Chapter 7

Evaluating the forecasting performance of monetary policy rules in South Africa

7.1. Introduction

Empirical evidence in the field of monetary policy continues to prove that the behaviour of central bankers is not symmetric either around a certain level of policy instrument, the inflation target or potential output. More recent examples include Hayat and Mishra (2010) and Martin and Milas (2010) among others. In these cases, besides the failure to reject the null hypothesis of linearity, nonlinear models are found to outperform their rival linear models in terms of goodness-of-fit. It is well known that one of the prime benefits of robust economic models is the predictive accuracy they have. In the field of monetary policy, for instance, a robust monetary policy reaction function can help monetary authorities to predict more accurately the future values of the policy instrument. Reid and Du Plessis (2010) advocate for greater transparency that could be achieved if the SARB were to publish a forecast of the expected path of its policy instrument. Furthermore, as propounded by the same authors, forecasts of the policy instrument would shed some lights on the forward-looking nature of monetary policy and thereby enhance the predictability of the SARB's policy stance.

Given the recent in-sample outperformance of nonlinear monetary policy reaction functions, one can expect the latter to predict the behaviour of central banks better than a simple linear policy rule. However, early in the 1990s, De Gooijer and Kumar (1992) concluded that there was no clear evidence in favour of non-linear over linear models in terms of forecast performance. More than a decade later, Clements *et al.* (2004) suspect that the situation has not changed very much, as we had not gone very far in the area of non-linear forecast models. The literature review by Clements *et al.* (2004) suggests that the forecasting performance of nonlinear models is on average not particularly good relative to rival linear models. As far as monetary policy rules are concerned, Qin and Enders (2008) find more challenging results as they report that the univariate models forecast better than the Taylor rules, linear and nonlinear. More recently, Naraidoo and Paya (2010) compare linear and nonlinear parametric models and, non-parametric and semi-parametric models in forecasting the South African Reserve Bank's repurchase rate. They find that a semi-parametric model that relaxes the functional form of the monetary policy rule outperforms other models especially in long horizon forecasting.

This chapter contributes to the scarce literature that uses Taylor rules to forecast the nominal interest rate out-of-sample. Some notable exceptions are Qin and Enders (2008), Moura and Carvalho (2010) and Naraidoo and Paya (2010). In this study about South Africa, we construct the forecasts from linear and nonlinear Taylor type rule models under a backward looking expectations formation for the target variables and examine their forecasting gains over the period 2006:M01 to 2010:M12. The aim of the chapter is to evaluate predictive accuracy of three competing models based on a number of forecasting tests; namely the mean squared prediction error (MSPE), median squared prediction error (MedSPE), the modified Diebold Mariano, and the Clark and West.

The rest of the chapter is organized as follows. In the next section, we discuss the linear and nonlinear Taylor rule versions to be evaluated for predictive ability. Section 3 discusses the data and forecasting methodology. Section 4 passes into review in-sample properties of the four alternative models by comparing their goodness of fit in terms of the Akaike information criterion (AIC). Section 5 reports an in-depth forecasting evaluation of different models with the aim to determine the best model in predictive ability. Section 6 concludes.

7.2. Alternative models

In this Chapter we make comparative forecasting evaluation among the models discussed in chapters 5 and 6. However, for forecasting purposes we consider backward looking versions rather than the forward looking ones. Although chapter 4 suggests that forward looking version of the Taylor rule describes better the behaviour of the SARB than the backward-looking, an out-of-sample forecasting exercise cannot use future values of variables in the pure forecasting sense. Therefore, models 1 to 3 are rewritten in their backward looking versions.

Model 1 (b):

$$i_t = \rho_i(L)i_{t-1} + (1-\rho_i)\{\rho_0 + \rho_\pi(\pi_{t-1} - \pi^*) + \rho_y y_{t-1} + \rho_f f_{t-1}\} \qquad (7.1)$$

Equation (7.1) is characterized by three modifications made on the original simple Taylor rule, namely interest rate smoothing, the forward-looking version and the inclusion of financial condition index.

The next step is to allow for nonlinearities in interest rate setting behaviour of the monetary authorities (see chapter 5 for more discussion). The first nonlinear version is axed on the widespread belief that central bankers' interventions through changes in a short-term interest rate are influenced by the state of the business cycle (see for instance, Bec *et al.*, 2002). This being the case, the following nonlinear policy rule is considered.[13]

Model 2 (b):

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left\{\rho_0 + \theta_t^y(y_{t-1};\gamma^y;\tau)M_{1t} + (1-\theta_t^y)(y_{t-1};\gamma^y;\tau)M_{2t}\right\} + \varepsilon_t \qquad (7.2)$$

where $M_{jt} = \rho_{j\pi}\pi_{t-1} + \rho_{jy}y_{t-1} + \rho_{jf}f_{t-1}$ for j=1,2 and the function $\theta_t^y(y_{t-1};\gamma^y;\tau)$ is the weight similar to equation (5.5). M_{1t} is a linear Taylor rule that represents the behaviour of policymakers during business cycle recessions and M_{2t} is a linear Taylor rule that represents the behaviour of policymakers during business cycle expansions. The weight $\theta_t^y(y_{t-1};\gamma^y;\tau)$ is modelled using the following logistic function (see e.g. van Dijk *et al.*, 2002):

[13] In chapter 2 it is reported that the nonlinear Taylor rule improves its performance with the advent of the financial crisis, providing the best description of in-sample SARB interest rate setting behavior.

$$\theta_t^y\left(y_{t-1};\gamma^y;\tau\right)=1-\frac{1}{1+e^{-\gamma^y(y_{t-1}-\tau)/\sigma(y_{t-1})}} \tag{7.3}$$

In (7.3) the smoothness parameter $\gamma^y > 0$ determines the smoothness of the transition regimes. We follow Granger and Teräsvirta (1993) and Teräsvirta (1994) in making γ^y dimension-free by dividing it by the standard deviation of y_{t-1}.

In chapter 6 it has been reported that opportunistic approach to monetary policy also deserves its particular attention in the context of the South African economy. On this regard, we choose a quadratic logistic function that was reported in chapter 6 to outperform all other models. As such, equation (7.2) is revised to accommodate the two features of opportunistic approach to monetary policy. The model is specified as follows:

Model 3 (b):

$$i_t = \rho_i(L)i_{t-1} + (1-\rho_i)\begin{Bmatrix} i^* + \theta_t\rho_{ZD}\left(\pi_{t-1}-\pi_{t-1}^I\right)+\left(1-\theta_t\right)\rho_{OZD}\left(\pi_{t-1}-\pi_{t-1}^I\right) \\ +\rho_y y_{t-1} + \rho_f f_{t-1} \end{Bmatrix} + \varepsilon_t \tag{7.4}$$

where π_t^I is the intermediate inflation target defined as $\pi_t^I = \mu\left(\frac{1}{n}\sum_{j=1}^{n}\pi_{t-j}\right)+\left(1-\mu\right)\pi^*$ and $\theta = pr\left\{-\delta \le E_t\left(\pi_{t-1}-\pi_{t-1}^I\right)\le\delta\right\}$ is the probability that inflation is within the zone of discretion.

$$\theta = pr\left\{-\delta \leq \left(\pi_{t-1} - \pi_{t-1}^{I}\right) \leq \delta\right\} = 1 - \frac{1}{1+e^{-\gamma\left[(\pi_{t-1}-\pi_{t-1}^{I}+\delta)\right]\left[(\pi_{t-1}-\pi_{t-1}^{I}-\delta)\right] \big/ \sigma^{2}_{(\pi_{t-1}-\pi_{t-1}^{I})}}} \tag{7.5}$$

Similarly, we follow Granger and Teräsvirta (1993) and Teräsvirta (1994) in making the smoothness parameter $\gamma > 0$ dimension-free by dividing it by the standard deviation of $\left(\pi_{t-1} - \pi_{t-1}^{I}\right)$. In equation (7.5) it is assumed that the policy maker responds to $\left(\pi_{t-1} - \pi_{t-1}^{I}\right)$. The response is assumed to depend on whether the inflation is within the target zone or not.

Within sample we would expect the fit of such alternative models to be barely distinguishable, given the high correlations between the interest rate and its lags. However, the key distinguishing feature amongst linear and nonlinear models lies in their forecast implications, namely that the equilibrium to which the reaction function returns depends on the size of the shocks/inflation and business cycle states. A linear Taylor type rule model will forecast the interest rate to stay roughly where it is if non-stationary; or, if stationary, to revert to some deterministic equilibrium. Thus the forecast implications of linear as opposed to nonlinear models are quite different. This is kept in mind when forecasting out-of-sample in section 5 below.

7.3. Forecasting methodology

In this chapter, in-sample observations spans from 2000:01 to 2005:12 and out-of-sample observations covers the period spanning from 2006:01 to 2010:12. 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 $T = R + P$. As we perform recursive out-of-sample forecasts, the in-sample observations increase from R to $T - h$. In the recursive exercise, the parameters of the model are re-estimated by employing data up to time $t - 1$ 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 forecasting nonlinear monetary policy rule can be described by the following model

$$i_t = F(X_{t-1};\theta) + \varepsilon_t \tag{7.6}$$

Where $\varepsilon_t \sim iid(0,\sigma^2)$ and X_t is a $(k \text{ x } 1)$ vector of the exogenous variables and lagged repo rate as defined in Section 2. The optimal one-step-ahead forecast equals

$$\hat{i}_{t+1/t} = E[i_{t+1} / X_t] = F(X_t;\theta) \tag{7.7}$$

which is equivalent to the optimal one-step-ahead for the alternative linear model. An easy way of obtaining a 2-step-ahead forecast is to draw it from the 1-step-ahead forecast and have

$$\hat{i}^{(n)}_{t+2/t} = F(X_{t+1};\theta). \tag{7.8}$$

However, this approach has been a subject of strong criticisms to the extent of being named 'naïve' by Brown and Mariano (1989) or 'skeleton' forecast by Tong (1990). These fair criticisms are based on the fact that equation (7.7) considers $E(\varepsilon_{t+1}/X_t) = 0$ and are supported by simulation evidence by Lin and Granger (1994) reporting substantial losses of efficiency.

As opposed to the so called 'naïve' or 'skeleton' approach numerical techniques are required in forecasting nonlinear models like the ones in section 2. Detailed discussions on the techniques are provided by Granger and Teräsvirta (1993), Franses and van Dijk (2000) and Fan and Yao (2003). In this chapter, the residuals ($\hat{\varepsilon}_t$) of the estimated model is obtained through bootstrapping. With this method, the density of $\hat{\varepsilon}_t$ is composed of N independent error vectors $\{\varepsilon_{t+1}^{(1)},\ldots,\varepsilon_{t+1}^{(N)}\}$ giving a better approximation of the 2-step-ahead forecast as follows:

$$i_{t+2/t}^{B} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} F\left(X_{t+1/t} + \varepsilon_{t+1}^{i};\theta\right) \tag{7.9}$$

To obtain h-step-ahead, one generates $\varepsilon_{t+1}^{(i)},\ldots,\varepsilon_{t+h}^{(i)}$, $i = 1,\ldots,N$ and sequentially computes N forecasts for $i_{t+1/t},\ldots,i_{t+h/t}$ with $h \geq 2$ and where a single point forecast for a particular point in time is obtained by simple averaging its corresponding N forecasts (see Teräsvirta, 2006).

Forecasting performance is evaluated using the Mean Squared Prediction Error (MSPE) and Median Squared Prediction Error (MedSPE) criteria. For robustness purpose, we also test the null hypothesis of equal forecasting accuracy using modified Diebold-Mariano statistics ($DM-t$, see Harvey *et al.*, 1997). The $DM-t$ for any two models denoted by 1 and 2 is computed as follows

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

where $\hat{d}_{t+h} = \hat{e}^2_{1,t+h} - \hat{e}^2_{2,t+h}$; $\hat{e}_{i,t+h}$ being h-step ahead prediction error for model i;

$\bar{d} = (P - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{d}_{t+h} = MSPE_1 - MSPE_2$;

$\hat{\Gamma}_{dd}(j) = (P - h + 1)^{-1} \sum_{t=R}^{T-h} \hat{d}_{t+h} \hat{d}_{t+h-j}$ for: $j \geq 0$ and $\hat{\Gamma}_{dd}(j) = \hat{\Gamma}_{dd}(-j)$;

$\hat{S}_{dd} = \sum_{j=-\bar{j}}^{\bar{j}} K(j/M) \hat{\Gamma}_{dd}(j)$ denotes the long-run variance of d_{t+h} estimated using a kernel-based estimator with function $K(.)$, bandwidth parameter M and maximum number of lags $\bar{j}$. We follow Harvey *et al.* (1997) in correcting for small-sample bias and so the corrected test statistic is obtained by multiplying the above $DM - t$ by

$$\zeta = \sqrt{\frac{P - 2h + h(h-1)/(P - h + 1)}{(P - h + 1)}}$$

The hypotheses to be tested are

$$H_0 : \hat{e}_{1,t+h} - \hat{e}_{2,t+h} = 0$$

and

$$H_1 : \hat{e}_{1,t+h} - \hat{e}_{2,t+h} \neq 0$$

The rejection of the null is based on Student's t distribution with (n – 1) degrees of freedom rather than the standard normal distribution (see Harvey *et al.*, 1997). It is worth to mention that nonlinear Taylor rule equations nest the linear equations and therefore their population errors are identical under the null hypothesis making the variance d_{t+h} equal to zero (see McCracken, 2007). Indeed, it has been argued that asymptotic distribution theory for the Diebold and Mariano (1995) test does not hold for nested models (see McCracken, 2000; Clark and McCracken, 2001 and Teräsvirta, 2005). However, Giacomini and White (2006) showed that when in-sample size remains finite, the asymptotic distribution of the Diebold and Mariano statistic (DM statistic) is still standard normal when forecasts are compared from nested models. Bhardwaj and Swanson (2006) also argue that the $DM-t$ statistic can still be used as an important diagnostic in predictive accuracy as the non-standard limit distribution is reasonably approximated by a standard normal in many contexts.

As far as the issue of nestedness is concerned, we apply the Clark and McCracken (2001) encompassing test ($ENC-t$) and Clark and West (2007). Both tests are designed to test the null hypothesis of equal forecasting accuracy for nested models. The $ENC-t$ statistic is given by

$$ENC-t=(P-1)^{1/2}\frac{\bar{c}}{\left(P^{-1}\sum_{t=R}^{T-1}(c_{t+h}-\bar{c})\right)^{1/2}},$$

where $c_{t+h}=\hat{e}_{1,t+h}(\hat{e}_{1,t+h}-\hat{e}_{2,t+h})=\hat{e}_{1,t+h}^{2}-\hat{e}_{1,t+h}\hat{e}_{2,t+h}$ and $\bar{c}=P^{-1}\sum_{t=R}^{T-h}c_{t+h}$. The $ENC-t$ has the same null hypothesis as the $DM-t$ test, but the alternative is $H_1:\hat{e}_{1,t+h}-\hat{e}_{2,t+h}>0$ which is more restrictive than the $DM-t$ that considers $H_1 = \hat{e}_{1,t+h} - \hat{e}_{2,t+h} \neq 0$. For $h = 1$, the limiting distribution is $N(0,1)$. By contrast, Clark and McCracken (2001) show that for multistep-ahead ($h > 1$) forecasts, the limiting distribution is non-standard. However, as noted by Bhardwaj and Swanson (2006), tabulated critical values are quite close to the $N(0,1)$ values when Newey and West (1987)-type estimator is used for $h > 1$. As such, standard normal distribution can be used as a rough guide for multistep-ahead forecasts comparison (see Clark and McCracken, 2001 for further details).

An alternative test for equal forecast errors is the Clark and West test (CW-test) statistics is given by

$$\hat{f}_{t+h} = (i_{t+h} - \hat{i}_{1t,t+h})^2 - [(i_{t+h} - \hat{i}_{2t,t+h})^2 - (\hat{i}_{1t,t+h} - \hat{i}_{2t,t+h})^2].$$

Where the period t forecast of the repo rate i_{t+h} from the two models are denoted $\hat{i}_{1t,t+h}$ and $\hat{i}_{2t,t+h}$ with corresponding period $t+h$ forecast errors $i_{t+h} - \hat{i}_{1t,t+h}$ and $i_{t+h} - \hat{i}_{2t,t+h}$. The test for equal MSPE is performed by regressing $\hat{f}_{t+h}$ on a constant and using the resulting t-statistic for a zero coefficient (see Clark and West, 2007). As above, the null hypothesis is equal MSPE while the alternative is model 2 has a smaller MSPE than model 1. In line with Clark and West (2007), the null is rejected if the t-statistic is greater than +1.282 (for a one sided 0.10 test) or +1.645 (for a one sided 0.05 test).

7.4. In-sample evaluation

Using the same set of data as above, this section reviews the in-sample properties of backward looking models that are going to be tested for out-of-sample properties in the next section. Tables 8 and 9 report estimates of the Taylor rule Models 1(b), 2(b) and 3(b) for the in-sample period which runs from 2000:M1 to 2005:M12. Model 3 (b) in Table 9 exhibits the lowers AIC and shows that the inflation outside the zone of discretion, output gap and financial index effects are statistically significant but not the inflation within the zone of discretion. The results are in line with the opportunistic approach theory.

Table 8: In-sample estimates for the backward looking versions of Models 1&2

Coefficients	Model 1 (Linear)	Model 2 (Nonlinear)
ρ_0	0.882***	6.876***
	(0.01)	(0.19)
ρ_1	0.478***	0.859***
	(0.04)	(0.01)
ρ_π	1.077***	
	(0.08)	
ρ_y	0.023**	
	(0.01)	
ρ_f	0.882***	
	(0.01)	
$\rho_{1\pi}$		0.697***
		(0.03)
ρ_{1y}		0.286
		(0.23)
ρ_{1f}		0.059***
		(0.01)
$\rho_{2\pi}$		0.062
		(0.09)
ρ_{2y}		0.116
		(0.08)
ρ_{2f}		-0.024**
		(0.01)
τ		0.00
		(0.00)
γ^y		5.00
AIC	1.173	1.205
S.E	0.418	0.416
$\bar{R}^2$	0.969	0.969
J-stat	0.248	0.230
λ-test	0.001	
λ_A-test	0.000	
g-test	0.001	

Notes:

(i) Where Model 1 is $i_t = \rho_i i_{t-1} + (1-\rho_i)\{\rho_0 + \rho_\pi \pi_{t-1} + \rho_y y_{t-1} + \rho_f f_{t-1}\} + \varepsilon_t$ and Model 2 is $i_t = \rho_i i_{t-1} + (1-\rho_i)\{\rho_0 + \theta_t^y(y_{t-1};\gamma^y;\tau)M_{1t} + (1-\theta_t^y)(y_{t-1};\gamma^y;\tau)M_{2t}\} + \varepsilon_t$ with $M_{jt} = \rho_{j\pi}\pi_{t-1} + \rho_{jy} y_{t-1} + \rho_{jf} f_{t-1}$ for j =1, 2 and y_t is the transition variable.

(ii) Numbers in parentheses are standard errors. *(**)[***] indicate that the parameter is significant at a 10(5)[1] % level respectively. AIC is the Akaike Information Criterion. J-stat is the p-value of a chi-square test of the model's over-identifying restrictions (Hansen, 1982). The set of instruments includes a constant, 1-6, 9, 12 lagged values of repo rate, the inflation, the output gap, the 10-year government bond, money (M3) growth, and the financial index.

Table 9: Backward looking version of the Opportunistic Approach Model 3

Coefficients	**Model 3**
ρ_i	0.832*** (0.01)
ρ_π	
ρ_{ZD}	0.396 (0.30)
ρ_{OZD}	1.147*** (0.04)
ρ_y	0.523*** (0.03)
ρ_f	0.008*** (0.00)
μ	0.530*** (0.03)
δ	2.05
S.E	0.394
AIC	**1.052**
$\bar{R}^2$	0.972
H_0: $\rho_{ZD} = \rho_{OZD}$ (*p* value)	0.000
J-statistic (*p* value)	0.249

Notes: Numbers in parentheses are standard errors. S.E is the regression standard error. AIC is Akaike Information criterion. J-statistic is the *p*-value of a chi-square test of the model's over-identifying restrictions (Hansen, 1982). The set of instruments includes a constant, 1-6, 9, 12 lagged values of repo rate, the inflation, the output gap, the 10-year government bond, money (M3) growth, and the financial index.

7.5. Out-of-sample evaluation

This chapter is aimed at evaluating the predictive accuracy of a variety of models for South Africa for the period spanning from 2000:M01 to 2010:M12. We split the sample into in-sample and out-of-sample periods for model estimation and recursive out-of-sample experiments. In-sample observations span from 2000:01 to 2005:12 and out-of-sample observations covers the period spanning from 2006:01 to 2010:12.

7.5.1. Testing predictive ability

One of the prime usages of robust economic models is to predict the future pattern of economic series. Therefore, most economic models, linear or non-linear can be judged in terms of their forecasting performance. As such, this chapter uses a variety of functional forms discussed in section 7.2 and section 7.4 with the aim of obtaining the best model in predictive ability. The forecast evaluation based on the mean squared prediction error (MSPE) and the median squared prediction error (MedSPE) have been reported. These two forecast error statistics are scale dependent. According to the criteria, smaller errors show better predictive ability and therefore the closer to zero the better the predictive ability of the model. The ranks of the 3 competing models' forecasts are shown in Tables 10 and 11. The comparison of forecast performance is made vertically for each horizon in terms of furcating test. As shown in Tables 10 and 11, nonlinear Model 2 (b) yields the smallest MSPE and MedSPE for the short and long horizons and so ranked the first in terms of these criteria. Comparing the remaining two models, one can observe that linear Model 1 (b) is ranked the second best for the very short horizon. However, multi-step ahead ($h > 3$) forecast evaluation reveals empirical evidence in favour of the nonlinear model 3(b) in terms of MSPE. It is known that significant in-sample evidence of predictability does not guarantee significant out-of-sample predictability. This might be due to a number of factors such as the power of tests (see Inoue and Kilian, 2004). In terms of MedSPE, the linear Model 1 (b) is ranked second. Average ranking respectively based on MSPE and MedSPE is reported in the last columns of Table 10 and 11 showing the superiority of nonlinear model 2 (b).

Table 10: Mean squared prediction error rank (recursive estimates)

Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12	Average rank
1 (b)	2	2	2	3	3	3	3	3	3	3	3	3	2.75
2 (b)	1	1	1	1	1	1	1	1	1	1	1	1	1
3 (b)	3	3	3	2	2	2	2	2	2	2	2	2	2.25

Notes: The Table reports the out-of-sample forecasting ranks of Models 1(b), 2(b) and 3(b) across the recursive windows for forecasting horizons *h*=1,…,12, using the Mean Squared Prediction Error (MSPE). The last column reports the average forecasting rank. Model 1(b) is the linear estimation, Model 2(b) is nonlinear with output as transition variable and Model 3(b) is a nonlinear estimation that accommodates the opportunistic approach to disinflation.

Table 11: Median squared prediction error rank (recursive estimates)

Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12	Average rank
1 (b)	2	2	2	2	2	3	3	2	2	2	2	2	2.16
2 (b)	1	1	1	1	1	1	1	1	1	1	1	1	1
3 (b)	3	3	3	3	3	2	2	3	3	3	3	3	2.83

Note: The Table reports the out-of-sample forecasting ranks of Models 1(b), 2(b) and 3(b) across the recursive windows for forecasting horizons *h*=1,…,12, using the Median Squared Prediction Error (MedSPE). The last column reports the average forecasting rank. See Table 10 for the forecasting model definitions.

The modified Diebold-Mariano (*DM-t*) test results are reported in Table 12. These examine the statistical significance of MSPE reductions with uniform weight placed on forecast losses. The Table provides pair wise out-of-sample forecast comparisons based on recursive estimates. Table 12 shows that the modified Diebold and Mariano (1995) test points to the superiority of the Model 2(b) over the linear model for the short and medium term horizons ($2 \leq h \leq 8$), but such dominance disappears as the forecast horizon lengthens ($h \geq 9$). On the other hand, the nonlinear Model 3 (b) is never significantly better than the linear one.

Turning to the tests designed to test the null hypothesis of equal forecasting accuracy for nested models, the judgment based on ENC_t and CW_t, respectively reported in Tables 13 and 14, is not much different from the one based on MSPE above. In fact, the results in Tables 13 and 14 reveal strong empirical evidence in favour of nonlinear models. Relative to the linear Model 1 (b), nonlinear Model 2 (b) is reported to yield the best predictive accuracy for all horizons in terms of both the encompassing (ENC_t) and Clark and West (CW_t) tests. Comparing predictive accuracy for linear model 1 (b) and nonlinear Model 3 (b) it is also clear that for multi-step ahead ($h > 3$), the nonlinear Model 3 (b) can be judged best ranked for these longer horizons. However, the linear Model 1 (b) can predict the near future ($h \leq 3$) better than the nonlinear Model 3 (b).

All in all, Model 2 (b) is best in closely matching the historical record for all the horizons. Overall ranking also shows that the nonlinear Model 3 (b) is second best in medium and long horizons. As such, the findings would alleviate the concern by Clements *et al.* (2004) who reported lack of predictive ability for most of nonlinear models relative to their benchmark linear ones.

Table 12: Forecast Accuracy Evaluation $(DM-t)$

	Step1	Step2	Step3	Step4	Step5	Step6	Step7	Step8	Step9	Step10	Step11	Step12
Model 1 (b) vs												
Model 2 (b)	0.02	1.46*	1.96**	2.06**	2.07**	1.78**	1.50*	1.31*	1.20	1.14	1.09	1.13
Model 3 (b)	-1.28	-1.08	-0.71	-0.34	-0.23	-0.18	-0.11	-0.08	-0.02	0.01	0.03	0.06
Model 2 (b) vs												
Model 3 (b)	-0.75	-2.08	-2.19	-1.82	-1.75	-1.60	-1.42	-1.26	-1.13	-1.07	-1.01	-1.05

Note: Table 12 shows forecast comparisons based on modified Diebold-Mariano statistics $(DM-t)$ for horizons extending from 1 to 12. 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 respectively denoted by two and one asterisks. For definitions of Models, see footnote for Table 10.

Table 13: Forecast Accuracy Evaluation $(ENC-t)$

	Step1	Step2	Step3	Step4	Step5	Step6	Step7	Step8	Step9	Step10	Step11	Step12
Model 1 (b) vs												
Model 2 (b)	1.38*	2.07**	2.43**	2.61**	2.91**	3.22**	3.54**	3.84**	4.20**	4.77**	5.14**	5.70**
Model 3 (b)	0.73	0.47	0.66	1.31*	1.67**	1.92**	2.25**	2.42**	2.57**	2.88**	3.08**	3.45**
Model 2 (b) vs												
Model 3 (b)	1.78**	1.23	0.98	1.20	1.16	1.09	1.02	0.93	0.77	0.70	0.65	0.55

Note: Table 13 shows forecast comparisons based on Clark and McCracken (2001) encompassing test statistics $(ENC-t)$ for horizons extending from 1 to 12. 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 respectively denoted by two and one asterisks. For definitions of Models, see footnote for Table 10.

Table 14: Forecast Accuracy Evaluation $(CW-t)$

	Step1	Step2	Step3	Step4	Step5	Step6	Step7	Step8	Step9	Step10	Step11	Step12
Model 1 (b) vs												
Model 2 (b)	1.732*	3.922**	4.693**	4.568**	4.796**	4.999**	5.017**	4.916**	4.705**	4.536**	4.309**	4.204**
Model 3 (b)	0.721	0.470	0.657	1.303*	1.635*	1.868**	2.173**	2.312**	2.432*	2.697**	2.855**	3.163**
Model 2 (b) vs												
Model 3 (b)	1.761**	1.221	0.969	1.192	1.140	1.064	0.980	0.889	0.731	0.652	0.598	0.503

Note: Table 14 shows forecast comparisons based on modified Clark and West statistics $(CW-t)$ for horizons extending from 1 to 12. 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 respectively denoted by two and one asterisks. For definitions of Models, see footnote for Table 10.

7.6. Conclusion

In this chapter, three functional forms of a Taylor type policy rule have been used for forecasting exercise with the aim of obtaining the best model in predictive ability. For forecasting purposes, models in chapters 5 and 6 have been rewritten in backward looking versions. Out-of-sample properties are assessed using point forecast for the linear model while forecast obtained by means of bootstrapping method is used for nonlinear models.

Comparison of the forecasts from nonlinear functional forms with those from their benchmark linear model, show the advantage of considering nonlinearities in monetary policy reaction functions for most of the cases. Indeed, based on several forecasting accuracy tests, overall ranking reveals the superiority of the nonlinear model that distinguishes between downward and upward movements in the business cycles in closely matching the historical record. As such, forecasting performance tests reveal that the SARB pays particular attention to business cycles movements when setting its policy rate.

Chapter 8

Conclusions and implications

8.1. Introduction

In this thesis we provide an in-sample and out-of-sample assessment of how the South African Reserve Bank (SARB) sets policy rate in the context of both linear and nonlinear Taylor-type rule models of monetary policy. The usual Taylor rule relates the interest rate to deviations of inflation and output from their targets. However, given the controversial debate on whether central banks should target asset prices for economic stability, we investigate whether the SARB pays close attention to asset and financial markets in their policy decisions. For instance, one of the SARB's primary goals is to protect the value of the currency and achieve and maintain financial stability. But the question is "how is financial stability maintained?" To answer to this question, the Taylor rule is augmented with a financial conditions index that reflects the state of the housing market, the stock market, the real exchange rate and credit risk measures.

In this thesis the repurchase rate (repo rate) measures the nominal interest rate, inflation is measured by the annual change in the consumer price index and output is alternatively measured using the coincident business cycle indicator or industrial production and we measure the output gap as the deviation from their Hodrick-Prescott

(1997) trend. We use monthly seasonally adjusted data sourced from the SARB database. The sample ranges from 2000:01 to 2010:12, which covers the inflation targeting regime in South Africa. The start of the sample (2000) is conditioned by the date the Ministry of Finance announced its decision of setting an inflation target range of 3-6%.

The thesis had the following objectives:

1. To investigate whether the SARB pays close attention to asset and financial markets in their policy decisions;
2. To test nonlinearities controlled by the output gap;
3. To do recursive and rolling estimation;
4. To test the opportunistic approach to disinflation;
5. To evaluate the out-of-sample forecast performance;
6. To propose measures that can enhance monetary policy rules for South Africa.

The first three objectives are tested in chapter 5. The opportunistic approach (4^{th} objective) is tested in chapter 6 and out-of-sample forecasts (5^{th} objective) are evaluated in chapter 7. Proposition of measures (6^{th} objective) emerges from overall findings.

8.2. Findings

8.2.1. Findings on the first three objectives (chapter 5)

Being augmented with the financial conditions index, both linear and nonlinear monetary policy rules are tested in the second chapter. The nonlinear one is a logistic smooth transition autoregressive (LSTAR) model which aims to test for the presence of asymmetric pattern over business cycle. We have five main findings:

1. The SARB policy-makers pay close attention to the financial conditions index when setting interest rates; the effect of the index remains significant even when nonlinearities are accounted for.

2. The nonlinear Taylor rule improves its performance with the advent of the financial crisis, providing the best description of in-sample SARB interest rate setting behaviour with fixed-length rolling window estimation. The latter estimation technique is better able to capture parameter shifts as the crisis unfolds.

3. The 2007-2009 financial crisis witnesses an overall increased reaction to inflation and financial conditions. In addition, the financial crisis saw a shift from output stabilisation to inflation targeting and a shift, from a symmetric policy response to financial conditions, to a more asymmetric response depending on the state of the economy.

4. Given that inflation has been relatively high during the second semester of 2008, the SARB's response of monetary policy to output during that period has dropped significantly although it was expected to be set according to the financial crisis.

5. Rolling estimation reveals that inflation, output gap and financial index coefficients are remarkably unstable since mid 2007 with the oncoming of the crisis.

8.2.2. Findings on opportunistic approach (chapter 6)

The Opportunistic Approach to monetary policy is tested in chapter 6. It is worth reminding the two features of the opportunistic approach. The first feature is that monetary policy should move inflation toward an intermediate inflation target which is a function of past inflation rates and the inflation target rather than inflation target itself. The second feature is related to the concept of the zone of discretion for which policymakers are supposed to behave opportunistically by accommodating shocks that tend to move inflation towards the desired level. The interest rate will be raised when inflation is above the zone of discretion and decreased if inflation is below the zone.

Empirical findings are reported bellow:

1. The models that include intermediate rather than simple inflation target improve the fit of the models.

2. Among linear and nonlinear models, a quadratic logistic function outperforms all other models and provides support that the monetary policymakers of the SARB behaved opportunistically by accommodating shocks when inflation is within the zone of discretion but reacting aggressively otherwise.

3. The outperforming model reveals that the zone of discretion is symmetrically extending from 2.05 percent below and above the intermediate inflation rate. Estimated inflation target range of 4.10 percent is reasonable for the SARB as the difference between the pre-announced lower bound and upper bound is 3 percent.

4. Taking the official target range of 3 to 6 percent as a benchmark to our estimates, we can suggest that estimated target zone spans from 2.45 to 6.55 percent.

5. Recursive estimation of the preferred model reveals that in general the 2007-2009 financial crisis witnesses an overall increased reaction to inflation and financial conditions. However, the relative importance turns to the output gap since early 2009 as a result of the relatively low inflation.

8.2.3. Findings on forecast evaluation (chapter 7)

The main aim of chapter 7 is to evaluate predictive accuracy of six competing models based on several forecasting accuracy tests; namely the mean squared prediction error (MSPE), the median squared prediction error (MedSPE) the modified Diebold and Mariano, the encompassing and Cark and West tests.

1. Forecast evaluation reveals empirical evidence in favour of nonlinear models.

2. Overall ranking reveals the superiority of the nonlinear model that distinguishes between downward and upward movements in the business cycles in closely matching the historical record. As such, forecasting performance tests reveal that the SARB pays particular attention to business cycles movements when setting its policy rate.

8.3. Policy implications

The aforementioned findings have clear policy implications:

1. The Taylor (1993) rule assumes that the response of policymakers is only limited to inflation and output. However, empirical evidences show that financial stability matters in setting the South African monetary policy instrument. Indeed, these findings are in light with the implicit financial stability mandate of the SARB. The response of the SARB policy-makers to financial conditions arguably has important policy implications as it might

shed some light on why the current downturn in South Africa where the financial market occupies 25 percent of its total output is less severe.

2. On the other hand the Taylor (1993) rule assumes a constant response of policymakers to changes in inflation and output deviations from their desired levels. However, findings reveal that:

    a. The response of the SARB is not constant as it is found to depend on the sign of deviation of actual output from the steady-state level.

    b. The response of the policymakers is not constant as it also depends on whether inflation is within the zone of discretion (target zone) or not. Also, unlike the Taylor (1993) rule which accommodates simple inflation target, this modified policy rule accommodates intermediate inflation target, which is a function of past inflation rates and the inflation target itself.

All in all, the consideration of nonlinearities, the accommodation of intermediate inflation and the inclusion of a proxy to account for financial stability can provide better understanding of the behaviour of the SARB. As such, the South African Reserve Bank is encouraged to design a policy rule that explicitly accommodate financial variables. It is also positive that the SARB does not turn a blind eye on periods of distress (inflationary, macroeconomic and probably financial). Indeed, the SARB is encouraged to keep reacting aggressively in periods of distress and respond passively in periods of calm. It would not make sense to be aggressive on stability which is, indeed, the ultimate goal of any economy.