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.

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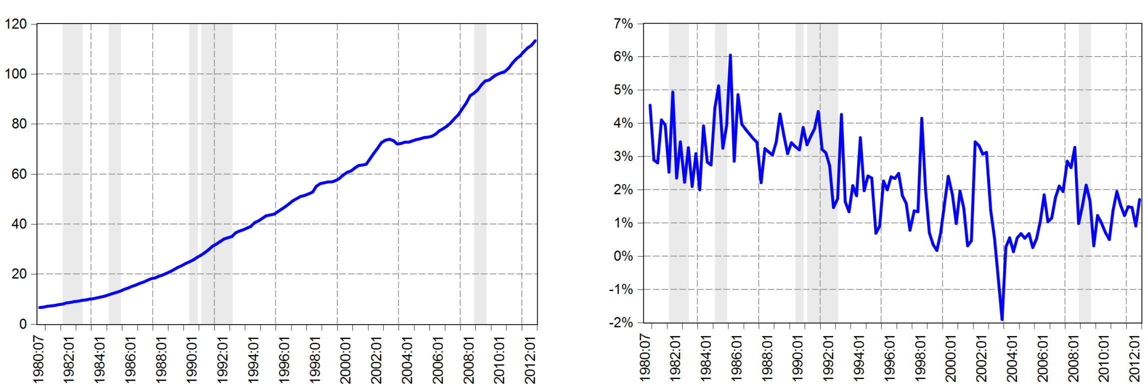
1 Introduction

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 modelling 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 (2010), Gupta and Kabundi (2011)), none of these papers incorporated financial frictions, information from large datasets into the DSGE models[1], or an error correction term into the reduced form models. The fact that our out-of-

Figure 1: Inflation in South Africa

(a) Consumer Price Index **(b)** Inflation Rate



Shaded periods represent two consecutive quarters of negative GDP growth. Data from the OECD.

[1]Our paper is an elaborate extension of the work of Gupta and Steinbach (2013), and helps in judging the

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 and Estimation

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. Forecasts are generated using recursively expanding windows with the first out of sample period set to 2000Q1, and are subsequently evaluated using root mean squared errors (RMSEs) which are discussed in Section 4.

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:

$$\Delta \mathbf{Y}_t = C + \Phi(L)\Delta \mathbf{Y}_{t-1} + \varepsilon_{y,t}, \tag{1}$$

$$\Delta \mathbf{Y}_t = \alpha(\delta' \mathbf{Y}_{t-1} + \rho_0) + \Phi(L)\Delta \mathbf{Y}_{t-1} + \alpha \perp \gamma_0 + \varepsilon_{y,t}, \tag{2}$$

robustness of the superiority of the DSGE-VAR approach.

where $\mathbf{Y}'_t = [Y'_{1,t}, Y'_{2,t}, Y'_{3,t}]$ 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, ρ_0 and γ_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:

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

where $\hat{\mathbf{F}}_t^{I(0)}$ 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:

$$\begin{bmatrix} \Delta\mathbf{Y}_t \\ \Delta\hat{\mathbf{F}}_t^{I(1)} \end{bmatrix} = \alpha(\delta' \begin{bmatrix} \mathbf{Y}_{t-1} \\ \hat{\mathbf{F}}_{t-1}^{I(1)} \end{bmatrix} + \rho_0) + \Phi(L) \begin{bmatrix} \Delta\mathbf{Y}_{t-1} \\ \Delta\hat{\mathbf{F}}_{t-1}^{I(1)} \end{bmatrix} + \alpha \perp \gamma_0 + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{f,t} \end{bmatrix}, \tag{4}$$

whereby the I(1) factors ($\hat{\mathbf{F}}_t^{I(1)}$) 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.

[2]Dimensions of $\hat{\mathbf{F}}_t^{I(0)}$ and $\hat{\mathbf{F}}_t^{I(1)}$ 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).

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 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

$$\tilde{x}_t = E_t[\tilde{x}_{t+1}] - \frac{1}{\tau}(\tilde{R}_t - E_t[\tilde{\pi}_{t+1}]) + (1-\rho_g)\tilde{g}_t + \rho_Z \frac{1}{\tau}\tilde{z}_t \tag{5}$$

$$\tilde{\pi}_t = \beta E_t[\tilde{\pi}_{t+1}] + \kappa[\tilde{x}_t - \tilde{g}_t] \tag{6}$$

$$\tilde{R}_t = \rho_R \tilde{R}_{t-1} + (1-\rho_R)(\psi_1\tilde{\pi}_t + \psi_2\tilde{x}_t) + \epsilon_{R,t} \tag{7}$$

$$\tilde{g}_t = \rho_g \tilde{g}_{t-1} + \epsilon_{g,t} \tag{8}$$

$$\tilde{z}_t = \rho_z \tilde{z}_{t-1} + \epsilon_{z,t}, \tag{9}$$

where x is the detrended output (divided by the non-stationary technology process), π 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 $\tilde{Z}_t = \left(\tilde{x}_t, \tilde{\pi}_t, \tilde{R}_t, \tilde{g}_t, \tilde{z}_t, E_t\tilde{x}_{t+1}, E_t\tilde{\pi}_{t+1}\right)$ 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 ϵ_t;

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

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

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

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

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):

$$\begin{aligned} \Delta\ln x_t &= \ln\gamma + \Delta\tilde{x}_t + \tilde{z}_t \\ \Delta\ln P_t &= \ln\pi^* + \tilde{\pi}_t \\ \ln R_t^a &= 4\left[(\ln r^* + \ln\pi^*) + \tilde{R}_t\right] \end{aligned} \tag{12}$$

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

$$Y_t = \Lambda_0\left(\theta\right) + \Lambda_1\left(\theta\right)\tilde{Z}_t + v_t \tag{13}$$

where $Y_t = (\Delta\ln x_t, \Delta\ln P_t, \ln R_t^a)'$, $v_t = 0$ and Λ_0 and Λ_1 are defined accordingly. For completeness, we write the matrices T, R, Λ_0 and Λ_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):

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

and

$$\widetilde{R}_t^k - \pi_t = \frac{r_*^k}{r_*^k + (1-\delta)} r_*^k \tag{15}$$

In these equations, r_*^k is the rental rate of capital of steady state, δ is the depreciation rate, $\widetilde{R}_t^k$ is the gross nominal return on capital for entrepreneurs, n_t is entrepreneurial equity which depends on equation (15) and $\widetilde{\sigma}_{\omega,t}$ 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 $\overline{k}_t$ and the amount of capital effectively rented out to firms k_t is:

$$k_t = u_t - z_t + \overline{k}_{t-1}$$

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

$$\begin{aligned} \Delta \ln y_t &= \ln \gamma + \Delta y_t + z_t \\ \Delta \ln P_t &= \ln \pi^* + \pi_t \\ \ln R_t^a &= 4\left[(\ln R^* + \ln \pi^*) + R_t\right] \\ SP_t &= SP_* + 100 E_t[\widetilde{R}_{t+1}^k - R_t] \end{aligned} \tag{16}$$

where all variables are measured in percent and π_*, R_* and SP_* measure the steady state level of inflation, short term interest rate and spread.

For the Bayesian estimations, we follow the setup proposed in Smets and Wouters (2007) and use the priors proposed in Bekiros and Paccagnini (2015).[4]

4 Results

In Table 1, we present the RMSEs from our various models for the inflation rate. 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

[4] 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.

DSGE-VAR model with the spread.[5]

At this stage, it is important to put into perspective our results relative to the existing ones for South Africa and in general. Our results tend to corroborate the overall observations made in the literature on forecast comparison of structural and non-structural models while forecasting inflation. This is because, we observe that at shorter forecasting horizons, atheoretical models perform better, and this is believed to be primarily because at these horizons, what is important is the persistence property of the inflation rates (along with long-run equilibrium relationships between the variables and/or factors), which the non-structural models captures accurately based on their lags, being backward-looking (Gupta et al. (2015)). However, for forecasting inflation at medium-run horizons, as is evident from our case, we need to have a structural framework, which allows for price rigidities through the New-Keynesian framework, given ample micro (firm)-level evidence of high mark-ups and rigidities in South Africa (Gupta and Steinbach (2013)). The role of financial frictions, via the modelling of the spread is also found to be important, over and above the price rigidity (given that the DSGE-VAR comes in close second), at longer horizons. This is not surprising given that the out-of-sample encompasses the periods of the global financial crisis, and hence incorporating financial risks in the structural framework is of paramount importance as well, over and above price rigidity (Bekiros and Paccagnini (2015)). So in sum, we can conclude that structural assumptions of price rigidity and financial frictions are important requirements in DSGE models, especially when forecasting inflation at medium- to long-run horizons, since the persistence property of inflation captured by backward-looking atheoretical models are only sufficient to produce good forecasts at shorter horizons.

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. From a policy perspective, it emphasizes caution against the

[5]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. In addition, we also estimated a small open economy DSGE model as in Gupta and Steinbach (2013), but this model could not outperform the closed economy DSGE models estimated here, with this result highlighting the fact that small open economy assumptions are not necessary to produce superior inflation forecasts - something discussed in detail by Gupta and Steinbach (2013). Complete details of these results are, however, available upon request from the authors.

over-reliance on one specific model or model class, encouraging central bankers to estimate and consider a variety of different models conditional on the horizon being forecast.

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Table 1: Root mean squared forecast error across all recursions

	Horizons								
Models	1	2	3	4	5	6	7	8	Average
AR	1.3182	1.8436	2.062	2.2560	2.4434	2.2793	2.2383	2.3287	2.0962
VAR	0.9041	1.6557	2.0582	2.3418	2.4844	2.5647	2.5898	2.5368	2.1419
VECM	**0.8425***	1.4723	1.7908	2.0627	2.1804	2.1659	2.0917	2.0005	1.8259
	[73.8513]								
FAVAR	0.9052	1.6354	2.0521	2.3331	2.4824	2.5672	2.5906	2.5384	2.1381
FECM	0.8476	**1.3207***	1.5523	1.8071	2.0291	2.1726	2.1958	2.2008	1.7657
		[47.4305]							
DSGE	1.5998	1.5628	1.5245	1.4653	1.4676	1.4575	1.4892	1.4253	1.499
DSGE-VAR	1.5344	1.511	**1.4682***	**1.4394***	**1.4448***	1.4181	1.4157	1.4055	**1.4547**
			[47.6502]	**[69.9116]**	**[87.4224]**				
DSGE-FAVAR	1.5659	1.5511	1.5156	1.4971	1.4989	1.4723	1.4747	1.4763	1.5065
DSGE-SPREAD	1.621	1.5536	1.5529	1.5226	1.5364	1.4953	1.5427	1.5193	1.543
DSGE-VAR-SPREAD	1.5451	1.5291	1.47	1.4415	1.4502	**1.4172***	**1.4032***	**1.3966***	*1.4566*
						[72.9967]	**[69.5012]**	**[78.3308]**	
DSGE-FAVAR-SPREAD	1.5529	1.5385	1.5063	1.4896	1.4936	1.4767	1.4815	1.4825	1.5027

Notes: Spread implies DSGE models with financial frictions; Bold entries indicate the model with the minimum RMSEs. Italics indicates the second-best model on average. * indicates significance of the *MSE-F* test statistic (listed in brackets) of McCracken (2007) at one percent level between the best model at a specific horizon and the AR model.