Forecasting Monetary Policy Rules in South Africa

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Abstract

This paper is the first one to: (i) provide in-sample estimates of linear and nonlinear Taylor rules augmented with an indicator of financial stability for the case of South Africa, (ii) analyse the ability of linear and nonlinear monetary policy rule specifications as well as nonparametric and semiparametric models in forecasting the nominal interest rate setting that describes the South African Reserve Bank (SARB) policy decisions. Our results indicate, first, that asset prices are taken into account when setting interest rates; second, the existence of nonlinearities in the monetary policy rule; and third, forecasts constructed from combinations of all models perform particularly well and that there are gains from semiparametric models in forecasting the interest rates as the forecasting horizon lengthens.

Keywords: Taylor rules, nonlinearity, nonparametric, semiparametric, forecasting

JEL classification: C14; C51; C52; C53; E52; E58

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1 Introduction

Six times a year, approximately every 8 weeks and sometimes more often, the South African Reserve Bank (SARB) announces its target for the key lending rate, the repo rate, which is the price at which the central bank lends cash to the banking system. The Reserve Bank's target for the repo rate is one of the most anticipated and influential decisions regularly affecting financial markets and is of interest to economic analysts, economic forecasters and policymakers. We first conjecture that this monetary policy decision can be described within the general form of Taylor rule models for a number of reasons. First, the SARB has a mandate to achieve and maintain price stability in the interest of balanced and sustainable economic growth and therefore output/employment stability. Second, the Monetary Policy Committee (MPC) of the South African Reserve Bank (SARB) has formulated policy in terms of the repo rate since 1998. This issue is relevant and currently debated in the case of South Africa, which has undergone important changes in its monetary policy settings over the last two decades, including central bank independence and inflation targeting of 3%-6% in 2000, having moved from a constant money supply growth rate rule first set in 1986.

The general benchmark of monetary policy rule has been the subject of intense debate in the last few years as recent economic events have turned the attention on the behaviour of certain asset prices (stock prices, house prices, exchange rates) and the concern by central banks over the maintenance of financial stability (see e.g. Bernanke and Gertler, 2001) in line with the current debate on central banks having additional objectives over and above inflation and output stabilisation (Walsh, 2009). If that is the case, it is most likely that the monetary policy reaction function responds to them once they reach certain "unsustainable" levels as opposed to when they follow their "fundamental" path.[1] This could indeed be the case with the SARB because its other primary goals, as defined in the Constitution, is to protect the value of the currency and achieve and maintain financial stability. Woglom (2003), in his discussion of how the introduction of inflation target in 2000 affected monetary policy in South Africa, points out that the response of the SARB to changes in the real value of its

[1] There has been some controversial debate as to whether the central bank should respond to financial asset prices (see e.g. De Grauwe, 2007; and Mishkin, 2008).

currency are far from clear and therefore a source of confusion.[2] It is also worth noting that South African financial institutions experienced no direct exposure to the sub-prime crisis in terms of interbank or liquidity problems of the type experienced in developed countries (see Mboweni, 2008, and Mminele, 2009). The first contribution of the paper is therefore to examine whether asset prices are one of the determinants of the interest rate setting by the SARB in the in-sample (IS) estimates. The fact that we include three different asset prices combined in a single index complements the work by Woglom (2003), where only changes in the real effective exchange rates are included in the determinants of the rule.

The second contribution is to analyse whether the Taylor rule followed by the SARB, with or without asset prices on them, displayed a nonlinear functional form. Recent research has motivated theoretically the possibility that a central bank might not follow a linear reaction function. Asymmetric preferences (e.g. a linex function as in Nobay and Peel, 2003) impose a higher cost to overshooting the inflation target rather than undershooting it. The opposite would be true for the output gap if booms are thought of as less costly than slumps. Aksoy *et al.* (2006) show that, under the opportunistic approach to disinflation, the policymaker would not actively respond to any deviation of inflation from target. For small enough deviations the policymaker concentrates on output stabilisation and will only act to bring inflation down when it exceeds a certain threshold.

A nonlinear policy rule also results from assuming a nonlinear Phillips curve. To the extent that nominal wages are downwards inflexible, inflation is a convex function of the unemployment rate (see e.g. Layard *et al.*, 1991). This, by Okun's law, means that inflation is also convex in the output gap. The nonlinear aggregate supply combined with a quadratic loss function leads to a policy rule where the response of interest rates to inflation is higher (lower) when inflation is above (below) target. For example, Surico (2007) argues that the response to inflation may be higher in periods of poor economic performance, while Cukierman and Muscatelli (2008) find that the opposite is true. Given the above strand of

[2] A different approach to the one used in our paper and in the literature cited here, is the analysis by Knedlik (2006) of the effect of real exchange rate deviations in the design of monetary policy rules. In that case optimal rules should provide optimal monetary conditions (internal stability) and should avoid volatility of capital flows (external stability). Such rules are derived for the case of South Africa from the estimation of the parameters of the estimated Monetary Conditions Index, MCI.

literature, we therefore try to shed some light on the specification of the particular monetary policy rule in South Africa.

Finally, we contribute to the scarce literature that uses Taylor rules to forecast the nominal interest rate out-of-sample (OOS). Some notable exceptions are Qin and Enders (2008) and Moura and Carvalho (2010). The former uses US data to compare the in-sample and out-of-sample properties of linear and nonlinear Taylor rules for different monetary policy regimes. The latter examines different specifications of Taylor rules in terms of their out-of-sample performance for the seven largest Latin American economies. In this study about South Africa, we construct the forecasts from linear and nonlinear parametric models as well as for the more flexible nonparametric and semiparametric models under three alternative expectations formation for the target variables. We examine forecasting gains from individual specifications as well as from the combination of all models.

2 Taylor Rules

2.1 Benchmark Linear Taylor Rule

Existing studies of the impact of inflation and output on monetary policy use a version of the Taylor rule after allowing for interest rate smoothing (Clarida *et al.*, 2000) by assuming that the actual nominal interest rate, r_t, adjusts towards the desired rate, r_t^*, as follows

$$r_t = \alpha_i(L)r_{t-1} + (1-\alpha_i)r_t^* \tag{1}$$

where $r_t^* = \bar{r} + \alpha_\pi E_t(\pi_{t+p} - \pi^*) + \alpha_y E_t(y_{t+p} - y^*) + \alpha_I E_t(I_{t+p} - I^*)$. r_t^* is the desired nominal interest rate, $\bar{r}$ is the natural interest rate, $E_t\pi_{t+p}$ is the inflation rate expected at time $t+p$, π^* is the inflation target, $(y_{t+p} - y^*)$ is the output gap expected at time $t+p$, α_π is the weight on inflation, α_y is the weight on the output gap and α_I is the weight on an index I of financial variables such as exchange rates, house prices, stock prices and other financial variables (where $I_{t+p} - I^*$ is the financial indicator gap used to augment the original rule). $\alpha_i(L) = \alpha_{i1} + \alpha_{i2}L + ... + \alpha_{in}L^{n-1}$ is the lag polynomial in the interest rate, showing interest rate persistence and smoothing.[3] We can thus write our benchmark linear model as:

$$r_t = \alpha_o + \alpha_i(L)r_{t-1} + (1-\alpha_i)[\alpha_\pi E_t\pi_{t+p} + \alpha_y E_t(y_{t+p} - y^*) + \alpha_I E_t(I_{t+p} - I^*)] + \varepsilon_t \qquad (2)$$

where $\alpha_o = (1-\alpha_i)(\bar{r} - \alpha_\pi \pi^*)$ and ε_t is an error term. Equation (2) represents a constant proportional response to inflation, output and financial indicator gaps. The theoretical basis of the linear Taylor rule (2) comes from the assumption that policymakers have a quadratic loss function and that the aggregate supply or Phillips curve is linear.

2.2 Benchmark Nonlinear Taylor Rule

More recently, however, the focus of the monetary policy literature increasingly has been placed on nonlinear models resulting from either asymmetric central bank preferences (e.g., Nobay and Peel, 2003), a nonlinear (convex) aggregate supply or Phillips curve (e.g., Dolado *et al.*, 2005; and Schaling, 2004) or, if the central bank follows the opportunistic approach to disinflation (Aksoy *et al.*, 2006).

We consider a number of regime-switching policy rules of the following form as a benchmark for nonlinear models:

$$r_t = \alpha_o + \alpha_i(L)r_t + (1-\alpha_i)R_{1t} + \lambda_t(1-\alpha_i)R_{2t} + \varepsilon_t \qquad (3)$$

where $R_{1t} = \alpha_{1\pi}E_t(\pi_{t+p} - \pi^*) + \alpha_{1y}E_t(y_{t+p} - y^*) + \alpha_{1I}E_t(I_{t+p} - I^*)$ and $R_{2t} = \alpha_{2\pi}E_t(\pi_{t+p} - \pi^*) + \alpha_{2y}E_t(y_{t+p} - y^*) + \alpha_{2I}E_t(I_{t+p} - I^*)$ and λ_t is a nonlinear function. The nonlinear function λ_t can take a number of specifications. It could take a threshold specification where the authorities would behave linearly but with different speeds of response depending on the value of a given variable (Bec *et al.,* 2002). The nonlinear function can be smooth rather than discrete and can allow the response of the interest rate to differ between two inflation regimes (higher than γ^π, and lower than γ^π):

$$\lambda_t(E_t\pi_{t+p}; \theta, \gamma^\pi) = \frac{1}{1 + e^{\theta(E_t\pi_{t+p} - \gamma^\pi)/\sigma_{E_t\pi_{t+p}}}} \qquad (4)$$

[3] We use a lag polynomial of order two in our estimation.

In equation (4), the transition function λ_t is assumed to be continuous and bounded between zero and one in the transition variable $E_t\pi_{t+p}$. As the transition variable tends to ∞, λ_t tends to 0 and as the transition variable tends to $-\infty$, λ_t tends to 1. The smoothness parameter θ determines the smoothness of the transition regimes.[4]

2.3 Nonparametric and Semiparametric Specifications

We outline above that monetary policy settings have come across so many innovations that even the linear and nonlinear parametric models might have problems to uncover the true data generating process of the interest rate. Rather than assuming that the functional form of an object is known, nonparametric and semiparametric methodologies substitute less restrictive assumptions, such as smoothness and moment restrictions.

To this end, we carry out the Nadaraya-Watson local constant regression estimator and then consider a more popular extension, namely the local linear regression method (Li and Racine, 2004).[5] A key aspect to sound nonparametric regression estimation is choosing the correct amount of local averaging (bandwidth selection). We therefore make use of two popular selection methods as a robustness check, namely the least-squares cross validation of Hall *et al.* (2004) and the AIC method of Hurvich et al. (1998).[6] More precisely, the nonparametric model for the monetary policy rule is given by

$$r_t = f((L)r_{t-1}, E_t\pi_{t+p}, E_t(y_{t+p} - y^*), E_t(I_{t+p} - I^*)) + \varepsilon_t \tag{5}$$

where $f(.)$ represents a function not known to lie in a particular parametric family.

Semiparametric models are a compromise between fully nonparametric and fully parametric specifications. They are formed by combining parametric and nonparametric mod-

[4] Note that in these models the response of interest rates to the lagged interest rate is linear, and that nonlinear policy rules can be defined using the output gap or the financial index as possible transition variables in the weighting function (4). Alternatively, one can use the quadratic logistic function as in Martin and Milas (2004). The advantage of this nonlinear form is that it allows for an inflation zone targeting regime. These nonlinear models were considered in the current paper but due to poor fits we do not report those results.

[5] In the empirical results below, we report only the best-performing nonparametric model.

[6] We make use of the methods that can be found in the R np package by Hayfield and Racine (2008).

els to reduce the curse of dimensionality of nonparametric models. We employ a popular regression-type model, namely, the partially linear model of Robinson (1988):

$$r_t = \alpha_i(L)r_{t-1} + f(E_t\pi_{t+p}, E_t(y_{t+p} - y^*), E_t(I_{t+p} - I^*)) + \varepsilon_t \tag{6}$$

where $\alpha_i(L)$ is a vector of unknown parameters to be estimated and the functional form of $f(.)$ is not specified.

3 Data

3.1 Data Discussion

Our analysis is based on monthly frequency, ranging from 1986:01 to 2008:12. The variables are described in the Appendix and displayed in Figure 1.[7] The sample period corresponds roughly to two monetary regimes, with the starting point of the sample denoting the starting point of the first regime as discussed in the introduction. In February 2000, the Ministry of Finance announced in the Budget speech that the government had decided to set an inflation target range of 3-6%. Before this announcement informal inflation targeting was already applied by the SARB with target ranges of 1-5% for core inflation from 1998.[8]

We construct a financial indicator index (I_t) designed to capture misalignments in the financial markets. It is expected that such an index is able to capture current developments of the financial markets and give a good indication of future economic activity. Castro (2008) obtains this index from the weighted average of the short-term real interest rate, the real effective exchange rate, real share prices and real property prices. The first two variables measure the effects of changes in the monetary policy stance on domestic and external

[7] We note that preliminary analysis suggests that the inflation series follows a nonstationary process. ADF and PP unit root tests do not reject the null with p-values of around 0.13. However, in line with common practice, inflation is treated as stationary.

[8] It is also worth noting that, during the first period, there was an emphasis on an eclectic set of economic indicators such as the exchange rate, asset prices, output gap, balance of payments, wage settlements, total credit extension and the fiscal stance. See Aron and Muellbauer (2000), and Jonsson (2001) for an extensive survey on the monetary regimes and institutions in place in South Africa since the 1960s.

demand conditions, whilst the other two collect wealth effects on aggregate demand. In our analysis, we compute I_t using a weighted average of the annual percentage rate of change of the nominal exchange rate of the rand against the US dollar, real share prices and real property prices. In particular, the weights for the exchange rate, stock price and property price changes are 0.6, 0.3, and 0.1, respectively. This follows from the fact that preliminary analysis of the individual series suggests that, in general, the exchange rate was the most significant financial indicator, followed by share prices and, finally, by house prices. We note the fact that it is difficult to provide a precise rationale for this exact figure about the significance of each variable, given that we examine many different regression specifications and time periods.

3.2 Expectations Formation

We have resorted to three ways by which the private sector can form its expectations of inflation, the output gap and the financial indicator gap. For the "forward-looking" case, we use a case of perfect foresight for inflation, output gap and financial indicator gap expectations by replacing expected future variables at time $t+1$ with their actual one-period-ahead inflation and then estimate by the Generalised Method of Moments (GMM), that is, $E_t\pi_{t+1} = \pi_{t+1}$, $E_t(y_{t+1} - y^*) = y_{t+1} - y^*$ and $E_t(I_{t+1} - I^*) = I_{t+1} - I^*$. For the "backward-looking" case, we use the first lag of all three variables as a measure of one-period-ahead expected inflation, output gap and financial indicator gap, $E_t\pi_{t+1} = \pi_{t-1}$, $E_t(y_{t+1} - y^*) = y_{t-1}$, $E_t(I_{t+1} - I^*) = I_{t-1} - I^*$.[9]

As a third way of expectation, we have implemented a learning rule. We compute the measure of expected future inflation by a simple inflation learning rule. After experiencing high inflation for a long period of time, there may be good reasons for the private sector not to believe the disinflation policy fully (see also Bomfim and Rudebusch, 2000). In his discussion of endogenous learning, King (1996) says that it might be rational for the private

[9] We tried different specifications and the first-period-ahead for the "forward looking" model and the first lag for the "backward looking" provided the best information. A current version for the variables as in the original Taylor seminal paper was also implemented but the results are not quantitativley different from the lag specification.

sector to suppose that, in trying to learn about the future inflation rate, many of the relevant factors are exogenous to the path of inflation itself. In light of this, King assumes that private sector inflation expectations follow a simple rule, which is a linear function of the inflation target and the lagged inflation rate. In this respect, we model the one-period-ahead expected inflation as $E_t\pi_{t+1} = \rho\pi^T + (1-\rho)\frac{1}{12}\sum_{i=1}^{12}\pi_{t-i}$ (where ρ captures the credibility of the new regime that we set at $\rho = 0.5$). This denotes that agents use the target inflation rate, π^T, (where $\pi^T = \frac{\pi^L+\pi^U}{2}$ is an average of the two pre-announced bands $\pi^L = 3\%$ and $\pi^U = 6\%$) and past information at higher lag order to form their view of what inflation would be in the next period.[10]

To sum up, we have two policy rules, linear and nonlinear, together with alternative flexible nonparametric and semiparametric models. Given that we have three types of expectation formation for each of those models, we therefore have twelve different models. Models 1 to 3 are the linear Taylor rule version of equation (2), Models 4 to 6 are the nonlinear Taylor rule version of equation (3), Models 7 to 9 are nonparametric versions of equation (5), and Models 10 to 12 are semiparametric versions of equation (6). Moreover, in our forecasting exercise, we employ combined forecasts by taking the median forecasts from amongst all different reaction functions over the same expectation formation. Forecasts are constructed by taking the median forecast values from Models 1, 4, 7 and 10 and we name this Model 13. Median forecast values from Models 2, 5, 8 and 11 form our Model 14, and median forecast values from Models 3, 6, 9 and 12 are named Model 15.

3.3 IS Analysis

In order to keep the IS analysis brief, in this section we report only a subset of all the models that will be used for forecasting purposes in the rest of the paper. In particular, Table 1 presents the results for the IS estimates of equations (2) and (3) in the case of backward-looking expectations for two different periods; the whole sample (1986-2008), and

[10] The choice of the parameter ρ is somehow *ad hoc*. Some sensitivity analysis where we try lower values than 0.5 on target inflation show that some results change, in particular, in the nonlinear Taylor rule estimation. It seems that as the transition variable becomes smoother (a moving average of past inflation) the nonlinearity gradually disappears.

the inflation targeting period (2000-2008). A few results are worth mentioning. First, nonlinear Taylor rules are not rejected by the data, especially for the latter period where the SARB explicitly targeted inflation. Looking at this latter period we can infer from the nonlinear estimates that, as inflation grows larger, the response from the Reserve Bank on both inflation and the output gap is more aggressive. Similar results are found in Castro (2008) for the cases of the ECB and the Bank of England but not for the Fed. The estimate suggests some evidence of a deflation bias to monetary policy as the response to inflation is larger when inflation exceeds the 4.56% target (the inflation threshold over the inflation targeting era). However it should be noted that the inflation effect is lower than one, therefore not satisfying the "Taylor principle" that inflation increases trigger an increase in the real interest rate. Similar results of the inflation effect being lower than one for the case of South Africa has been noted by Woglom (2003) and Naraidoo and Gupta (2009). The latter paper used the quadratic logistic function and noted that the response of monetary policy to inflation is nonlinear as interest rates respond more when inflation is further from the zone target. Hayat and Mishra (2010), using a semiparametric model, find that the Fed's monetary policy has only reacted significantly to changes in inflation when they were between approximately 6.5–8.5%, in the post-war period.

Second, the financial indicator index seems to play a role, though not a prominent one, in the monetary policy reaction function of the SARB.[11] This is also in line with the findings of Castro (2008) for the case of the ECB, which he argues made the Eurozone less vulnerable to the recent credit crunch. Our nonlinear estimates suggest that "financial disequilibria" are explicitly addressed with monetary policy when inflation is not too high, otherwise the focus is on inflation deviations from target and the output gap.

Third, the parameters of the monetary policy rule seem to change over time. For instance,

[11] Financial conditions can indeed be closely related to inflation movements (see D'Agostino and Surico, 2009). A Granger causality test between inflation and our financial indicator index (I_t) shows causality running from the financial conditions index to inflation. Contemporaneous correlation between the two series is not significantly different from zero but there exists significant correlations between inflation and lagged I_t (I_{t-k}). A rolling correlation coefficient between inflation and I_{t-k} (up to 12 lags, $k = 12$) shows that the correlation between the series significantly increased in the latter period of our sample. More complex relationships between these two series will be the subject of further research.

according to the linear rule, the SARB did not respond to output gap in the inflation target (IT) period, while it did so before IT. Similar, but not identical, inference can be made from the nonlinear Taylor rule. In that case, the output gap is significant but with a decreasing coefficient and the response of the Reserve Bank to inflation is more gradual according to its deviations from target in the latter period.[12] Some of the changes we find in the way monetary policy has been implemented in SA coincide with the results found in Woglom (2003) and Naraidoo and Gupta (2009). They also find lower levels of interest rate smoothing, increased response to inflation deviations and a decreased importance of the output gap in the Taylor rule. On the other hand, Woglom finds no significant response to changes in the real effective exchange rate in the IT period. Two reasons why our results may differ are, first, our sample for the IT period is considerably longer and, second, our financial conditions include changes in the rand-dollar exchange rate as well as stock and house prices. Lastly, the nonlinear models record the lowest Akaike Information Criterion (AIC) compared to the linear models suggesting some minor evidence of in-sample outperformance. This result is in line with the findings of Boinet and Martin (2009) and Martin and Milas (2010) among others who have recorded that nonlinear monetary policy rules tend to provide more information than their linear counterparts in-sample.

It is also worthwhile to put some of our results into the context of recent monetary policy in South Africa by using two examples. One is the period from 2006 until mid-2007, where output is close to potential, inflation is within the target zone but the financial conditions index is on the rise. Our estimates suggest an increase in the repo rate, which actually happened, contrary to what a rule without the asset prices in it would have suggested. The other interesting period is the onset of the global financial crisis in 2008. Despite the fall in the stock market and property prices the financial index gap is high because of the depreciation of the rand against the dollar. This fact, together with rising inflation, could have contributed to the fact that the SARB kept its policy rate high when faced with the incoming crisis and a negative output gap.

[12] This third result will be dealt with in the forecasting section by using both recursive and rolling window methodologies.

4 OOS Analysis

4.1 Methodology

We use the alternative models described in Section 2 as the basis for a repeated forecasting test where we obtain both short- and long-term OOS forecasts based on two types of regression estimation schemes, namely, rolling and recursive. The number of in-sample and out-of-sample observations is denoted by R and P, respectively, so that the total number of observations is $T = R + P$. In the case of the rolling window the number of in-sample observations, R, is fixed, and the parameters are re-estimated for each window in order to obtain forecasts up to horizon h. In the recursive scheme, the in-sample observations increase from R to $T - h$ and the parameters of the model are re-estimated by employing data up to time t so as to generate forecast for the following h horizons. The number of forecasts corresponding to horizon h is equal to $P-h+1$. The first estimation window in both schemes is 1986:01 to 1997:12. We calculate one-, three-, six-, and twelve-step ahead forecasts for the period 1998:01 onwards.

In general, closed-form solutions for multi-step forecasts from nonlinear models are not available. To this end, we employ bootstrap integration techniques (see e.g. Clements and Smith, 1997). The forecast evaluation criteria used are the mean squared prediction error (MSPE) and median squared prediction error (MedSPE). We extend the forecast accuracy analysis by testing the null hypothesis of equal MSPEs between any two competing models following the methodology of Diebold and Mariano (1995) and West (1996), DM$-t$ statistic, and Clark and West (2007), $CW - t$ statistic.

The DM $- t$ is computed as follows

$$\text{DM} - t = (P - h + 1)^{1/2} \frac{\bar{d}}{\widehat{S}_{dd}^{1/2}}, \tag{7}$$

where $\widehat{d}_{t+h} = \widehat{e}^2_{1,t+h} - \widehat{e}^2_{2,t+h}$, $\bar{d} = (P - h + 1)^{-1} \sum_{t=R}^{T-h} \widehat{d}_{t+h} = \text{MSPE}_1 - \text{MSPE}_2$, $\widehat{\Gamma}_{dd}(j) = (P - h + 1)^{-1} \sum_{t=R+j}^{T-h} \widehat{d}_{t+h}\widehat{d}_{t+h-j}$: for : $j \geqslant 0$: and : $\widehat{\Gamma}_{dd}(j) = \widehat{\Gamma}_{dd}(-j)$, and $\widehat{S}_{dd} = \sum_{j=-\bar{j}}^{\bar{j}} K(j/M)\widehat{\Gamma}_{dd}(j)$ denotes the long-run variance of d_{t+h} estimated using a kernel-based estimator with function $K(\cdot)$, bandwidth parameter M and maximum number of lags $\bar{j}$.

A number of issues are worth mentioning. First, multi-step forecasting, $h > 1$, induces serial correlation in the forecast error term and, accordingly, we use Heteroskedasticity and Autocorrelation-Consistent (HAC) estimators (see Clark, 1999). Second, we use the Harvey *et al.* (1997) small sample bias correction of the estimated variance d_{t+h} and comparing the statistic to the Student's t distribution with $P - h$ degrees of freedom. Third, the nonlinear Taylor rule equation (3) nests the linear equation (2) and therefore their population errors are identical under the null hypothesis making the variance d_{t+h} equal to zero (see McCraken, 2004). However, Busetti et al. (2009) show that under certain scenarios the $\mathrm{DM} - t$ statistic has good size and power properties.[13] Nevertheless, we employ the Clark and West (2007) test for equal accuracy of nested models. In order to implement this test we first compute

$$\widehat{f}_{t+h} = \widehat{e}^2_{1,t+h} - [\widehat{e}^2_{2,t+h} - (\widehat{r}_{1,t+h} - \widehat{r}_{2,t+h})^2] \tag{8}$$

where $\widehat{r}_{i,t+h}, i = 1, 2$ are the $h-$step ahead point forecast from model 1 (the restricted model, in our case, the linear) and from model 2 (the unrestricted model, the nonlinear). The $CW - t$ statistic is obtained from regressing $\widehat{f}_{t+h}$ on a constant and testing the null hypothesis that the constant equals zero. For $h > 1$ HAC standard errors are used, and the critical values for all horizons are obtained through bootstrap simulation as suggested by Clark and West.

4.2 Out-of-sample forecasting comparisons

In Table 2 we begin the comparison of forecasts with an overall view of how each individual model ranks against all the other models across different forecast horizons (one, three, six and twelve months). Columns (i)-(ii) present the average out-of-sample forecasting rankings using recursive windows for the fifteen models, according to two evaluation criteria, the mean squared prediction error (MSPE) and the median squared prediction error (MedSPE). Columns (iii)-(iv) report our forecasting rankings based on sequences of fixed-length rolling

[13] Busetti *et al.* (2009) examine the size and power properties of different forecast accuracy tests for nested and nonnested models.

windows.[14] Better or higher-ranked forecasting methods have lower numerical ranks. In examining the average rank results of Table 2, it is useful to note that if the average rank of Model i is higher than the average rank of Model j according to either the MSPE or the MedSPE, then Model i outperforms Model j according to the particular criterion for more than 50% of the forecast horizons, that is, for at least two out of the four forecast horizons used.

First, we analyse the results obtained using the recursive estimates. In this case, the forecasting models that provide the best results are the combined ones. In particular, according to the MSPE evaluation criterion, Models 13, 14 and 15 are ranked first, third and second, respectively. In terms of the MedSPE, those models come in second, fifth and third place. A result worth mentioning is that Model 4, the nonlinear Taylor rule with "backward looking" expectations, produces the best MSPE and MedSPE among all Taylor rule models and also outperforms nonparametric and semiparametric models. When we consider the rolling window scheme, that is, where observations of the early part of the sample are lost as we move forward into the future, combination of forecasts as well as semiparametric models do particularly well.

Finally, Table 2 columns (v)-(vi) compute the average MSPE and MedSPE for the recursively estimated models relative to the rolling ones. An average of less than one implies that the recursive estimates produce more accurate forecasts than the rolling estimates. In terms of MSPE, recursive estimates always produce more accurate forecasts than rolling estimates, whilst in terms of MedSPE, recursive estimates are more accurate in fourteen out of the fifteen models.[15]

Tables 3 and 4 provide a more detailed evaluation of the forecasting performance of each model against alternative ones for each forecast horizon ($h = 1, 3, 6$ and 12) and expectations

[14] The 'average out-of-sample forecasting rank' of a model is computed as an average of the rankings of a particular model across all its forecasting horizons under a particular evaluation criteria.

[15] In Table 2a we verify the forecasting performances of the rules in the last two years of the sample (2007:1 to 2008:12), which has been a period of particular uncertainty in monetary policy formulation. The combined models improve their forecasting performance with the recursive estimates. Combined and semiparametric models do particularly well with rolling estimation. A closer look at the results show that semiparametric models outperform all other models with 12-step-ahead forecasts.

formation (Panel A for backward looking, Panel B for forward looking, and Panel C for learning). These tables report the modified $DM - t$ statistic (7) and the $CW - t$ statistic (8) for the case of linear versus nonlinear models as discussed in the previous section.[16] We have named the models as follows: Model L for the linear Taylor rule models, Model NL for the nonlinear Taylor rule models, Model NP for the nonparametric models, Model SP for the semiparametric models and Model P (pooled model) for taking the median forecasts across all models (L, NL, NP and SP).[17] Table 3 provides pairwise out-of-sample forecast comparisons based on recursive estimates. Several results are worth mentioning. First, recalling that combined forecasts were usually ranked at the top in Table 2, we observe that Model P has forecast superiority over the remaining models, though this superiority is not always statistically significant. Second, parametric models (L and NL) do significantly better than non- and semiparametric models (NP and SP) over the short term horizons ($h = 1$ and 3), but such dominance disappears as the forecast horizon lengthens. Third, the nonlinear Taylor rules are never significantly better than the linear ones.

Table 4 presents the evaluation of models under a rolling window scheme. The dominance of the combined models highlighted above, especially over the very short term $h = 1$, is supported here. Consistent with results in Table 2, Model P hardly beats SP. Actually, semiparametric models significantly outperform the rest as the forecasting horizon lengthens. The third result now is that under forward looking expectations nonlinear Taylor rules are significantly more accurate than the linear ones.[18]

We acknowledge that one of the limitations and therefore criticism of any forecasting

[16] Due to space consideration, each model is compared with the others only at similar expectations formation. Full results are available upon request from the authors.

[17] We have also tried other combined forecasts, such as taking the median forecasts from all models across the three types of expectations, for e.g., Model 1 through 3. None of these forecasts was ranked any higher than the combined forecasts reported in the paper.

[18] The two recent studies mentioned in the introduction that use Taylor rules to forecast interest rates, Quin and Enders (2008) for the US and Moura and Carvalho (2010) for Latin America, do not test statistically the forecast accuracy of different Taylor rules among each other. In that sense, we contribute to the literature in comparing directly the forecast ability of different parametric Taylor rules. The result is not clear-cut as the superior performance of one set of rules versus the other depends on the expectations formation and the sample used.

exercise is that it is sample dependent. That has recently been pointed out by Rogoff and Stavrakeva (2008) in the context of short-horizon exchange rate forecasting. Both the recursive and rolling results will be affected by the different sample sizes and the number of forecasts produced under each scheme. We have undertaken some additional estimates and forecasts for different window sizes that we do not report for brevity, but discuss here.[19] The number of OOS observations used above (132) is complemented with sizes of 180 (IS: 1986-1993); 108 (IS: 1986-2000); and 48 (IS: 1986-2004). The results for the different window sizes are similar in terms of the combination of forecasts performing consistently well, and the semiparametric model being particularly helpful for horizons longer than one. The results regarding the linear and nonlinear Taylor rules differ a bit more. In the case of the rolling scheme, as the window shortens, the nonlinear rules are in general more accurate than linear ones. This result is broadly intuitive given that the SARB's instruments and policies in the most recent period of the sample can be considered more in line with the arguments in favor of nonlinearities described in previous sections. In that respect it is also worth noting that, as the window size gets shorter, rolling forecasts for all models improve, and sometimes are more accurate, on average than the recursive ones.

Overall, our study seems to suggest that for the case of South Africa the best a practitioner or policymaker can do is to use our array of models and use the combinations of those as the best forecast. In the case that a single method has to be used, the semiparametric one seems the most reliable for forecasts longer than one month ahead.

5 Conclusion

In this paper we examine the SARB's monetary policy reaction function by presenting IS as well as OOS results for different models or specifications of the monetary policy rule. First, we augment the "traditional Taylor rule" with a financial condition index and find that asset prices have some role in the interest rate setting of South Africa. Second, nonlinearities in the rule by which the level of response of the Reserve Bank to inflation, the output gap and

[19] However, the case of the IS period 1986-2004 with OOS observations until 2008 is widely discussed and analysed in a working paper version of this paper, see Naraidoo and Paya (2009).

financial conditions depend on the deviation of inflation from target, is not rejected by the data. Third, forecasts constructed from pooling all the models usually perform the best, and there are gains from semiparametric models in forecasting interest rates as the forecasting horizon lengthens.

References

Aksoy, Y., Orphanides, A., Small, D., Weiland, V., & Wilcox, D. (2006). A quantitative exploration of the opportunistic approach to disinflation. *Journal of Monetary Economics, 53*, 1877-1893.

Aron, J., & Muellbauer, J. (2000). Estimating monetary policy rules for South Africa. Working Papers Central Bank of Chile 89, Central Bank of Chile.

Bec, F., Ben, S., & Collard, F. (2002). Asymmetries in monetary policy reaction function: Evidence for US, French and German central banks. *Studies in Nonlinear Dynamics and Econometrics, 6, Article 3*.

Bernanke, B., Gertler, M. (2001). Should Central Banks Respond to Movements in Asset Prices? *American Economic Review, 91*, 253-257.

Boinet, V., & Martin, C. (2008). Targets, Zones and Asymmetries: A Flexible Nonlinear Model of Recent UK Monetary Policy. *Oxford Economic Papers, 60*, 423-439.

Bomfimm, A., & Rudebusch, G. (2000). Opportunistic and deliberate disinflation under imperfect credibility. *Journal of Money, Credit, and Banking, 32*, 707-721.

Busetti, F., Marcucci, J., & Veronese, G. (2009). Comparing Forecast Accuracy: A Monte Carlo investigation. Bank of Italy Working Paper 2009.

Castro, V. (2008). Are central banks following a linear or nonlinear (augmented) Taylor rule? The Warwick Economics Research Paper Series (TWERPS) 872, University of Warwick, Department of Economics.

Clarida, R., Gali, J., & Gertler, M. (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics, CXV* , 147–180.

Clark, T. (1999). Finite-sample properties of tests for equal forecast accuracy. *Journal of Forecasting, 18*, 429-450.

Clark, T., & West, K. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics, 138*, 291-311.

Clark, T., & McCracken, M. (2005). Evaluating direct multistep forecasts. *Econometric Reviews, 24*, 369-404.

Clements, M., & Smith, J. (1997). The performance of alternative forecasting methods for SETAR models. *International Journal of Forecasting, 3*, 463-475.

Cukierman, A., & Muscatelli, A. (2008). Nonlinear Taylor rules and asymmetric preferences in central banking: Evidence from the United Kingdom and the United States. *The B.E. Journal of Macroeconomics, 8*, 977-997.

D'Agostino, A., & Surico, P. (2009). Does global liquidity help to forecast US inflation?. *Journal of Money, Credit and Banking, 41*, 479-489.

De Grauwe, P. (2007). Central banks should prick asset bubbles. Article in *The Financial Times*, Nov 1, 2007.

Demertzis M, Viegi N 2009."Inflation Targeting: A Framework for Communication," The B.E. Journal of Macroeconomics, Vol 9(1).

Diebold, F., & Mariano, S. (1995). Comparing predictive accuracy. *Journal of Business and Economics Statistics, 13*, 253-263.

Dolado, J., Maria Dolores, R., & Naveira, M. (2005). Are monetary policy reaction functions asymmetric? *European Economic Review, 49*, 485–503.

Hall, P., Racine, J., & Li, Q. (2004). Cross-validation and the estimation of conditional probability densities. *Journal of the American Statistical Association, 99*, 1015–1026.

Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*, 281-291.

Hayat, A., & Mishra, S. (2010). Federal Reserve monetary policy and the nonlinearity of the Taylor rule. *Economic Modelling, 27*, 1292-1301.

Hayfield, T., & Racine, J. (2008). Nonparametric econometrics: The np package. *Journal of Statistical Software, 27*, 5, 1-32.

Hurvich, C., Simonoff, J., & Tsai, C. (1998). Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion. *Journal of the Royal Statistical Society Series B, 60*, 271–293.

Jonsson, G. (2001). Inflation, money demand, and purchasing power parity in South Africa. IMF Staff Papers, 48, No. 2.

Knedlik, T. (2006). Estimating monetary policy rules for South Africa. *South African Journal of Economics, 74*, 629-641.

King, M. (1996). How should central banks reduce inflation? - Conceptual Issues. *Economic Review Federal Reserve Bank of Kansas City, 81*, 25-52.

Layard, R., Nickell, S., & Jackman, R. (1991). *Unemployment.* Oxford: Oxford University Press.

Li, Q., & Racine, J. (2004). Cross-validated local linear nonparametric regression. *Statistica Sinica, 14*, 485–512.

Martin, C., Milas, C. (2004). Modelling monetary policy: inflation targeting in practice. *Economica, 71*, 209-221.

Martin, C., Milas, C. (2010). Testing the opportunistic approach to monetary policy. *Manchester School, 78*, 110-125.

Mboweni, T. (2008). Origins and Causes of the Recent Financial Market Turbulence and its Implications for the CMA. *Public Lecture* delivered in Windhoek, Namibia.

McCracken, M. (2007). Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics, 140*, 719-752.

Mishkin, F. (2008). How Should we respond to asset price bubbles? Speech at the *Wharton Financial Institutions Center and Oliver Wyman Institute's Annual Financial Risk Roundtable*, Philadelphia, Pennsylvania.

Mminele, A. (2009). Recent economic developments in South Africa. Remarks at the *Citigroup Global Issues Seminar*, The Ritz Carlton Hotel, Istanbul, Turkey.

Moura, M., & de Carvalho, A. (2010). What can Taylor rules say about monetary policy in Latin America?. *Journal of Macroeconomics, 32*, 392-404.

Naraidoo, R., & Gupta, R. (2009). Modelling monetary policy in South Africa: Focus on inflation targeting era using a simple learning rule. University of Pretoria, mimeo.

Naraidoo, R, & Paya, I. (2009). Forecasting monetary policy rules in South Africa. Working paper No 200926, Department of Economics, University of Pretoria, Available from: http://web.up.ac.za/sitefiles/file/40/677/WP_2009_26.pdf.

Nobay, A., Peel, D. (2003). Optimal discretionary monetary policy in a model of asymmetric central bank preferences. *Economic Journal, 113*, 657-665.

Qin, T., & Enders, W., (2008). In-sample and out-of-sample properties of linear and nonlinear Taylor rules. *Journal of Macroeconomics, 30*, 428-443.

Robinson, P. (1988). Root-N consistent semiparametric regression. *Econometrica, 56*, 931–954.

Rogoff, K., & Stavrakeva, V. (2008). The continuing puzzle of short-horizon exchange rate forecasting. *NBER Working Paper* 14071.

Schaling, E. (2004). The nonlinear Phillips curve and inflation forecast targeting: Symmetric versus asymmetric monetary policy rules. *Journal of Money, Credit, and Banking, 36*, 361-386.

Surico, P. (2007). The Fed's monetary policy rule and U.S. inflation: The case of asymmetric preferences. *Journal of Economic Dynamics and Control, 31*, 305-324.

Walsh, C. (2009). Using monetary policy to stabilize economic activity. *Financial Stability and Macroeconomic Policy*, Federal Reserve Bank of Kansas City, Jackson Hole Symposium, 245-296.

West, K. (1996). Asymptotic inference about predictive ability. *Econometrica, 64*, 1067–1084.

West, K. (2006). *Forecast Evaluation.* In Handbook of Economic Forecasting, eds. Elliot G, Granger CWJ, and Timmerman A, London: North Holland, Vol. 1.

Woglom, G. (2003). How has inflation targeting affected monetary policy in South Africa? *South African Journal of Economics, 71*, 198-210.

Table 1. In-sample estimates of linear and nonlinear Taylor rules

$$r_t = \beta_1 r_{t-1} + \beta_2 r_{t-2} + (1-\beta_1-\beta_2)[\alpha_1 + \alpha_\pi \pi_{t-1} + \alpha_y y_{t-1} + \alpha_I I_{t-1}] +$$
$$+ (1-\beta_1-\beta_2)[\delta_\pi \pi_{t-1} + \delta_y y_{t-1} + \delta_I I_{t-1}] \frac{1}{1+e^{\theta(\pi_{t-1}-\gamma^\pi)/\sigma_\pi}} + \varepsilon_t$$

	Linear Rule		Nonlinear Rule	
Parameter	1986-2008	2000-2008	1986-2008	2000-2008
β_1	1.26	1.18	1.24	1.04
	(0.13)	(0.08)	(0.14)	(0.11)
β_2	-0.30	-0.26	-0.28	-0.15
	(0.13)	(0.07)	(0.12)	(0.10)
α_1	9.01	7.81	4.20	8.90
	(1.33)	(0.68)	(2.55)	(0.97)
α_π	0.34	0.47	0.70	0.29
	(0.19)	(0.14)	(0.21)	(0.10)
α_y	1.13		2.10	0.72
	(0.28)		(0.62)	(0.40)
α_I	0.21	0.11		
	(0.13)	(0.06)		
δ_π				-1.78
				(0.56)
δ_y			-5.49	-1.48
			(2.93)	(0.75)
δ_I			0.75	0.31
			(0.57)	(0.13)
θ			0.67	1.74
			(0.37)	(0.71)
			[0.10]	[0.05]
γ^π			6.22	4.56
			(2.13)	(1.34)
AIC	1.43	0.65	1.42	0.59
se	0.489	0.327	0.485	0.312

Notes: Figures in brackets are HAC standard errors. Figures in squared brackets are bootstrapped p-values under the null of a linear model. We report coefficients only for variables that are significant at least at the 10% level.

Table 2. Average out-of-sample forecasting ranks

	Model i	(i) MSPE (recursive)	(ii) MedSPE (recursive)	(iii) MSPE (rolling)	(iv) MedSPE (rolling)	(v) Relative MSPE ratio	(vi) Relative MedSPE ratio
	1	5.75	5.25	8.5	6.75	0.33	0.29
L	2	7.25	6.5	12	14.25	0.24	0.12
	3	7.5	7.5	8.75	8.25	0.33	0.28
	4	5.75	4.25	14.75	13.25	0.18	0.11
NL	5	12.5	12.75	10.25	11.25	0.54	0.63
	6	9	10.5	13.5	13.5	0.24	0.23
	7	13.75	13.5	7.75	8	0.75	0.77
NP	8	13.75	12.5	9.25	9	0.58	0.71
	9	12	11.75	6.75	6.75	0.78	0.86
	10	7.75	4.75	8.25	6.5	0.45	0.28
SP	11	8	7.75	3	1.75	0.91	1.13
	12	8	6.75	5.25	4.25	0.65	0.59
	13	1.5	4.5	2.75	4	0.40	0.30
P	14	4.25	6.75	5.5	6.75	0.36	0.27
	15	3.25	5	3.75	5.75	0.41	0.29

Notes: Columns (i)-(ii) report the average out-of-sample forecasting rank of Model i across the recursive windows and forecasting horizons h=1, 3, 6 and12, using the Mean Squared Prediction Error (MSPE) and the Median Squared Prediction Error (MedSPE) criteria. Columns (iii)-(iv) do the same for rolling windows. Columns (v)-(vi) report the average MSPE and MedSPE for the recursively estimated models relative to the MSPE and MedSPE for the rolling ones across all estimated windows and forecasting horizons h=1, 3, 6 and 12. See section 3 for definitions of Model i.

Table 2a. Average out-of-sample forecasting ranks

Model i		(i) MSPE (recursive)	(ii) MedSPE (recursive)	(iii) MSPE (rolling)	(iv) MedSPE (rolling)	(v) Relative MSPE ratio	(vi) Relative MedSPE ratio
	1	6.5	6.25	8.75	8.75	0.36	0.32
L	2	5	5.25	10.5	11.25	0.29	0.19
	3	3.75	3.75	9.5	12.5	0.38	0.33
	4	10	8.25	14	12.25	0.19	0.19
NL	5	14.25	12.25	6.75	10.25	0.57	0.67
	6	12.25	12.5	12.75	14.75	0.28	0.28
	7	11.75	12.5	7.75	5.75	0.79	0.79
NP	8	13.5	13.75	10	7.5	0.60	0.78
	9	10	10	7.5	3.75	0.81	0.91
	10	6	6.75	8.25	4.25	0.56	0.35
SP	11	6.75	7	4.5	2	0.98	1.17
	12	9	6.75	6.75	5.5	0.69	0.63
	13	3.75	2.75	3	4.5	0.45	0.33
P	14	2.5	7.75	5.25	8.25	0.39	0.31
	15	5	4.5	4.75	8.75	0.47	0.32

Notes: Columns (i)-(ii) report the average out-of-sample forecasting rank of Model i across the recursive windows and forecasting horizons h=1, 3, 6 and12, using the Mean Squared Prediction Error (MSPE) and the Median Squared Prediction Error (MedSPE) criteria. Columns (iii)-(iv) do the same for rolling windows. Columns (v)-(vi) report the average MSPE and MedSPE for the recursively estimated models relative to the MSPE and MedSPE for the rolling ones across all estimated windows and forecasting horizons h=1, 3, 6 and 12. See section 3 for definitions of Model i.

Table 3. Forecast Accuracy Evaluation. Recursive Estimation

Panel A. Backward looking					Panel B. Forward Looking					Panel C. Learning				
	Steps Ahead					Steps Ahead					Steps Ahead			
	1	3	6	12		1	3	6	12		1	3	6	12
L vs					L vs					L vs				
NL	-0.69*	-0.48*	-0.66	-0.90	NL	-0.06	1.35	2.29	0.31	NL	-0.57*	-0.92**	-1.74**	-1.90**
NP	-2.97**	-2.71**	-1.04	-0.03	NP	-3.99**	-2.27**	-1.25	-0.46	NP	-2.76**	-2.54**	-0.95	0.04
SP	-2.64**	-1.08	0.17	0.50	SP	-1.52	-1.23	0.33	0.74	SP	-2.50**	-1.16	0.14	0.34
P	-0.98	1.62	1.25	0.93	P	-0.36	-0.10	1.56	1.07	P	-1.37	1.28	1.07	0.82
NL vs					NL vs					NL vs				
NP	-3.10**	-2.49**	-0.96	-0.84	NP	-3.33**	-1.59	0.05	0.36	NP	-2.72**	-2.10**	-0.59	-0.42
SP	-2.02**	-0.99	0.22	-0.01	SP	-1.46	0.57	1.85*	1.77*	SP	-1.33	-0.57	0.71	0.17
P	0.13	1.21	1.33	0.95	P	1.04	4.28**	2.61**	1.91*	P	0.69	1.53	2.51**	1.54
NP vs					NP vs					NP vs				
SP	1.68*	1.76*	1.15	0.65	SP	-0.68	1.63	1.31	1.02	SP	1.48	1.74*	1.05	0.36
P	3.15**	2.96**	1.70*	1.71*	P	4.32**	2.22**	1.55	1.07	P	2.86**	2.81**	1.69*	1.81*
SP vs					SP vs					SP vs				
P	2.34**	1.72*	0.68	0.54	P	1.52	1.26	0.36	-0.14	P	2.00**	1.93*	0.74	0.49

Notes: The Table presents forecast comparisons based on recursive estimates, across forecasting horizons h = 1, 3, 6 and 12, using the modified Diebold-Mariano statistic, $DM-t$ and the Clark and West (2007) statistic, $CW-t$ for the case of linear versus nonlinear models. The entries in the Table show the test statistics for the null hypothesis that Model i's forecast performance as measured by MSPE is not superior to that of Model j at the 5% and 10% significance level and vice versa (denoted by two and one asterisks respectively). See Section 3 for model definitions.

Table 4. Forecast Accuracy Evaluation. Rolling Estimation

Panel A. Backward looking					Panel B. Forward looking					Panel C. Learning				
	Steps Ahead					Steps Ahead					Steps Ahead			
	1	3	6	12		1	3	6	12		1	3	6	12
L vs					L vs					L vs				
NL	-1.21**	-0.67**	0.12	0.97	NL	-0.33	3.41**	4.76**	2.87	NL	-1.55**	-2.34**	-2.65**	-3.73**
NP	1.51	-0.64	-0.74	0.23	NP	1.46	-1.72*	0.37	0.81	NP	1.18	-0.53	0.31	0.23
SP	-0.27	-0.85	0.36	0.93	SP	0.99	1.63	2.95**	1.46	SP	1.00	0.56	1.00	1.08
P	2.53**	1.70*	1.73*	0.97	P	2.79**	3.52**	3.17**	1.56	P	2.57**	1.99**	2.33**	1.15
NL vs					NL vs					NL vs				
NP	2.26**	0.86	0.75	0.84	NP	1.47	-1.71*	-0.48	0.23	NP	1.81*	0.73	1.43	0.85
SP	0.41	0.52	1.52	1.17	SP	1.06	0.94	2.22**	1.56	SP	1.50	1.53	1.84*	1.37
P	3.15**	2.28**	2.23**	1.22	P	2.67**	1.28	1.41	1.50	P	3.23**	2.73**	2.49**	1.47
NP vs					NP vs					NP vs				
SP	-1.64*	-0.37	0.90	0.85	SP	-0.32	2.51**	2.89**	2.17**	SP	0.13	1.38	0.61	0.94
P	-0.17	2.15**	1.54	0.91	P	-0.11	2.42**	1.84*	0.66	P	0.25	1.87*	0.87	0.57
SP vs					SP vs					SP vs				
P	1.46	1.74*	0.87	-0.20	P	0.25	-0.22	-2.25**	-1.26	P	0.05	0.45	0.15	-0.73

Notes: The Table presents pair-wise out-of-sample forecast comparisons for the forecasting models based on fixed window rolling estimates. See notes to Table 3.

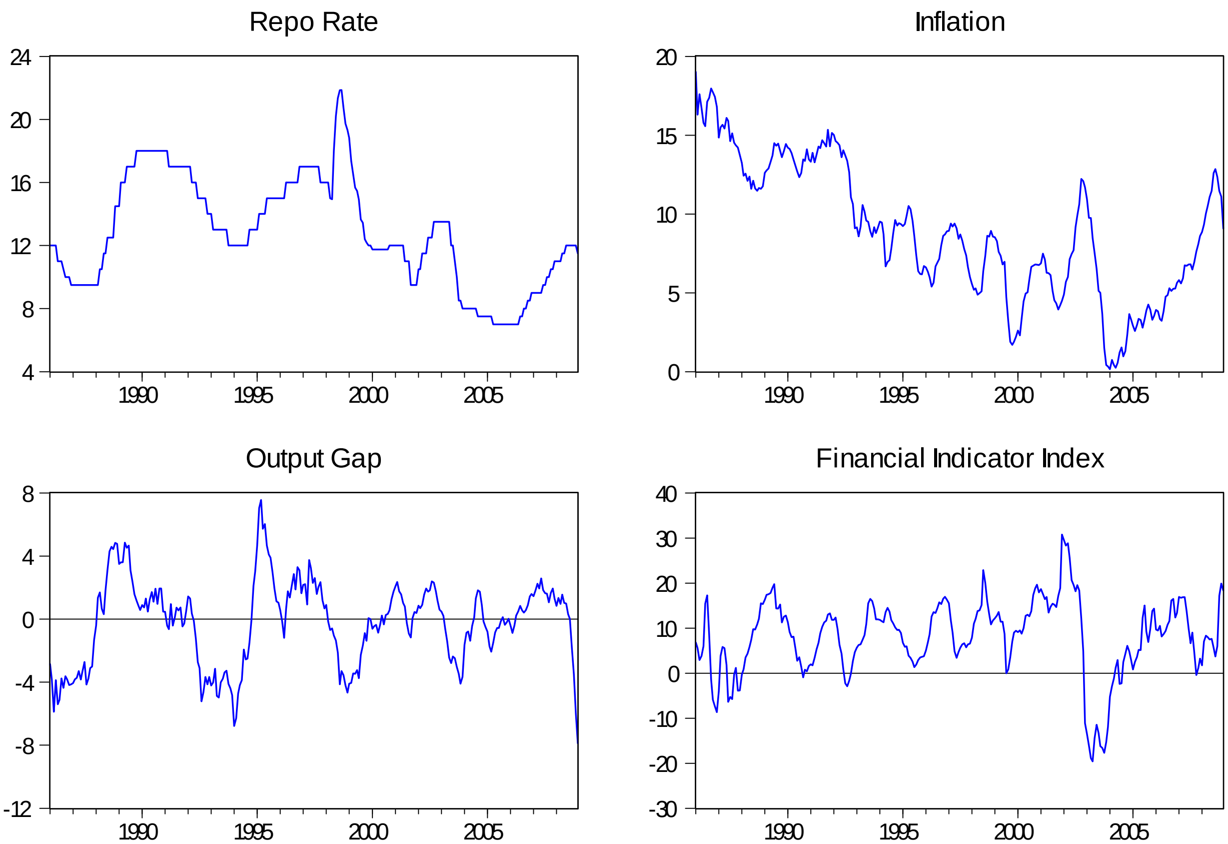

Figure 1. Evolution of the Main Variables

Appendix 1: Description of the variables and sources

Variables	Description
r_t	Repo rate
π_t	Inflation rate computed as the annual rate of change of the consumer price index (CPI); base year: 2008 =100, seasonally adjusted
$y_t - y^*$	Output gap computed as the percentage deviation of the Coincident business cycle indicator (computed by the SARB) from its Hodrick-Prescott trend
$I_t - I^*$	Financial indicator gap computed as the weighted average annualised growth rate of real house prices, real share prices and nominal exchange rate
gh_t	Annualised growth rate of the monthly real house price index (2000=100; CPI deflated)
gs_t	Annualised growth rate of the Johannesburg Stock Exchange (JSE) All Share Price index (2000=100; CPI deflated)
ge_t	Annualised growth rate of the South African rand to the US dollar

Sources: South African Reserve Bank (http://www.reservebank.co.za)

Descriptive statistics of the main variables

	r_t	π_t	$y_t - y^*$	$I_t - I^*$	gh_t	gs_t	ge_t
Min	7.00	0.20	-7.90	-19.61	-9.67	-48.44	-39.42
Max	21.86	19	8.70	30.83	30.51	48.79	41.31
Mean	12.85	9.20	-0.10	8.01	10.36	11.58	5.70
Median	12.00	9.10	0.28	8.90	12.65	13.03	7.27
Std. Deviation	3.48	4.34	2.85	8.52	7.93	19.50	14.68
Skewness	0.16	-0.02	0.05	-0.69	-0.26	-0.66	-0.64
Kurtosis	2.24	2.13	2.96	4.21	3.29	3.25	3.92