Forecasting Inflation in an Inflation Targeting Economy: Structural Versus Non-Structural Models
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Forecasting Inflation in an Inflation Targeting Economy:  
Structural Versus Non-Structural Models  

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Abstract  
We propose a comparison between atheoretical and theoretical models in forecasting the inflation rate for an inflation-targeting country such as South Africa. In a pseudo real-time environment, our results show that for shorter horizons, the atheoretical error correction models, with and without factors, perform better; while for longer horizons, theoretical (DSGE based) models outperform their competitors.  

JEL CODES: C11, C32, C52  
KEYWORDS: Inflation, South Africa, Structural, Atheoretical, Factors, DSGE  

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1 Introduction

Following Stock and Watson (2010), recent papers have relied on high dimensional datasets when forecasting inflation, and a detailed literature review can be found in Faust and Wright (2013). From a structural perspective, besides trying to model financial frictions into Dynamic Stochastic General Equilibrium (DSGE) models to capture drastic events of the recent financial crisis, DSGE models have also been extended to account for information from large datasets (Bekiros and Paccagnini (2015)). Against this backdrop, the objective of this paper is to compare the ability of various small- and large-scale atheoretical models with small and large-scale DSGE models (with and without financial frictions) in forecasting the inflation rate in South Africa. Inflation forecasts are of paramount importance in the formulation of monetary policy decisions in any economy, but, naturally, more so in an inflation targeting country.

Given that the majority of the modeling strategies mentioned above are applied to developed economies (namely the US), our paper aims to make the first attempt to analyse the success or failure of such models in forecasting the inflation rate of an emerging economy over the period of 2000:Q1-2012:Q3 (based on an in-sample of 1980:Q1-1999:Q4). The starting point of the pseudo real-time forecasting exercise corresponds to the adoption of the inflation targeting regime in South Africa. Though there exists work for South Africa which compares the forecasting ability of (FA)VAR and DSGE models (Gupta and Kabundi (2008)), none of these papers incorporated financial frictions, information from large datasets into the DSGE models\footnote{Our paper is an elaborate extension of the work of Gupta and Steinbach (2013), and helps in judging the robustness of the superiority of the DSGE-VAR approach.}, or an error correction

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{inflation.png}
\caption{Inflation in South Africa}
\label{fig:inflation}
\end{figure}

\textit{Shaded periods represent two consecutive quarters of negative GDP growth. Data from the OECD.}
term into the reduced form models. The fact that our out-of-sample period includes the recent financial crisis motivates the decision to incorporate financial frictions into the DSGE model. On the other hand, in terms of the atheoretical models, just as a VAR in first-differences is misspecified if there are cointegrating relationships between the variables, so is the FAVAR, motivating the inclusion of FECMs and VECMs in our model set. The remainder of this paper is organized as follows. Section 2 briefly describes the data used in the empirical analysis. Section 3 introduces the models estimated. In Section 4, we discuss our results. Section 5 concludes.

2 Data

We construct a quarterly ‘macro panel’ dataset consistent with the factor literature for South Africa between 1980Q2-2012Q3. Our dataset contains series on gross fixed capital formation, GDP by sector, employment, wages, and other related variables, and we deflate where appropriate. We exclude our three primary endogenous variables GDP (from the OECD), CPI (from the OECD) and interest rate (from the South African Reserve Bank - SARB) from the panel for factor extraction. The spread variable used in the DSGE models with financial frictions is defined as the difference between the ESKOM corporate bond yield and the ten-year long-term government bond yield.

3 Model set

3.1 Non-structural models

Our univariate benchmark is based on the algorithm of Hyndman and Khandakar (2008). We take a ‘grid’ style approach, estimating an ARIMA(p,d,q) for each of our three endogenous variables, searching up to four AR(p) and MA(q) terms, pretesting up to the second difference with a KPSS test, (with identification using the Bayesian Information Criteria (BIC)), re-estimating recursively using maximum likelihood. Our endogenous variable is either the (log of) real GDP, inflation or interest rates (levels). We also consider corresponding (symmetric) VARs and VECMs as per Equation 1 and 2:

\[ \Delta Y_t = C + \Phi(L)\Delta Y_{t-1} + \varepsilon_{y,t}, \]  

\[ \Delta Y_t = \alpha(\delta'Y_{t-1} + \rho_0) + \Phi(L)\Delta Y_{t-1} + \alpha \perp \gamma_0 + \varepsilon_{y,t}, \]  

where \( Y_{t}' = [Y_{1,t}', Y_{2,t}', Y_{3,t}'] \) and lag length is again determined recursively by the BIC. We use the Johansen Trace Test at the 5% level to determine the co-integrating rank (as the FECM
models below, and per Banerjee et al. (2014), with no restrictions on the factor space). Our deterministic specification ($C$ in Eq. 1, $\rho_0$ and $\gamma_0$ in Eq. 2) is based on the assumption that the levels data have linear trends but the cointegrating equations have only intercepts.

We estimate our FAVAR model as the ‘two-step’ variant of Bernanke et al. (2004), where the factors are (recursively) extracted as per Stock and Watson (2002), prior to the estimation of the FAVAR. Thus, the reduced form representation of our FAVAR is:

$$\begin{bmatrix} \Delta Y_t \\ \hat{F}_{t}^{I(0)} \end{bmatrix} = C + \Phi(L) \begin{bmatrix} \Delta Y_{t-1} \\ \hat{F}_{t-1}^{I(0)} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{f,t} \end{bmatrix}, \quad (3)$$

where $\hat{F}_{t}^{I(0)}$ is a matrix containing stacked stationary factors\(^2\), extracted from suitably transformed (i.e. I(0)) data. While a full derivation of the model, from VAR to VECM to FECM, is provided in Banerjee and Marcellino (2008), we merely show the final reduced form of the FECM to be estimated:

$$\begin{bmatrix} \Delta Y_t \\ \Delta \hat{F}_{t}^{I(1)} \end{bmatrix} = \alpha(\delta' \begin{bmatrix} Y_{t-1} \\ \hat{F}_{t-1}^{I(1)} \end{bmatrix} + \rho_0) + \Phi(L) \begin{bmatrix} \Delta Y_{t-1} \\ \Delta \hat{F}_{t-1}^{I(1)} \end{bmatrix} + \alpha \perp \epsilon_{0} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{f,t} \end{bmatrix}, \quad (4)$$

whereby the I(1) factors ($\hat{F}_{t}^{I(1)}$) are extracted from the dataset using the methodology of Bai (2004).

### 3.2 Structural models

We estimate two DSGE models. The first one is the small-scale model implemented by Del Negro and Schorfheide (2004) with the same three endogenous variables as per Equations 1-2. The second model is augmented by a financial friction (the spread), as proposed in Bekiros and Paccagnini (2015). Besides a Bayesian estimation, the DSGE models are evaluated using hybrid methods\(^3\) which combine the advantage of having economic restrictions through the priors on the parameters, with the forecasting power of reduced form representations such as the VAR and FAVAR, as discussed below.

#### 3.2.1 Small scale DSGE models

In our DSGE setup, the economy is made up of four components. The first component is the representative household with habit persistent preferences. This household maximizes an additively separable utility function which is separable into consumption, real money balances

\(^2\)Dimensions of $\hat{F}_{t}^{I(0)}$ and $\hat{F}_{t}^{I(1)}$ determined recursively by the IPC\(_2\) of Bai and Ng (2002).

\(^3\)This is based on the study of dummy priors of proposed by Ingram and Whiteman (1994).
and hours worked over an infinite lifetime. The household gains utility from consumption relative to the level of technology, real balances of money, and disutility from hours worked. The household earns interest from holding government bonds and earns real profits from the firms. Moreover, the representative household pays lump-sum taxes to the government. The second component is a perfectly competitive, representative final goods producer which is assumed to use a continuum of intermediate goods as inputs, and the prices for these inputs are given. The producers of these intermediate goods are monopolistic firms which use labour as the only input. The production technology is the same for all the monopolistic firms. Nominal rigidities are introduced in terms of price adjustment costs for the monopolistic firms. Each firm maximizes its profits over an infinite lifetime by choosing its labour input and its price. The third component is the government which spends in each period a fraction of the total output, which fluctuates exogenously. The government issues bonds and levies lump-sum taxes, which are the main part of its budget constraint. The last component is the monetary authority, which follows a Taylor rule regarding the inflation target and the output gap. There are three economic shocks: an exogenous monetary policy shock (in the monetary policy rule), and two autoregressive processes, AR(1), which model government spending and technology shocks. To solve the model, optimality conditions are derived for the maximization problems. After linearization around the steady-state, the economy is described by the following system of equations

\[ \tilde{x}_t = E_t[\tilde{x}_{t+1}] - \frac{1}{\tau}(\tilde{R}_t - E_t[\tilde{\pi}_{t+1}]) + (1 - \rho_g)\tilde{g}_t + \rho_Z \frac{1}{\tau} \tilde{z}_t \]  

(5)

\[ \tilde{\pi}_t = \beta E_t[\tilde{\pi}_{t+1}] + \kappa[\tilde{x}_t - \tilde{g}_t] \]  

(6)

\[ \tilde{R}_t = \rho_R \tilde{R}_{t-1} + (1 - \rho_R)(\psi_1 \tilde{\pi}_t + \psi_2 \tilde{x}_t) + \epsilon_{R,t} \]  

(7)

\[ \tilde{g}_t = \rho_g \tilde{g}_{t-1} + \epsilon_{g,t} \]  

(8)

\[ \tilde{z}_t = \rho_z \tilde{z}_{t-1} + \epsilon_{z,t} \]  

(9)

where \( x \) is the detrended output (divided by the non-stationary technology process), \( \pi \) is the gross inflation rate, and \( R \) is the gross nominal interest rate. The tilde denotes percentage deviations from a steady state or, in the case of output, from a trend path. The model can be solved by applying the algorithm proposed by Sims (2002). Define the vector of variables \( \tilde{Z}_t = (\tilde{x}_t, \tilde{\pi}_t, \tilde{R}_t, \tilde{g}_t, \tilde{z}_t, E_t \tilde{x}_{t+1}, E_t \tilde{\pi}_{t+1}) \) and the vector of shocks as \( \epsilon_t = (\epsilon_{R,t}, \epsilon_{g,t}, \epsilon_{z,t}) \). Therefore
the previous set of equations, Eq. 5 - 9, can be recast into a set of matrices \( (\Gamma_0, \Gamma_1, C, \Psi, \Pi) \) accordingly to the definition of the vectors \( \tilde{Z}_t \) and \( \epsilon_t \):

\[
\Gamma_0 \tilde{Z}_t = C + \Gamma_1 \tilde{Z}_{t-1} + \Psi \epsilon_t + \Pi \eta_t \tag{10}
\]

where \( \eta_{t+1} \), such that \( E_t \eta_{t+1} \equiv E_t (y_{t+1} - E_t y_{t+1}) = 0 \), is the expectations error.

As a solution to Eq. 10, we obtain the following transition equation as a policy function:

\[
\tilde{Z}_t = T (\theta) \tilde{Z}_{t-1} + R (\theta) \epsilon_t \tag{11}
\]

In order to provide the mapping between the observable data and those computed as deviations from the steady state of the model, we set the following measurement equations as in Del Negro and Schorfheide (2004):

\[
\begin{align*}
\Delta \ln x_t &= \ln \gamma + \Delta \tilde{x}_t + \tilde{z}_t \\
\Delta \ln P_t &= \ln \pi^* + \tilde{\pi}_t \\
\ln R^a_t &= 4 \left[ (\ln r^* + \ln \pi^*) + \tilde{R}_t \right]
\end{align*}
\]

where \( \ln \) denotes 100 times log and \( \Delta \ln \) refers to the log difference. They can be also cast into matrices as

\[
Y_t = \Lambda_0 (\theta) + \Lambda_1 (\theta) \tilde{Z}_t + v_t \tag{13}
\]

where \( Y_t = (\Delta \ln x_t, \Delta \ln P_t, \ln R^a_t)' \), \( v_t = 0 \) and \( \Lambda_0 \) and \( \Lambda_1 \) are defined accordingly. For completeness, we write the matrices \( T, R, \Lambda_0 \) and \( \Lambda_1 \) as a function of the structural parameters in the model, \( \theta = (\ln \gamma, \ln \pi^*, \ln r^*, \kappa, \tau, \psi_1, \psi_2, \rho_R, \rho_g, \rho_Z, \sigma_R, \sigma_g, \sigma_Z)' \). Such a formulation derives from the rational expectations solution. For more details, see Del Negro and Schorfheide (2004).

The second model proposed is a simple DSGE model obtained as a special case of Smets and Wouters (2007). We augment the small scale DSGE model by financial frictions as shown in Del Negro and Schorfheide (2004) and summarized in the following equations. The arbitrage condition between the return to capital and the riskless rate is modified as proposed by Del Negro and Schorfheide (2004):

\[
E[\tilde{R}_{t+1}^k - R_t] = \zeta_{sp} (\bar{k}_t - n_t) + \tilde{\sigma}_{\omega,t} \tag{14}
\]

and

\[
\tilde{R}_t^k - \pi_t = \frac{r^*_k}{r^* + (1 - \delta)} r^*_k \tag{15}
\]

In these equations, \( r^*_k \) is the rental rate of capital of steady state, \( \delta \) is the depreciation rate, \( \tilde{R}_t^k \) is
the gross nominal return on capital for entrepreneurs, \( n_t \) is entrepreneurial equity which depends on equation (15) and \( \sigma_{\omega,t} \) captures mean-preserving changes in the cross-sectional dispersion of ability across entrepreneurs and follows an AR(1) process with parameters \( \rho_{\sigma_{\omega}} \) and \( \sigma_{\sigma_{\omega}} \). The first condition determines the spread between the expected return on capital and the riskless rate (if \( \zeta_{sp} = 0 \), the financial friction shocks are zero), while the second condition defines the return on capital. Capital is subject to variable capacity utilization \( u_t \), and the relationship between \( k_t \) and the amount of capital effectively rented out to firms \( k_t \) is:

\[
k_t = u_t - z_t + \bar{k}_{t-1}
\]

The measurement equations for real output growth, inflation, short term interest rate, and spread:

\[
\Delta \ln y_t = \ln \gamma + \Delta y_t + z_t
\]

\[
\Delta \ln P_t = \ln \pi^* + \pi_t
\]

\[
\ln R^a_t = 4 \left[ (\ln R^* + \ln \pi^*) + R_t \right]
\]

\[
SP_t = SP_* + 100E_t[\bar{R}_t + 1 - R_t]
\]

where all variables are measured in percent and \( \pi^*, R^* \) and \( SP_* \) measure the steady state level of inflation, short term interest rate and spread.

### 3.2.2 Bayesian estimation

For the Bayesian estimations, we follow the setup proposed in Smets and Wouters (2007) and use the priors proposed in Bekiros and Paccagnini (2015). For the hybrid models, the estimation initializes with an unrestricted VAR:

\[
Y = X\Phi + \varepsilon,
\]

where \( Y \) contains the same stacked endogenous vectors as in Section 3, and \( X \) is a \((T \times k)\) matrix \((k = 1 + np, p = \text{number of lags})\) with rows \( X'_t = [1, Y'_{t-1}, ..., Y'_{t-p}] \), \( \varepsilon \) is a \((T \times n)\) matrix with rows \( \varepsilon'_t \) and \( \Phi = [\Phi_0, \Phi_1, ..., \Phi_p]' \) is a \( k \times n \) matrix of coefficients. The log-likelihood is a function of \( \Phi \) and \( \Sigma_{\varepsilon} \):

\[
L(Y|\Phi, \Sigma_{\varepsilon}) \propto |\Sigma_{\varepsilon}|^{-\frac{T}{2}} \exp \left\{ -\frac{1}{2} tr \left[ \Sigma_{\varepsilon}^{-1} (Y'Y - \Phi'X'Y'Y - Y'X\Phi + \Phi'X'X\Phi) \right] \right\}.
\]

\footnote{We now turn to using a representation equivalent to Equation 1, but which is more common to this strand of literature (suppressing subscripts).}
The prior distribution for the VAR parameters proposed by Del Negro and Schorfheide (2004) is based on the statistical representation of the DSGE model given by a VAR approximation. Let $\Gamma_{xx}^*$, $\Gamma_{yy}^*$, $\Gamma_{xy}^*$ and $\Gamma_{yx}^*$ be the theoretical second-order moments of $Y$ and $X$ implied by the DSGE model, where:

$$
\Phi^* (\theta) = \Gamma_{xx}^* (\theta)^{-1} \Gamma_{xy}^* (\theta), \\
\Sigma^* (\theta) = \Gamma_{yy}^* (\theta) - \Gamma_{yx}^* (\theta) \Gamma_{xx}^* (\theta)^{-1} \Gamma_{xy}^* (\theta).
$$

(19)

Conditional on the vector of structural parameters in the DSGE model ($\theta$), the prior distributions for the VAR parameters $p(\Phi, \Sigma_\epsilon | \theta)$ are of the Inverted-Wishart (IW) and Normal forms:

$$
\Sigma_\epsilon | \theta \sim IW \left((\lambda T \Sigma_\epsilon^* (\theta), \lambda T - k, n), \Phi \right), \\
\Phi | \Sigma_\epsilon, \theta \sim N \left(\Phi^* (\theta), \Sigma_\epsilon \otimes (\lambda T \Gamma_{XX} (\theta)^{-1})\right).
$$

(20)

where the parameter $\lambda$ controls the degree of model misspecification with respect to the VAR.

The posterior distributions of the VAR parameters are also of Inverted-Wishart and Normal form. Given the prior distribution, posterior distributions follow:

$$
\Sigma_\epsilon | \theta, Y \sim IW \left((\lambda + 1) T \hat{\Sigma}_{\epsilon,b} (\theta), (\lambda + 1) T - k, n\right),
$$

(21)

$$
\Phi | \Sigma_\epsilon, \theta, Y \sim N \left(\hat{\Phi}_b (\theta), \Sigma_\epsilon \otimes \left[\lambda T \Gamma_{XX} (\theta) + X'X\right]^{-1}\right),
$$

(22)

$$
\hat{\Phi}_b (\theta) = \left(\lambda T \Gamma_{XX} (\theta) + X'X\right)^{-1} \left(\lambda T \Gamma_{XY} (\theta) + X'Y\right),
$$

(23)

$$
\hat{\Sigma}_{\epsilon,b} (\theta) = \frac{1}{(\lambda + 1) T} \left[\left(\lambda T \Gamma_{YY} (\theta) + Y'Y\right) - \left(\lambda T \Gamma_{XY} (\theta) + X'Y\right) \hat{\Phi}_b (\theta)\right].
$$

(24)

where the matrices $\hat{\Phi}_b (\theta)$ and $\hat{\Sigma}_{\epsilon,b} (\theta)$ have the interpretation of maximum likelihood estimates of the VAR parameters based on the combined sample of actual observations and artificial observations generated by the DSGE.

The DSGE-FAVAR includes both the vector of observable variables and the vector of unobserved factors extracted from a large data-set of macroeconomic time series that capture
additional economic information relevant to model the dynamics of the observables as per Equation 3. In the simple DSGE model, the vector of endogenous variables is as above, and in the DSGE with financial frictions $Y_t = (\Delta \ln x_t, \Delta \ln P_t, \ln R_t, SP_t)$. Contrary to Boivin and Giannoni (2006)), here the FAVAR is not interpreted as the reduced form of the DSGE model, but as the statistical representation of the observed series.

4 Results

In Table 1, we present the Mean Square Errors (MSEs) from our various models for the inflation rate alone. Forecast evaluations for GDP and the interest rate are also contained in the supplementary material which accompanies this paper. The VECM and FECM performs the best at one and two-quarter-ahead horizons, indicating the importance of incorporating long-run relationships, as well as information from a large data set in forecasting inflation at shorter horizons. Following this, we show that over the horizons of three- to five and eight quarters ahead, the DSGE-VAR performs best, and for the remaining horizons, it is the DSGE-VAR model with the spread.\footnote{We also estimated a large-scale Bayesian VAR as in Bańbura et al. (2010). However, this model performed poorly at all horizons relative to the models reported in the text. Complete details of these results are, however, available upon request from the authors.}

5 Conclusions

In this paper we compare a wide array of atheoretical and theoretical models in forecasting the inflation rate of South Africa - an inflation-targeting emerging market economy. Our results indicate that while atheoretical models tend to perform better at shorter horizons, we need microfounded hybrid DSGE-VAR models (with and without financial frictions) to forecast inflation accurately at medium to long-run horizons. Our results highlight the importance of a modelling approach which imposes theory on an otherwise atheoretical framework given the overall superiority of such models.

References


### Table 1: Mean squared forecast error across all recursions

<table>
<thead>
<tr>
<th>Models</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<td>1.8436</td>
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<td>2.2793</td>
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<td>2.3418</td>
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Notes: Spread implies DSGE models with financial frictions; Bold entries indicate the model with the minimum MSEs. Italics indicates the second-best model on average. * indicates significance of the MSE-F test statistic at one percent level between the best model at a specific horizon and the AR model.