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Commitment, Loose Commitment or Discretion? Monetary Policy Objectives and Preferences in South Africa

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1 Introduction

In 2000, the South African Reserve Bank (SARB) adopted the inflation-targeting (IT) framework with the aim of maintaining inflation within the 3% - 6% range. In addition to this primary objective, employment and financial stability are also enshrined in the central bank's mission. However, there is a belief that the SARB does not adequately support the government's goals of employment creation and economic growth (see, for example, Vermeulen (2020); van Niekerk (2023)). The African National Congress (ANC), one of the largest political parties in the country, argues that the Reserve Bank should take into account other objectives, such as employment creation and economic growth (ANC, 2017). This view is also echoed by others, such as the Economic Freedom Fighters (EFF) political party[1]. Indeed, there is no clear indication of the bank's monetary policy preferences or the relative importance it assigns to its different objectives, particularly those related to employment and financial stability.

We use a simple structural model with external habits to analyze the monetary policy objectives and preferences of the SARB. Unlike much of the literature, which relies on monetary instrument rules such as the Taylor rule, we focus on a targeting regime. The former approach depends on the policymaker's ability to make credible commitments (Liu et al., 2020). However, there have been instances where past promises were not upheld. In contrast, the targeting regime is based on an objective or loss function optimized by the policymaker, with assigned weights reflecting their priorities (Walsh, 2017). In this context, the literature has primarily employed two optimal policy approaches: the full commitment and the discretionary policy. Under full commitment, the policymaker selects a once-and-for-all optimized plan for the policy rate, while under discretion, a new optimization is conducted at each period. As Debortoli et al. (2014) note, these two extremes are unrealistic. Full commitment assumes that policymakers never default on their past promises, while discretion precludes the possibility that policy makers may reap the benefit of making and keeping promises. Therefore, this article considers, in addition to these two polar cases, the intermediate case of loose commitment. Under this policy framework, there is a probability that committed policymakers may renege on their promises. Debortoli and Nunes (2007) highlight that this may be due to political turnover or time inconsistency. The arrival of a new policymaker for example may lead to new policy plans being formulated, rendering obsolete the old ones.

As in Chen et al. (2017b), the model allows the weights on the different objectives in the loss function and the volatility of the structural shocks to switch according to an independent two-state Markov chain process. The weights of the loss function switch between a low and a high regime depending on the degree of conservatism of the central bank. In the low regime, the central bank attaches a weaker response to inflation deviation while in the high regime it reacts strongly. The structural shocks switch between a

[1]See EFF (2024).

low and a high regime depending on their volatility. The model is estimated separately for each optimal policy using quarterly South African data from 1994Q1 to 2022Q2. To ensure that the economy is better characterized by a model that incorporates regime switches, we first estimate a constant-parameters model separately for each optimal policy. According to this specification, the SARB is fully committed but with a weaker preference for inflation stability. This is at odd with the Central Bank's mandate. We compute the log marginal data density (MDD) to compare the regime-switching model with the constant-parameters model and select the one that fits the data better. We find that the regime-switching model for each policy provides a better fit to the data. The SARB's preference is identified as a loose commitment policy, with reoptimization occurring on average every two quarters. This frequent reoptimization does not indicate a lack of credibility. Indeed, South Africa is a small emerging economy subject to numerous shocks and spillovers. The central bank must account for these factors when formulating policies, making a high level of commitment difficult in an uncertain and volatile environment. We also find that the central bank follows a flexible IT framework, placing a strong emphasis on inflation stability. Due to the presence of external habit formation, the divine coincidence does not hold. As a result, technological and preference shocks lead to a trade-off between output and inflation, rendering difficult the stabilization of the latter. We conduct series of counterfactual simulations. The results indicate that the SARB could have achieved lower inflation volatility by adopting a full commitment policy or by reoptimizing less frequently. However, in the latter case, there is a modest increase in output and interest rate volatility, though not substantial. There is a strong response to a technological shock and a better but challenging stabilization of inflation under full commitment following a cost-push shock.

This article contributes to the literature in several ways. To the best of our knowledge, this is the first attempt to analyze the monetary policy objectives and preferences of the SARB within the framework of optimal policy. Indeed, the bulk of the literature has focused on monetary instrument rules, as seen in Ortiz and Sturzenegger (2007); Harjes and Ricci (2008); Naraidoo and Raputsoane (2010), among others. In addition to the two extreme cases of optimal policy, this article considers the intermediate case of loose commitment and estimates the probability of reoptimization. Furthermore, we contribute to the growing literature on nonlinear models by incorporating regime switches in parameters and the volatility of structural shocks. This is particularly important given the ubiquity of nonlinearities in economic systems.

The remainder of the article is structured as follows. Section 2 reviews the structural model used in the analysis. Since the estimation strategies for full commitment and discretion are well-documented in the literature, Section 3 briefly presents the loose commitment framework and the data used. Section 4 focuses on the empirical results, while Section 5 examines the counterfactual exercise. Section 6 provides a robustness check and Section 7 concludes the article.

2 The linearized model

This article follows the structural model of Liu et al. (2020). The model consists of households, intermediate and final goods producers and a government. It incorporates external habit formation in consumption and price rigidity. The Euler equation is given by expression (1) below[2].

$$\hat{x}_t = E_t\hat{x}_{t+1} - \frac{1}{\sigma}(\hat{r}_t - E_t\hat{\pi}_{t+1} - E_t\hat{a}_{t+1}) - \hat{\delta}_t + E_t\hat{\delta}_{t+1}; \tag{1}$$

where $\hat{x}_t$ is the habit-adjusted consumption, $\hat{r}_t$ is the short term nominal interest rate, $\hat{\pi}_t$ is the inflation rate, σ is the inverse of the elasticity of intertemporal substitution (IES), $\hat{a}_t$ is a productivity shock and, $\hat{\delta}_t$ is a preference shock. In addition, $\hat{x}_t = (1-\eta)^{-1}(\hat{y}_t - \eta\hat{y}_{t-1})$ with $\hat{y}_t$ denoting the output and η is the habit persistence parameter. As emphasized by Liu et al. (2020), the elasticity of consumption with respect to the interest rate depends on both σ and η. The labour supply decision can be expressed as:

$$\sigma\hat{x}_t + \varphi\hat{y}_t = \hat{mc}_t - \hat{\mu}_t; \tag{2}$$

where $\hat{mc}_t$ is the real marginal cost, φ denotes the inverse of the Frisch elasticity of labour supply and $\hat{\mu}_t = \bar{\tau}\hat{\tau}_t/(1-\bar{\tau})$ is a cost-push shock resulting from variations in the labor income tax rate.

The New Keynesian Phillips Curve (NKPC) arises from the firm's profit maximization problem and is written as:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\gamma}E_t\hat{\pi}_{t+1} + \frac{\gamma}{1+\beta\gamma}\hat{\pi}_{t-1} + \kappa\hat{mc}_t; \tag{3}$$

where β is the discount factor, γ indicates the degree of price indexation and κ is the slope of the NKPC given by $(1-\alpha\beta)(1-\alpha)/(\alpha(1+\beta\gamma))$. Here, α measures price stickiness as in Calvo (1983). This NKPC captures both rational expectations and the potential persistence of inflation.

The stochastic dynamics are driven by three orthogonal structural shocks: a productivity, a preference and a cost push shock. These shocks follow a first-order autoregressive AR(1) process given respectively by:

$$\hat{a}_t = \rho_a\hat{a}_{t-1} + \sigma_a(S_t^{Vol})\varepsilon_t^a \tag{4}$$

$$\hat{\delta}_t = \rho_\delta\hat{\delta}_{t-1} + \sigma_\delta(S_t^{Vol})\varepsilon_t^\delta \tag{5}$$

$$\hat{\mu}_t = \rho_\mu\hat{\mu}_{t-1} + \sigma_\mu(S_t^{Vol})\varepsilon_t^\mu; \tag{6}$$

where ε_t^a, ε_t^δ and ε_t^μ represent independent and identically distributed stochastic processes following a

[2] A variable with a hat, $\hat{x}_t$, denotes the log deviation of this variable, x_t, from its steady state, $\bar{x}$.

$\mathcal{N}(0,1)$. The volatility of these structural shocks is captured by σ_a, σ_δ and σ_μ respectively. These volatilities are allowed to switch according to an indendependent two-state Markov process given by:

$$S_t^{Vol} \in \{Low, High\};$$

where $(S_t^{Vol} = High)$ corresponds to the state in which the volatility of the structural shocks is high and $(S_t^{Vol} = Low)$ corresponds to the state with low volatility.

The central bank minimizes a loss function given by equation (7), as in Debortoli et al. (2014); Debortoli and Lakdawala (2016) and Liu et al. (2020), among others.

$$\mathcal{L} = \beta E_t \sum_{t=0}^{\infty} \left(\omega_\pi(S_t^{Pol})\hat{\pi}_t^2 + \omega_y(S_t^{Pol})\hat{y}_t^2 + \omega_r(S_t^{Pol})(\hat{r}_t - \hat{r}_{t-1})^2\right); \tag{7}$$

where ω_π, ω_y and ω_r are the weights put on inflation, output and the interest rate respectively. Unlike much of the literature, we do not normalize ω_π to 1. The weight on the interest rate, as in Coibion and Gorodnichenko (2012), reflects the central bank's desire to smooth interest rates, which aligns with its goal of maintaining financial stability. We allow the parameters of the loss function to be governed by an independent two-state Markov process given by:

$$S_t^{Pol} \in \{Low, High\}$$

The high state, $(S_t^{Pol} = High)$, occurs when the SARB assigns a larger weight to inflation deviations. This represents the most conservative policy stance. The low state, $(S_t^{Pol} = Low)$, is the least conservative, with a lower weight on inflation. The other two parameters of the loss function, ω_y and ω_r, are also allowed to switch, though not necessarily in the same direction. To account for the loose commitment policy, we introduce the commitment probability parameter, ω_{LC}. This parameter measures the SARB's likelihood of adhering to its past promises and is also used to gauge the credibility of the policymaker, as seen in Debortoli and Lakdawala (2016); Lakdawala and Wu (2017). The next section discusses the loose commitment estimation strategy and the data used in the analysis.

3 Estimation and data

The article uses three optimal policies: the full commitment, the loose commitment and the discretion case. In this section, we briefly review the estimation framework for the loose commitment policy, as the two extreme cases, the full commitment and discretion; are well-documented in the literature. We then discuss the data and the measurement equations used in the analysis.

3.1 Optimisation under loose commitment

Debortoli et al. (2014) propose a framework for solving optimal policy plans under loose commitment.[3] The structural equations of a linear model can be expressed as:

$$A_{-1}y_{t-1} + A_0 y_t + A_1 E_t y_{t+1} + B v_t = 0; \tag{8}$$

where y_t is a vector of endogenous variables and v_t is a vector of serially uncorrelated exogenous processes with $v_t \sim (0, \Sigma_v)$. The central bank's loss function, derived from a second-order approximation of a utility function, can be represented as:

$$\sum_{t=0}^{\infty} \beta^t y_t' W y_t \tag{9}$$

Under loose commitment, the policy maker commits to an interest path but may deviate from it. This reoptimization follows a two-state Markov process given by:

$$\eta_t = \begin{cases} 1 & \text{with probability } \omega_{LC} \\ 0 & \text{with probability } (1 - \omega_{LC}) \end{cases}$$

If $\eta_t = 1$, commitments are honored with a probability $0 \leq \omega_{LC} \leq 1$. However, when $\eta_t = 0$, promises are reneged and reoptimization occurs, leading to the formulation of a new policy. This specification encompasses two extreme cases. Whenever $\omega_{LC} = 0$, the policy corresponds to the discretionary case, while the full commitment case is recovered by setting $\omega_{LC} = 1$.

As in Schaumburg and Tambalotti (2007) and Debortoli and Nunes (2010), the policy problem can be written as:

$$y_{-1}^{'} P y_{-1} + d = \min_{\{y_t\}_{t=0}^{\infty}} E_{-1} \sum_{t=0}^{\infty} (\beta\gamma)^t \left[y_t' W y_t + \beta (1-\gamma) (y_t' P y_t + d) \right] \tag{10}$$

$$\text{s.t.} \quad A_{-1}y_{t-1} + A_0 y_t + \gamma A_1 E_t y_{t+1} + (1-\gamma) A_1 E_t y_{t+1}^r + B v_t = 0; \quad \forall_t \geq 0$$

where $y_{-1}^{'} P y_{-1} + d$ is the value function at time t when reoptimization occurs. Here, P and d are obtained through the solution procedure. The objective function is discounted at $\beta\gamma$, which reflects the scenario in which reoptimization never occurs. The expectations of future variables are a weighted average of two terms in any period t. The first, y_{t+1} with weight γ, represents the allocation when current plans are honored. The second term, y_{t+1} with weight $(1-\gamma)$, reflects the choices made in $t+1$ if reoptimization occurs. Expectations about choices following reoptimization depend on the state variables,

[3] This is a brief summary. For more details, refer to Debortoli et al. (2014).

such that:

$$E_t y^r_{t+1} = \tilde{H} y_t \tag{11}$$

$\tilde{H}$ is taken as given as the policymaker cannot directly determine the allocation implemented when reoptimization occurs. For any $\tilde{H}$, the Lagrangian of the optimal policy problem can be expressed as:

$$\begin{aligned} \mathcal{L} \equiv & E_{-1} \sum_{t=0}^{\infty} (\beta\gamma)^t \Bigg\{ y_t' \left[W + (1-\gamma)\beta P\right] y_t + \lambda_{-1}' \beta^{-1} A_1 y_t \\ & + \lambda_t' \left[A_{-1} y_{t-1} + \left(A_0 + (1-\gamma) A_1 \tilde{H} \right) y_t + B v_t \right] \Bigg\}; \end{aligned} \tag{12}$$

where $\lambda_{-1} = 0$, $\tilde{H}$ and y_{-1} are both given. The solution of the problem is given by a time-invariant policy function:

$$\begin{bmatrix} y_t \\ \lambda_t \end{bmatrix} = \begin{bmatrix} H_{yy} & H_{y\lambda} \\ H_{\lambda y} & H_{\lambda\lambda} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ \lambda_{t-1} \end{bmatrix} + \begin{bmatrix} G_y \\ G_\lambda \end{bmatrix} v_t; \tag{13}$$

where the H and G matrices depend on the unknown matrix $\tilde{H}$. When there is reoptimization in period t, the vector λ_{t-1} is reset to zero. Thus $y_t^r = H_{yy} y_{t-1} + G_y v_t$. Moving this equation by one period and taking expectations, we get $E_t y^r_{t+1} = H_{yy} y_t$. In a rational expectation equilibrium, for this expression to be consisent with equation (11), it should be the case that:

$$H_{yy} = \tilde{H} \tag{14}$$

The loose commitment optimal policy is the solution of a fixed point problem in the matrix H. Debortoli et al. (2014) propose an algorithm to solve for that fixed point. Solving for the Lagrangian given by (12), for a given guess of matrix H and using the law of motion from (13) to compute expectations terms, one obtains:

$$\Gamma_0 \begin{bmatrix} y_t \\ \lambda_t \end{bmatrix} + \Gamma_1 \begin{bmatrix} y_{t-1} \\ \lambda_{t-1} \end{bmatrix} + \Gamma_v v_t = 0; \tag{15}$$

with

$$\Gamma_0 \equiv \begin{bmatrix} A_0 + A_1 H_{yy} & \gamma A_1 H_{y\lambda} \\ 2W + \beta A_{-1}' H_{\lambda y} & A_0' + (1-\gamma) H_{yy}' A_1' + \beta\gamma A_{-1}' H_{\lambda\lambda} \end{bmatrix};$$

$$\Gamma_1 \equiv \begin{bmatrix} A_{-1} & 0 \\ 0 & \beta^{-1} \mathcal{I}_\gamma A_1' \end{bmatrix}; \qquad \Gamma_v \equiv \begin{bmatrix} B \\ 0 \end{bmatrix}.$$

The resulting law of motion is given by:

$$\begin{bmatrix} y_t \\ \lambda_t \end{bmatrix} = -\Gamma_0^{-1}\Gamma_1 \begin{bmatrix} y_{t-1} \\ \lambda_{t-1} \end{bmatrix} - \Gamma_0^{-1}\Gamma_v v_t; \tag{16}$$

where the matrix Γ_0 is assumed to be nonsingular.

The final step is to verify that this law of motion coincides with the initial guess, such as $H = -\Gamma_0^{-1}\Gamma_1$. If not, the guess-and-verify procedure is repeated until convergence is achieved. Debortoli et al. (2014) note that this framework is more efficient and has the additional advantage that the unique full commitment solution serves a natural initial guess. Starting from this point, the probability of commitment is gradually reduced to the discretionary case using the solution from the previous iteration. This approach reduces the possibility of multiple solutions. Once the matrices H and G are obtained, the model can be simulated and second moments as well as impulse response functions (IRFs) can be computed.

3.2 Data and observation equations

The article uses quarterly South African data from 1994Q1 to 2022Q2. Three observable variables are used: real GDP growth (RGDP), inflation (INF) and the nominal short-term interest rate (INT). RGDP is computed as the log difference of seasonally adjusted real GDP. INF is the annualized log difference of the seasonally adjusted consumer price index (CPI) and INT is the annualized nominal short-term interest rate, proxied by the South African treasury bill rate. The data are sourced from the FRED database of the Federal Reserve Bank of St. Louis.[4] To link the model variables with the data, the measurement equations are specified as:

$$\begin{aligned} RGDP_t &= \hat{y}_t - \hat{y}_{t-1} + \hat{a}_t + a^Q; \\ INF_t &= 4\hat{\pi}_t + 4\pi^Q; \\ INT_t &= 4\hat{R}_t + 4a^Q + 4\pi^Q + 4r^Q; \end{aligned}$$

where $a^Q \equiv 100(\bar{a} - 1)$; $\pi^Q \equiv 100(\bar{\pi} - 1)$ and $r^Q \equiv 100(1/\beta - 1)$ represent respectively the quarterly RGDP, INF and INT at the steady state.

[4] Section A.1 of the appendix provides more details of the data used.

4 Empirical results

This section focuses on the empirical results. First, we determine which model, between the constant parameters and the regime switching, best fits the data. Once this is established, we identify the optimal policy preference of the SARB. Both exercises are conducted using the log marginal data density (MDD) of the different models. We then discuss the estimated parameter modes, analyze the IRFs and conduct counterfactual analyses.

4.1 Model comparison

We estimate a regime-switching model to identify the monetary policy objectives and preferences of the SARB. We allow the parameters in the loss function and the volatility of the structural shocks to switch independently between two states. To demonstrate that the economy is better characterized by a model that accommodates these switches, we first estimate a constant parameters model. This is done by obtaining an approximate likelihood using the Kalman filter. We then combine this likelihood with our priors to derive the posterior distribution. The posterior is maximized using the stochastic search approach of the Artificial Bee Colony (ABC) optimization routine.[5] Starting from the obtained modes, we sample the posterior using the Random Walk Metropolis-Hastings (RWMH) algorithm. We run two parallel Markov chains, generating half a million draws for each optimal policy model, with a burn-in of 100,000 draws. To control for serial correlation, we retain every 5th draw. All the estimations are conducted using the Maih's (2015) Rationality in Switching Environments (RISE) Toolbox of Matlab.

The regime switching model is estimated following the same procedure as the constant parameters model, except that the likelihood is obtained using a modified version of the Kim and Nelson's (1999) filter as in Maih (2015). Using the obtained posteriors, we compute the log MDD for both models based on the Laplace approximation. Table 1 presents the results. Notably, the different policies under the regime switching model have a larger log MDD compared to their constant parameters counterparts. We can therefore conclude that the regime switching model provides a better fit to the data.

While the constant parameters model identifies full commitment as the preferred policy, the regime switching retains loose commitment instead. This indicates that loose commitment better characterizes the SARB's preferences. Furthermore, the volatility of the structural shocks and the degree of conservatism of the SARB have not remained constant over time. By employing a regime switching model, we are able to more accurately identify the SARB's policy preferences, which clearly differ from the full commitment policy identified under the constant parameters model.

[5] Table 5 of the Appendix presents the priors and posterior modes of the constant parameters model.

Table 1: Model comparison

Model	Full commitment	Loose commitment	Discretion
Constant parameters	-633.25	-733.23	-672.35
Regime Switching	-509.85	-491.19	-511.77

4.2 Priors and posterior modes

We now turn to our model of interest. Table 2 presents the prior and posterior modes for the full commitment, loose commitment and discretion policies under the regime switching model. We calibrate the steady-state values of RGDP, INF and INT to match their sample averages. The discount factor, β, is calibrated to align with the average INT. For the remaining parameters, we set their priors using quantiles of the respective distributions rather than specifying their moments.[6]

We first examine the posterior maximization results for the loose commitment policy as it provides the best fit to the data. The probability that previous commitments are honored is $\omega_{LC} = 0.43$, implying that policy reoptimization occurs on average every two quarters. The Calvo parameter, $\alpha = 0.9$, indicates that price contracts last for two and a half years. There is a modest degree of price indexation, $\gamma = 0.03$; a low inverse Frisch labour supply elasticity, $\varphi = 0.001$; but a significant degree of external habit formation, $\eta = 0.7$ and a high elasticity of substitution, $\sigma = 13.1$. These deep parameters are similar to those of the full commitment and discretion policies, with a few exceptions. Under full commitment, the elasticity of substitution decreases to $\sigma = 8.9$. Under discretion, this elasticity drops substantially to $\sigma = 3.07$, while the degree of price indexation increases tenfold to $\gamma = 0.26$. This rise in price indexation is due to the lack of history dependence under discretion, as inflation inertia carries more weight, as discussed in Liu et al. (2020).

The cost-push shocks account for most of the volatility in the data across all three policies and both states. Notably, both preference and cost-push shocks are highly persistent under loose and full commitment policies. Their persistence modes are estimated at $\rho_\delta = 0.83$, $\rho_\mu = 0.97$ for loose commitment, and $\rho_\delta = 0.88$, $\rho_\mu = 0.91$ for full commitment, respectively. Under discretion, the persistence of productivity and cost-push shocks is significantly reduced.

For the loss function, we find that the weights on inflation are substantial under the full commitment, $\omega_\pi = 1.26$; followed by the loose commitment, $\omega_\pi = 0.87$; under the high-response state. However, under the low-response state, both weights decrease significantly. For the discretionary case, these

[6] The same calibration and prior distributions were used for the constant parameters model.

weights are relatively small. The weights on output, ω_y, are larger under the low regime compared to the high regime for both full commitment and loose commitment policies. This indicates that when the SARB is less conservative, it reacts more strongly to output deviations. In the discretionary case, there is a strong reaction to output deviations under the high regime. The interest rate smoothing, representing the objective of financial stability, is the less dominant goal for monetary policy albeit larger for the full commitment, $\omega_r = 0.72$, in the high regime.

As in Chen et al. (2017b); Liu et al. (2020), the differences in these estimates break the divine coincidence present in a canonical New Keynesian model. Not only does the cost-push shock create a trade-off between inflation and output, but preference and productivity shocks also contribute to this trade-off. This is due to the presence of external habit formation and inflation inertia in the model.

Under discretion, there is a stabilization bias arising from the policymaker's inability to make credible promises, leading to higher inflation volatility than the optimal level (Paez-Farrell, 2023). To fit the data better under discretion, there is a substantial increase in inflation inertia through the degree of price indexation. On the other hand, as in Chen et al. (2017b), the full commitment policy is characterized by large and persistent cost-push shocks to generate meaningful trade-offs. Consequently, it requires substantial weights on output and the interest rate in the loss function to better fit the data. In contrast, the discretionary case is characterized by high volatility in cost-push shocks, but these shocks are not very persistent. In the next section, we examine the responses of the endogenous variables to the shocks that drive business cycles.

Table 2: Priors and posterior modes - Regime switching model

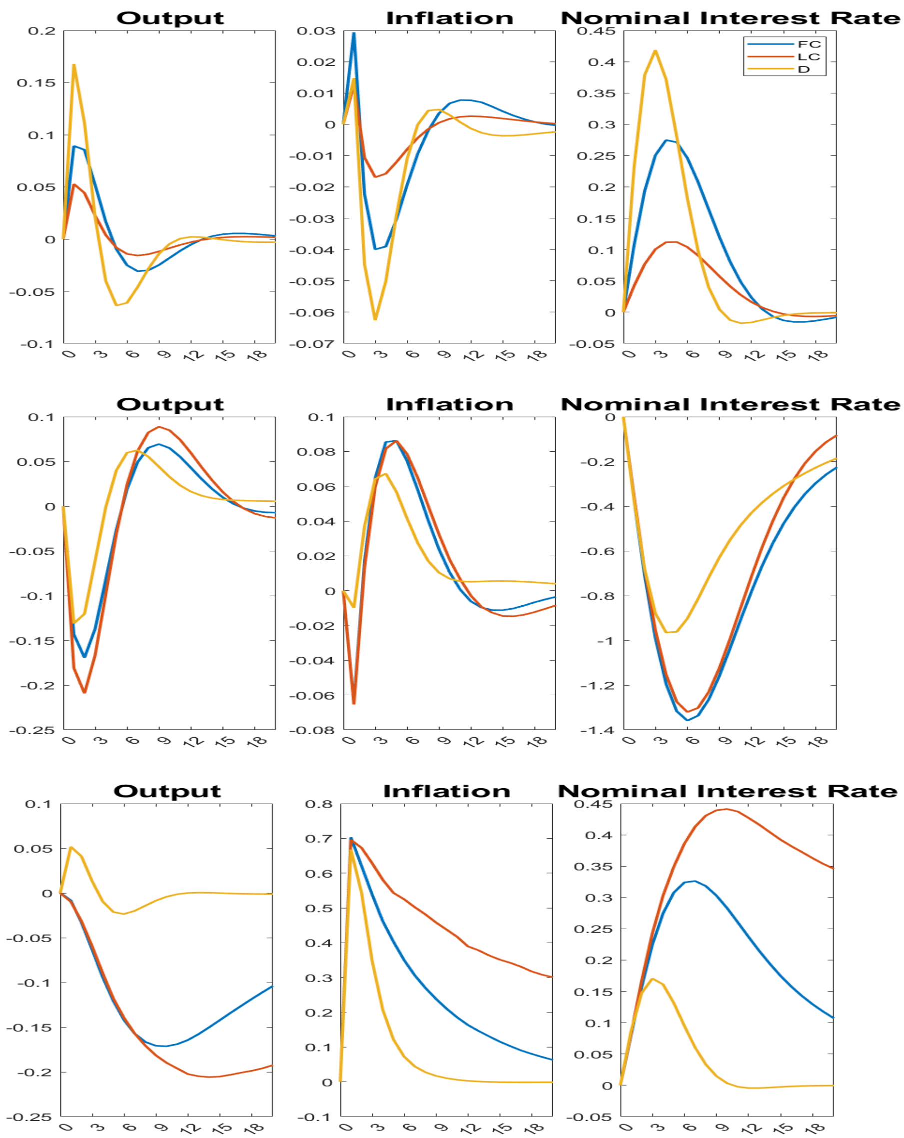
Parameters	Prob. Dist.	Low	High	Full commitment	Loose commitment	Discretion
ω_{LC}	Beta	0.001	0.900	-	0.4283	-
α	Beta	0.010	0.900	0.8991	0.9274	0.8558
γ	Beta	0.010	0.900	0.0262	0.0278	0.2561
η	Beta	0.010	0.900	0.6979	0.6486	0.6890
σ	Normal	0.010	30.00	8.8794	13.085	3.0706
φ	Normal	0.010	30.00	0.0010	0.0010	0.0010
ρ_a	Beta	0.100	0.980	0.5542	0.4187	0.4795
ρ_δ	Beta	0.100	0.980	0.8841	0.8318	0.8996
ρ_μ	Beta	0.100	0.980	0.9123	0.9722	0.5844
Coef_TP_L_H	Beta	0.001	0.900	0.0399	0.0515	0.0279
Coef_TP_H_L	Beta	0.001	0.900	0.0418	0.0596	0.0297
$\omega_r(S_t^{Pol} = Low)$	Gamma	0.01	3.000	0.1950	0.1359	0.3227
$\omega_r(S_t^{Pol} = High)$	Gamma	0.01	3.000	0.7154	0.4170	0.1131
$\omega_y(S_t^{Pol} = Low)$	Gamma	0.01	3.000	1.1153	0.6360	0.4415
$\omega_y(S_t^{Pol} = High)$	Gamma	0.01	3.000	0.9564	0.5573	0.7993
$\omega_\pi(S_t^{Pol} = Low)$	Gamma	0.01	3.000	0.0010	0.0010	0.0010
$\omega_\pi(S_t^{Pol} = High)$	Gamma	0.01	3.000	1.2574	0.8732	0.0010
Vol_TP_L_H	Beta	0.001	0.900	0.0282	0.0177	0.0167
Vol_TP_H_L	Beta	0.001	0.900	0.0485	0.0226	0.0193
$\sigma_a(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	0.4842	0.5244	0.4863
$\sigma_a(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	10.000	8.3115	8.3822
$\sigma_\delta(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	2.0748	1.4942	3.8762
$\sigma_\delta(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	3.1346	1.8377	5.3035
$\sigma_\mu(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	7.2989	8.5831	8.1486
$\sigma_\mu(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	8.6558	8.9962	9.0185

4.3 Impulse response functions

The generalized IRFs of the estimated models are reported in Figure 1. As noted earlier, the presence of external habit formation breaks the divine coincidence. As a result, there is a trade-off between output and inflation even in the presence of technological and preference shocks. This is evident from the IRFs, as inflation cannot be perfectly stabilized following these shocks. The optimal response to a technological shock is a positive output gap and an initial increase in inflation, followed by a decline in the short run. Given the initial inflationary pressures, the nominal interest rate rises to mitigate the undesirable effects of habit formation, as discussed in Leith et al. (2012).

The high persistence of the cost-push shock under the full and loose commitment policies leads to more persistent inflation compared to the discretionary case. Due to the modest interest rate smoothing under loose commitment, there is a prolonged rise in the interest rate. For the central bank to lower expectations of future inflation, output must remain below potential for a sustained period, as highlighted in Steinsson (2003). Therefore, high persistence of cost-push shocks is optimal for both commitment cases. Walsh (2017) notes that reducing inflation expectations improves the trade-off between inflation and output variability. Finally, it is important to note that the responses of the variables under loose commitment do not always fall between the two extreme cases of full commitment and discretion. This, as emphasized by Debortoli et al. (2014), is a feature of the loose commitment policy, which introduces uncertainty about future reoptimization.

Figure 1: IRFs of estimated models



Note: The figure plots the Generalized IRFs following a technology shock (first row), a preference shock (second row) and a cost push shock (last row) of the estimated model under full commitment, loose commitment and discretion.

4.4 Smoothed state probabilities

In this subsection, we examine the evolution of the economy across different states. Figure 2 presents the smoothed probabilities of being in the high-response state (on the right axis) alongside the inflation rate (on the left axis).[7] Recall that the high-response state corresponds to periods with a larger weight on inflation in the loss function, representing the inflation-conservative phase. From the figure, we observe that the SARB has been inflation-conservative for most of the sample, except for a few short-lived periods.

Specifically, the SARB was less conservative during 2002–2003, coinciding with the small bank crisis in South Africa. During this period, the SARB pursued a loose monetary policy, reducing the repo rate and fueling a rise in credit extension, which ultimately led to the collapse of Saambou Bank. This triggered contagion among small and medium-sized banks in the country (Havemann, 2021). The second period of reduced conservatism occurred during the 2007 global financial crisis, when the economy slipped into recession. The SARB responded by cutting the policy rate to mitigate the crisis, reaching one of its lowest recorded levels by 2012. The final period occurred in early 2020, when the country recorded its first cases of COVID-19 and, a few months later, implemented a series of lockdowns. To address the crisis, the SARB implemented a series of policy rate cuts.

Figure 2: Inflation and smooth probability $S_t^{Pol} = High$

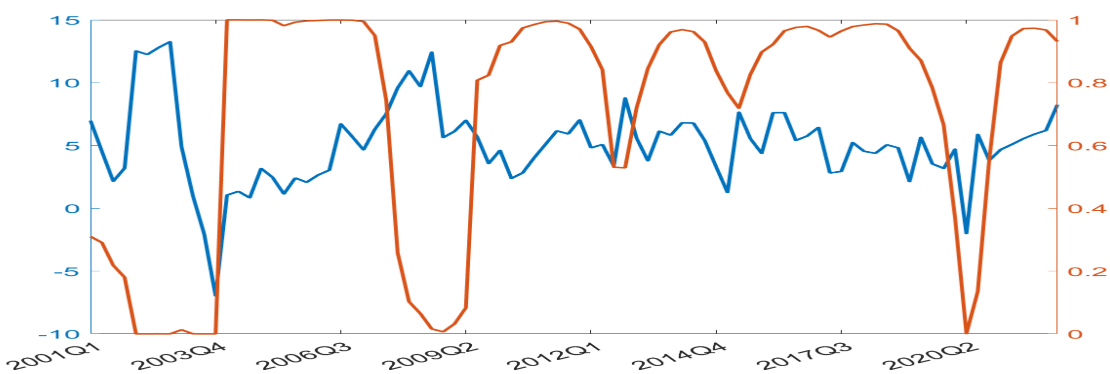
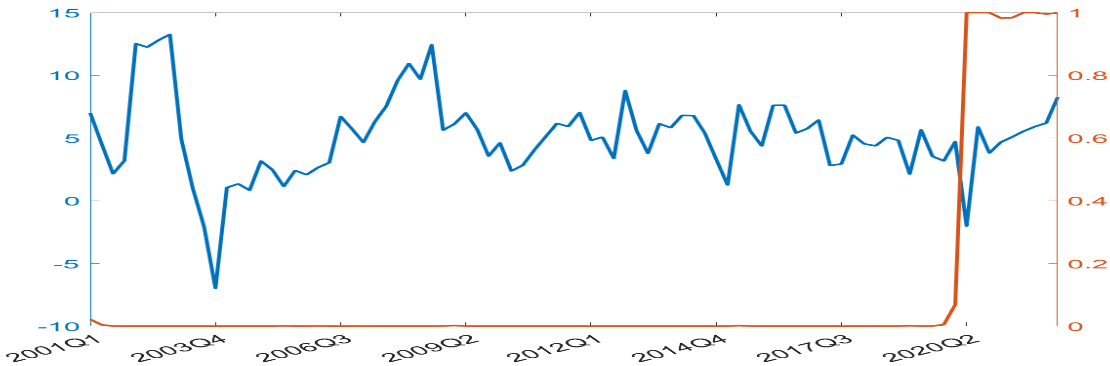


Figure 3 plots the smoothed probabilities of being in the high-volatility state (on the right axis) alongside the inflation rate (on the left axis). The only period of high volatility that stands out occurred during the COVID-19 pandemic. This is unsurprising, given the unprecedented nature of the shock. Indeed, the pandemic caused significant supply chain disruptions, leading to a prolonged recession.[8]

[7] Inflation is measured as the percentage deviation of the annualized inflation rate from its steady state.

[8] We imposed various restrictions when estimating the model, all of which resulted in the same smoothed probabilities of high volatility.

Figure 3: Inflation and smooth probability $S_t^{Vol} = High$



5 Counterfactuals

In this section, we conduct a counterfactual exercise. Given that loose commitment is the optimal policy that best fits the data, we analyze what the outcomes would have been if the SARB had followed a full commitment or discretionary policy. In addition to these polar cases, we also consider a loose commitment policy with a higher commitment probability parameter, $\omega_{LC} = 0.80$, which is typically observed in central banks of developed economies. For example, Debortoli and Lakdawala (2016) report such a parameter for the US Federal Reserve.[9]

Table 3 presents the volatility of output, inflation and the short-term interest rate under these scenarios. The results indicate that the SARB could have achieved lower inflation volatility by adopting a full commitment policy or a loose commitment policy with a high commitment probability ($\omega_{LC} = 0.80$). Specifically, the volatility under these policies is almost one-third of the volatility observed in the data and more than half of that under discretion. There is also a reduction in output and interest rate volatility under full commitment, while the difference under loose commitment is not substantial. Thus, the SARB could have achieved better outcomes in terms of price stability by being more committed.

Table 3: Counterfactual volatility

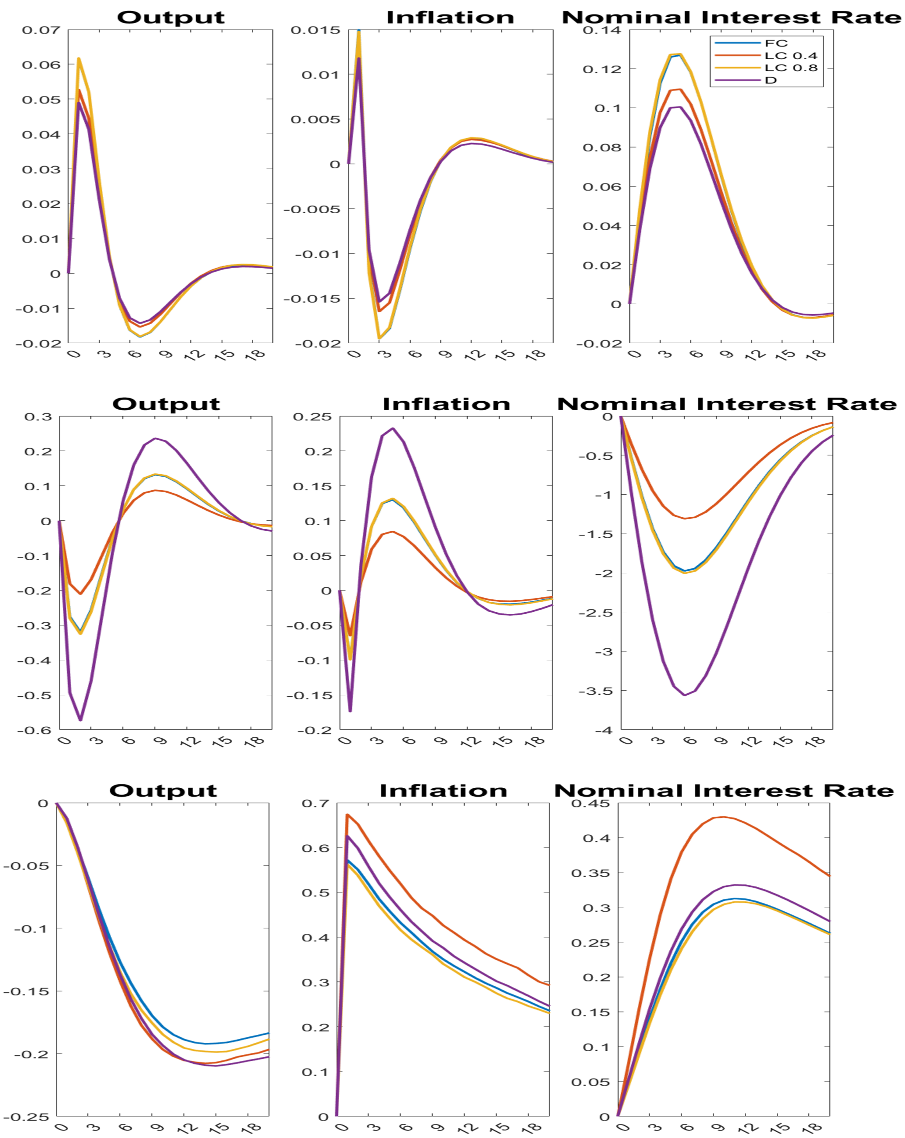
Variables	FC	LC $\omega_{LC} = 0.80$	D	LC $\omega_{LC} = 0.43$	Data
Output	0.606	2.465	8.899	7.250	2.258
Inflation	0.982	0.963	2.510	1.385	3.378
Interest Rate	12.147	15.824	33.602	17.607	14.088

Note: Standard deviation under full commitment (FC), loose commitment (LC), discretion (D) counterfactuals, estimated model (LC Model) and the data.

[9] With this commitment parameter, reoptimization occurs on average every five quarters. It is worth noting that Lakdawala and Wu (2017) obtained a lower commitment parameter, 0.6, when considering the term structure of interest rates for the US.

We present the generalized IRFs of the respective counterfactuals in Figure 4. The IRFs show hump-shaped responses of output and inflation following the different shocks. Notably, the central bank has a stronger incentive to respond aggressively to shocks, particularly after a technological shock, when moving from discretion to full commitment. Following a positive cost-push shock, Walsh (2017) emphasizes that the only tool available to offset the impact on inflation under discretion is the output gap. However, under commitment, the central bank can leverage both the output gap and inflation expectations to manage the shock. We can note a better stabilization of inflation, under commitment, after a cost-push shock.

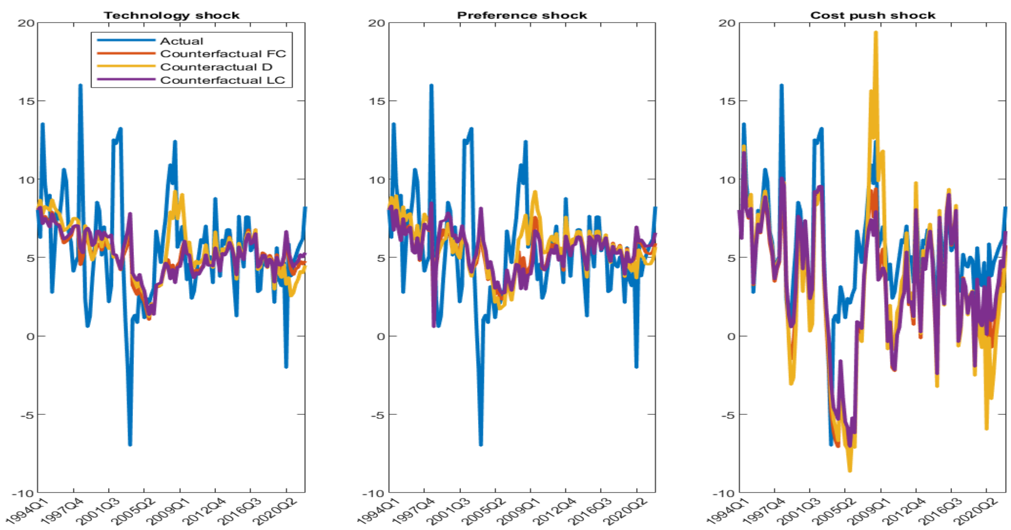
Figure 4: IRFs counterfactuals



Note: The figure plots the counterfactuals Generalized IRFs following a technology shock (first row), a preference shock (second row) and a cost push shock (last row) of the estimated models under full commitment, loose commitment and discretion.

Lastly, we examine what the inflation rate would have been under the counterfactual scenarios. We analyze this by isolating each shock separately. Figure 5 plots the actual inflation data alongside the counterfactual inflation series for full commitment, loose commitment and discretion. These counterfactuals support the estimation results. Specifically, without cost-push shocks, the inflation rate would have remained stable and, for most of the sample period, below the actual data, regardless of the optimal policy. This reinforces the significant role played by cost-push shocks in explaining the volatility observed in the data. However, under the d, the inflation rate would have been higher compared to the other policies for most of the sample period when cost-push shocks are present. Moreover, the inflation rate under this policy would have exceeded the actual data during certain periods, particularly between 2008 and 2009, which recorded the highest inflation rates. Thus, cost-push shocks render difficult the stabilization of inflation.[10]

Figure 5: Counterfactual: Commitment vs Discretion



6 Robustness

Chen et al. (2017a) stress that the estimation of optimal policies depends on the specification of the objective function. We therefore reestimate our model using their proposed loss function.[11] Their loss function is consistent with the underlying model and is given by:

$$\mathcal{L} = \beta E_t \sum_{t=0}^{\infty} \left(\omega_\pi (S_t^{Pol}) \hat{\pi}_t^2 + \omega_y (S_t^{Pol}) \left(\hat{y}_t - \frac{\sigma}{\varphi} \hat{\delta}_t \right)^2 + \omega_x (\hat{X}_t + \hat{\delta}_t)^2 + \omega_p (\hat{\pi}_t - \hat{\pi}_{t-1})^2 \right) \quad (17)$$

Under this specification, we allow only ω_π and ω_y to be governed by independent two-state Markov processes, as in the simple loss function from equation (7). This loss function does not include interest rate smoothing. Table 4 presents the priors and posterior modes for this exercise. We observe that the posterior mode for the loose commitment parameter is $\omega_{LC} = 0.43$, consistent with the ad hoc loss function from equation (7). For the other parameters, we find similarities with the previous model. Specifically,

[10] The data represent the deviation of the annualized inflation rate from its target.

[11] We also reestimate our model using a uniform distribution prior on the interval $[0, 1]$ for ω_{LC} as in Debortoli and Lakdawala (2016). With this choice, the posterior is entirely determined by the data. We find $\omega_{LC} = 0.545$. The results are available upon request.

the cost-push shock volatility continues to drive the business cycle and inflation stability remains the primary goal of monetary policy.

Therefore, we conclude that we are able to identify not only the monetary policy objectives of the SARB, characterized by a flexible inflation-targeting framework, but also its preferences. These preferences are characterized by a loose commitment policy with frequent reoptimization.

Table 4: Priors and posterior modes - Regime switching optimal policy

Parameters	Prob. Dist.	Low	High	Full commitment	Loose commitment	Discretion
ω_{LC}	Beta	0.001	0.900	-	0.4283	-
α	Beta	0.010	0.900	0.7598	0.7611	0.6005
γ	Beta	0.010	0.900	0.6391	0.6230	0.0530
η	Beta	0.010	0.900	0.8330	0.7771	0.6993
σ	Gamma	0.010	30.00	6.6112	8.5207	4.3189
φ	Gamma	0.010	30.00	5.881	5.9641	5.4608
ρ_a	Beta	0.100	0.980	0.0168	0.0176	0.010
ρ_δ	Beta	0.100	0.980	0.9705	0.9678	0.9193
ρ_μ	Beta	0.100	0.980	0.4435	0.4276	0.9800
Coef_TP_L_H	Beta	0.001	0.900	0.0105	0.0080	0.0091
Coef_TP_H_L	Beta	0.001	0.900	0.0207	0.0270	0.0282
ω_p	Gamma	0.001	3.000	0.0010	0.0010	0.0707
ω_x	Gamma	0.001	3.000	3.000	2.8148	1.9651
$\omega_y(S_t^{Pol} = Low)$	Gamma	0.001	3.000	2.970	2.1030	1.9279
$\omega_y(S_t^{Pol} = High)$	Gamma	0.001	3.000	0.0010	0.0010	0.001
$\omega_\pi(S_t^{Pol} = Low)$	Gamma	0.001	3.000	0.7369	0.4333	0.6168
$\omega_\pi(S_t^{Pol} = High)$	Gamma	0.001	3.000	0.7516	0.4372	0.7859
Vol_TP_L_H	Beta	0.001	0.900	0.0415	0.0408	0.0324
Vol_TP_H_L	Beta	0.001	0.900	0.0270	0.1452	0.1319
$\sigma_a(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	0.6386	0.6415	0.6616
$\sigma_a(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	7.2927	7.2627	6.6059
$\sigma_\delta(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	1.8332	1.2528	1.6462
$\sigma_\delta(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	6.9756	4.9892	6.4197
$\sigma_\mu(S_t^{Vol} = Low)$	Inv. Gamma	0.001	30.00	7.1025	7.2836	3.3243
$\sigma_\mu(S_t^{Vol} = High)$	Inv. Gamma	0.001	30.00	10.00	10.000	7.6190

Can these results be related to the credibility of the SARB? The loose commitment parameter indicates that policy reoptimization occurs more frequently. Debortoli and Lakdawala (2016) link the loose commitment parameter to the notion of central bank credibility, suggesting that frequent reoptimization is a feature of less credible central banks. However, South Africa is a small emerging economy facing political and economic challenges. It is subject to numerous exogenous shocks, with supply shocks playing a significant role, as well as spillovers from developed economies, as highlighted by Pirozhkova et al. (2024).

This creates a high level of uncertainty, making it difficult to commit to and honor long-term promises. Therefore, the results do not imply a lack of credibility but rather reflect the necessity for the SARB to respond flexibly to these various shocks and challenges in a highly volatile environment.

7 Conclusion

In 2000, the SARB adopted an inflation-targeting framework with the aim of maintaining inflation within the 3%–6% range. In addition to this primary objective, the central bank is also tasked with achieving full employment and financial stability. However, employment and economic growth have remained stagnant, raising questions about the role played by the central bank. Indeed, there is no clear indication of the bank's preferences or the relative importance it assigns to its various monetary policy objectives.

This article analyzes the monetary policy objectives and preferences of the SARB using a structural model with external habit formation. Instead of relying on a monetary policy rule, we employ an optimal policy framework. Monetary policy rules depend on the policymaker's ability to fully commit to an interest rate path, but policymakers do not always keep their promises. In addition to the two polar cases of discretion and full commitment, we also consider the intermediate case of loose commitment. This optimal policy framework allows us to estimate the loose commitment parameter, which measures the probability that a policymaker will keep their promises. This parameter is closely related to the notion of central bank credibility. Using quarterly South African data from 1994Q1 to 2022Q2, we estimate the different optimal policies separately. We find that a model incorporating regime switches in policy parameters and the volatility of structural shocks fits the data better than a constant-parameters model. Furthermore, the loose commitment policy is identified as the most appropriate optimal policy, with the central bank reoptimizing on average every two quarters.

We also conduct counterfactual analyses. Our results indicate that the SARB could have achieved lower inflation volatility by following a full commitment policy or by reoptimizing less frequently. Although the literature often links optimal policy to the notion of central bank credibility, we argue that the frequent reoptimization is a result of the SARB's need to respond to various exogenous shocks in a highly volatile environment.

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A Appendix

A.1 Data description

The article uses quarterly South African data from 1994Q1 to 2022Q2. All the series are from the FRED database of the Federal Reserve Bank of St. Louis. They are as follow:

- Real GDP: Real Gross Domestic Product for South Africa, Domestic Currency, Quarterly, Seasonally Adjusted (NGDPRSAXDCZAQ);
- CPI: Consumer Price Index. All Items for South Africa, Index 2015=100, Monthly, Not Seasonally Adjusted (ZAFCPIALLMINMEI);
- INT: Treasury Bills for South Africa, Percent per Annum, Monthly, Not Seasonally Adjusted (INTGSTZAM193N).

The CPI was seasonally adjusted and, together with the INT series, transformed to quarterly frequency using monthly averages.

A.2 The constant parameters model

Table 5: Priors and posterior modes - Constant parameters model

Parameters	Prob. Dist	Low	High	Full commitment	Loose commitment	Discretion
ω_{LC}	Beta	0.001	0.900	-	0.4283	-
ω_{π}	Gamma	0.001	3.000	0.0010	0.1859	0.3413
ω_r	Gamma	0.001	3.000	0.3180	0.8175	0.0376
ω_y	Gamma	0.001	3.000	0.2390	0.0010	0.5409
α	Beta	0.010	0.900	0.8882	0.5061	0.7293
γ	Beta	0.010	0.900	0.0253	0.9458	0.9368
η	Beta	0.010	0.900	0.0010	0.0010	0.6147
σ	Gamma	0.010	30.00	2.3529	23.3170	3.2923
φ	Gamma	0.010	30.00	0.0100	0.0100	0.0100
ρ_a	Beta	0.100	0.980	0.0639	0.0278	0.0910
ρ_{δ}	Beta	0.100	0.980	0.9385	0.9800	0.9391
ρ_{μ}	Beta	0.100	0.980	0.8379	0.5593	0.2786
σ_a	Inv. Gamma	0.001	30.00	2.4813	2.6030	2.7328
σ_{δ}	Inv. Gamma	0.001	30.00	6.5666	5.6904	3.4653
σ_{μ}	Inv. Gamma	0.001	30.00	6.6501	10.000	8.3979