the choice of measure might not be of particular importance (see Fig. 1). Generally, the high level of similarity of alternative output gap estimates between the models is a common finding in the existing literature (Chagny and Döpke, 2001; Altar et al., 2010; Saulo et al., 2010; Kemp, 2014, Fedderke and Mengisteab, 2016; Pham, 2020).

Tables 2 to 6 display the correlation of our output gap estimates from the different models to analyze the similarities or lack thereof among them. A strong and positive correlation between alternative estimates suggests that the models capture the deviation of actual output above or below potential output in a similar manner for the countries and time periods analysed in this paper. This indicates strong similarities in the way the models interpret data. Conversely, low or negative correlations suggest a lack of consensus and significant differences in output gap estimates.

The correlation coefficients between HPF and BPF results are relatively high, between 0.67–0.96. However, the MVHPF and SVAR estimates have low correlation with HPF and BPF estimates, probably reflecting the different methodological assumptions. The correlations are positive and strong between our methods

Table 2
Correlation of output gap estimates: Brazil.

Method	BCB Estimates	HPF	BPF	MVHPF	SVAR
BCB Estimates	1.00	0.71	0.56		
HPF		1.00			
BPF		0.82	1.00		
MVHPF	0.14	–0.03	–0.01	1.00	
SVAR	0.21	0.40	0.14	–0.02	1.00

Note: BCB — Bank of Brazil.
Source: Author's calculations.

Table 3
Correlation of output gap estimates: China.

Method	HPF	BPF	MVHPF	SVAR
HPF	1.00			
BPF	0.87	1.00		
MVHPF	0.38	0.20	1.00	
SVAR	0.17	–0.01	–0.05	1.00

Source: Author's calculations.

Table 4
Correlation of output gap estimates: India.

Method	HPF	BPF	MVHPF	SVAR
HPF	1.00			
BPF	0.68	1.00		
MVHPF	1.00	0.68	1.00	
SVAR	0.71	0.30	0.69	1.00

Source: Author's calculations.

Table 5
Correlation of output gap estimates: Russia.

Method	HPF	BPF	MVHPF	SVAR
HPF	1.00			
BPF	0.96	1.00		
MVHPF	0.30	0.36	1.00	
SVAR	–0.28	–0.27	–0.26	1.00

Source: Author's calculations.

Table 6
Correlation of output gap estimates: South Africa.

Method	SARB estimates	HPF	BPF	MVHPF	SVAR
SARB estimates	1.00	0.83	0.63		
HPF		1.00			
BPF		0.67	1.00		
MVHPF	0.78	0.99	0.63	1.00	
SVAR	0.54	0.69	0.22	0.70	1.00

Note: SARB — South African Reserve Bank.
Source: Author's calculations.

(especially the HPF) and the central bank estimates for Brazil and South Africa. This indicates similarities between the methods we used and those employed by the central banks of Brazil and South Africa.

The low correlations imply different characteristics of the business cycle. Chagny and Döpke (2001) find similar results for the eurozone and report that although the estimates exhibit similar dynamics, the statistical comparison (like correlations) suggests stark contrasts.

5.3. Full sample Phillips-curve estimation

The null hypothesis is that the output gap has no information content about inflation (see $\alpha_{2j} = 0$ in equation 8). If the null hypothesis cannot be rejected, then the output gap does not influence current and future inflation and hence does not help inflation forecasts. In Tables 7 to 11, the statistical significance of gap models suggests that the output gap is useful for inflation forecasting. For four of the five BRICS countries except Russia, at least one of the gap models is helpful for inflation forecast. In fact, for South Africa, all the output gap models perform well. In addition, the *R*-squared values show that the output gap measures have moderate explanatory power for the inflation of South Africa. These findings are consistent with some of the existing studies focusing on the South African

Table 7
Estimated Phillips curve for Brazil.

Variable	CPI inflation model (quarter-on-quarter percent change)			
	BPF	HPF	MVHPF	SVAR
dcpi (–1)	0.552***	0.573***	0.517***	0.472***
BPF	0.242*			
HPF		0.095		
MVHPF			–0.022	
SVAR				0.006***
Constant	0.006***	0.007**	0.007***	0.009***
Observations	40	40	40	40
R-squared	0.37	0.32	0.33	0.67

Note: ***, **, * denotes rejection of null hypothesis at 1, 5 and 10 percent level, respectively.
Source: Author's calculations.

Table 8
Estimated Phillips curve for China.

Variable	Inflation model (quarter-on-quarter percent change)			
	BPF	HPF	MVHPF	SVAR
dcpi (–1)	–0.012	0.001	0.054	0.102
BPF	0.236*			
HPF		0.147*		
MVHPF			0.008	
SVAR				0.004*
Constant	0.005**	0.005*	0.006*	0.005*
Observations	40	40	40	40
R-squared	0.09	0.09	0.02	0.08

Note: ***, **, * denotes rejection of null hypothesis at 1, 5 and 10 percent level, respectively.
Source: Author's calculations.

Table 9
Estimated Phillips curve for India.

Variable	Inflation model (quarter-on-quarter percent change)			
	BPF	HPF	MVHPF	SVAR
dcpi (–1)	0.188	0.123	0.127	0.156
BPF	0.294			
HPF		0.213*		
MVHPF			0.197*	
SVAR				0.004
Constant	0.011***	0.011***	0.011***	0.010***
Observations	40	40	40	40
R-squared	0.08	0.11	0.1	0.09

Note: ***, **, * denotes rejection of null hypothesis at 1, 5 and 10 percent level, respectively.
Source: Author's calculations.

Table 10
Estimated Phillips curve for Russia.

Variable	Inflation model (quarter-on-quarter percent change)			
	BPF	HPF	MVHPF	SVAR
dcpi (–1)	0.163	0.163	0.181	0.390**
BPF	0.109			
HPF		0.095		
MVHPF			–0.008	
SVAR				0.002
Constant	0.022***	0.022**	0.021***	0.021***
Observations	28	28	28	24
R-squared	0.08	0.09	0.03	0.03

Note: ***, **, * denotes rejection of null hypothesis at 1, 5 and 10 percent level, respectively.
Source: Author's calculations.

Table 11
Estimated Phillips curve for South Africa.

Variable	Inflation model (quarter-on-quarter percent change)			
	BPF	HPF	MVHPF	SVAR
dcpi (–1)	0.196	0.396***	0.354**	0.408***
BPF	0.514***			
HPF		0.217**		
MVHPF			0.257**	
SVAR				0.002***
Constant	0.011***	0.009***	0.009***	0.009***
Observations	40	40	40	40
R-squared	0.40	0.34	0.36	0.68

Note: ***, **, * denotes rejection of null hypothesis at 1, 5 and 10 percent level, respectively.
Source: Author's calculations.

economy (Akinboade, 2005; Fedderke and Mengisteab, 2016). Similar findings for India are reported by Virmani (2004).

The estimated coefficient on lagged inflation has the expected sign, except for China. For instance, in the case of South Africa, a one percentage point increase in price levels in a given quarter is predicted to increase the price levels in the next quarter by 0.51 when the BPF is used, while the same coefficient is

0.22 for HPF, 0.26 for MVHPF and 0.002 for SVAR (see Table 11). However, we note that the estimated coefficient for lagged inflation is not statistically significant for China, India, and Russia. The coefficients of the output gaps also have the expected sign. A one percentage point increase in the output gap is predicted to induce an increase in inflation in the short run. The estimated sign is negative only in the case of MVHPF for Brazil and Russia, although these estimates are statistically not significant.

Our results for Russia are contrary to the only other study we know, Kloudova (2015), which assessed the output gap for Russia and found the HPF method to perform well for the Russian economy. Although the HPF has the expected positive coefficient sign, it is insignificant. In the case of China, Gerlach and Peng (2006) shows that the standard Phillips curves tend not to fit the country's data well likely due to omitted structural and institutional variables, such as price deregulation, trade liberalization, and changes in the exchange rate regime.

5.4. Inflation forecasts

Tables 12 to 14 present the percentage point averages for mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE) obtained in an iterative procedure described in Section 3. We consider the 2010Q1–2022Q4 out-of-sample period. A negative value of the forecast error means the actual value for inflation is lower than its forecast value. Analogously, the positive value of the forecast error means the actual value is higher than the forecast. The ME indicator is useful to check whether the average of the forecast errors is close to zero, while MAE and RMSE indicators treat positive and negative forecast errors similarly and thus do not depend on the sign of the error.

Table 12
Average mean error of out-of-sample projected inflation over, 2010Q1–2022Q4.

Country	AR benchmark	Gap models			
	dcpi(–1)	BPF	HPF	MVHPF	SVAR
Brazil	–0.97	–1.02	–0.42	–0.54	–0.88
China	0.07	–0.61	0.40	–0.78	–0.04
India	–0.43	–2.26	0.07	–0.30	–0.35
Russia	–5.67	–5.37	–4.84	–3.34	–4.83
South Africa	–1.17	–1.94	–0.13	–1.09	–0.98

Source: Author's calculations.

Table 13
Average mean absolute error of out-of-sample projected inflation over, 2010Q1–2022Q4.

Country	AR benchmark	Gap models			
	dcpi(–1)	BPF	HPF	MVHPF	SVAR
Brazil	2.45	2.71	2.64	2.52	2.59
China	1.23	1.57	1.17	1.54	1.24
India	2.47	3.03	2.58	2.43	2.36
Russia	6.38	6.10	5.83	5.22	5.95
South Africa	1.49	2.35	1.38	2.00	1.43

Source: Author's calculations.

Table 14
Average root mean squared error of out-of-sample projected inflation over, 2010Q1–2022Q4.

Countries	AR benchmark	Gap models			
	dcpi(–1)	BPF	HPF	MVHPF	SVAR
Brazil	2.99	3.17	3.23	3.07	3.14
China	1.69	1.92	1.75	1.82	1.69
India	2.97	3.73	3.06	2.95	2.88
Russia	7.22	6.90	6.66	5.86	6.72
South Africa	1.83	2.65	1.87	2.70	1.78

Source: Author's calculations.

According to MAE and RMSE, the inflation AR-benchmark model produces smaller forecast errors than the gap models in most cases (Tables 13 and 14). However, compared to the inflation AR-benchmark model, the MVHPF and HPF models appear to be good models for forecasting inflation for India and South Africa, respectively. Moreover, amongst the gap models, the MVHPF produces smaller forecast errors in most cases. The ME shows a general consistency in terms of the direction (the sign) of the errors between the different models. There are very few cases where the inflation AR-benchmark model and gap models are producing conflicting signs.

Table 15 shows the ratio of MSFEs from the three gap models and the AR-benchmark model for each country, expressed as percent of the AR-benchmark model. Thus, an MSFE value below one hundred indicates that the output gap model outperforms the AR-benchmark model over the period 2010Q1–2022Q4. Clark and West (2007) test the null hypothesis that the MSFEs of a larger model and a nested benchmark model are equal. We use their test to calculate the p-values of the null hypothesis of equal forecast accuracy against the one-sided alternative that the output gap model is better than the benchmark model. We report these p-values in parenthesis in Table 15.

The Clark and West (2007) test shows diverse results across BRICS economies. For Brazil, the AR-benchmark model performs better than the gap models in the longer forecast horizon (twelve quarters ahead, 12Q) than in the short-term (one-quarter and four-quarters ahead, 1Q and 4Q). The p-values are consistent with MSFEs, as we reject the null hypothesis which states that the gap and AR-benchmark model are equal. Moreover, the MVHPF model is less accurate than the HPF and BPF models for the Brazilian economy. We find a similar case for the Russian economy, and the gap models are not performing well in all forecast horizons. This result is consistent with the findings from the Phillips-curve estimation.

For China, India and South Africa, the gap models are generally more useful than the AR-benchmark model in forecasting inflation in most forecast horizons. However, there are specific variations in the results. For China, the AR benchmark performs better in short forecast horizons (1Q and 4Q), but it is still surpassed by the HPF model, which performs well even compared to other gap models in all forecast horizons. In the case of South Africa, the HPF is the worst-performing model in longer forecast horizons (12Q). For India, the MVHPF is performing well in 1Q and 12Q forecast horizons under our evaluation.

Table 15
Recursive estimation, out-of-sample forecast evaluation, 2010Q1–2022Q4, mean squared forecast errors (CPI inflation AR benchmark = 100).

Model	Forecast horizon in quarters		
	1Q	4Q	12Q
Brazil			
BPF	103.3	106.4	56.7
	(0.8204)	(0.5984)	(0.0801)
HPF	106.8	116.0	86.4
	(0.7290)	(0.6889)	(0.1377)
MVHPF	99.6	100.4	97.5
	(0.2950)	(0.6069)	(0.0721)
SVAR	97.9	102.2	108.3
	(0.1279)	(0.5936)	(0.9322)
China			
BPF	98.4	98.3	197.9
	(0.0833)	(0.0666)	(0.7610)
HPF	106.5	108.7	105.3
	(0.4873)	(0.2412)	(0.7610)
MVHPF	99.2	101.8	162.5
	(0.1283)	(0.2557)	(0.6073)
SVAR	101.8	99.8	99.4
	(0.9980)	(0.3351)	(0.0541)
India			
BF	109.8	164.6	234.7
	(0.8075)	(0.6415)	(0.8418)
HP	104.6	123.4	110.7
	(0.8251)	(0.9033)	(0.6791)
MVHPF	106.8	124.3	95.2
	(0.8723)	(0.7259)	(0.1205)
SVAR	100.8	101.2	101.5
	(0.8756)	(0.9559)	(0.9225)
Russia			
BPF	98.4	94.5	88.4
	(0.2126)	(0.0691)	(0.0051)
HPF	98.4	92.9	83.0
	(0.1919)	(0.0691)	(0.0051)
MVHPF	88.9	69.5	60.9
	(0.1919)	(0.0691)	(0.0051)
SVAR	94.2	86.3	82.4
	(0.0259)	(0.0012)	(0.0002)
South Africa			
BPF	103.3	149.4	213.8
	(0.1622)	(0.4778)	(0.9729)
HPF	106.2	92.0	86.4
	(0.3880)	(0.0017)	(0.0005)
MVHPF	126.3	218.0	226.8
	(0.8106)	(0.8625)	(0.7820)
SVAR	101.4	102.1	92.7
	(0.4698)	(0.5068)	(0.0009)

Note: Table shows the ratio of the mean squared forecast errors (MSFEs) from the four gap models and the AR-benchmark model (Zsolt and Schepp, 2020; Zsolt, 2021). The AR-benchmark model is set at 100. If the MSFEs for output gap model is below 100, we conclude that the output gap model outperforms the AR-benchmark model over the period 2010Q1–2020Q4 (Zsolt and Schepp, 2020; Zsolt, 2021). The Clark and West (2007) test the null hypothesis that the MSFEs of the output gap model and the AR-benchmark model are equal. We use the *p*-values in parenthesis to reject or fail to reject the null hypothesis.
Source: Author's calculations.

5.5. Discussion

We have found that there is no one size fits all model. Based on our overall results we cannot claim that gap models perform better than the Inflation AR-benchmark model. Nor we can claim outright that the benchmark model is a better measure. We may assert that to an extent our results reflect the diverse economic structures of the BRICS economies.

Similarly to existing research, the inflation equation (the Philips curve) suggests that both lagged inflation and the output gap help forecast inflation. The importance of the role of backward-looking information in the inflation dynamics is underscored by studies that have used a hybrid New Keynesian Phillips curve (NKPC) to capture the true data-generating process of inflation (Hubert and Mirza, 2019). The NKPC aims to establish the role of backward- and forward-looking information in the inflation expectation formation process. The general finding from the literature, however, is that the influence of backward-looking information tends to diminish over time (Hubert and Mirza, 2019).

The MSFE evaluation method shows that the statistical significance of the results varies with the forecast horizon for the studied sample periods of the BRICS countries. For Brazil, the Inflation AR-benchmark model is more reliable for a longer forecast horizon. For China, the benchmark model is more reliable in short forecast horizons. For Russia, the benchmark model is the best-performing model for all forecast horizons. For India and South Africa, the gap models are more accurate than the benchmark model in almost all forecast horizons.

Generally, there were notable fluctuations in inflation in BRICS countries over the period 2000–2022. Nonetheless, the gap models have performed much better for countries that have implemented inflation targeting, India and South Africa in particular, which had the second and third lowest inflation variability (after China) among the five countries. This result might suggest that the gap models are more accurate in forecasting inflation under the environment of increased inflation stability and monetary policy transparency.

When we compare the gap models to each other, again it depends on which economy you are looking at. The MSFE gives the impression that the MVHPF and SVAR model are better in most cases. However, this result does not hold for all the different forecast horizons in the respective countries. For example, MVHPF is the best-performing model in short forecast horizons for Brazil and Russia and performs better in the longer term for India.

Increased stability in inflation which is possible due to inflation targeting in Brazil, and India could explain why MVHPF performs better than BPF and HPF for these countries. Recall that the MVHPF model can incorporate inflation expectations, for which the literature has shown that expectations tend to be well anchored under the inflation targeting framework (Suh and Kim, 2021). In addition, the MVHPF model possibly captures the business cycle movements much better than HPF and BPF, as the model incorporates current and lagged output gap changes in estimating inflation. Since the BRICS countries have experienced varying business cycles, the differences in terms of the role of gap models in forecasting inflation should not be surprising (see discussion in Section 2). This discussion reinforces the argument that univariate models may omit helpful information contained in economic relationships.

5.6. Forecast unbiasedness

Table C1 in Appendix C reports *p*-values for the hypothesis test, in which the null hypothesis states that the forecasts are unbiased. We start from a 1-quarter ahead forecast, then a 2-quarter ahead forecast, a 3-quarter ahead forecast, and so on. For each forecast horizon, we test the unbiasedness of the forecasts given by each of the four methods (BPF, HPF, MVHPF and SVAR). For HPF MVHPF and SVAR methods, the null hypothesis of unbiasedness cannot be rejected (considering *p*-values larger than 10%) in most cases, particularly between 1-quarter to 10-quarters ahead. The BPF method rejects the null hypothesis at a 1% level of significance, except for Brazil and China. In other words, we find the BPF forecasts to be biased. In addition, the SVAR becomes biased from the 11- to 20-quarters ahead.

5.7. Robustness

We check the robustness of the results for inflation forecasting to alternative sample periods (such as the post-global financial crisis period after 2010Q1) and the method to calculate out-of-sample forecasts (rolling forecast scheme with various window sizes, ranging from five years to thirty-one years, instead of our default recursive scheme). The results are not considerably different from our initial analysis.

6. Conclusion

This paper uses four simple output gap models to estimate the output gap and forecast inflation for the BRICS countries. Our results show that while visually, the output gap estimates from the alternative methods show similar dynamics over time, in some cases, correlation is low among them. This finding suggests distinct differences between the methods, especially in the cases of Brazil, China, and Russia.

Our main goal was to find whether some alternative output gap estimates lead to different conclusions about the ability of the output gap to forecast inflation in BRICS countries in the 2000–2022 sample period. Our results suggest that this is the case. For instance, in the case of Brazil, the AR-benchmark model performs better than the gap models in a longer forecast horizon. For China, the AR benchmark performs better in short forecast horizons. Moreover, amongst the gap models, the MVHPF produces smaller forecast errors in most cases. Based on this result, we can conclude that using various multivariate models might provide more insight into the BRICS business cycles. We also find some indications of a better inflation forecasting ability of the output gap in countries with inflation targeting, suggesting that the improved transparency related to inflation targeting might support the inflation forecasting process.

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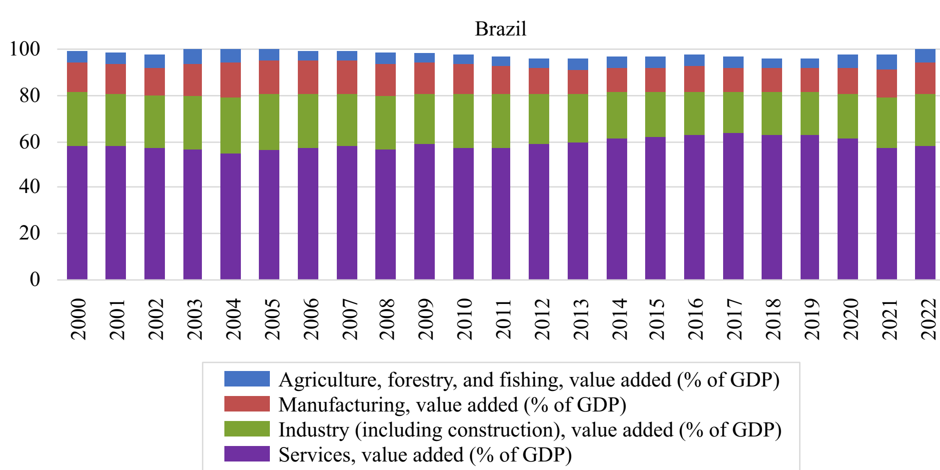
Appendix A. Value added by sector



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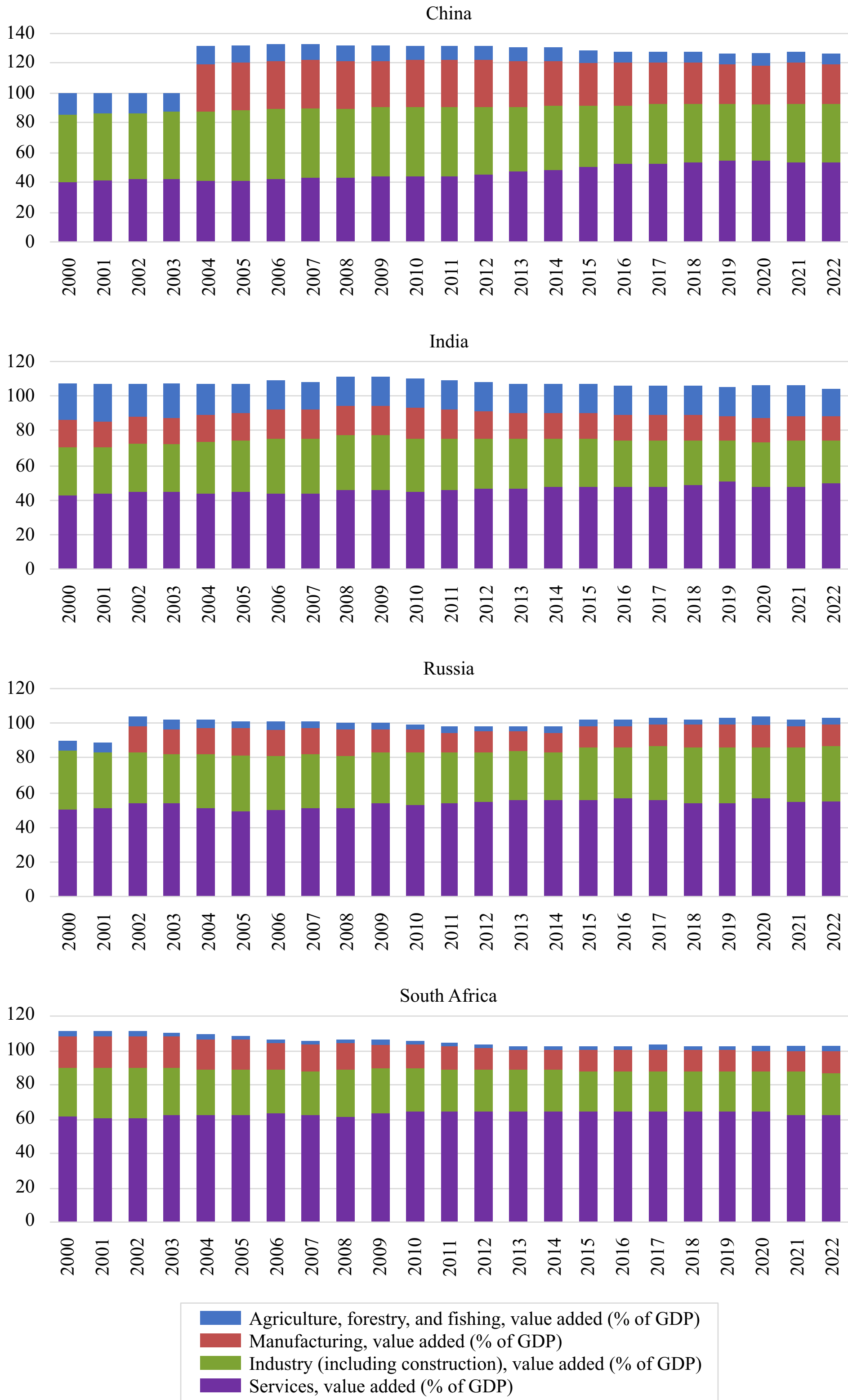
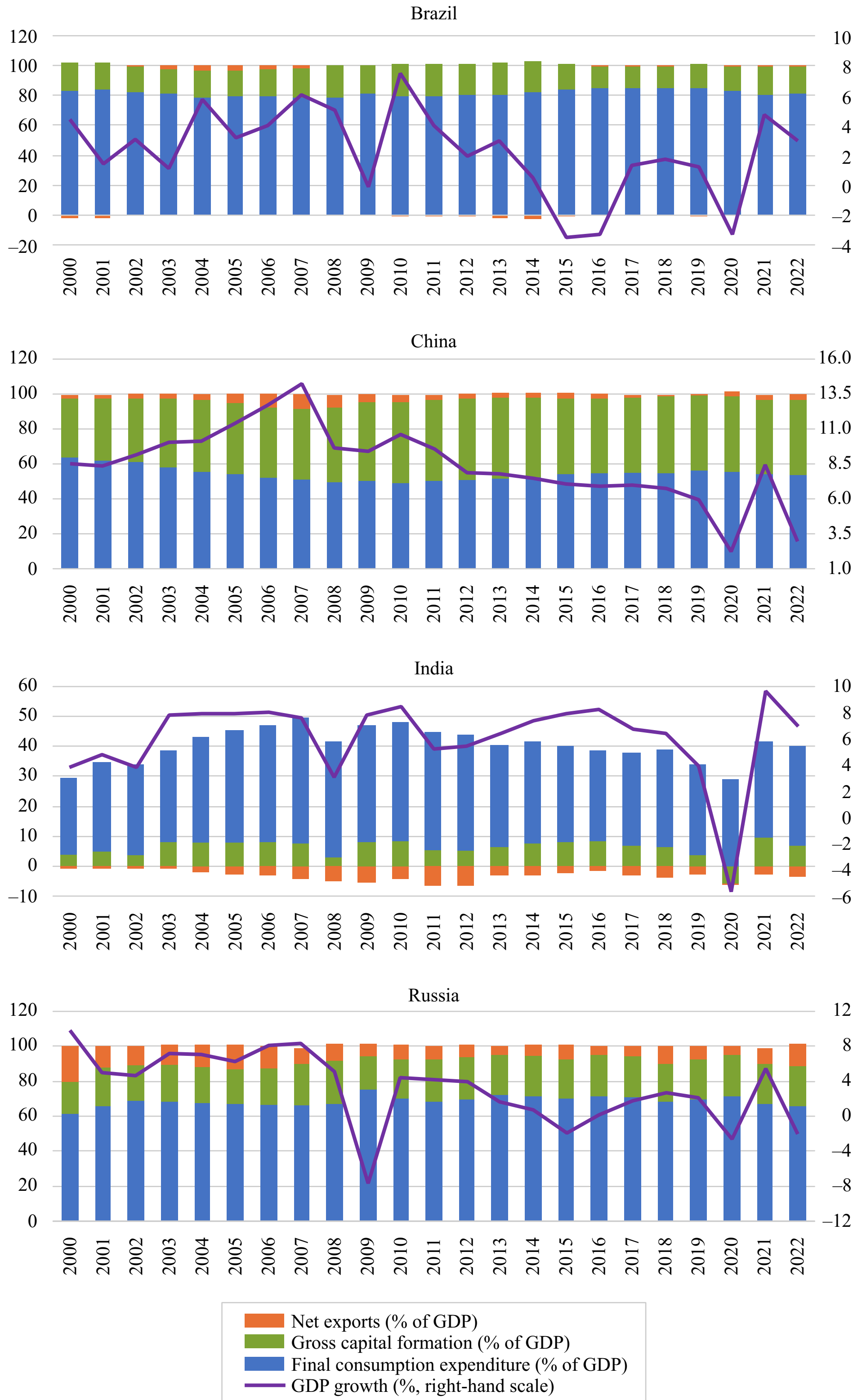
Appendix A *(continued)*



Source: World Bank Database.

Appendix B. GDP and its components



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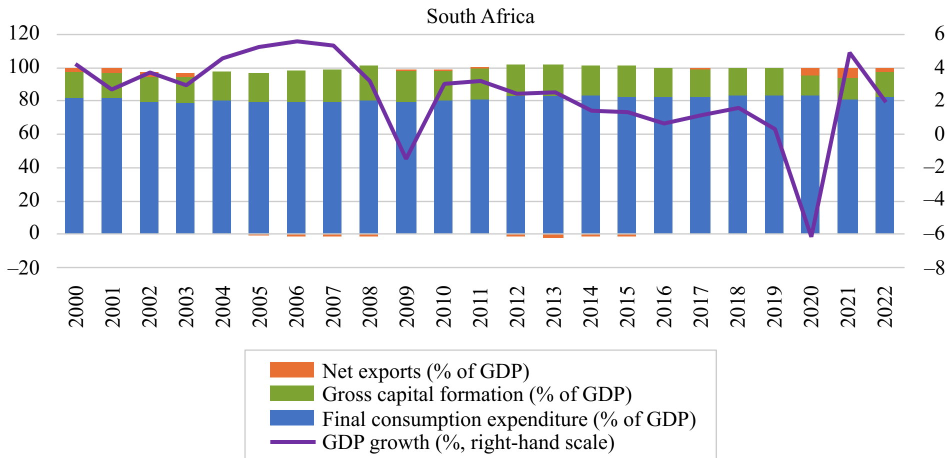
Appendix B *(continued)*



Source: World Bank Database.

Appendix C. Forecast unbiasedness

Table C1
Test for forecast unbiasedness for out-of-sample forecasts, 2010Q1–2022Q4.

Forecast horizon	$p \geq 10\%$	$10\% > p \geq 5\%$	$5\% > p \geq 1\%$	$p < 1\%$
1	3			1
2	3			1
3	3			1
4	3			1
5	3			1
6	3			1
7	3			1
8	3			1
9	3			1
10	3			1
11	2			2
12	2			2
13	2			2
14	2			2
15	2			2
16	2			2
17	2			2
18	2			2
19	2			2
20	2			2

Note: The number corresponding to the forecast horizon and the *p*-values are simply indicating the number of output gap models. The distribution of the number of output gap models varies according to the results. For example, 3 refers to three output gap models and 1 refers to one output gap model.
Source: Author's calculations.