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# Inflation persistence in BRICS countries based on fractional integration

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## Abstract

**Purpose** – As a result, the primary purpose of the study is to assess the influence of these two shocks on the inflation persistence of the BRICS countries.

**Design/methodology/approach** – The most current occurrence of global instability, the COVID-19 outbreak and the ongoing Russia/Ukraine war, provide a unique research opportunity to determine if inflation volatility, generated by the pandemic and the war, is irrevocably linked to its persistence. We apply fractional integration techniques to the price series.

**Findings** – Our results indicate high levels of persistence in all countries, with orders of integration higher than 1 in practically all cases. This result holds independently of using data ending in January 2020 or January 2024. India is the only country with an order of integration significantly below 1 in the two cases, and thus showing evidence of mean reversion and transitory shocks.

**Originality/value** –

**Keywords** Inflation, BRICS, Fractional integration, Persistence, Shocks

**Paper type** Research paper

## 1. Introduction

The international economy has lately been battered by two external shocks having universal costs: the COVID-19 epidemic and the energy crunch caused by Russia's conquest of Ukraine. Both have had an impact not just on the actual economy, but likewise on prices, which have grown dramatically globally. One of the most essential indicators in economy is inflation because rising prices reduce the aggregate demand for goods and services available. This causes a halt in economic development that might influence other crucial sectors, including purchasing power and standards of living (Girdzijauskas *et al.*, 2022). Thus, it is visible that inflation is still one of the main engaging theoretical and empirical subjects in macroeconomics. An important question is if the impacts of price shocks will continue long enough to allow for appropriate policy responses. The primary goal of monetary policy is to maintain inflation as low and steady as feasible. As a result, despite monetary authorities, academics are also interested in measuring the persistence of inflation, which demonstrates their capacity to restore price level equilibrium following a shock. Increased nominal salary

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demands result in higher pricing, which increases persistence (Blanchard and Bernanke, 2023). Unfunded fiscal shocks produce persistent inflationary pressures (Bianchi *et al*., 2023).

There exists a widespread consensus that inflation's volatility and persistence have varied throughout time (Mirco, 2020). A similarly significant question is if the degree of persistence of inflation has altered during the time, potentially as an effect of the implementation of new monetary policy frameworks. One of the most common goals of monetary policy is inflation targeting. For example, Eichengreen *et al*. (2020) show that the Reserve Bank of India is better characterized as pursuing flexible inflation targeting, providing evidence that inflation has become more stable. According to Lansing (2022), the role of persistent shocks in inflation has been increasing in the United States since the middle of 2019. Similarly, Caporale *et al*. (2022) discovered substantial changes in the assessed degree of integration of the series among subsamples and G7 countries, indicating that the degree of persistence has not been constant in the last fifty years. On the contrary, Alex (2021) finds that after implementing inflation targeting, the volatility of trend shocks decreases in all of the BRICS countries.

The goal of this study is to offer more thorough data regarding this concern of evaluating the stochastic inflation volatility of BRICS countries over the last twenty years by providing evidence on the degree of inflation persistence in each of these member states in a sample including both the COVID-19 pandemic and the Russia–Ukraine war. The approach aims to dive further into accounting for nonlinearities, long memory and breaks, besides reviewing empirical data to identify policy ramifications.

Our study employs a fractional integration methodology that is more comprehensive than the traditional one, like ARIMA (Auto-Regressive Integrated Moving Average), because it is based on the distinction between I(0) stationarity and I(1) nonstationarity. It specifically provides for both fractional and integer degrees of differentiation. Furthermore, it generates a direct measure of persistence, the estimated fractional differencing parameter d. Finally, it explains whether the consequences of shocks are temporary or permanent, as well as the nature of the dynamic adjustment mechanism. This study contributes to the empirical literature by being critical for policymakers, like monetary authorities to make proper decisions. It should be noted that our study is univariate and so cannot reveal the exact routes via which shocks might impact inflation. Nevertheless, it remains convenient to policymakers because understanding if the impacts of shocks will persist may help the monetary authorities to decide whether or not to intervene. To the best of our knowledge, this is the first study to explore the link between exogenous components (COVID-19 and Russia–Ukraine war) and inflation persistence in BRICS countries. This invention was inspired by the necessity for monetary authorities to correctly comprehend the nature of external shocks when deciding whether or not to intervene through policies to achieve price stability.

The arrangement of the paper is as follows: Section 2 conducts a quick overview of the relevant literature. Section 3 stretches the data and explains the methodology. Section 4 deliberates the empirical results. Section 5 reflects some concluding observations.

## 2. Literature review

Appropriate knowledge of the structure and fluctuations of inflation persistence is critical for the monetary authority, primarily because it enables efficient monetary policy actions to preserve price levels and economic stability (Bernanke *et al*., 1997). Papadamou *et al*. (2017) argue that an independent central banker is more effective in managing inflation expectations, and consequently, in reducing inflation persistence, even in the presence of ongoing public investment shocks. Payne (2008) finds that inflationary shocks lead to a high degree of volatility persistence in both the Bahamas and Jamaica, whereas Barbados exhibits significantly lower persistence levels. The research on inflation persistence is substantial, with the majority of studies centered on assessing various models. Research has looked at the variabilities of inflation persistence in various states. For example, Chhabra *et al*. (2022) apply a Dynamic Common Correlated Effect (DCCE) model to examine the long-run relationship between trade openness and the output gap on inflation in BRICS countries and indicate that a more open trade policy can assist in minimizing increasing domestic inflation. In a recent study, Zhang (2023) discovered that climate risk has an influence on inflation in China, India, and Russia, with Russia having more structural breakpoints than the other nations when one-way Granger causality tests are estimated. Li and Guo (2022) examine the asymmetric effects of oil prices and component shocks on inflation in BRICS countries. Using a novel multiple threshold nonlinear autoregressive distributed lag model (MTNARDL), they find that large asymmetries between oil prices and inflation just occur in the short term in China, meaning that the inflationary influence is more evident as oil prices decline. Caporale *et al*. (2024) present convincing evidence that both of the exogenous shocks investigated, the COVID-19 pandemic and the Russia–Ukraine war, have generally increased price persistence in the EU27, while recursive estimates indicate that their influence may have peaked and is currently diminishing.

There has been marginal research on the connectedness between the BRICS economies' inflation volatility, the COVID-19 outbreak, and the continuing Russia–Ukraine war. In this context, Xu and Lien (2024) assessed the cross-category inflation spillovers of Chinese consumption markets, as well as the influence of the COVID-19 pandemic on connectedness, demonstrating that pandemic-induced shocks have both prompt and long-term effects on cross-category inflation spillovers. According to Gaglianone *et al*. (2018), there was a steady reduction in inflation inertia in Brazil, owing in large part to the inflation-targeting regime, as well as a recent period of growing inertia from 2014 to mid-2016, owing mostly to the controlled pricing dynamics experienced during the same time.

Insufficient investigations have looked at fractional integration as a potential method of measuring inflation persistence. For example, Moreira *et al*. (2018) applied the fractional integration technique to evaluate inflation deviation inertia in Brazil within an inflation targeting regime, revealing a long-memory tendency in inflation deviation. Also, Silva *et al*. (2022) employed a similar method and discovered that all price categories and aggregate inflation for Brazil follow a stationary pattern with reversion to the long-term mean. Fractional integration is also applied by Dua and Goel (2021), assessing inflation persistence in the Indian economy (from 1996m4 to 2017m02) and concluding that it is significant; specifically, wholesale price inflation has intermediate memory, but consumer prices have a long memory. Oloko *et al.* (2021a, b) explored the impact of oil price shocks on the persistence of inflation in the main oil-exporting and importing countries. After estimating a large number of countries, they determined that any internal shock to the inflation rate would persist indefinitely in Brazil and Russia, with strong inflation persistence; China's inflation rate is mean-reverting, while India's inflation rate is not.

Several researchers have investigated essential variables as potential drivers of inflation persistence. The vast majority of these studies addressed internal variables. Examples are the papers by Younsi and Bechtini (2020), Oloko *et al.* (2021a, b) and Hieu and Hai (2023). Oloko *et al*. (2021a, b) analyzed the impact of gold prices on inflation persistence. Their findings reveal that the gold price shock has a long-term influence on the persistence of inflation rates in developing economies, but only a short-term impact on the persistence of inflation rates in advanced economies. Similarly, Hieu and Hai (2023) investigated the influence of environmental, social, and governance scores, economic growth, FDI, net national income, and inflation in achieving sustainable development goals (SDGs) in BRICS countries. The findings demonstrated that inflation in the BRICS countries contributes to the achievement of SDGs through increased profitability, revenues, and money in circulation. In addition, Younsi and Bechtini (2020) studied the correlation between economic growth, financial development, and income inequality in BRICS countries using yearly time series data from 1990 to 2015. Researchers discovered a substantial correlation between inflation and income disparity.

As observed in the preceding paragraphs, there has already been a significant number of studies on inflation persistence. Nevertheless, none of them give BRICS indicators derived using fractional integration that may be more effective in catching inflationary characteristics, permitting potential nonlinearities and differences in persistence, as well as giving a policy explanation of the empirical results based on monetary authority's reputation and credibility. The novel study contributes to the current literature in each of these areas.

## 3. Data and methodology

### *3.1 Data*

We measure inflation for BRICS (Brazil, Russia, India, China and South Africa) by means of the total consumer price index (CPI). The data sources used in the research paper are the following: for Brazil, Instituto Brasileiro de Geografia e Estadistica; for Russia, Federal State Statistics Service; for India, OECD; for China, National Bureau of Statistics of China; and for South Africa, Statistics South Africa. All the data we exploit are published monthly, nonseasonally adjusted (NSA) and in annual rates. The time series starts in January 2000 and ends in January 2024; therefore, the number of observations amounts to 288.

Table 1 shows the main descriptive statistics for BRICS. Considering the whole dataset, Russia presents the highest inflation rate in BRICS (9.94% on average), while China shows the lowest (2.09%). In fact, China is the only emerging economy that fulfills price stability like advanced countries (2% in the medium term). Additionally, the Chinese economy is also the only country that has experienced deflation. In terms of volatility, Russia exhibits the highest Standard Deviation (5.33) and China the lowest (1.92).

Applying before and after COVID criteria, we observe a decline in inflation rates in BRICS on average, from 6.20% to 5.17%. In particular, Russia has experienced the most significant reduction in inflation (from 10.40% to 7.54%; despite the Ukraine War when CPI rose strongly), followed by India (6.43 vs 5.44%), China (2.24 vs 1.32%) and South Africa (5.62 vs 5.16%). However, Brazilian CPI has remained the same before and after the pandemic (around 6.4%).

Figure 1 offers a dynamic perspective of inflation. Russia shows not only the highest YoY CPI but also the most volatile evolution in different time periods. They present high inflation and instability. China, nonetheless, experiences the opposite behavior: low inflation and more stability. The rest of the countries (Brazil, India and South Africa) exhibit classical ups and downs depending on the economic booms and busts.

**Table 1.** Descriptive analysis of BRICS inflation

| | N | Minimum | Maximum | Mean | Stand. Dev |
|---|---|---|---|---|---|
| *Before COVID* | | | | | |
| Brazil | 241 | 2.46 | 17.24 | 6.35 | 2.70 |
| Russia | 241 | 2.20 | 28.90 | 10.40 | 5.37 |
| India | 241 | 1.08 | 16.22 | 6.43 | 2.96 |
| China | 241 | −1.80 | 8.70 | 2.24 | 1.99 |
| South Africa | 241 | 0.00 | 13.73 | 5.62 | 2.45 |
| *After COVID* | | | | | |
| Brazil | 47 | 1.88 | 12.13 | 6.40 | 3.07 |
| Russia | 47 | 2.30 | 17.80 | 7.54 | 4.44 |
| India | 47 | 3.16 | 7.54 | 5.44 | 0.82 |
| China | 47 | −0.50 | 5.20 | 1.32 | 1.28 |
| South Africa | 47 | 2.00 | 7.85 | 5.16 | 1.63 |
| *Full Dataset* | | | | | |
| Brazil | 288 | 1.88 | 17.24 | 6.36 | 2.76 |
| Russia | 288 | 2.20 | 28.90 | 9.94 | 5.33 |
| India | 288 | 1.08 | 16.22 | 6.27 | 2.75 |
| China | 288 | −1.80 | 8.70 | 2.09 | 1.92 |
| South Africa | 288 | 0.00 | 13.73 | 5.55 | 2.33 |

**Source(s):** Authors' own work

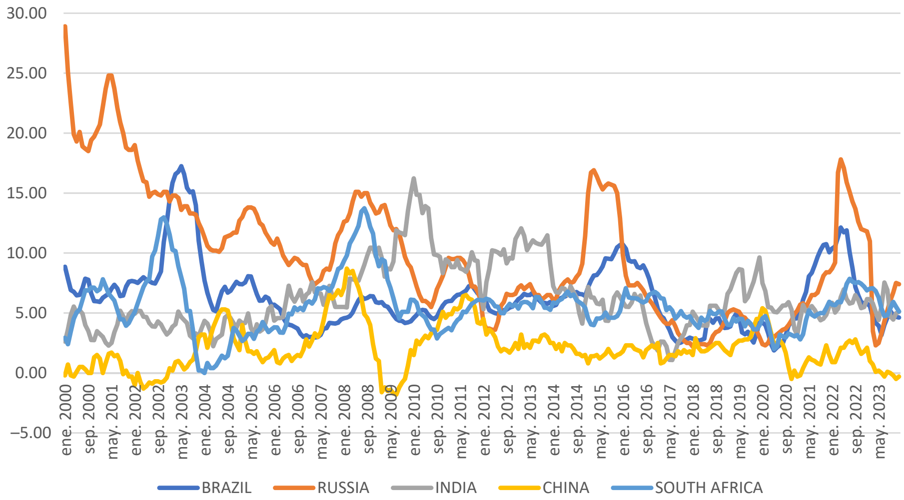


**Figure 1.** BRICS inflation (YoY, Total CPI). Source: Local Government Statistical Entity (LGSE) datastream and national statistical offices

**4. Methodology**

Fractional integration is the methodology used in the article. This signifies that the number of differences required in a series to render it stationary $I(0)$ is a fractional value. In other words, a time series $\{x_t, t = 1, 2, \ldots\}$ is integrated of order $d$ (denoted as $I(d)$) if it can be expressed as:

$$(1 - L)^d x_t = u_t;\ t = 1, 2, \ldots \tag{1}$$

where $L$ refers to the lag-operator, i.e. $Lx_t = x_{t\text{-}1}$), $d$ is a noninteger value and $u_t$ is integrated of order 0 or $I(0)$ that means that it is a covariance stationary process with a spectral density function that is positive and bounded at the zero frequency. In that respect, $x_t$ may be a white noise process but also an AutoRegressive Moving Average (ARMA) in case of serial correlation or time dependence.

Based on the potential fractional nature of $d$, the polynomial in $L$ in the left-hand side of equation (1) can be expressed as:

$$(1 - L)^d = \sum\nolimits_{j=1}^{\infty} \frac{\Gamma(\mathrm{d} - 1)\,(-L)^j}{\Gamma(\mathrm{d} - \mathrm{j} + 1)\,\Gamma(\mathrm{j} + 1)},$$

where $\Gamma$ is the gamma function, which is defined as:

$$\Gamma(\mathrm{z}) = \int_0^{\infty} t^{z-1} e^{-t} d(t).$$

Alternatively, using a Binomial expansion, it can also be expanded as:

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots$$

and thus, equation (1) can be expressed as:

$$x(t) = d\,x(t-1) - \frac{d(d-1)}{2}\,x(t-2) + \ldots + u(t),$$

where u($t$) is $I(0)$. In other words, if $d$ is a noninteger value, $x(t)$ can be represented in terms of all its past history, and the higher the value of $d$ is, the higher the level of association between the observations.

In the empirical application carried out in the following section, we permit $x_t$ to be the errors in a regression model that may contain deterministic terms like an intercept and a linear time trend. That is,

$$y_t = \beta_0 + \beta_1 t + x_t;\ t = 1, 2, \ldots \tag{2}$$

where $y_t$ is the observed data, and $\beta_0$ and $\beta_1$ are unknown parameters to be estimated from the data.

In this context, the parameters to be estimated are $\beta_0$ and $\beta_1$ along with d and $\sigma^2$ which is the variance of the error term and finally, the set of parameters referring to the short run (ARMA) structure. Of particular interest is $d$, which indicates the degree of long-range dependence on the data. Different values of d produce alternative model specifications such as.

(1) anti-persistence (if $d < 0$),

(2) short memory (if $d = 0$),

(3) stationary long memory (if $0 < d < 0.5$),

(4) nonstationary with mean reversion (if $0.5 \leq d < 1$),

(5) unit roots (if $d = 1$),

and.

(6) explosive patterns (if $d > 1$).

From a policy-making perspective, the crucial value to look for is 1, since mean reversion and transitory nature only occur whenever $d$ is strictly smaller than such value. On the contrary, if $d$ is equal to or higher than 1, there is lack of mean reversion and thus permanency of shocks, making it imperative for policy makers to take action.

## 5. Empirical results

The estimated model is the one that combines Equations (1) and (2), i.e.

$$y_t = \beta_0 + \beta_1 t + x_t;\ (1-L)^d x_t = u_t;\ t = 1, 2, \ldots \tag{3}$$

where $y_t$ represents the time series of interest, $\beta 0$ and $\beta 1$ are unknown and represent the intercept and the coefficient of a linear time trend, $x_t$ is assumed to be $I(d)$, with d being any real number, allowing for fractional degrees of integration. In this situation, $u_t$ is considered first to be a white noise process, and then, autocorrelated; in the latter instance, we employ Bloomfield's (1973) nonparametric spectral model that approximates AR structures in a fairly compact way.

The estimation of the parameters in Equation (3) are obtained by maximizing the log-likelihood function in the frequency domain, using a testing approach developed in Robinson (1994) and widely used in empirical applications in many different fields (e.g. economics and finance, Abbritti *et al*., 2016; environmental sciences, Infante *et al*., 2024; etc.).

Tables 2–5 show the estimates of $d$ under three alternative specifications: 1) with no deterministic terms (i.e. $\beta 0 = \beta 1 = 0$ *a priori* in (3)); 2) only with a constant (i.e. $\beta 0$ unknown

**Table 2.** Estimates of *d* using data ending in January 2020

| Country | No terms | An intercept | A linear time trend |
|---|---|---|---|
| i) With no autocorrelation | | | |
| Brazil | 1.19 (1.09, 1.31) | *1.60 (1.47, 1.78)* | 1.61 (1.47, 1.78) |
| China | *1.07 (0.99, 1.17)* | 1.08 (0.99, 1.18) | 1.08 (0.99, 1.17) |
| India | 1.02 (0.91, 1.16) | *1.02 (0.90, 1.17)* | 1.02 (0.90, 1.17) |
| Russia | 0.92 (0.84, 1.03) | 1.68 (1.53, 1.87) | *1.70 (1.53, 1.88)* |
| South Africa | 1.32 (1.23, 1.43) | *1.35 (1.25, 1.46)* | 1.35 (1.25, 1.46) |
| ii) With autocorrelation | | | |
| Brazil | 1.14 (0.93, 1.39) | *1.11 (0.91, 1.34)* | 1.11 (0.89, 1.35) |
| China | *1.24 (1.02, 1.45)* | 1.22 (1.03, 1.44) | 1.22 (1.03, 1.44) |
| India | 0.79 (0.67, 0.96) | *0.73 (0.61, 0.88)* | 0.73 (0.62, 0.89) |
| Russia | 0.86 (0.74, 1.03) | 1.18 (0.97, 1.45) | *1.18 (0.97, 1.45)* |
| South Africa | 1.31 (1.11, 1.62) | *1.25 (1.05, 1.53)* | 1.24 (1.05, 1.51) |

**Source(s):** Authors' own work

**Table 3.** Estimated coefficients based on the selected model. Data ending in January 2020

| Country | d (95% band) | Intercept (t-value) | Time trend (t-value) |
|---|---|---|---|
| i) With no autocorrelation | | | |
| Brazil | 1.60 (1.47, 1.78) | 9.281 (25.55) | – |
| China | 1.24 (1.02, 1.45) | – | – |
| India | 1.02 (0.90, 1.17) | 2.589 (3.12) | – |
| Russia | 1.18 (0.97, 1.45) | 31.785 (57.15) | −2.312 (−3.84) |
| South Africa | 1.35 (1.25, 1.46) | 2.924 (5.97) | – |
| ii) With autocorrelation | | | |
| Brazil | 1.11 (0.91, 1.34) | 8.988 (22.09) | – |
| China | 1.24 (1.02, 1.45) | – | – |
| India | 0.73 (0.61, 0.88)$^{MR}$ | 3.314 (4.53) | – |
| Russia | 1.18 (0.97, 1.45) | 29.826 (53.51) | −0.173 (−1.92) |
| South Africa | 1.25 (1.05, 1.53) | 2.892 (5.73) | – |

**Source(s):** Authors' own work

**Table 4.** Estimates of *d* using the whole sample size (ending in January 2024)

| Country | No terms | An intercept | A linear time trend |
|---|---|---|---|
| i) With no autocorrelation | | | |
| Brazil | 1.22 (1.13, 1.33) | *1.58 (1.46, 1.73)* | 1.59 (1.46, 1.73) |
| China | *1.08 (1.00, 1.18)* | 1.08 (1.00, 1.18) | 1.08 (1.00, 1.18) |
| India | 1.02 (0.91, 1.17) | *1.01 (0.90, 1.17)* | 1.01 (0.90, 1.17) |
| Russia | 0.97 (0.89, 1.08) | *1.40 (1.28, 1.56)* | 1.40 (1.28, 1.55) |
| South Africa | 1.30 (1.22, 1.41) | *1.34 (1.25, 1.45)* | 1.34 (1.25, 1.45) |
| ii) With autocorrelation | | | |
| Brazil | 1.09 (0.92, 1.28) | *1.21 (0.99, 1.43)* | 1.21 (0.99, 1.43) |
| China | *1.14 (0.94, 1.34)* | 1.14 (0.94, 1.33) | 1.14 (0.94, 1.33) |
| India | 0.70 (0.60, 0.84) | *0.68 (0.58, 0.80)* | 0.68 (0.58, 0.80) |
| Russia | 0.89 (0.76, 1.07) | *1.02 (0.85, 1.23)* | 1.02 (0.85, 1.23) |
| South Africa | 1.17 (1.01, 1.41) | *1.14 (0.95, 1.36)* | 1.14 (0.95, 1.35) |

**Source(s):** Authors' own work

**Table 5.** Estimated coefficients based on the selected models using the whole sample size

| Country | d (95% band) | Intercept (t-value) | Time trend (t-value) |
|---|---|---|---|
| i) With no autocorrelation | | | |
| Brazil | 1.58 (1.46, 1.73) | 9.276 (24.01) | – |
| China | 1.08 (1.00, 1.18) | – | – |
| India | 1.01 (0.90, 1.17) | 2.604 (3.19) | – |
| Russia | 1.40 (1.28, 1.56) | 30.268 (37.96) | – |
| South Africa | 1.34 (1.25, 1.45) | 2.921 (6.05) | – |
| ii) With autocorrelation | | | |
| Brazil | 1.21 (0.99, 1.43) | 9.082 (21.24) | – |
| China | 1.14 (0.94, 1.34) | – | – |
| India | 0.68 (0.58, 0.80)$^{MR}$ | 3.505 (5.19) | – |
| Russia | 1.02 (0.85, 1.23) | 29.020 (34.21) | – |
| South Africa | 1.14 (0.95, 1.36) | 2.882 (5.72) | – |

**Source(s):** Authors' own work

and $\beta 1 = 0$), and with a constant plus a linear time trend (both $\beta 0$ and $\beta 1$ are estimated from the data), with the significant coefficients (on the basis of the t-statistics) given in bold.

Starting with the data ending in January 2020, that is, the period before COVID-19, we see in Tables 2 and 3 the estimations of d and their 95% confidence intervals for the two scenarios: when assuming that $u_t$ in (1) is a white noise process (upper half) and autocorrelated errors (bottom half) using Bloomfield's (1973) nonparametric technique rather than the traditional AutoRegressive Moving Average (ARMA) structure. In both scenarios, the selected model is based on the statistical significance of the regressors and comprises three alternative conditions: with no deterministic terms (for China), only with an intercept (for Brazil, India and South Africa) and an intercept plus a linear time trend (for Russia). Under the premise of white noise errors, the constant and the time trend for Russia is found to be significant; only the constant for Brazil, India and South Africa, whereas in the case of China, only without deterministic terms is significant. The estimations of d are relatively large and higher than 1, which implies the presence of long memory ($d > 0$). Further, the large confidence intervals indicate that the unit root null hypothesis (no mean reversion) cannot be rejected for any of the five countries. When autocorrelated residuals are taken into account, the estimations of $d$ are somewhat lower than in the prior scenario. With the exception of India, all other countries show evidence of unit roots (or absence of mean reversion).

Next, we examine the fractional integration among each series for the whole sample size that includes the data ending in January 2024 (see Tables 4 and 5). The first thing we notice in this table is that the findings are remarkably similar in the three scenarios: no deterministic terms, an intercept, and an intercept and a linear time trend. Besides, the constant and the time trend is now found to be insignificant in any of the cases. Under the premise of uncorrelated errors (see Table 4), the deterministic term is found to be significant in the case of China, while in any other case, just the constant is important. Similarly to the results for the period before COVID-19, the estimations of d are also higher than 1, in all cases where the hypothesis cannot be rejected. This implies the presence of long memory ($d > 0$) and that the unit root null hypothesis I(1) (no mean reversion) cannot be rejected for all countries. With autocorrelation, the I(1) cannot be rejected in any single case except for India, where $d = 0.68$, where reversion to the mean takes place. As a result, the influence of COVID-19 shock in India will be temporary, eventually disappearing in the long term. In contrast, regarding the remaining cases, shocks are likely to be permanent.

**Table 6.** Comparison of persistence

| Country | Ending at January 2020 | Ending at January 2024 |
|---|---|---|
| i) With no autocorrelation | | |
| Brazil | 1.60 (1.47, 1.78) | 1.58 (1.46, 1.73) |
| China | 1.24 (1.02, 1.45) | 1.08 (1.00, 1.18) |
| India | 1.02 (0.90, 1.17) | 1.01 (0.90, 1.17) |
| Russia | 1.18 (0.97, 1.45) | 1.40 (1.28, 1.56) |
| South Africa | 1.35 (1.25, 1.46) | 1.34 (1.25, 1.45) |
| ii) With autocorrelation | | |
| Brazil | 1.11 (0.91, 1.34) | 1.21 (0.99, 1.43) |
| China | 1.24 (1.02, 1.45) | 1.14 (0.94, 1.34) |
| India | 0.73 (0.61, 0.88)$^{MR}$ | 0.68 (0.58, 0.80)$^{MR}$ |
| Russia | 1.18 (0.97, 1.45) | 1.02 (0.85, 1.23) |
| South Africa | 1.25 (1.05, 1.53) | 1.14 (0.95, 1.36) |

**Source(s):** Authors' own work

The re-estimation of the model by extending the sample to January 2024, thus including the COVID-19 period, shows the constant and the time trend coefficient to be insignificant in all cases. The estimates of the degree of persistence are lower in all cases compared to those for the sample ending in January 2020, with the exception of Russia with no autocorrelation and Brazil with autocorrelated errors (see Table 6 for a direct comparison), with India ($d = 0.68$) being the only country displaying mean-reverting behavior.

External shocks such as the COVID-19 pandemic and the Russia–Ukraine war have intensified inflation persistence by transmitting global price pressures into domestic economies. The impact varies across BRICS nations—Brazil and Russia exhibit higher persistence than India, China, and South Africa—due to structural and policy differences.

## 6. Conclusions

The analysis reveals strong and persistent inflation dynamics across BRICS countries. The fractional differencing parameter d typically exceeds 1, indicating a long-memory process where inflation shocks have long-lasting effects. This persistence reflects a transferred inflation rate that does not fade quickly, complicating monetary control and reinforcing the need for sustained policy action. The study also affirms the effectiveness of fractional integration techniques like ARFIMA in capturing these complex dynamics more accurately than traditional models.

These findings indicate that the BRICS economies face significant challenges in controlling inflation, especially in the context of external shocks. From an economic policy perspective, the results emphasize the necessity of implementing customized monetary strategies in the BRICS countries. When formulating measures to stabilize prices, policymakers need to consider the significant and fluctuating levels of inflation persistence. The enduring impact of shocks on inflation indicates that changes in the inflation rate have long-lasting consequences, requiring continuous policy measures to control inflation expectations and uphold price stability.

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