Assessing the Effectiveness of Inflation Targeting in BRICS Nations

A Dissertation

by

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for the partial fulfilment of the MSc in Economics of Dr. B. R. Ambedkar School of Economics University, Bengaluru

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DR B R AMBEDKAR SCHOOL OF

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DECLARATION

I S.Rajiv, the undersigned, certify that the dissertation entitled "Assessing the Effectiveness of Inflation Targeting in BRICS Nations" is carried out under the guidance of Irfan Ali K C, Assistant Professor, Dr. B. R. Ambedkar School of Economics University, Bengaluru.

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Abstract

This study evaluates the effectiveness of inflation targeting (IT) as a monetary policy framework in achieving and maintaining price stability across BRICS nations, excluding China. Using econometric models such as the Structural Change Model, Markov Regime-Switching Model, and Panel Data (Fixed Effect) Model, the analysis spans pre- and post-IT periods for the BRICS Nations which are Brazil, Russia, India, and South Africa excluding China. Key findings reveal diverse outcomes influenced by domestic challenges and external shocks. While IT has reduced inflation volatility and improved credibility in some cases, its success is contingent on robust institutional frameworks and complementary fiscal policies. The study contributes to understanding IT's role in shaping macroeconomic stability in emerging markets.

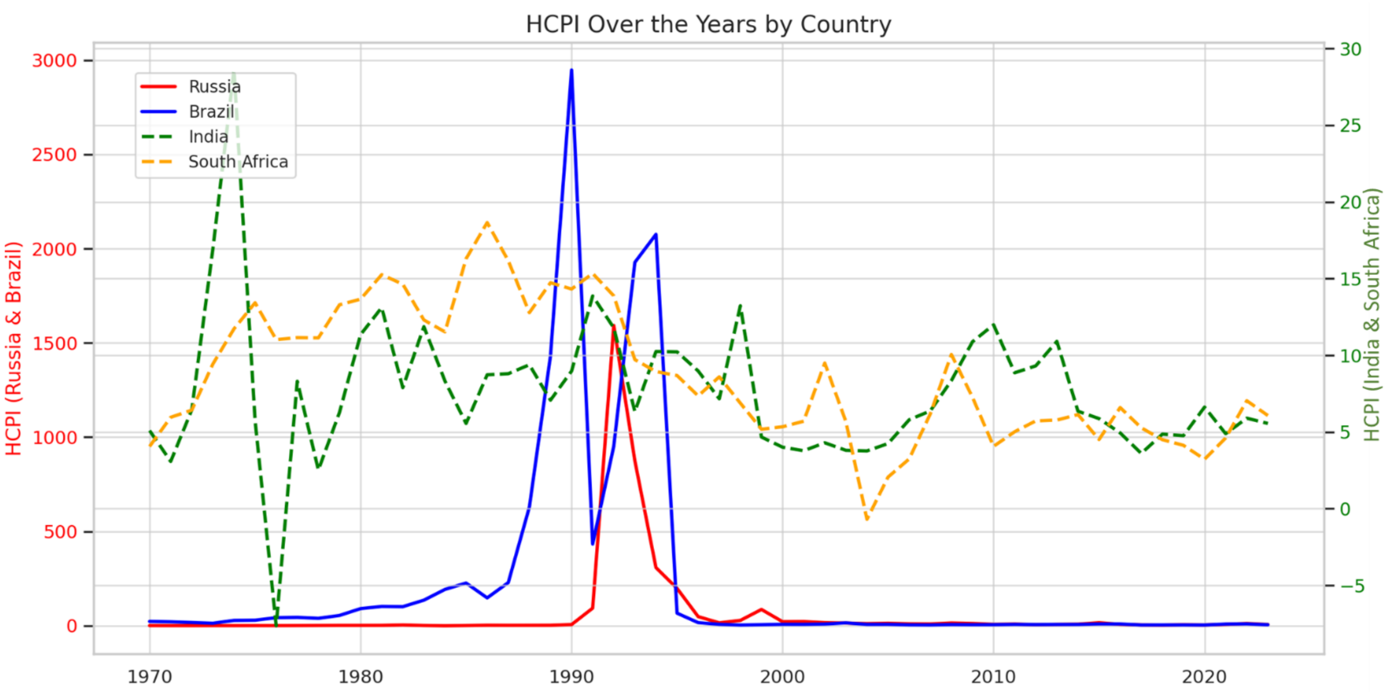
Keywords: Inflation Targeting; BRICS; Pre-IT and Post-IT; Volatility

Chapter 1

Introduction

The global economic instability and fluctuating price levels have resulted in many countries turning to Inflation Targeting as a monetary policy framework to achieve and maintain price stability. The BRICS nations of Brazil, Russia, India, China, and South Africa represent a diverse group of emerging economies that have adopted varying degrees of IT in their monetary policies. The adoption of IT in these countries (excluding China) has been motivated by the desire to anchor inflation expectations, enhance the credibility of central banks, and ultimately foster economic growth. Since the late 1990s and early 2000s, these nations have witnessed significant shifts in their inflation rates, prompting a closer examination of the effectiveness of IT in achieving price stability.

Figure 1: Inflation Trends by Country



The theoretical underpinnings of IT suggest that by publicly announcing an inflation target, central banks can influence inflation expectations, thereby reducing inflation volatility. This framework aims to mitigate the time inconsistency problem in monetary policy, where short-term objectives may conflict with long-term goals. As a result, IT has gained traction among central banks worldwide, with over 40 countries currently employing this strategy (Mishkin, 2004). The BRICS nations, each with their unique economic contexts and challenges, provide a compelling case study for evaluating the effectiveness of IT in maintaining price stability as the experiences of BRICS countries with IT have been mixed, with some nations achieving notable success while others have struggled to maintain their inflation targets amidst external shocks and domestic challenges.

In India, the Reserve Bank of India (RBI) officially adopted IT in 2016, setting a target of 4% inflation with a tolerance band of ±2% (Eichengreen & Gupta, 2021). The Central Bank of Russia adopted inflation targeting in 2014 and the current target is 4% (Kuklinova & Ilyashenko, 2022). The Central Bank of Brazil adopted inflation targeting in 1999 and the current target is 3.25% the South African Reserve Bank adopted inflation targeting in 2000 with the current target range being 3-6% (Arestis et al., 2011 & Aron et al., 2006)**.** Since then, inflation rates have shown a downward trend, but the decline can be attributed to a combination of factors, including fiscal policies and global commodity price fluctuations. Russia and South Africa have faced challenges in adhering to their inflation targets, raising questions about the robustness of IT in these economies.

This dissertation aims to investigate the effectiveness of inflation targeting in achieving and maintaining price stability across the BRICS countries. By analysing the impact of IT on the inflation rate, GDP output gap, fiscal deficit, and exchange rates, this study seeks to contribute to the existing literature on inflation targeting in emerging markets using the Structural change model, Markov regime switch model, and Panel data model.

This dissertation proceeds as follows. Section II delves into the existing literature on inflation targeting, examining its implementation and observed outcomes across diverse economies. Section III outlines the research methodology and specifies the data sources employed in this study. Section IV presents the empirical analysis and discusses the key findings derived from the research. Section V concludes by exploring the policy implications and offering recommendations for enhancing the effectiveness of inflation targeting within the BRICS nations.

Chapter 2

Literature Review

Inflation targeting has emerged as one of the most widely adopted monetary policy frameworks across both developed and emerging economies since the 1990s. In essence, IT is a strategy where central banks announce an explicit inflation target and commit to achieving that target over a specified period, usually by manipulating short-term interest rates. Mishkin (2004) examines the challenges and effectiveness of Inflation Targeting in Emerging Market Economies (EMEs), focusing on case studies of Chile and Brazil. The study identifies five key challenges: weak fiscal institutions, fragile financial systems, low central bank credibility, currency substitution, and vulnerability to capital flow volatility. The study has employed a comparative approach, analysing economic indicators such as inflation rates, GDP growth, and institutional reforms. Findings suggest that IT can effectively control inflation in EMEs when supported by strong institutions, such as fiscal discipline and central bank independence. Chile's experience demonstrates the success of a gradual and flexible approach to IT. The study concludes that while IT has potential in EMEs, its success depends on comprehensive reforms to address institutional weaknesses. Brazil's experience highlights the importance of institutional reforms and central bank transparency for the successful implementation of IT.

On a similar note, Lin and Ye (2009) investigate the impact of inflation targeting on inflation levels and variability in 52 developing countries. Using Propensity Score Matching (PSM) to address selection bias, the study compares IT adopters with non-adopters. Their findings reveal that IT significantly reduces inflation and its variability in developing countries, particularly in those with better fiscal discipline and lower initial inflation levels. However, the impact is less pronounced in countries with higher debt or fixed exchange rate regimes. Sticking to Propensity Score Matching, Kazemi Zaroomi et al. (2020) examine the impact of inflation targeting on direct tax revenues in both oil-importing and oil-exporting countries from 1990 to 2016 to address selection bias, the study compares IT adopters with non-adopters. The study indicates that IT positively affects direct tax revenues in oil-importing countries, particularly by enhancing income, corporate, and property taxes. In contrast, the effect is less significant in oil-exporting countries due to reliance on oil revenues. On the contrary, Ardakani et al. (2018) assess the impact of inflation targeting on macroeconomic outcomes using a novel semiparametric single index model. This approach addresses biases inherent in traditional parametric propensity score matching by accommodating non-linear relationships and relaxing distributional assumptions. The study analyses data from 98 countries (27 IT adopters, 71 non-adopters) from 1990 to 2013 where it suggests that IT's impact on inflation is less pronounced than anticipated, particularly in developing economies. Gerlach and Amato (2001) analyse the adoption and implications of inflation targeting frameworks in Emerging markets and Transition Economies (EMEs). The study employs a qualitative methodology, reviewing existing literature, case studies, and theoretical models. Findings suggest that IT has been largely successful in reducing inflation and improving central bank credibility in EMEs. However, its success is contingent on factors like fiscal stability, exchange rate regimes, and central bank independence.

Eichengreen and Gupta (2021) evaluate India's inflation targeting framework adopted in 2016. The study examines the historical shift from fiscal dominance to a more structured monetary policy focused on inflation control. The analysis employs empirical methods, including reaction function estimation and inflation expectation surveys, to assess IT's impact. Findings indicate that IT has been successful in reducing average inflation from 8% to around 4% and anchoring inflation expectations, leading to improved policy credibility. However, IT has not significantly impacted economic growth, which remains constrained by structural issues. The transmission of monetary policy through interest rates remains weak, particularly due to the influence of food price fluctuations. The study concludes that while IT has stabilized inflation, further policy reforms are necessary to balance inflation control with growth objectives. The authors suggest that IT should be complemented with measures to address broader economic challenges, such as unemployment and structural reforms.

Examining South Africa's experience with IT from 2000 to 2014, Svensson (2014) analyses the SARB's flexible IT framework, which aimed to reduce inflation variability and anchor expectations within a 3-6% target range. The analysis utilizes empirical data on inflation, GDP growth, interest rates, and external shocks, where it is indicated that IT successfully lowered average inflation from 9.7% to 6.3%, enhancing policy credibility and stabilizing inflation expectations. However, challenges arose from exchange rate volatility, high unemployment, and global commodity price shocks. Comparing African and European nations, Nene et al. (2022) examine the impact of inflation targeting on inflation uncertainty and economic growth in South Africa, Ghana, Poland, and the Czech Republic. The study utilizes advanced econometric methods, including GARCH and Panel Vector Autoregressive (PVAR) models, to analyse the impact of IT in both African and European contexts where they find that IT significantly reduces inflation uncertainty in European countries, while its effects are less pronounced in African countries. Additionally, IT positively impacts economic growth in Europe, but has little effect in Africa, suggesting that the success of IT is context-dependent.

Kuklinova and Ilyashenko (2022) investigate the impact of the Bank of Russia's 2015 inflation targeting regime on the Sverdlovsk oblast. The study employs statistical analysis to examine the relationship between inflation control and regional economic sustainability, focusing on indicators such as industrial production, investment, and regional GDP growth. Findings indicate that while IT effectively stabilized inflation, it led to a decline in industrial output and investment. The authors suggest that the policy's tight monetary controls may have hindered economic growth in the region. Sticking to Europe, Stevanovic (2022) examines the impact of inflation targeting on economic growth in four Southeast European countries: Serbia, Turkey, Albania, and Romania, between 1993 and 2020. The study utilizes GARCH models to analyse inflation volatility and regression analysis to assess the relationship between IT, inflation, and GDP growth and the findings indicate that IT generally reduces inflation volatility, particularly in Romania. However, its impact on GDP growth is mixed. In Turkey and Serbia, IT led to higher GDP volatility and lower growth. In Albania, IT had no significant impact on either inflation or GDP. Cvijanović et al. (2024) investigated the impact of inflation targeting on economic outcomes in 19 Central, Eastern, and Southeastern European (CESEE) countries from 1990 to 2020. The study employs the Difference-in-Difference (DID) methodology to compare IT adopters with non-adopters, focusing on inflation rates, inflation volatility, and GDP volatility. The analysis controls for initial inflation levels and removes data from periods of hyperinflation. Results show that IT countries generally experience lower inflation and reduced volatility in both inflation and GDP compared to non-IT countries. However, the study finds that IT is more effective at stabilizing inflation volatility than directly reducing inflation rates, emphasizing the role of pre-existing conditions in shaping the success of IT.

Arestis (2011) analyses Brazil's transition from an exchange rate-based monetary policy to an Inflation Targeting framework in 1999. This shift was driven by the limitations of exchange rate pegs, particularly in the face of financial crises in the 1990s where he examined macroeconomic data before and after the IT adoption, assessing its impact on inflation, GDP growth, and interest rates. Findings indicate that IT successfully reduced inflation. However, challenges persisted, including exchange rate volatility and high interest rates. While achieving price stability, IT's impact on economic growth was mixed, as Brazil continued to grapple with structural issues like unemployment and external vulnerabilities. For the impact of inflation targeting on emerging markets, Batini (2006) examines its effectiveness in stabilizing inflation and promoting economic growth. The study compares 13 emerging economies that adopted IT between 1997 and 2002 with 22 non-IT economies, utilizing regression analysis to measure inflation, volatility, and output performance where it indicates that IT significantly reduces inflation and its volatility in emerging economies without negatively impacting output growth or volatility. IT also improves inflation expectations and reduces exchange rate crisis probabilities. However, the study emphasizes the importance of strong institutional frameworks and technical capabilities for successful IT adoption in emerging markets.

Using robust econometric techniques, including 2SLS, PSM, and GMM, Tapsoba (2011) investigates the impact of inflation targeting on fiscal discipline in 58 countries from 1980 to 2003 and analyse the relationship between IT adoption and the primary fiscal balance as a proxy for fiscal discipline. Its findings suggest that IT does not have a significant effect on fiscal discipline across all countries. However, in developing economies, IT adoption leads to significant improvements in fiscal discipline. The analysis also reveals that partial IT regimes yield stronger and more immediate fiscal benefits than full-fledged IT. The study concludes that IT may improve fiscal discipline, particularly in developing economies, when implemented with supportive institutional reforms. Ben Romdhane et al. (2023) investigate the impact of inflation targeting on economic growth and financial stability in 35 emerging economies. The study employs a multi-method approach, utilizing Qualitative Comparative Analysis (QCA) to identify preconditions for IT adoption, Principal Component Analysis (PCA) to construct a Financial Stability Index (FSI), and a Panel VAR model with GMM to assess the dynamic relationships between inflation, growth, and financial stability which indicate that IT improves economic stability, particularly in the short term, by enhancing financial stability and promoting economic growth. While short-term benefits are evident, long-term benefits are more significant in IT countries. The analysis also shows that partial IT regimes may have a stronger immediate impact than full-fledged IT.

Charfeddine and Guegan (2007) investigate the dynamics of U.S. inflation using structural change models (Markov Switching, Bai-Perron) and long memory processes (ARFIMA). Initial analysis suggested significant long memory in inflation. However, after filtering out structural breaks identified by the Markov Switching and Bai-Perron models, the evidence for long memory diminished. This suggests that perceived long memory may be spurious, primarily driven by structural shifts rather than inherent persistence. The Markov Switching model, which effectively captured regime changes and volatility, provided the best fit for the data, highlighting the crucial role of structural breaks in understanding U.S. inflation dynamics.

Chapter 3

Data and Empirical Analysis

3.1. Data

In the beginning, the paper uses Headline Consumer Price Index (HCPI) data for India, Brazil, Russia, and South Africa. Monthly data from the World Bank spanning 2011-2021 for India, 1994-2004 for Brazil, 2010-2020 for Russia, and 1995-2005 for South Africa are utilized. The analysis divides the sample into pre- and post-IT periods, considering a five-year window around IT adoption. An IT Dummy variable, taking a value of 0 before and 1 after IT implementation, is incorporated into the econometric models of the Structural Change Model and Markov Regime Switch Model to isolate the impact of IT on inflation. Further, a panel data analysis is conducted for the four economies: India (2003-2023), Brazil (1986-2023), Russia (2002-2023), and South Africa (1987-2023) is taken (see Tapsoba, 2011). The analysis focuses on the period preceding IT adoption (13-14 years prior) for each country. Annual inflation rates are derived from HCPI data. To enrich the analysis, the study incorporates macroeconomic control variables such as real GDP and potential GDP which are further used to calculate the GDP output gap from the IMF database. Data on fiscal deficit, M2 (broad money supply), M3 (broad money supply in case of India), and trade openness from the World Bank database. A panel data analysis is conducted, with inflation rate as the dependent variable and an IT Dummy variable (0 for pre-IT, 1 for post-IT) and other macroeconomic variables as independent controls.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	25th Percentile	Median	75th Percentile	Max
Real GDP	3.11	3.39	-7.8	1.2	3.15	5.3	9.7
Potential GDP	3.08	1.9	0.6	1.54	2.53	3.79	6.93
Output Gap	-9.07	171.06	-1129.21	-30.61	15.64	56.4	714.08
IT Dummy	0.56	0.5	0	0	1	1	1
Inflation Rate	10.98	57.23	-96.82	-24.21	3.08	38.44	175.52
Fiscal Deficit	-3.94	3.66	-12.86	-6.14	-4.16	-2.36	7.8
Trade Openness	40.55	13.58	14.39	27.75	43.83	50.39	65.97
Money Supply	63.39	19.39	20.66	48.91	65.33	76.89	111.33

3.2. Empirical Methodology

This study will employ a Structural Change Model, Markov-Regime Switching Model, and an Unbalanced Panel Data Analysis. Structural change models are econometric tools that analyse how relationships between economic variables evolve. These models pinpoint significant shifts, or "breakpoints," in these relationships, which can be triggered by events like financial crises, policy changes, or technological advancements. By recognizing that these relationships aren't always constant, these models offer a more accurate understanding of how economies function. Techniques used to identify these breakpoints include the Chow test, Bai-Perron tests, and Markov-switching models.

These models are valuable in empirical research, as they help determine whether policy changes or other external factors significantly alter economic behavior. In analysing inflation targeting in BRICS countries, a structural change model could reveal if this policy shift fundamentally altered inflation dynamics.

$$y_t = \alpha_k + \beta_k x_t + \varepsilon_t, \quad \text{for } t \in (t_{k-1}, t_k] \qquad (1)$$

Here, the dependent variable (y_t) at the time (t) is influenced by an independent variable (x_t), with the relationship varying across different segments defined by breakpoints (t_1, t_2, …,

t_k). Each segment, or regime, is characterized by its intercept (α_k) and slope (β_k), allowing for distinct linear relationships within each interval ($(t_{k-1}, t_k$). The number of regimes (K) is determined by the number of breakpoints, specifically (K - 1) breakpoints resulting in (K) distinct segments. The error term accounts for the variability in the dependent variable that is not explained by the independent variable within each regime (Charfeddine & Guegan, 2007).

The Markov Regime-Switching Model (MRSM) is a statistical framework used to analyse systems that transition between different states or regimes over time. It operates on the principle of a Markov process, where the probability of moving to a new state depends solely on the current state, not on past states. This model is particularly valuable in time series analysis, allowing for the identification of distinct regimes, such as high and low growth phases or periods of volatility in financial markets. Key components of MRSM include discrete regimes, each characterized by specific parameters like mean and variance. The transitions between these regimes are captured in a transition probability matrix, which quantifies the likelihood of moving from one regime to another. Within each regime, the observed data is modelled using distinct statistical processes, such as linear regression or autoregressive models.

The regime at any given time is latent, meaning it is inferred from the observed data rather than directly observed. Estimation techniques, such as maximum likelihood estimation or expectation-maximization algorithms, are employed to identify transition probabilities and regime parameters. MRSM has diverse applications, including modelling business cycles, analysing stock market volatility, and detecting shifts in volatile states (assessing BRICS nations in this case).

$$y_t = \mu_{s_t} + \beta_{S_t} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \theta_{s_t}^2\right) \qquad (2)$$

Here, each regime (S_t) is defined by its own set of parameters, including the mean (μ_{s_t}), the slope (β_{S_t}), and the variance ($\theta_{s_t}^2$). This framework allows the model to effectively capture and represent varying behaviors across different segments, such as shifts in volatility or changes in trend. By assigning distinct parameters to each regime, the model can adapt to the unique characteristics of the data within those intervals, providing a more accurate and nuanced understanding of the underlying relationships (Charfeddine & Guegan, 2007).

The Panel data model is also used in the analysis, specifically an unbalanced panel data which consists of observations on multiple entities where some entities have missing data for certain periods. This results in an irregular structure with varying numbers of observations across entities.

3.3. Empirical Analysis

We examine each country separately by employing the Structural Change Model to determine the breakpoints where the structural break occurred and how it affected inflation. The effectiveness of IT is then assessed using the Markov-Regime Switching Model, and its effect on inflation is finally analysed using Panel Data Regression.

3.3.1 Structural Change Model

The first is the Structural Change Model, which identifies particular "breakpoints" that are brought about by events such as financial crises, changes in regulations, or advances in technology.

3.3.1.1 Brazil

The Structural breaks in Brazil's inflation dynamics are analysed by focusing on the relationship between the Headline Consumer Price Index (HCPI) and the implementation of Inflation Targeting policies. An IT Dummy variable is employed, which is a binary indicator that takes a value of 1 during periods of inflation targeting and 0 otherwise.

Table 2.1: Summary of Structural Breakpoints and Model Performance

Segments	Breakpoints	RSS	BIC
m = 1	1995-07	3050.7	818.4
m = 2	1995-07,1997-08	1843.1	766.5
m = 3	1995-07,1997-08, 2000-02	1588.8	761.6
m = 4	1995-07,1997-08, 2000-02, 2001-10	1558.6	773.7
m = 5	1995-07,1997-08, 2000-02, 2001-10, 2003-05	1556.8	788.2

The structural breakpoints are analysed using the Residual Sum of Squares (RSS) and the Bayesian Information Criterion (BIC). In the one-breakpoint model (m=1), a single break is identified at observation in July 1995. The two-breakpoint model (m=2) identifies breakpoints at observations in July 1995 and August 1997, demonstrating a better fit compared to the one-breakpoint model, as indicated by a lower BIC. The three-breakpoint model (m=3) finds breakpoints at observations in July 1995, August 1997, and February 2002 exhibiting the lowest BIC and suggesting the most efficient balance between model fit and complexity. In contrast, models with four or more breakpoints (m=4, m=5) show only slight improvements in RSS, but the BIC increases, indicating potential overfitting.

As, the three-breakpoint model is the most efficient fit, according to the breakdates the results indicate three significant breakpoints on the dates July 1995, August 1997, and February 2002. The first breakpoint, occurring shortly after the Plano Real reforms, reflects a period of stabilization following hyperinflation. The second breakpoint coincides with the official adoption of inflation targeting in Brazil in 1999, marking a significant shift in monetary policy towards explicit inflation targets. The third breakpoint likely reflects the consolidation of the inflation targeting regime and its increasing effectiveness in anchoring inflation expectations (Arestis et al., 2011).

Table 2.2: Regression Coefficients for Each Segment

Segment	Estimate	Std_Error	p_Value
Intercept (Segment 1)	21.17	1.593	0.001
Segment 2	13.93	1.835	0.001
Segment 3	25.64	1.969	0.001
Segment 4	15.67	2.253	0.001

Table 2.3: Model Performance Metrics

Metric	Value
Residual Standard Error	6.943
Multiple R-squared	0.5767
Adjusted R-squared	0.5668
F-statistic	58.14

The regression table examines the impact of four segments on the HCPI. All segments have statistically significant effects, with Segment 3 (2000-02) demonstrating the strongest influence (Estimate = 25.64). Segment 2 (1997-08) has the weakest effect (Estimate = 13.92). The model has a moderate explanatory power with an Adjusted R-squared of 0.5668, indicating that 56.68% of the variance in the dependent variable is explained by the model. The model's overall significance is very strong ($p < 0.001$), suggesting it is robust. The residual standard error of 6.94 indicates a reasonable fit.

Figure 2.1: Structural Change for Brazil

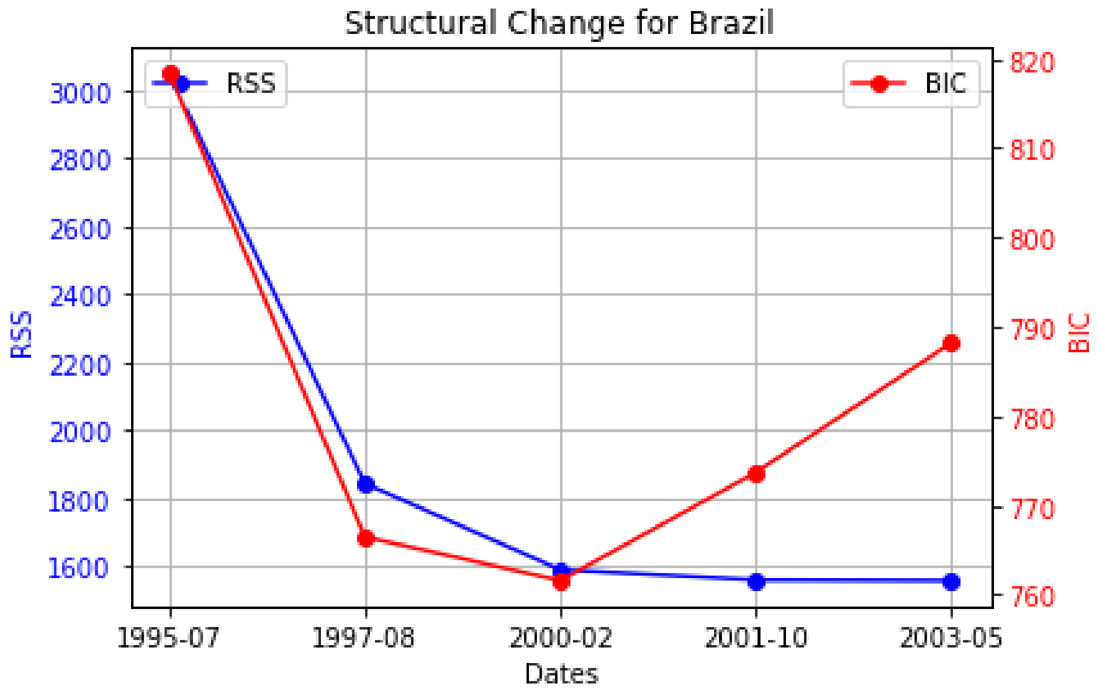
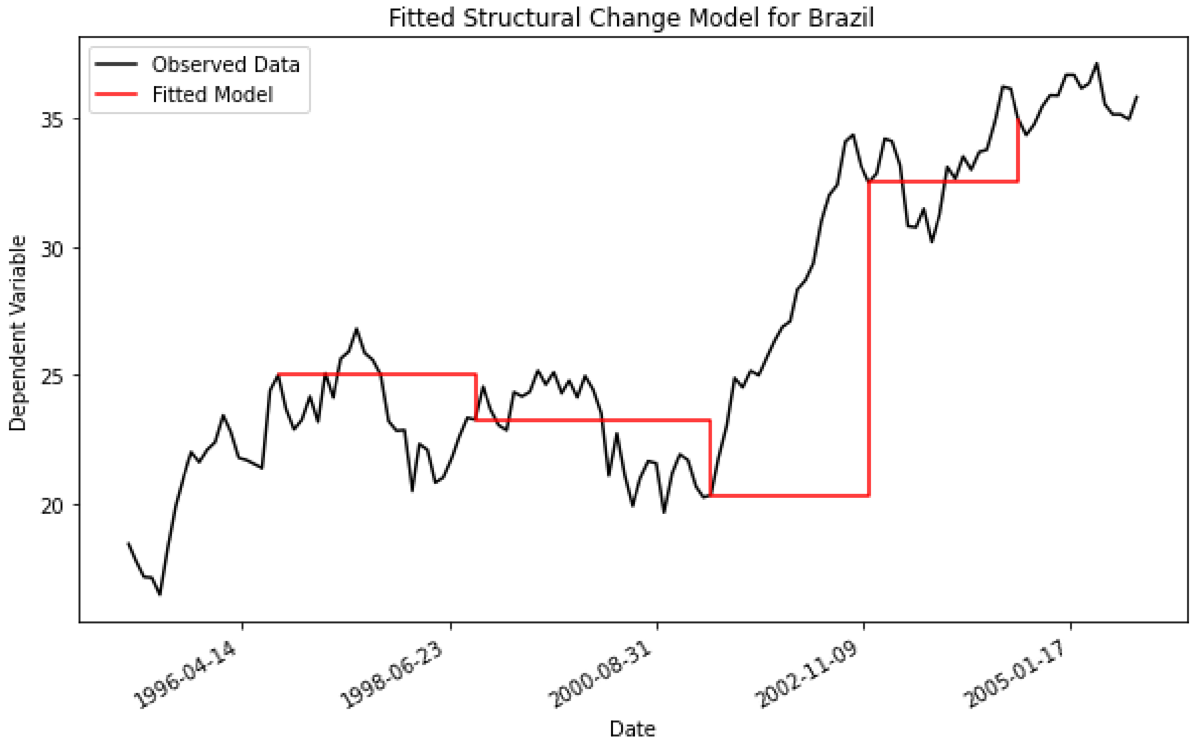


Figure 2.2: Fitted Structural Change Model for Brazil



3.3.1.2. South Africa

South Africa, in the One Breakpoint (m=1), with a single break in November 1996 has a relatively high RSS and the highest BIC, suggesting a less efficient model. The Two Breakpoints (m=2) with breaks in November 1996 and July 1998, demonstrate a significant improvement. The lower BIC suggests a better fit, potentially aligning with the adoption of inflation targeting. The Three Breakpoints (m=3) added breakpoints in February 2000 further improving the model's fit, as indicated by a lower BIC. In Four Breakpoints (m=4) with adding breaks in September 2001, the model achieves the lowest BIC, indicating the best trade-off between model fit and complexity. This suggests that four distinct phases best capture the structural shifts in South African inflation dynamics. While introducing a Fifth breakpoint (m=5) in May 2003, RSS decreases and the BIC increases slightly which suggests potential overfitting.

Table 3.1: Summary of Structural Breakpoints and Model Performance

Segments	Breakpoints	RSS	BIC
m = 1	1996-11	40.71	248.63
m = 2	1996-11, 1998-07	25.76	202.88
m = 3	1996-11,1998-07, 2000-02	19.33	179.62
m = 4	1996-11, 1998-07, 2000-02, 2001-09	16.02	169.48
m = 5	1996-11, 1998-07, 2000-02, 2001-09, 2003-05	14.41	170.15

South Africa, in the One Breakpoint (m=1), with a single break in November 1996 has a relatively high RSS and the highest BIC, suggesting a less efficient model. The Two Breakpoints (m=2) with breaks in November 1996 and July 1998, demonstrate a significant improvement. The lower BIC suggests a better fit, potentially aligning with the adoption of inflation targeting. The Three Breakpoints (m=3) added breakpoints in February 2000 further improving the model's fit, as indicated by a lower BIC. In Four Breakpoints (m=4) with adding breaks in September 2001, the model achieves the lowest BIC, indicating the best trade-off

between model fit and complexity. This suggests that four distinct phases best capture the structural shifts in South African inflation dynamics. While introducing a Fifth breakpoint (m=5) in May 2003, RSS decreases and the BIC increases slightly which suggests potential overfitting.

Based on the results the model with four breakpoints provides the best fit, balancing model. These breakpoints occur at 1996-11, 1998-07, 2000-02, and 2001-09. The first breakpoint, in November 1996, reflects the early years of South Africa's transition post-apartheid, characterized by economic challenges and policy adjustments. The second breakpoint, in July 1998, coincides with the impact of the Asian Financial Crisis and other global economic pressures, highlighting the influence of external factors on South Africa's inflation trajectory. The most significant breakpoint occurred in February 2000, marking the introduction of inflation targeting in South Africa. This policy shift aimed to stabilize inflation expectations and guide monetary policy decisions. The fourth breakpoint, in September 2001, reflects the early outcomes of the IT policy, coinciding with global economic volatility from the dot-com bubble burst and other external shocks. This period likely saw the initial effects of the new policy framework on inflation dynamics, demonstrating the interplay between domestic policy and global economic conditions.

Table 3.2: Regression Coefficients for Each Segment

Segment	Estimate	Std_Error	p_Value
Intercept (Segment 1)	36.69	0.31	0.001
Segment 2	6.83	0.56	0.001
Segment 3	10.6	0.56	0.001
Segment 4	16.73	0.55	0.001

Table 3.3: Model Performance Metrics

Metric	Value
Residual Standard Error	2.034
Multiple R-squared	0.94
Adjusted R-squared	0.93
F-statistic	498.7

The regression model reveals significant relationships between HCPI and identified structural breaks, with the first segment (1996-11) showing a high intercept of 36.6995. Subsequent segments indicate increasing coefficients, particularly during the introduction of inflation targeting in 2000, which reflects transitional adjustments. Model performance metrics demonstrate robustness, with a Residual Standard Error of 2.034 and a Multiple R-squared value of 0.94, indicating that 94.01% of HCPI variation is explained by the model (Aron et al., 2006).

Figure 3.1: Structural Change for South Africa

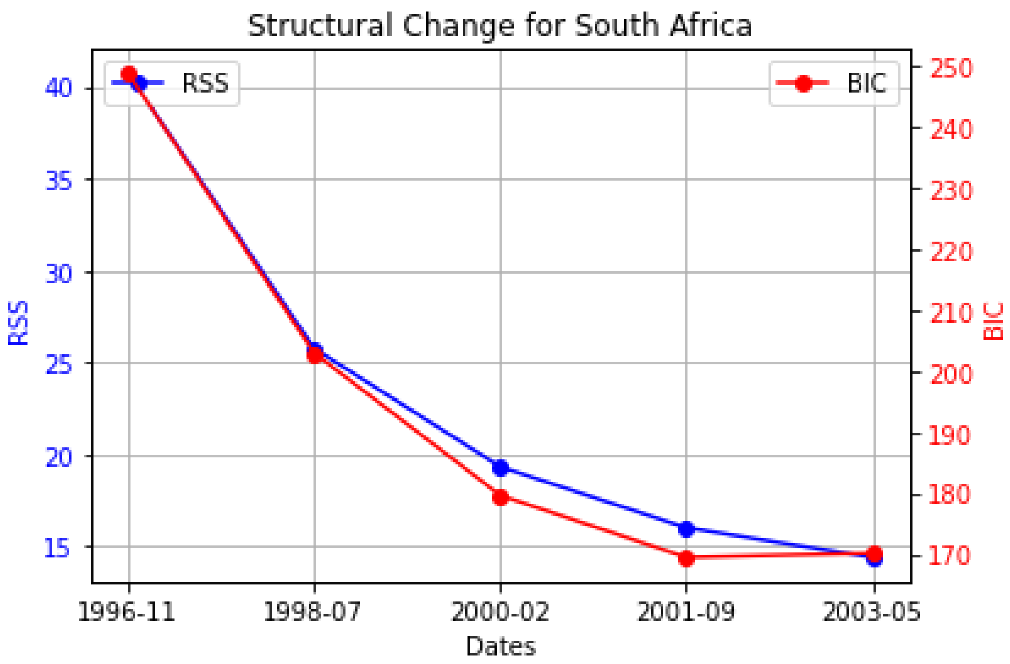
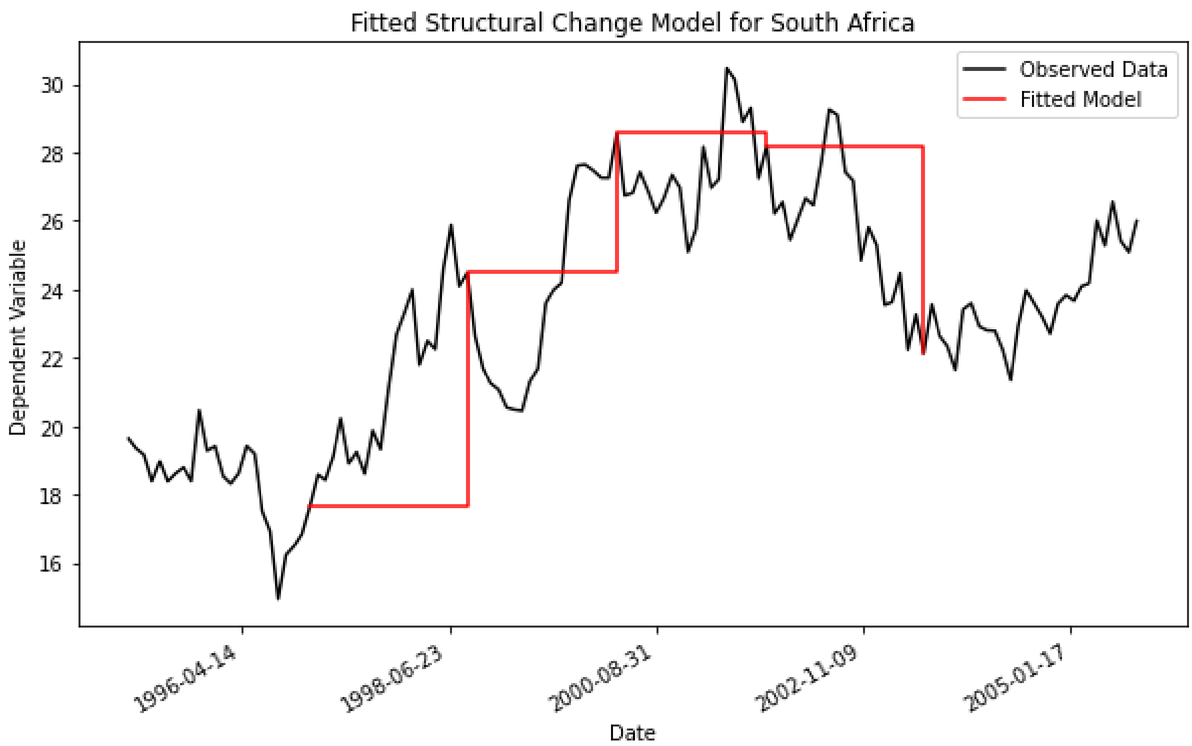


Figure 3.2: Fitted Structural Change Model For South Africa



3.3.1.3 Russia

In Russia’s case, the one-breakpoint model (m=1), a single broad shift captures high RSS and the highest BIC, indicating a poor fit. The two-breakpoint model (m=2) identifies two shifts, improving the fit compared to the one-breakpoint model, as evidenced by a lower BIC. The three-breakpoint model (m=3) captures shifts before and after the introduction of IT, leading to a further reduction in the BIC. The four-breakpoint model (m=4) achieves the lowest BIC before the five-breakpoint model (m=5) which exhibits the lowest BIC, suggesting it is the most efficient model.

Table 4.1: Summary of Structural Breakpoints and Model Performance

Segments	Breakpoints	RSS	BIC
m = 1	2011-07	294.7	509.91
m = 2	2011-07, 2013-05	170.06	451.99
m = 3	2011-07, 2013-05, 2014-12	117.44	417.76
m = 4	2011-07, 2013-05, 2014-12, 2016-07	91.36	399.27
m = 5	2011-07, 2013-05, 2014-12, 2016-07, 2018-11	70.18	379.09

In Russia’s case, the one-breakpoint model (m=1), a single broad shift captures high RSS and the highest BIC, indicating a poor fit. The two-breakpoint model (m=2) identifies two shifts, improving the fit compared to the one-breakpoint model, as evidenced by a lower BIC. The three-breakpoint model (m=3) captures shifts before and after the introduction of IT, leading to a further reduction in the BIC. The four-breakpoint model (m=4) achieves the lowest BIC before the five-breakpoint model (m=5) which exhibits the lowest BIC, suggesting it is the most efficient model.

Based on the best-performing model (m=5), breakpoints occur in 2011-07, 2013-05, 2014-12, 2016-07, and 2018-11. The first breakpoint, occurring in July 2011, reflects high inflation under pre-IT policies, likely influenced by various domestic and global factors. The second breakpoint in May 2013 indicates rising inflation due to economic instability, potentially tied to global factors such as the 2014 oil price crash and the impact of economic sanctions on

Russia. The third breakpoint in December 2014 marks a critical juncture with intensifying inflationary pressures, likely exacerbated by the oil price crash and economic sanctions. The fourth breakpoint in July 2016 coincides with the adoption of inflation targeting in 2015-2016, reflecting transitional inflationary trends as the central bank implemented and adjusted its policies within the new framework. Finally, the fifth breakpoint in November 2018 shows signs of stabilization in the post-IT period, suggesting the potential effectiveness of IT in anchoring expectations and improving economic stability (Stevanovic et al., 2022).

Table 4.2: Regression Coefficients for Each Segment

Segment	Estimate	Std_Error	p_Value
Intercept (Segment 1)	102.91	0.98	0.001
Segment 2	11.22	1.34	0.001
Segment 3	25.27	1.39	0.001
Segment 4	52.04	1.39	0.001

Table 4.3: Model Performance Metrics

Metric	Value
Residual Standard Error	4.29
Multiple R-squared	0.98
Adjusted R-squared	0.97
F-statistic	1253

The regression analysis shows that the intercept for the first segment (pre-2011) is estimated at 102.91, indicating moderately high inflation. Subsequent segments show significant increases, particularly during 2013-2014 (Segment 3) and 2014-2016 (Segment 4), reflecting external shocks like the oil price crash and economic sanctions. The estimates for Segments 5 and 6 (post-2016) indicate a stabilization in inflation, suggesting the effectiveness of inflation targeting policies. Model performance metrics reveal a high R-squared value of 0.98, indicating that the model explains 98.03% of the variation in HCPI, while a low Residual Standard Error (RSE) of 4.29 confirms a good fit.

Figure 4.1: Structural Change for Russia

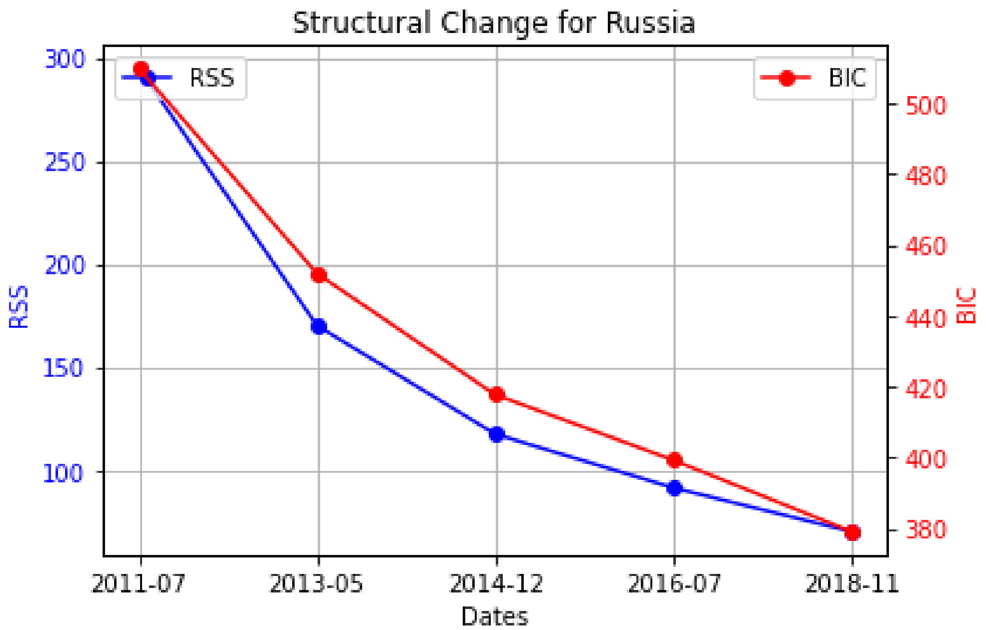
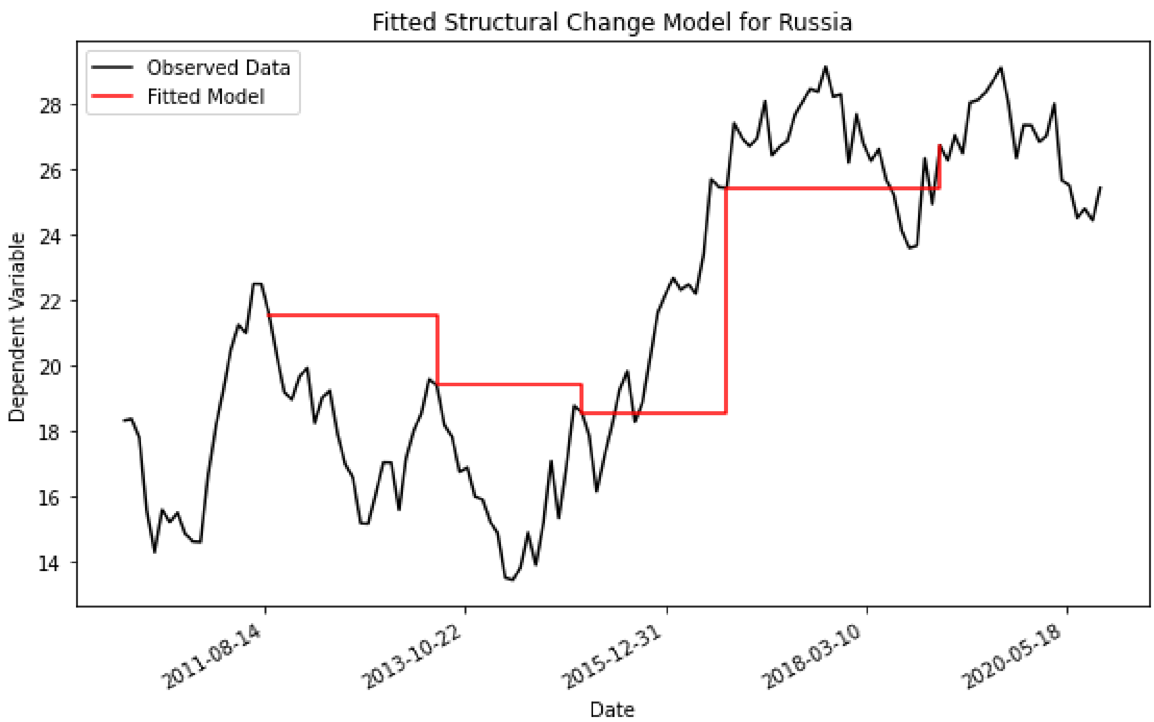


Figure 4.2: Fitted Structural Change Model for Russia



3.3.1.4 India

The analysis of breakpoints of India shows in the one-breakpoint model (m=1), the RSS is 290.7, indicating high unexplained variance due to the lack of segmentation. As additional breakpoints are introduced, the RSS decreases, with the two-breakpoint model (m=2) showing an RSS of 213.7, reflecting a significant improvement in fit. The three-breakpoint model (m=3) achieves an optimal balance of fit and complexity, with an RSS of 187.1, while the four-breakpoint model (m=4) has an RSS of 173.4. The five-breakpoint model (m=5) shows a small additional improvement with an RSS of 171.3, indicating diminishing returns.

Table 5.1: Summary of Structural Breakpoints and Model Performance

Segments	Breakpoints	RSS	BIC
m = 1	2013-06	290.7	508.1
m = 2	2013-06, 2015-04	213.7	482.1
m = 3	2013-06, 2015-04, 2016-11	187.1	479.3
m = 4	2013-06, 2015-04, 2016-11, 2018-06	173.4	483.9
m = 5	2013-06, 2015-04, 2016-11, 2018-06, 2020-01	171.3	496.9

The analysis of breakpoints of India shows in the one-breakpoint model (m=1), the RSS is 290.7, indicating high unexplained variance due to the lack of segmentation. As additional breakpoints are introduced, the RSS decreases, with the two-breakpoint model (m=2) showing an RSS of 213.7, reflecting a significant improvement in fit. The three-breakpoint model (m=3) achieves an optimal balance of fit and complexity, with an RSS of 187.1, while the four-breakpoint model (m=4) has an RSS of 173.4. The five-breakpoint model (m=5) shows a small additional improvement with an RSS of 171.3, indicating diminishing returns.
The BIC values support these findings, with the three-breakpoint model yielding the lowest BIC of 479.3, suggesting it is the most efficient representation of the data.

The breakpoints at 2013-06, 2015-04, and 2016-11 achieve the best balance fit. The first breakpoint, June 2013, marks a period of persistent inflation as it was driven by supply-side constraints and external factors, such as rising global commodity prices. The second breakpoint was April 2015, during which inflation moderated slightly due to tighter monetary policy and improved fiscal discipline. The third breakpoint, November 2016, marks the transition to the IT phase as the adoption of inflation targeting by the RBI took place during which inflation stabilization began (Eichengreen & Gupta, 2021).

Table 5.2: Regression Coefficients for Each Segment

Segment	Estimate	Std_Error	p_Value
Intercept (Segment 1)	78.24	1.06	0.001
Segment 2	19.75	1.38	0.001
Segment 3	29.93	1.65	0.001
Segment 4	47.94	1.37	0.001

Table 5.3: Model Performance Metrics

Metric	Value
Residual Standard Error	5.7
Multiple R-squared	0.9
Adjusted R-squared	0.91
F-statistic	427

The regression analysis shows that in Segment 1 (before 2013-06), the intercept of 78.24 indicates a baseline HCPI level. Segment 2 (2013-06 to 2015-04) shows a change in HCPI of 19.75, reflecting moderated inflation due to tighter monetary policy and declining global commodity prices. Segment 3 (2015-04 to 2016-11) indicates a higher change of 29.93, highlighting inflation adjustments during the transition to inflation targeting. Finally, Segment 4 (post-2016) shows the largest change of 47.94, demonstrating the effectiveness of inflation targeting in stabilizing inflation trends despite external pressures, such as the COVID-19 pandemic. The model performance metrics, including a high R-squared value of 0.90 and a low Residual Standard Error (RSE) of 5.70, confirm the robustness of the model in capturing these dynamics.

Figure 5.1: Structural Change for India

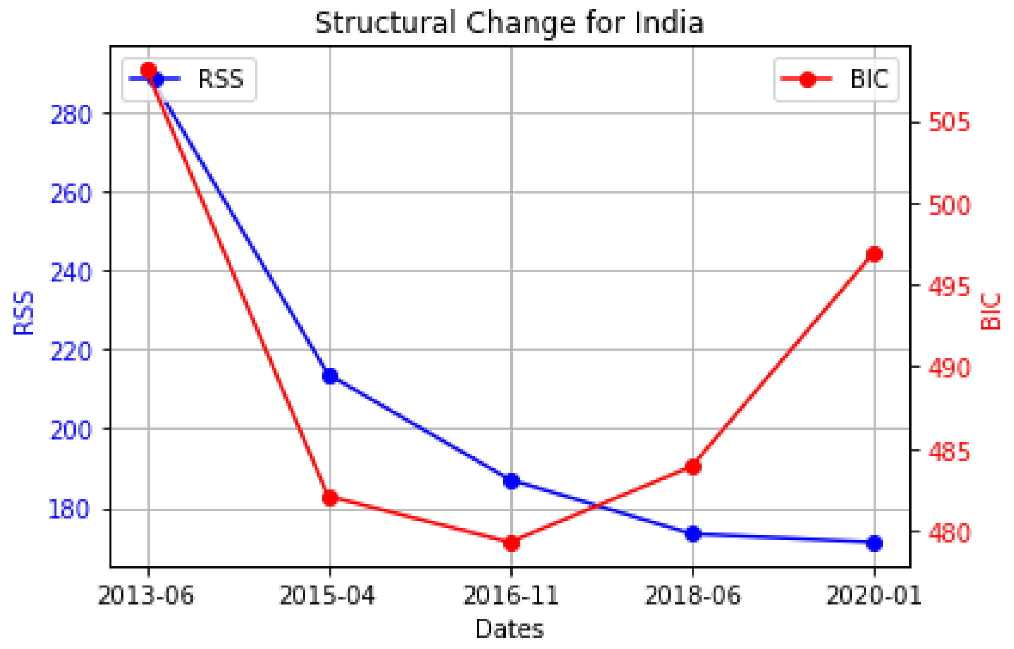
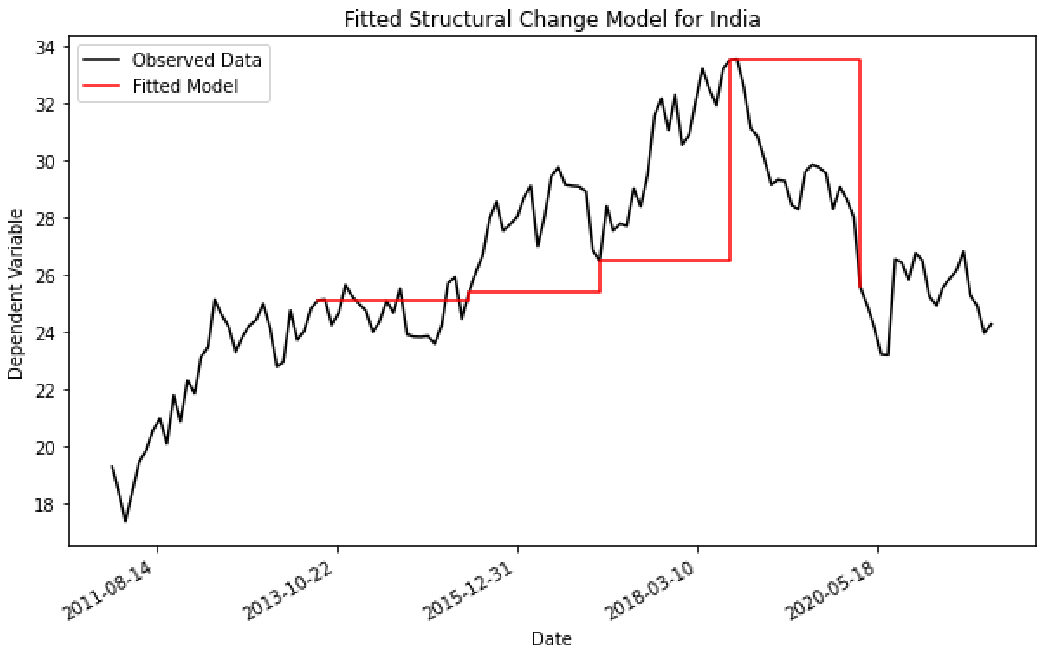


Figure 5.2: Fitted Structural Model for India



3.3.2 Markov-Regime Switching Model (MRSM)

The application of a Markov Regime-Switching Model (MRSM) to the time series data of BRICS countries reveals significant structural changes in their inflation dynamics. Each country exhibits two distinct regimes, characterized by different intercepts, impacts of the Inflation Targeting (IT) dummy, residual errors, R-squared values, and transition probabilities.

Table 6: Summary of Regime-Switching Results for BRICS Countries

Country	Regime	Intercept (Estimate)	IT Dummy (Estimate)	Residual Std. Error	R-Squared	Transition Probabilities
Brazil	Regime 1	32.51	4.86	1.59	0.69	0.98 (R1→R1), 0.015 (R1→R2)
Brazil	Regime 2	21.61	26.72	6.03	0.82	0.015 (R2→R1), 0.985 (R2→R2)
India	Regime 1	78.21	50.31	5.42	0.95	0.984 (R1→R1), 0.014 (R1→R2)
India	Regime 2	95.73	13.1	4.25	0.7	0.016 (R2→R1), 0.985 (R2→R2)
Russia	Regime 1	124.1	38.68	7.46	0.8665	0.987 (R1→R1), 0.014 (R1→R2)
Russia	Regime 2	105.65	76.98	4.77	0.9848	0.013 (R2→R1), 0.982 (R2→R2)
South Africa	Regime 1	39.5	16.79	0.66	0.99	0.962 (R1→R1), 0.013 (R1→R2)
South Africa	Regime 2	38.33	10.32	3.72	0.65	0.038 (R2→R1), 0.987 (R2→R2)

Brazil demonstrates two regimes, the first, a Stable Growth Phase, has an intercept of 32.51 and a modest IT dummy impact of 4.86, indicating stable inflation conditions with low variability (Residual Std. Error: 1.59). The second regime, a Volatile/Exceptional Period, shows a lower intercept of 21.61 but a significant IT dummy impact of 26.72, reflecting heightened inflationary pressures and instability (Residual Std. Error: 6.03). Transition probabilities indicate a strong likelihood of remaining in either regime, with 98.4% in Regime 1 and 98.5% in Regime 2. India exhibits a Strong Growth Phase in Regime 1, characterized by a high intercept of 78.21 and a substantial IT dummy impact of 50.31, suggesting a robust reliance on IT industries. The model fits well with an R-squared of 0.95. In Regime 2, the Moderate Growth Phase, the intercept rises to 95.73, but the IT dummy impact decreases to 13.10, indicating a shift in growth dynamics. Transition probabilities show a high likelihood of remaining in Regime 1 (98.4%) and a slightly lower probability in Regime 2 (98.5%).

Russia presents a Moderate Stability Phase in Regime 1, with a high intercept of 124.10 and a moderate IT dummy impact of 38.68, indicating stable inflation dynamics. The second regime, a High-Growth Phase, has a lower intercept of 105.65 but a strong IT dummy impact of 76.98, reflecting significant growth influenced by external shocks. The model fits exceptionally well in this regime, with an R-squared of 0.98. Transition probabilities suggest a strong tendency to remain in the same regime, with 98.7% in Regime 1 and 98.2% in Regime 2. South Africa shows a Highly Stable Phase in Regime 1, with an intercept of 39.5035 and a noticeable IT dummy impact of 16.79, indicating strong stability and a very low residual standard error of 0.66. In Regime 2, the Unstable Phase, the intercept is similar at 38.33, but the IT dummy impact drops to 10.32, reflecting increased variability (Residual Std. Error: 3.72). The model's fit is weaker in this regime, with an R-squared of 0.65.

Transition probabilities indicate a strong persistence within each regime, with 96.2% in Regime 1 and 98.7% in Regime 2.

3.3.3 Panel Data

The general panel data equation used in the analysis for all four countries is as follows:

$$\mathrm{Inflation}_{\mathrm{Rate}_{\mathrm{it}}} = \beta_0 + \beta_1\left(\mathrm{IT}_{\mathrm{Dummy}_{\mathrm{it}}}\right) + \beta_2\left(\mathrm{Fiscal}_{\mathrm{Deficit}_{it}}\right) + \beta_3\left(\mathrm{Money}_{\mathrm{Supply}_{it}}\right)$$

$$+ \beta_4\left(\mathrm{Trade}_{\mathrm{Openness}_{it}}\right) + \beta_5\left(\mathrm{Output}_{\mathrm{Gap}_{it}}\right)$$

$$+ \beta_6\left(\mathrm{IT}_{\mathrm{Dummy}_{\mathrm{it}}}.\mathrm{Trade}_{\mathrm{Openness}_{\mathrm{it}}}\right) + \mu_{\mathrm{i}} + \epsilon_{\mathrm{it}}$$

where i represents the individual country, t represents the time period, μ_i is the country-specific fixed effect and ϵ_{it} is the error term. For the Model Diagnostic tests, the Hausman test results ($\chi^2 = 12.61$, $p < 0.01$) reject the null hypothesis, that the random effects model is consistent. This indicates that the fixed effects model is preferred due to the inconsistency of the random effects model. Whereas, Residual Diagnostics show no evidence of heteroskedasticity in the Breusch-Pagan Test for Heteroskedasticity. Breusch-Godfrey/Wooldridge Test for Serial Correlation shows weak evidence of serial correlation and the Durbin-Watson Test cannot compute due to model constraints.

So, the fixed effects model is selected as the appropriate specification based on the Hausman test.

3.3.3.1 The Fixed Effect Model

The fixed effects model results are presented in Table 1. The IT dummy variable has a statistically significant negative effect ($\beta = -124.90$, $p < 0.001$) on inflation rate.

Table 7: Fixed Effect Model Results

	Estimate	Std. Error	p-value
IT Dummy	-124.9	29.48	0.001***
Output Gap	0.03	0.028	0.28
Trade Openness	-1.64	0.83	0.05
Fiscal Deficit	2.7	2.16	0.21
Money Supply	1.05	0.28	0.001***
IT Dummy*Trade Openness	1.94	0.7	0.01**

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Table 8: Model Summary

Statistic	Value
R-Squared	0.22159
Adj. R-Squared	0.16369
Number of Entities (n)	4
Time Periods (T)	21-30
Total Observations (N)	131

Trade openness ($\beta = -1.64$, $p \approx 0.05$) and its interaction with the IT dummy ($\beta = 1.93$, $p < 0.01$) also play significant roles. Other variables, such as Output Gap and Fiscal Deficit, are not statistically significant at conventional levels. The model explains approximately 22.2% of the variance, and the overall F-statistic confirms the joint significance of predictors.

The significant increase in the money supply has been shown to drive inflation, confirming the role of monetary expansion in this phenomenon. Conversely, the implementation of inflation targeting policies has a strong effect in reducing inflation. Furthermore, in countries that adopt inflation targeting, trade openness appears to have a less negative, or even positive, effect on inflation compared to those without such policies, highlighting the moderating influence of inflation targeting on the relationship between trade and inflation.

Chapter 4

Conclusion

The adoption of inflation targeting as a monetary policy framework has yielded mixed results across the BRICS nations of Brazil, Russia, India, and South Africa. This study demonstrates that while IT has been instrumental in anchoring inflation expectations, reducing inflation volatility, and enhancing the credibility of central banks, its effectiveness is shaped by a range of domestic and external factors. These factors include the strength of institutional frameworks, fiscal discipline, exchange rate regimes, and vulnerability to global economic shocks.

Brazil and South Africa show moderate success, with IT contributing to greater price stability but encountering challenges like high unemployment and external commodity price shocks. Russia's experience highlights the influence of geopolitical risks and global oil price fluctuations, which complicate the implementation of IT despite some progress in inflation stabilization. Meanwhile, India, as a late adopter of IT, demonstrates its potential to mitigate inflation trends; however, its effectiveness is constrained by structural issues, including food price volatility and weak monetary policy transmission.

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