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Abstract

This paper is the first one to analyze 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. We augment the traditional Taylor rule with indicators of asset prices in order to account for potential financial stability targets implicitly considered by the SARB. Using an in-sample period of 1986:01 to 2004:12, we compare the out-of-sample forecasting ability of the models over the period 2005:01 to 2008:12. Our results indicate that the semiparametric models perform particularly well relative to the Taylor rule models currently dominating the monetary policy literature, and that nonlinear Taylor rules improve their performance under the new monetary regime.

Keywords: Monetary policy, 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, 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. In this paper, we start by employing a standard Taylor rule type model of the SARB's repo rate setting as a benchmark. More precisely, we make use of a modified specification by Clarida et al. (2000) and investigate its forecasting performance over the inflation targeting period using linear and nonlinear versions of the Taylor rule. A rule of this general form describing Reserve Bank's policy is intuitively plausible. Firstly, the SARB has a mandate to achieving and maintaining price stability in the interest of balanced and sustainable economic growth and therefore output/employment stability. And secondly the Monetary Policy Committee (MPC) of the SA Reserve Bank 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.

This 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 behavior of certain asset prices (stock prices, house prices, the exchange rate) and the concern by central banks over the maintenance of financial stability (see e.g. Bernanke and Gertler 2001). 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] It is worth noting that the SARB's other primary goals, as defined in the Constitution, is to protect the value of the currency and achieve and maintain financial stability though the South African financial institutions experienced no direct exposure to the sub prime crisis in

[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).

terms of interbank or liquidity problems of the type experienced in developed countries (see Mboweni, 2008, and Mminele, 2009). In this context, we modify the benchmark model and consider whether the interest rate setting by the Reserve Bank depends on asset prices.

We contribute to the scarce literature that uses Taylor rules to forecast the nominal interest rate in a number of ways.[2] First, we follow Castro (2008) and augment the reaction function with an alternative variable that collects and synthesizes the information from the asset and financial markets. Second, we consider three alternative expectations formation for the target variables. Third, we construct the forecasting for linear and nonlinear parametric models as well as for the more flexible nonparametric and semiparametric models. Finally, we examine forecasting gains from combining 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 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 interest rate, showing interest rate persistence and smoothing.[3] We can thus write our benchmark linear model as:

[2] A notable exception is Qin and Enders (2008) who use US data to compare the in-sample and out-of-sample properties of linear and nonlinear Taylor rules.

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

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

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

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

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

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 the two inflation regimes; deflationary and inflationary:

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

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

[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 weight 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 the best performing nonparametric model only.

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

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

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. 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.[7]

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

[7] It is also worth noting that during the first period there was also 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.

3.2 Expectations Formation

We have resorted to three ways by which the private sector can form their expectations of inflation, output gap and 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 Generalized 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 inflation, output gap and financial indicator gap as a measure of one-period ahead expected inflation, output gap and financial indicator gap, $E_t\pi_{t+1} = \pi_{t-1}$, $E_t(y_{t+1} - y^*) = y_{t-1}$, $E_t(I_{t+1} - I^*) = I_{t-1} - I^*$.[8]

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 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, that 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, we set $\rho = 0.5$), denotes that agents use the target inflation rate (where $\pi^T = (\pi^L + \pi^U)/2$ 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.

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 ex-

[8] 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.

pectation formation we therefore have twelve different models. Models 1 to 3 are linear Taylor rule version of equation (2), Models 4 to 6 are 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). In our forecasting exercise, we employ three straightforward procedures 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 call this Model 13, median forecast values from Models 2, 5, 8 and 11 and we call this Model 14, and median forecast values from Models 3, 6, 9 and 12 and we call this Model 15.

4 Forecasting Analysis

4.1 Methodology

We use the alternative models described above as the basis for a repeated forecasting test where we obtain both short- and long-term out-of-sample forecasts based on two types of regression estimation schemes, namely, rolling and recursive.[9] 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 2004:12. We calculate one-, three-, six-, and twelve-step ahead forecasts for the period 2005:01 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

[9] It is worth noting that we choose the first window of estimation to go up to 2004:12, i.e., four years in the second monetary regime discussed in the previous section so that the amount of parameter drift, if any, is reduced to some extent.

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)

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

where $\widehat{d}_{t+h}=\widehat{e}_{1,t+h}^{2}-\widehat{e}_{2,t+h}^{2}$, $\bar{d}=(P-h+1)^{-1}\sum_{t=R}^{T-h}\widehat{d}_{t+h}=\mathrm{MSPE}_1-\mathrm{MSPE}_2$, $\widehat{\Gamma}_{dd}(j)=(P-h+1)^{-1}\sum_{t=R+j}^{T-h}\widehat{d}_{t+h}\widehat{d}_{t+h-j}$: 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, West (2006) shows that if the fraction P/R is less than 0.1 normal critical values for $DM-t$ would still approximately hold.[10]

4.2 Out-of-sample forecasting comparisons

Columns (i)-(ii) of Table 1 present the average out-of-sample forecasting rankings across the recursive windows and four forecast horizons of the fifteen models according to two evaluation criteria, the mean squared prediction error (MSPE) and the median squared prediction error (MedSPE). Columns (iii)-(iv) of Table 1 report our forecasting rankings based on sequences

[10] See also Busetti et al. (2009) for an examination of size and power properties of different forecast accuracy tests for nested and nonnested models. We have also computed the MSE-F test of Clark and McCracken (2005) for the nested models but results are qualitatively similar.

of fixed-length rolling windows.[11] Better or higher ranked forecasting methods have lower numerical ranks. In examining the average rank results of Table 1, 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 analyze the results obtained using the recursive estimates. In this case, the estimation technique that provides the best results is the semiparametric one. In particular, Model 10 with "backward looking" expectation is ranked highest according to both evaluation criteria. The recursive technique produces better forecasts using the linear Taylor rule specification equation (2) than either the nonlinear equation (3), and the nonparametric equation (5). As expected, there are some gains from combining all the models, and this forecasting methodology (Models 13, 14, and 15) produces outcomes in the top five according to the two evaluation criteria. Another result worth mentioning is that, on average, a model specification embodying a simple 'inflation learning rule' for the future inflation rate seems to provide a better understanding of the prediction of the decision process made by the SARB in its interest rate setting policy and this applies to most models.

These results are supported generally by the rolling window forecasts. However, it is worth noting that the nonlinear Taylor rule Models 4, 5 and 6 are performing better than their linear counterparts. Moreover, Model 4, the nonlinear Taylor rule with "backward looking" expectations, produces the best MSPE and MedSPE among all Taylor rule models. 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 the previous section. In that sense, the rolling estimates increasingly attach more weight to the 'new' monetary policy framework relative to the recursive method given that the rolling one looses one observation from the 'old' regime each time.

Finally in Table 1 columns (v)-(vi) we compare the forecasts of the recursively estimated models with the rolling ones by computing the average MSPE and MedSPE for the recursively

[11] 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.

estimated models relative to the rolling ones across forecasting horizons (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 produce more accurate forecasts than rolling estimates for eleven out of fifteen models. However, in terms of MedSPE, rolling estimates are more accurate in eight out of the fifteen models implying that the adverse results in terms of MSPE might be driven by few very bad outcomes.

The statistical significance of alternative forecasts is evaluated in Tables 2 and 3. Table 2 provides pairwise out-of-sample forecast comparisons for the different forecasting models based on recursive estimates across forecasting horizons $h = 1, 3, 6$ and 12, using the modified $DM - t$ statistic.[12] 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 for taking the median forecasts across the different Models L, NL, NP and SP. Recalling that Model 10 (the semiparametric model with "backward looking") is ranked first in Table 1, we observe that Model SP forecasting superiority over the remaining models is much stronger for $h > 1$, though its superiority over Model P is not statistically significant in many cases. Model P fares second best after Model SP and is the only model that does better than Model SP with "forward looking" expectations data. Model L is doing particularly well over $h = 1$ step, that is, over the very short term. However, one can see that such dominance quickly disappears as the forecasting horizon extends.

Table 3 presents the results as we move to forecasting under a rolling window scheme. One can see that Model SP increases its forecasting dominance over all models with the forecasting dominance over the second best model, Model P, being statistically significant in generating significant MSPE reductions. It is also worth noting that the pooled of forecasts is the best performing model over the very short term, at $h = 1$. In terms of Taylor rule models, the nonlinear one is in general more accurate than the linear model, especially under backward looking expectations.[13]

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

[13] 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

5 Conclusion

In this paper we examine the forecasting performance of linear and nonlinear Taylor rule type models in inflation, output and a measure of financial conditions that account for financial stability targets stipulated in the SARB's goals. These parametric models were in turn compared with more flexible models that relax the assumption of a Taylor rule specification, such as, nonparametric and semiparametric models. Our findings support the forecasting superiority of the semiparametric models which allow interest rate smoothing to be linear while allowing a more flexible nonparametric structure with respect to observable economic variables. These models are best suited in forecasting the rate of interest setting behavior of the South African Reserve Bank. In this respect, it is worth mentioning that the model closest to the true data generating process would be expected to forecast best on unseen data hence this might indicate misspecification of popular models. It is also worth noting that there are gains from combining all forecasts and these models come only second after the semiparametric ones. Those results are consistent to the forecasting methodology (recursive or rolling window), and to the hypothesis used to construct the expectation formation. Finally, nonlinear Taylor rule models forecast out-of-sample better than linear models based on rolling estimates that place increasingly more weight on the current monetary policy regime relative to the recursive estimates.

In order to further assess the importance of targeting financial conditions for economic stability, a more detailed study would allow (both in-sample and out-of-sample) for linear and regime switching behavior in a full macroeconomic model. Further, it would be interesting to estimate our model using data for different Central Banks in order to investigate the ability of linear, nonlinear, nonparametric and semiparametric models to predict in-sample and out-of-sample fluctuations in interest rates. We intend to extend our work to this very direction.

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Table 1. 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	8.5	9.75	10.75	10.5	0.85	0.93
L	2	8.25	9.75	10.75	13	0.83	0.72
	3	8	9	12	11.25	0.78	0.72
	4	12.75	11	6.75	8.25	2.46	3.44
NL	5	13	11.5	11.25	13.75	1.62	1.49
	6	11.25	10.5	9.5	10	1.77	2.54
	7	10.5	10.5	11.5	10	0.80	1.14
NP	8	11.75	9.75	14.5	11.25	0.47	0.57
	9	8.5	7.75	10.25	5.5	0.76	1.11
	10	3.25	3.25	1	1.25	0.93	1.05
SP	11	7.25	5.75	4	2.5	1.18	1.40
	12	4.25	4.25	2.75	3.25	0.81	0.95
	13	5	6	4	4.25	0.82	1.14
P	14	3.25	5.75	7	8.75	0.52	0.47
	15	4.5	5.5	4	6.5	0.72	0.75

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 2. 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	-0.82	-2.29	-2.77	-2.23	NL	-1.05	-2.36	-1.61	-2.08	NL	-0.39	-1.82	-2.16	-1.90
NP	-2.12**	-0.62	0.31	0.92	NP	-2.42**	-0.97	-0.16	0.61	NP	-1.85*	0.73	0.54	0.96
SP	-0.88	2.17**	3.57**	1.56	SP	-1.75*	0.68	3.03**	1.15	SP	-1.17	2.12**	3.15**	1.73*
P	-0.48	1.87*	3.24**	1.32	P	0.49	1.91**	2.25**	1.64	P	-0.96	2.66**	3.10**	1.68*
NL vs					NL vs					NL vs				
NP	-2.05**	0.44	1.85*	1.34	NP	-2.04**	0.99	1.37	1.09	NP	-1.82*	1.29	1.39	1.02
SP	-0.52	2.43**	2.89**	1.83*	SP	-1.45	1.86*	1.61	1.16	SP	-0.81	2.10**	2.29**	1.37
P	0.45	2.35**	2.52**	1.61	P	0.94	2.55**	1.89*	1.31	P	-0.26	2.31**	2.15**	1.28
NP vs					NP vs					NP vs				
SP	1.79*	1.91*	1.94*	2.09*	SP	0.28	1.60	1.70*	0.85	SP	1.59	1.21	1.59	1.38
P	2.12**	1.71*	1.95*	0.76	P	2.95**	2.01**	3.13**	1.14	P	1.83*	1.00	1.62	0.43
SP vs					SP vs					SP vs				
P	0.80	-1.49	-1.03	-1.92*	P	2.00**	0.49	1.06	0.06	P	0.90	-0.61	-1.10	-1.54

Notes: The Table presents pair-wise out-of-sample forecast comparisons for the forecasting models based on recursive estimates, across forecasting horizons h = 1, 3, 6 and 12, using the modified Diebold-Mariano statistic, $DM - t$. 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 the forecasting model definitions.

Table 3. 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	1.92	1.58	3.05	0.84	NL	0.19	0.82	-1.02	-1.43	NL	0.85	1.27	0.97	-0.13
NP	-1.43	-1.40	0.38	0.76	NP	-1.11	-1.89*	-0.68	-1.23	NP	-1.41	-0.34	1.19	1.16
SP	1.21	2.46**	4.28**	1.61	SP	0.08	2.05**	2.31**	3.09**	SP	0.71	3.19**	3.19**	2.08**
P	3.06**	3.14**	3.31**	1.18	P	1.74*	3.18**	1.83*	0.28	P	2.55**	3.07**	2.51**	2.20**
NL vs					NL vs					NL vs				
NP	-1.53	-1.57	-0.83	1.12	NP	-1.12	-1.85*	-0.56	-0.77	NP	-1.47	-0.66	-0.05	0.55
SP	1.04	2.51**	7.70**	3.53**	SP	0.05	1.31	2.68**	3.42**	SP	0.60	2.65**	1.84*	1.06
P	2.81**	2.26**	3.23**	5.35**	P	2.12**	1.79*	2.40**	6.70**	P	2.47**	2.45**	1.29	0.85
NP vs					NP vs					NP vs				
SP	1.76*	2.45**	2.88**	1.70*	SP	1.22	2.45**	2.21**	2.33**	SP	1.57	2.06**	2.01**	1.28
P	1.91*	2.21**	2.36**	1.60	P	1.51	2.40**	1.49	1.49	P	1.82*	1.53	1.51	0.42
SP vs					SP vs					SP vs				
P	-0.24	-1.67*	-4.62**	-1.69*	P	0.56	-0.62	-2.84**	-2.03**	P	-0.13	-2.08**	-2.60**	-1.87*

Notes: The Table presents pair-wise out-of-sample forecast comparisons for the forecasting models based on fixed window rolling estimates, across forecasting horizons h = 1, 3, 6 and 12, using the modified Diebold-Mariano statistic $DM - t$. 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 the forecasting model definitions.

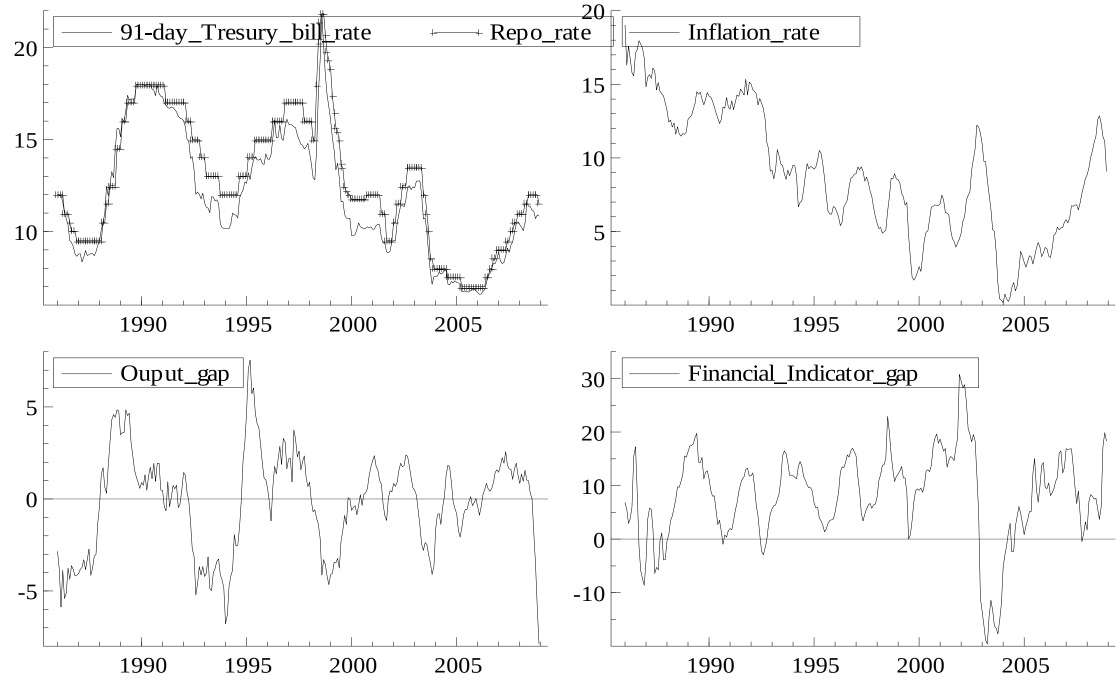

Figure 1. Evolution of the main variables

Appendix 1: Description of the variables and sources

Variables	Description
r_t	91-day Treasury bill 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	6.60	0.20	-7.90	-19.61	-9.67	-48.44	-39.42
Max	22.20	19	8.70	30.83	30.51	48.79	41.31
Mean	12.53	9.20	-0.10	8.01	10.36	11.58	5.70
Median	11.90	9.10	0.28	8.90	12.65	13.03	7.27
Std. Deviation	3.71	4.34	2.85	8.52	7.93	19.50	14.68
Skewness	0.42	-0.02	0.05	-0.69	-0.26	-0.66	-0.64
Kurtosis	2.43	2.13	2.96	4.21	3.29	3.25	3.92