Forecasting Core Inflation: The Case of South Africa

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Abstract Underlying, or core, inflation is likely the most important variable for monetary policy. It is considered to be the optimal nominal anchor as it is stable, excludes relative price shocks, and reflects underlying trends in the behaviour of price-setters and demand conditions in the economy. Despite its importance there is sparse literature on estimating and forecasting core inflation in South Africa, with the focus still on measuring it. This paper emphasises predicting core inflation from small, medium and large time-varying parameter vector autoregressive models (TVP-VARs), factor augmented VARs (FAVAR), and structural break models using quarterly data from 1981Q1 to 2013Q4. We use mean squared forecast errors (MSFE) and predictive likelihoods to evaluate the forecasts. In general, we find that (i) time-varying parameter models consistently outperform constant coefficient models (ii) small TVP-VARs outperform all other models; (iii) models where the errors are heteroscedastic do better than models with homoscedastic errors; and (iv) allowing for structural breaks does not improve the predictability of core inflation. Overall, our results imply that additional information on the growth rate of the economy and the interest rate is sufficient to forecast core inflation accurately, but the relationship between these three variables needs to be modelled in a time-varying (non-linear) fashion.

Keywords Core inflation · forecasting · small- and large-scale vector autoregressive models · constant and time-varying parameters

JEL Classification: C22, C32, E27, E31.

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1 Introduction

Like many central banks targeting inflation, the South African Reserve Bank (SARB) uses forecasts of headline inflation as its operational target. However, headline inflation can be volatile, making it difficult to distinguish between increases in generalised prices and relative price shocks. This volatility typically arises from a small number of goods and services, most commonly food and energy prices. Petrol prices are a good example of this type of shock, reacting quickly to changes in the international product price and the exchange rate, and having the ability to shift headline inflation by a couple of percentage points in months. However, these movements do not reflect the underlying trends in the behaviour of price-setters or demand conditions in the economy, the issues that matter for a central bank.

In the mid-2000s, prior to the financial crisis, some monetary economists including Goodfriend (2007) and Woodford (2003) argued that monetary policy had reached a consensus, namely, that core inflation rather than headline inflation was the best nominal anchor for monetary policy[1]. Core inflation is more stable and would serve as a better anchor for inflation expectations. Woodford (2003, :14) stated that "central banks should target a measure of 'core' inflation that places greater weight on those prices that are stickier". These authors were talking about a conventional definition of core inflation as in "inflation that excludes volatile prices of such goods as food and oil" (Goodfriend, 2007, :62). In South Africa, SARB generally refers to core inflation as *headline consumer prices less food, non-alcoholic beverages, petrol, and energy* (SARB, 2016).

Only one central bank, however, targets a measure of core inflation[2]. Despite the use of headline inflation as the operational target, central banks depend just as heavily on core inflation in their decision-making processes. In SARB's March 2015 Monetary Policy Committee (MPC) statement, the MPC stated that oil prices would lead to a breach of the 3-6 per cent inflation target range and that the bank would "look through these developments" (Kganyago, 2015a). Similarly, in the May 2015 statement, the MPC stressed that "[w]hile monetary policy should generally look through supply side shocks, such as large electricity tariff increases and oil price changes, we have to be mindful of the second-round effects of such shocks" (Kganyago, 2015b). These statements reflect the value of core inflation in determining a path for monetary policy.

The critical importance of core inflation in the monetary policy process, especially a forward-looking process, as in South Africa, requires accurate forecasts of core inflation. To ensure that the best possible estimates of core inflation are available to the central bank, we looked at a host of possible models that the existing literature shows to have some success in forecasting, and that incorporate a wide variety of new techniques. These include models that take account of large datasets of information, that address possible breaks in the inflation series as monetary policy regimes change, that address the changing relationship between macroeconomic variables and inflation or the structure of the economy, and that provide mechanisms to look at the importance of volatility. We consider core inflation to be defined as *targeted consumer prices less food, non-alcoholic beverages, petrol, and energy*, as this is the measure used by policymakers in communicating issues surrounding underlying prices. We used targeted inflation because the target variable has changed from headline CPI less mortgage interest (CPIX) to headline CPI after the introduction of the CPI basket, based on the Classification of Individual Consumption by Purpose (COICOP) in 2009.

The first contribution of this paper is that we employed methods for forecasting core inflation in large TVP-VARs, developed by Koop and Korobilis (2013). These models use forgetting factors for computational feasibility.

[1] Monetary policy is subject to a new debate on policy frameworks, including nominal income targeting and price-level targeting, following the global financial crisis (see, for example, Woodford et al., 2014).

[2] Only Norway operationally targets core inflation, while its mandate is in terms of headline inflation. There are a number of reasons why headline inflation has become the variable of choice for central banks, including that communication with the public is thought to be easier; wide public understanding; and that people care about a cost-of-living index, the basket of goods they actually consume, rather than core inflation.

Second, and in addition to the models in Koop and Korobilis (2013), we also assessed the performance power of factor-augmented VARs. As stated in Camba-Mendez and Kapetanios (2005), dynamic factor models tend to perform well in comparison to traditional measures. Third, the paper adds value by also considering structural break models. Du Plessis et al. (2015) states that South African core inflation data has recently been subjected to a structural break given changes in the basket of goods and services and the methodology used in constructing this index. To deal with the structural break dilemma, we combined the Pesaran et al. (2006) (PPT) and the Koop and Potter (2007) (KP) methods. The basic idea of the methodology was to use the PPT prior for the break process and the KP prior in conditional mean and variance. We followed Koop and Korobilis (2012, 2013) and Stock and Watson (1999) in the selection of data, which is motivated by a basic New Keynesian model with a generalised Phillips curve. We used quarterly data starting from 1981Q1 to 2013Q4 for 21 variables that include activity variables, labour market variables, financial variables and other prices.

To the best of our knowledge, this is the first paper to forecast core inflation formally in South Africa. The only other relevant paper is that of Gupta et al. (2015), where the authors used the latent state-information recovered from a dynamic stochastic general equilibrium (DSGE) model to forecast core inflation, which, however, was not modelled within the DSGE model explicitly. This means that it was not possible to identify the variables that could help forecast core inflation. Allowing for a large number of predictors, in line with the empirical literature on forecasting inflation based on a New-Keynesian Phillips curve, we were able to determine, which variables contain predictive information for core inflation.

The main results of this paper are that addressing changing dynamics by introducing time-varying parameters generates forecasts of core inflation that are more accurate. More information does not necessarily mean better forecasts, as small models outperform large models. In general, i) time-varying parameter models consistently outperform constant coefficient models; (ii) small time-varying parameter vector autoregressive models (TVP-VARs) outperform all other models tested; (iii) models where the errors are heteroscedastic do better than models with homoscedastic errors; (iv) models assuming that the forgetting factor remains 0.99 throughout the forecast period outperform models that allow for the forgetting factors to change with time; and (v) allowing for discrete structural breaks does not improve the predictability of core inflation.

The rest of the paper is as follows: section 2 places this paper in the context of the literature, section 3 discusses the methodology followed by section 4 discussing the data. Section 5 follows with a discussion of the results before concluding in section 6.

2 Literature review

Most of the literature on core inflation has evolved around defining a practical measure of core inflation rather than on forecasting that measure. This is because core inflation is an unobservable only defined theoretically. Theory provides two broad definitions of core inflation expounded in Roger (1998): as a ‘persistence’ concept as defined by Friedman et al. (1963) or as a ‘generalised’ concept as defined initially by Eckstein (1981). Friedman et al. (1963, pg. 25) highlights two distinct characteristics of inflation “...between a steady inflation, one that proceeds at a more or less constant rate, and an intermittent inflation, one that proceeds by fits and starts...” the former being core inflation. Eckstein (1981, pg. 7), on the other hand, describes core inflation as “...the trend increase of the cost of the factors of production” which “...originates in the long-term expectations of inflation in the minds of households and businesses, in the contractual arrangements which sustain the wage-price momentum, and in the tax system”. These theoretical definitions have seen exclusion-, model- and statistical-based methods all developed in order to estimate a practical measure of core inflation (see for example Cogley, 2002; Cristadoro et al., 2005; Quah and Vahey, 1995; and Bryan and Cecchetti, 1993).

The South African literature has similarly been focused exclusively on defining a measure of core inflation rather than forecasting this measure (see Rangasamy, 2009; Blignaut et al., 2009; Ruch and Bester, 2013 and Du Plessis et al., 2015). Blignaut et al. (2009) and Rangasamy (2009) create exclusion-based measures of inflation which exclude important components of inflation depending on their volatility and persistence respectively. Ruch and Bester (2013) use a statistical method of singular spectrum analysis to filter out the more volatile components of inflation in the frequency rather than time domain. Finally, Du Plessis et al. (2015) compare and contrast a number of alternative methods and introduce wavelet and dynamic factor model based measures of core inflation.

There is an element to this literature that does provide some guidance on the forecastability of core inflation but only as a means to an end. One of the defining characteristics of a good core inflation measure is that it helps predict future headline inflation (see Clark, 2001 and Blinder, 1997). To this end Nolazco et al. (2016), Bryan and Cecchetti (1993) and Camba-Mendez and Kapetanios (2005) internationally, and Ruch and Bester (2013) and Du Plessis et al. (2015) domestically, are examples that look at the in- and out-of-sample performance of core inflation measures to help predict headline inflation.

However, core inflation does not only form part of the information set of headline inflation. It is by definition that part of inflation a central bank should most be concerned about. Core inflation measures attempt to examine the component of inflation that is related to broad trends in economic conditions and pricing behaviour, and which are likely to be more persistence (Ranchhod, 2013). Bryan and Cecchetti (1994) further describe core inflation as a process that should be highly persistent, forward looking and strongly linked to monetary policy dynamics. Recognising core inflation's central role in policy deliberation, Sun (2004), Morana (2007), and Kapetanios (2004) directly look at the ability to forecast core inflation. Sun (2004) proposes an approach to forecast Thailand core inflation. He combines a short-term model which attempts to filter the forecasting power of a variety of monthly indicators based on goodness-of-fit criteria, with an equilibrium-correction model linking core inflation to its longer-run structural determinants. Morana (2007) uses a principal components frequency domain approach which is suited to estimate systems of fractionally co-integrated processes to estimate and forecast core inflation for the euro area. Kapetanios (2004) propose the use of large datasets using factor models in modeling and forecasting core inflation.

There is only one paper in the South African literature that directly addresses our ability to forecast core inflation. Gupta et al. (2015) use the latent state-information recovered from a Dynamic Stochastic General Equilibrium (DSGE) model to forecast core inflation, which was, however, not modeled within the DSGE model explicitly. This meant that, it was not possible to identify the variables that could help forecast core inflation. The domestic literature tends to focus on forecasting headline inflation (for detailed literature reviews, see Woglom, 2005; Kanda et al., 2016; and Gupta et al., 2015).

3 Methodology

The methods used in this paper to forecast are motivated by the desire to improve simple models in areas that have been shown to lead to bias and poor forecast performance. Models were extended in four important dimensions in an attempt to be all-encompassing. First, recent methodological and computing gains have made it possible to increase the dimensionality of models, solving the omitted variable bias in smaller VARs, to include up to a hundred variables when analysing and forecasting macroeconomic variables. Bańbura et al. (2010), Giannone et al. (2014), and Carriero et al. (2015) show that increasing the number of variables leads to better forecasting accuracy but that this does have its limitations. Bańbura et al. (2010) and Koop (2013) provide evidence that this limit is in the region of 20 variables. We considered a number of model sizes, with up to 21 variables.

Second, a common assumption in simple models of analysis and forecasting is that the errors are homoscedastic. Of course, macroeconomic shocks are not. Engle (1982) first introduced heteroscedastic errors using an autoregressive conditional heteroscedastic (ARCH) process and showed with this seminal piece that inflation in the United Kingdom had significant and changing volatility, especially during the 1970s. Fedderke and Liu (2016) highlight the "surprising" lack of work taking into account ARCH effects in SA inflation, especially given the substantial focus on the effects of the exchange rate on inflation. This paper, however, looks at another version of heteroscedasticity called stochastic volatility first introduced to VARs by Uhlig (1997). Both homoscedastic and heteroscedastic error structures are used.

Third, significant changes in the structure of the SA economy over the last four decades have made it unlikely that relationships between economic variables remained constant or that there were not any structural breaks. Structural breaks are a significant cause of poor forecasting performance (Stock and Watson, 1996; Ang and Bekaert, 2002; Clements and Hendry, 1998; and Bauwens et al., 2011). To address changing relationships, time-varying parameters were introduced. Primiceri (2005) importantly shows that monetary policy has changed over time in the US. One recent example of changing relationships in SA is provided by Jooste and Jhaveri (2014), who show that the exchange rate pass-through to inflation is time-varying and has declined recently. These changing relationships also matter for forecasting. To deal with structural breaks, two methods were used. First, discrete breaks were taken into account using methods introduced by Bauwens et al. (2011). Second, we used dynamic dimension selection (DDS) as in Koop and Korobilis (2010), allowing for switches between entirely different models to accommodate these breaks.

Fourth, the way large information sets are collated may affect the forecasting accuracy of models. So, instead of estimating large VARs it may be that factor augmented VARs – where information is combined into a smaller number of common factors that remove noise – provide better forecasts. Factor models have been shown to improve forecasting accuracy compared with naive models over short horizons by Giannone et al. (2008) and Kabundi et al. (2016).

This section introduces the methodologies that were followed.

3.1 Large TVP-VARs

We followed the specification in Koop and Korobilis (2013) and specified the time-varying parameter vector-autoregressive model (TVP-VAR) as:

$$y_t = Z_t \beta_t + \varepsilon_t \tag{1}$$

and

$$\beta_{t+1} = \beta_t + \mu_t \tag{2}$$

where ε_t is an independently and identically distributed (i.i.d.) error with $N(0, \Sigma_t)$ and μ_t is i.i.d. $N(0, Q_t)$. ε_t and μ_t are independent of one another for all s and t. y_t for $t = 1, ..., T$ is an $M \times 1$ vector containing observations on M time-series variables and Z_t is an $M \times k$ matrix, defined so that each TVP-VAR equation contains an intercept and p lags for each of the M variables for $k = (1 + pM)$. Following Koop and Korobilis (2013), Fagin (1964), Jazwinski (2007), and Raftery et al. (2005), we used forgetting factors instead of standard Bayesian statistical inference, since the latter tends to work well only with small TVP-VARs. Forgetting factors allow the Kalman filter to be run only k times, providing an accurate approximation of the likelihood function as the state vector becomes independent across models (for further details on formulating the Kalman filter see, among others, Koop and Korobilis, 2013; as well as Frühwirth-Schnatter, 2006). In estimating a TVP-VAR using forgetting factors, let $y^s = (y_1, ..., y_s)'$ denote observations through time s. The standard Kalman filter states the following:

$$\beta_{t-1}|y^{t-1} \sim N(\beta_{t-1|t-1}, V_{t-1|t-1}) \tag{3}$$

The formulae for $\beta_{t-1|t-1}$ and $V_{t-1|t-1}$ are given in Frühwirth-Schnatter (2006). Further,

$$\beta_t|y^{t-1} \sim N(\beta_{t|t-1}, V_{t|t-1}) \tag{4}$$

where

$$V_{t|t-1} = V_{t-1|t-1} + Q_t \tag{5}$$

To estimate using the forgetting factor, we replaced Equation 5 with the following equation:

$$V_{t|t-1} = \frac{1}{\lambda} V_{t-1|t-1} \tag{6}$$

λ is the forgetting factor, and varies between $0 < \lambda \leq 1$. Equation 6 implies that observations for t periods in the past have weight λ^t in the filter estimate of β_t. This controlled the degree of time-variation of the coefficients. Equations 5 and 6 also imply that $Q_t = (\lambda^{-1} - 1)V_{t-1|t-1}$; if $\lambda = 1$, then we get constant coefficients. Raftery et al. (2010) set $\lambda = 0.99$, while Koop and Korobilis (2012) use $[0.8, 0.95, 0.99]$. In this paper, we show results for $\lambda = 0.99$, and we followed the approach in Koop and Korobilis (2013) of estimating λ at each point in time[3].

We also used a decay factor, κ, to simplify the implementation of multivariate stochastic volatility in ε_t. An exponential weighted moving average (EWMA) was used to estimate Σ_t following RiskMetrics (1996):

$$\hat{\Sigma}_t = \kappa \hat{\Sigma}_{t-1} + (1 - \kappa)\hat{\varepsilon}_t \hat{\varepsilon}_t' \tag{7}$$

where $\hat{\varepsilon}_t = y_t - \beta_{t|t} Z_t$ is estimated by the Kalman filter. We set the decay factor equal to 0.96.

Although TVP-VARs work relatively well for modelling the gradual evolution of coefficients, they tend to work poorly for abrupt changes of the coefficients. One solution to this problem is allowing for switches between entirely different models to accommodate these breaks. We used methods developed in Raftery et al. (2010) and Koop and Korobilis (2012, 2013) for doing dynamic model averaging (DMA), which can also be used for dynamic model selection (DMS). DMA refers to the averaging of a large set of j models, weighted based on their predictive content, to forecast at a specific point in time, i.e. calculating the likelihood function for $j = 1, ..., J$ and averaging these likelihoods to generate a forecast. This produces a probability $\pi_{t|t-1,j}$ with $j = 1, ..., J$. $\pi_{t|t-1,j}$ varies over time, and the forecasting model can switch over time. Once the $\pi_{t|t-1,j}$ for $j = 1, ..., J$ are obtained, they can be used either to achieve model selection or model averaging. DMS refers to when the single best model – which can change overtime, given selection over a large number of predictors – is used to forecast at each point in time, that is, selecting the model with the highest likelihood. The advantage of this approach is that optimal values for λ, κ and the VAR shrinkage parameter can be selected in a time-varying manner.

To construct a dynamic model selection, we followed the basic algorithm in Raftery et al. (2010) and Koop and Korobilis (2012, 2013). Given the initial condition $\pi_{0|0,j}$ for $j = 1, ..., J$, the model prediction equation using the forgetting factor approach was derived as follows:

$$\pi_{t|t-1,j} = \frac{\pi^{\alpha}_{t-1|t-1,j}}{\sum_{l=1}^{J} \pi^{\alpha}_{t-1|t-1,l}} \tag{8}$$

[3] Estimating λ involves using dynamic model selection to choose a value of $\lambda \in \{0.97, 0.98, 0.99, 1\}$ at each point in time. For more details, see Koop and Korobilis (2013, :9).

with a model updating equation of:

$$\pi_{t|t,j} = \frac{\pi_{t|t-1,j}\, p_j(y_t|y^{t-1})}{\sum_{l=1}^{J} \pi_{t|t-1,l}\, p_l(y_t|y^{t-1})} \tag{9}$$

where $p_j(y_t|y^{t-1})$ is the predictive likelihood, measuring the forecast performance. $\pi_{t|t-1,j}$ can be written as follows:

$$\pi_{t|t-1,j} \propto \prod_{i=1}^{t-1} [p_j(y_{t-i}|y^{t-i-1})]^{\alpha^i} \tag{10}$$

The above equation can be interpreted as follows: if $\alpha = 0.99$, then the forecast performance five years ago receives 80 per cent as much weight as the forecast performance for the last period, but if $\alpha = 0.95$, then the weight for the forecast performance five years ago will only be 35 per cent. $\alpha = 1$ corresponds to conventional model averaging using maximum likelihood.

The forgetting and decay factors introduced help to deal with the time-varying nature of the model and negate the need for priors on the covariance matrices Q_t and Σ_t. However, equally important is how the parameters β_t are estimated. Since we are estimating large VARs and time-varying VARs, and hence could have run into overfitting problems (see Bańbura et al., 2010 as well as Koop and Korobilis, 2013), we used a tight Minnesota prior for β_0, specified in Koop and Korobilis (2013). After transforming the data to stationarity, the prior mean was set equal to $E(\beta_0) = 0$. The Minnesota prior covariance matrix for β_0 is a diagonal matrix such that $var(\beta_0) = \underline{V}$ and $\underline{V}_i$ denotes the diagonal elements. The prior covariance matrix was then defined as:

$$\underline{V}_i = \begin{cases} \frac{\gamma}{r^2} & \text{for coefficients on r for r=1,...,p} \\ \underline{a} & \text{for the intercept} \end{cases} \tag{11}$$

where p is the lag length. γ determines the degree of shrinkage on the VAR coefficients, as they are lagged further into the past. Generally, training samples are used to determine appropriate values of priors, as would be the case with a normal Minnesota prior. Here instead, γ is estimated in a similar way as the forgetting factors using DMS with a wide grid for $\gamma \in [10^5, 0.001, 0.005, 0.01, 0.05, 0.1]$. In practice this means that there were a number of different prior values for γ, with the optimal one being chosen by maximising the predictive likelihood. γ is small, since a large degree of shrinkage is needed to produce reasonable forecast performance in large VARs and TVP-VARs[4]. $\underline{a}$ was set to equal 10^2.

We also augmented the model space with models of different dimensions. In particular, we did dynamic model selection for small (including only three variables), medium (including seven variables) and large (including 21 variables) TVP-VARs. As discussed in Koop and Korobilis (2013) – and as used by Ding and Karlsson (2014) – working with TVP-VARs of different dimensions, y_t will be of different dimension, and therefore predictive densities $p_j(y_{t-1}|y^{t-i-1})$ will not be comparable. This can be resolved by using the predictive densities for the small VARs (these are variables that are included in all models). In this analysis it means that the dynamic model selection is determined by the joint predictive likelihood for economic growth, core inflation and the three-month Treasury Bill rate.

[4] Unlike the normal Minnesota prior, which has two hyperparameters for own lags and other lags, we used one shrinkage parameter to simplify computation.

3.2 FAVAR models

Although work by Koop and Korobilis (2013) and Bańbura et al. (2010) provide techniques to shrink the parameter space in order to make large VAR estimation and analysis feasible, it may be that using other methods such as data shrinkage from factor augmented VARs (FAVARs) provide better forecasts of core inflation. We therefore estimated a FAVAR model using a two-step process (as in Bernanke et al., 2005). This method is simpler and easier to implement. First, the factors are estimated using principal components analysis with the number of factors determined according to the information criterion by Alessi et al. (2010)[5]. Next, the FAVAR model was estimated. Equations 1 and 2 then became:

$$\bar{F}_{t+1} = \bar{F}_t \beta_t + \varepsilon_t \tag{12}$$

and

$$\beta_{t+1} = \beta_t + \mu_t \tag{13}$$

where $\bar{F}_t = [F_t, x_t]$ with F_t the factors and x_t being core inflation. In the estimation step, F_t was replaced with an estimate $\hat{F}_t$ from step one.

3.3 Structural break models

South Africa underwent substantial changes in its economic structure over the past four decades including financial liberalisation with the end of Apartheid, the great moderation, and disinflation from inflation rates closer to 20 per cent to rates around the South African Reserve Bank's upper target of 6 per cent. Similarly the monetary policy target and the methodology used to calculate inflation has changed. Given the importance of these breaks in both levels and differences data we also consider a structural break model to forecast core inflation. Structural breaks are a significant cause of poor forecasting performance (Stock and Watson, 1996; Ang and Bekaert, 2002; Clements and Hendry, 1998; and Bauwens et al., 2011). We consider a combination of the PPT and the KP priors. The model uses the PPT prior for the break process and the KP prior in conditional mean and variance. We use the same framework as in Bauwens et al. (2011) and a detailed discussion is presented there. We specify the linear regression model framework for the structural break models as:

$$y_t = Z_t \beta_{s_t} + \sigma_{s_t} \varepsilon_t \tag{14}$$

Where y_t is the dependent variable, Z_t contains the lagged dependent variables or lagged exogenous variables available for forecasting y_t, ε_t is i.i.d. $N(0,1)$. β_{s_t} determines the conditional mean coefficients and σ_{s_t} represents volatilities. This regression allows for β_{s_t} and σ_{s_t} to vary over time with $s_t \in 1,...,K$ a random variable indicating which regime applies at time t.

We use the KP prior in conditional mean and variance which adopts a hierarchical prior motivated by the state space literature on time-varying parameter models (discussed in detail in Bauwens et al., 2011). The random walk evolution of coefficients is specified as:

$$\beta_j = \beta_{j-1} + \mu_j \tag{15}$$

Where μ_j is i.i.d. $N_m(0, B_0)$ which is equivalent to $\beta_j | \beta_{j-1} \sim N_m(\beta_{j-1}, B_0)$. This means that if a structural break occurs, the conditional mean of β_j will be drawn from a distribution with mean β_{j-1} such that the next

[5] We employed numerous other methods, including Bai and Ng (2002) and Onatski (2010) to ensure that we were getting the correct number of factors.

regime is determined by the most recent regime. The parameters β_{j-1} and B_0 are unknown and can be estimated from the data.

To model the break process, we consider an approach in Chib (1998) and used in PPT. Assume that the restricted Markov process for s_t is given by:

$$Pr(s_t = i|s_{t-1} = i) = p_i \tag{16}$$

and

$$Pr(s_t = i+1|s_{t-1} = i) = 1 - p_i \tag{17}$$

This equation is interpreted as a hierarchical prior and implies a geometric prior distribution for $d_i = \tau_t - \tau_{t-1}$ - which measure the durations of regimes. Therefore if regime i holds at time $t-1$, then at time t the process can either remain in regime i with probability p_i or moves to regime $i+1$ with probability $1-p_i$ if a break occurs. To select the number of breaks, we rely on the specification in Bauwens et al. (2011) and set the maximum breaks allowed to five such that: $K = 1, ..., K^{max}$.

4 Data

The data used was motivated by a generalised New Keynesian Phillips curve, as in Koop and Korobilis (2012) and Stock and Watson (1999). Table 1 provides details of the 21 variables included in the dataset, the VAR these variables were used in, as well as the transformation imposed. The data is quarterly and ranges from 1981Q1 to 2013Q4. All data was transformed to be stationary (see transformation in Table 1). This includes activity variables such as real GDP and capacity utilisation; labour market variables such as unit labour cost, wages and employment; financial variables such as stock returns and money stock; and other prices such as producer price inflation, oil prices and non-energy commodity prices. Note that the start and end dates of our sample were driven purely by the available data on the various variables used, at the time of writing this paper.

Core inflation is defined as *targeted inflation less food, non-alcoholic beverages, petrol, and energy*, obtained from data collected by StatsSA. This is the core inflation most commonly used by SARB when communicating issues of monetary policy and also the core inflation measure used in the Bank's main econometric model. Targeted inflation refers to headline CPI less mortgage interest (CPIX) prior to 2009 and as headline CPI thereafter. This takes into account the new CPI basket introduced in 2009, based on Classification of Individual Consumption According to Purpose (COICOP). It is seasonally adjusted.

5 Results

5.1 Determining the number of factors in the FAVAR model

We implement a modified Bai and Ng (2002) information criterion as developed in Alessi et al. (2010) that chooses the number of factors by minimising the variance of the idiosyncratic component of the approximate factor model, subject to a penalisation in order to avoid over-parameterisation. The information criterion is:

$$\hat{r}^T_{c,M} = \underset{0 \leq w \leq r_{max}}{\text{argmin}} \, IC^{T*}_{\alpha,M}(w) \tag{18}$$

where

$$IC^{T*}_{\alpha,M}(w) = log[\frac{1}{MT}\sum_{i=1}^{M}\sum_{i=1}^{T}(x_{it} - \hat{\beta}_i^{(w)}\hat{F}_t^{(w)})^2] + cwp_a(M,T) \text{for a=1,2} \tag{19}$$

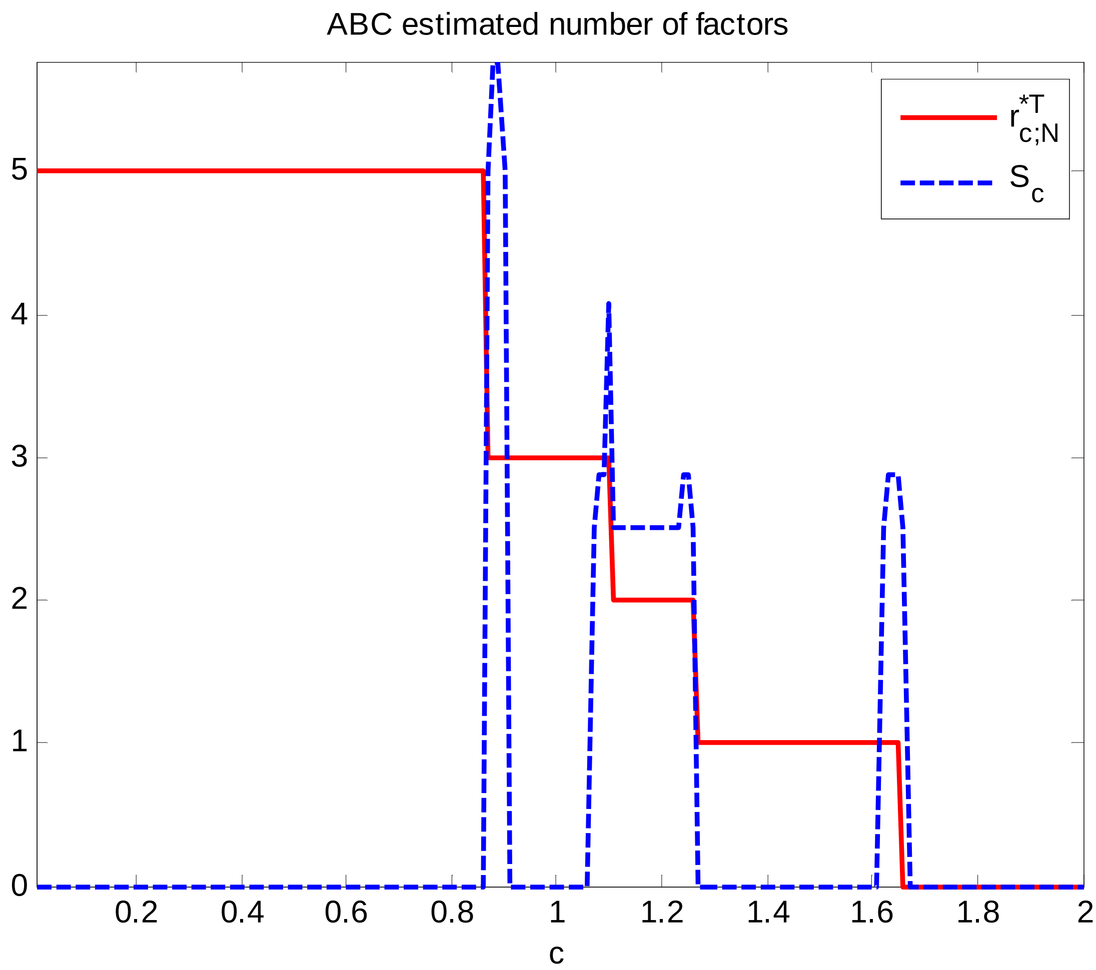
For w common factors, M is the number of variables, T the number of observations, $x_{it} - \hat{\beta}_i^{(w)} \hat{F}_t^{(w)}$ the idiosyncratic error, c an arbitrary positive real number and $p_a(M,T)$ the penalty function. The penalty function is multiplied by c since Hallin and Liška (2007) show that $p(M,T)$ leads to consistent estimation of w, the number of factors, if and only if $cp(M,T)$ does as well.

The behaviour of $\hat{r}_{c,M}^{T}$ can only be determined from analysing subsamples of sizes (m_h, t_h). For any h, we can compute $\hat{r}_{c,m_h}^{t_h}$ which is a monotonic non-increasing function in c. Therefore, there exist moderate values of c such that $\hat{r}_{c,M}^{T}$ converges from above to w. This has to occur independent of h for the criterion to be stable. This is measured by the variance of $\hat{r}_{c,m_h}^{t_h}$ as a function of h:

$$S_c = \frac{1}{H} \sum_{h=1}^{H} [\hat{r}_{c,m_h}^{t_h} - \frac{1}{H} \sum_{h=1}^{H} \hat{r}_{c,m_h}^{t_h}]^2 \tag{20}$$

We use all data included in the large VAR (excluding core inflation itself) to estimate factors for a FAVAR model. The transformed data is standardised. Figure 1 plots the criterion estimate for the number of factors on the y-axis and an arbitrary positive real number c on the x-axis. We run the results over a number subsample sizes in order to ensure that they are robust. To determine the number of factors we have to find the first value of $\hat{r}_{c,M}^{T}$ where S_c is zero. The results suggest that the number of factors should be three.

Fig. 1: Estimating the number of factors



Other methods were also used including the original Bai and Ng (2002) information criterion and a method proposed by Onatski (2010). The Bai and Ng (2002) method did not converge, a common problem with smaller datasets[6]. According to Onatski (2010), three factors were also chosen.

5.2 Forecasting performance

The main results of this paper are presented in Table 2 and Table 3. These show the iterated forecasts for horizons 1 to 8 quarters ($h = 1, ..., 8$) with a forecast evaluation period of 2000Q1 to 2013Q4, i.e. the starting point of the out-of-sample period corresponds to the starting quarter of the inflation targeting era in South Africa. We look at one- to eight-quarters-ahead forecasts, since the SARB carries out its monetary policy decisions based on inflation forecasts till two-years-ahead, i.e., eight quarters.[7] The VAR models are estimated with $p = 1$ based on the Bayesian Information Criteria (BIC). In the appendix we include models with $p = 4$. The following models are presented:

- A full approach which uses all three VAR model sizes using DMS; referred to as dynamic dimension selection (DDS). This is labeled TVP-VAR-DDS in the tables;
- TVP-VAR model using the three different size VARs including a small (S) VAR using three variables; a medium (M) VAR using seven variables; and a large (L) VAR using 21 variables;
- Heteroscedastic VARs using the three dimensions setting $\lambda = 1$ and $\kappa = 0.96$;
- Homoscedastic VARs using the three dimenstions setting $\lambda = 1$ and $\kappa = 0.6$;
- A structural breaks model using PPT and KP priors;
- A random walk model;
- TVP-AR models;
- A small VAR estimated using Ordinary Least Squares (OLS);
- FAVAR models;
- and an AR(1) model using OLS.

Since the use of iterated forecast increases the computational burden we follow Koop and Korobilis (2013) and do the predictive simulation in two ways. First, we assume that the that the VAR coefficients remain unchanged between T and $T+h$, i.e. $\beta_{T+h} = \beta_T$. Second, we assume that these coefficients change out-of-sample and simulate from equation 2 to produce draws of β_{T+h} and is labeled as $\beta_{T+h} \sim RW$ in the tables. Both methods provide β_{T+h}, which we use to simulate draws of y_{T+h} conditional on β_{T+h} to approximate the predictive density.

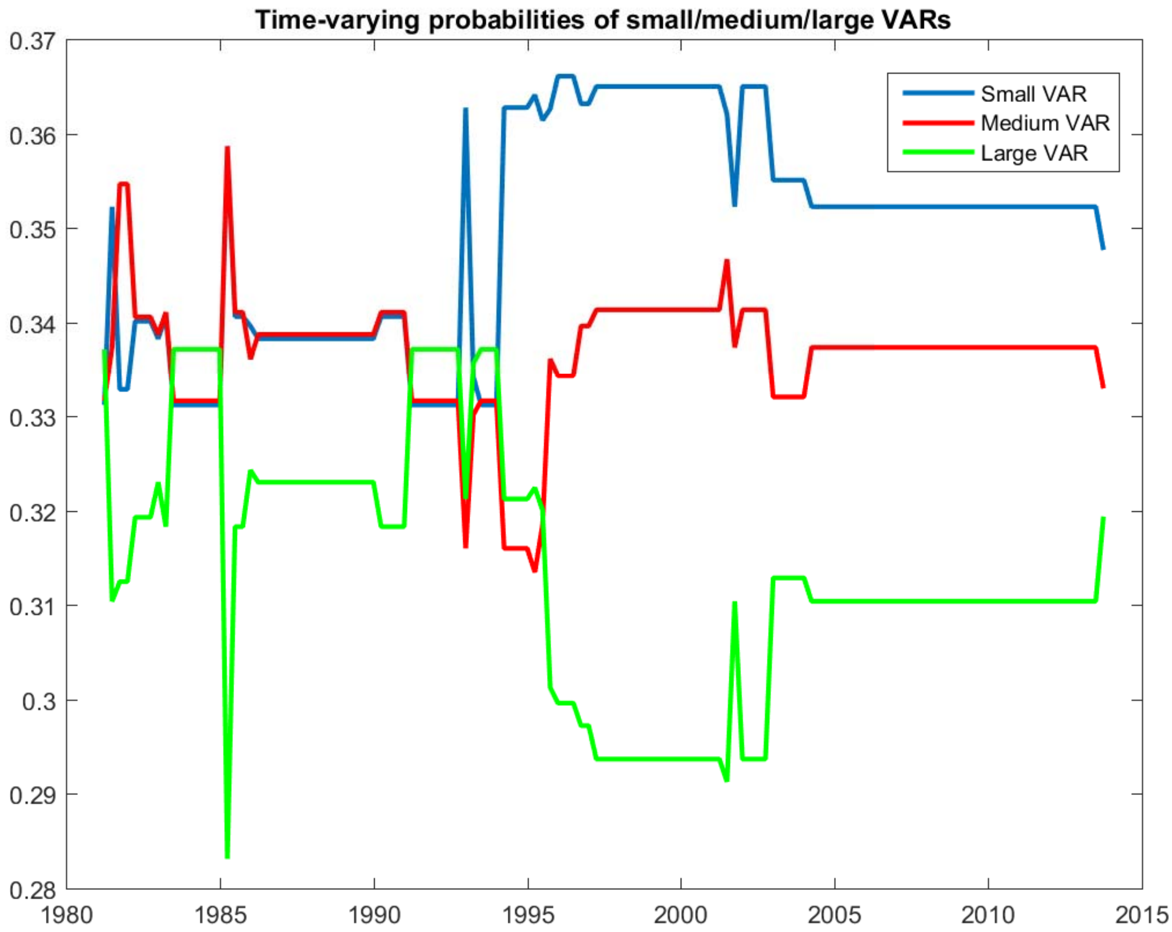
To evaluate the forecast performance we use mean squared forecast errors (MSFE) and the predictive likelihood. The MSFE and the predictive likelihood in Table 2 and 3 are presented as relative to the random walk model. This means that the numbers in Table 2 are the ratios of a particular model specification divided by the random walk model. For Table 3, the results presented are the sum of log predictive likelihood of different models minus the sum of log predictive likelihood obtained for the random walk model.

DDS forecasts use the TVP-VAR of dimension with the highest probability. We therefore plot the time-varying probabilities associated with the TVP-VAR of each dimension in Figure 2. Between 1981 and 1994 DMS switches between all three models with periods where each model dominates. In general the medium VAR tends to have the highest probability throughout this period. From 1994 onwards the small VAR dominates with the large VAR consistently having the lowest probability. This means that DMS is using the small VAR to produce forecasts of core inflation.

[6] In factor analysis, usually $M \geq 100$. See Forni et al. (2009) as a example of convergence problems.

[7] However, we also conducted our analysis till twelve-quarters-ahead. Our basic results in terms of the ranking of the models based on their forecast performances, continued to remain unchanged when compared till eight-quarters-ahead. Complete details of these results are available upon request from the authors.

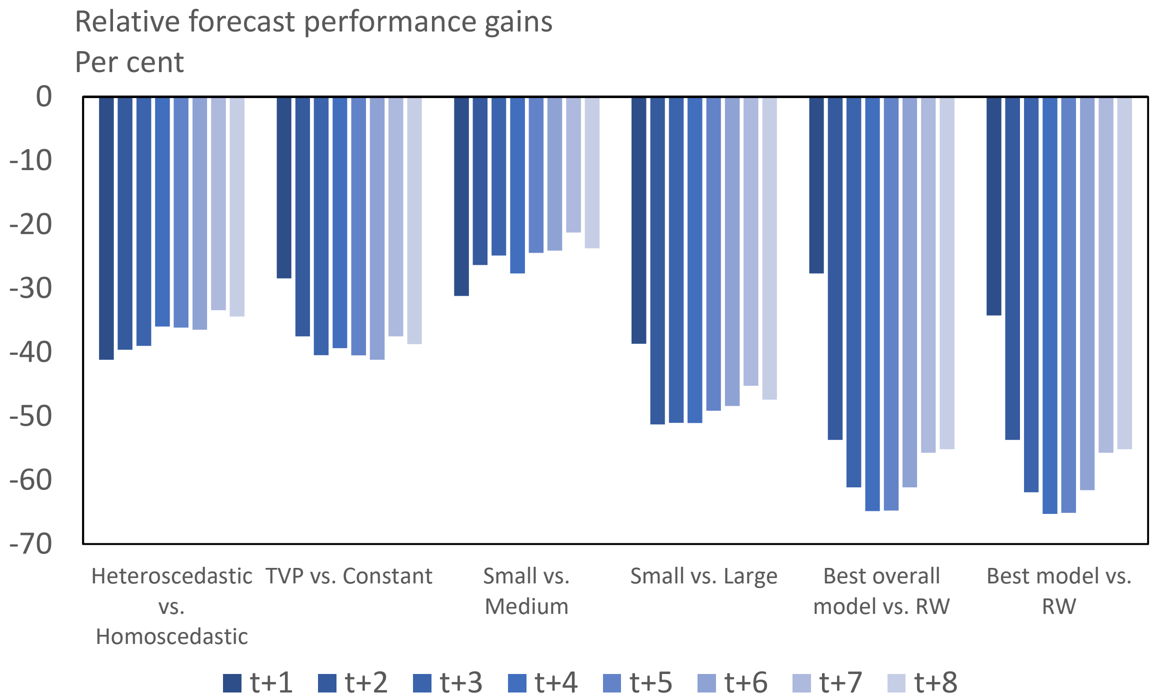
Fig. 2: Estimated Dynamic Dimension Selection probabilities of the small, medium and large TVP-VARs



In general, most models (full model, TVP-AR, small and medium TVP-VARs and FAVAR) and different specification (excluding the VAR with homoscedastic errors) perform better than the random walk model. The models perform particularly much better for $h = 3,4,5,6$. The average performance of all models excluding the benchmark models improve the forecast of core inflation relative to the random walk model by between 20 and 40 per cent. The only horizon where we do not see any gains is one period ahead ($h = 1$). The full model and the TVP-AR are preferred for core inflation across all horizons and model specifications. For the small and medium TVP-VARs as well as the FAVAR only the VAR with homoscedastic errors is outperformed by the random walk model at some horizons. The large TVP-VAR and the benchmark models tend to compete with the random walk model since they perform better in some horizons and worse in others. The large TVP-VAR outperforms the random walk model only when $h = 4,5,6$.

Figure 3 provides a summary of the relative performance of different types of models. It compares models with heteroscedatic errors to those with homoscedastic errors, time-varying parameter models with its constant parameter counterparts, Different sizes of models, the overall best performing model – the small TVP-VAR model with $\lambda = 0.99$ and $\beta_{T+h} \sim RW$ – to the random walk model, and the best model at each forecast horizon with the random walk model. The results are discussed below. The figure reports the percentage gain in performance; i.e. Small VAR models outperform Large VAR models by about 40 per cent one-quarter ahead.

Fig. 3: Result Summary: Relative performance gains



Small VAR models outperform its larger variants by a significant margin. The average outperformance of the small VARs compared to the large VARs is 48 per cent while compared to the medium VAR is it 25 per cent. The best outperformance compared to the large VARs occurs at $h = 2$ at 51 per cent while the least outperformance occurs at $h = 1$ of 39 per cent. Generally the expectation of more information should improve forecasts of core inflation. This result is not universal across variables as a similar exercise on real GDP growth reveals that Large VARs tend to do better than small VARs. This implies that the additional variables included in the medium and large VARs do not have any predictive power for core inflation.

Over all models and all horizons time-varying parameter models outperform constant coefficient models by an average 31 per cent[8]. The minimum improvement is at $h = 1$ at 22 per cent and the best outperformance is at $h = 3, 5, 6$ of 33 per cent. The importance of time-varying parameters highlights the changing economic relationships over the past three decades and particularly since the financial crisis. Jooste and Jhaveri (2014), for example, show that exchange rate passthrough in South Africa has changed significantly over time with important implications for inflation. This is a particularly important result since most models used to forecast the main macroeconomic variables by professional forecasters and the central bank are constant coefficient models including the model used in De Jager (1998). Of course these forecasts include judgment but time-varying parameter models provide a better starting point. Moving to time-varying parameter models can improve forecasts by a $\frac{1}{3}$.

VARs with stochastic volatility outperform models with homoscedastic errors at all horizons improving forecasts of core inflation by 37 per cent with the best outperformance occurring at $h = 1$ where stochastic volatility VARs outperform by 41 per cent. However, performances are variable. Relative to the random walk model the small and large homoscedastic VAR models outperform at the majority of horizons while this is not the case with the medium and FAVAR. The poor performance of the homoscedastic VAR model highlights the importance of

[8] We also included models with only time-varying intercept terms as an alternative TVP strategy. These models do not outperform models where all parameters are allowed to vary but do better than the constant coefficient models.

allowing for heteroscedastic errors in getting the shape of the predictive density. In general, these results show that the models employed in this paper provide an effective way of estimating even large VARs with heteroscedastic errors and choosing prior shrinkage.

From Table 2, there are no significant gains when simulating β_{T+h} from the random walk model compared to just assuming that the VAR coefficients remain unchanged over the forecast horizon. The noticeable comparison can be made between models where $\lambda = 0.99$ and models with $\lambda = \lambda_t$. Models where the forgetting factor is pre-specified outperform models where the forgetting factors are allowed to change over time.

The Bayesian information criterion chose one lag for the VAR models. However, it may be that longer lag orders perform better at forecasting despite the risk of overfitting and higher parameter uncertainty. Table A1 in appendix A looks at the MSFE relative to the random walk model for models with lag length four. In general, more lags improves the forecasting performance of all models by around 14 per cent compared to models with one lag. The overall relative performance of models generally mimics the main results of this paper with a few exceptions. Models with time-varying parameters outperform models with constant coefficients by an average of 47 per cent over all horizons. Small VARs outperform Large VARs. Models with stochastic volatility improve forecasts by an average of 72 per cent compared to models with homoscedastic errors. In essence, the full model, TVP-AR, the small and medium TVP-VAR models, as well as the FAVAR (excluding the VAR with homoscedastic errors) perform better on average relative to the other models and the random walk model. Specifically, the small TVP-VAR has the smallest MSFE relative to all models employed.

With regards to the predictive likelihood results presented in Table 3, all VAR specifications perform significantly better than the random walk model, confirming somewhat the results presented in Table 2. Even in this case, models with $\lambda = 0.99$ perform better than models where $\lambda = \lambda_t$. Also, the VARs with heteroscedastic errors outperform the VARs with homoscedastic errors. Even with the predictive likelihood, the benchmark models tend to perform poorly relative to the random walk model. Only the $AR(1)$ structural break model performs better than the random walk model for $h = 3$ onwards. When taking the average of the models, the full model, TVP-AR, the small and medium TVP-VAR models, as well as the FAVAR (excluding the VAR with homoscedastic errors) perform better on average relative to the other models - as in the case in Table 2. Similar to the results using the MSFE, the small TVP-VAR has the largest predictive likelihoods relative to all other models for all specifications.[9]

To summarize our findings, in Tables 4 and 5, we present the results for point and density forecasts of core inflation of the best models on average (over the eight forecast horizons) in a specific category relative to that small-scale TVP-VAR model with $\lambda = 0.99$, $\beta_T + h = \beta_T$, which in turn is the best performing model across all categories of models considered. As can be seen the gains are relatively large compared to the large-scale TVP-VAR and the benchmark models. The TVP-VAR-DDS, $\lambda = 0.99$,$\beta_T + h = \beta_T$, however, does reasonably well, when it comes to density forecasts. When compared to the literature, our results that small-scale TVP-VAR models with stochastic volatility performs better than constant parameter versions of the same are in line with the results found in Amisano and Serati (2004), D'Agostino et al. (2013), and Korobilis (2013) for the Euro Area, US and UK respectively. However, the superior performance of the small-scale TVP-VAR to large-scale TVP-VARs in our case is opposite to those detected by Koop (2013), and Amisano et al. (2015) for the US economy.

The modelling and forecasting literature on South African inflation tends to suggest that what is most important in modelling inflation, is persistence (Gupta and Steinbach, 2013; De Waal et al., 2015), with little role from open economy features in the model. In addition, a recent study has shown that South African inflation persistence is time-varying (Balcilar et al., 2016; Gupta et al.,forthcoming). Finally, Balcilar et al. (2017) show that the relationship between inflation, output growth and interest rates is also theoretically non-linearly related based on

[9] We also estimated the small-scale TVP-VAR models, without the approximation based on the forgetting factors. However, this version of the small-scale TVP-VAR model was outperformed by all the other small-scale TVP-VAR models reported in the paper both in terms of point and density forecasts. Complete details of these results are available upon request from the authors.

non-linear DSGE models. This suggest that to forecast inflation, we need a model that is non-linear allowing for time-varying persistence and a small set of information from growth and interest rate. This type of a model is not unrealistic if one looks at the history of South African inflation, with it being primarily driven by growth and various forms of monetary policy before 1999, and then by interest rate policies post this period in the inflation targeting era (Gupta and Steinbach, 2013; Balcilar et al., 2017). This result is echoed in Stock and Watson (1999) who also find that a single index of overall economic activity is the only variable that improves the forecast of the most successful univariate models. In our case, economic growth seems to function in a similar manner by representing overall economic activity.

6 Conclusion

In this paper, we use a suite of econometric models to forecast quarterly core inflation in South Africa using 21 variables for the period covering 1981Q1 to 2013Q4. The forecasts are evaluated using the MSFE and the predictive likelihood relative to the random walk model for 1 to 8 quarters ahead. We find that most VAR models (specifically the small TVP-VARs and excluding the large TVP-VARs) perform better than the random walk model and other benchmark models for both forecast evaluation methods and for all horizons. Allowing for structural breaks does not improve the forecast performance for core inflation. The structural model only performs better than the random walk model for $h = 3$ onwards, but is outperformed by other models. Further, the forecasts where we allow for heteroscedastic errors in getting the shape of the predictive density outperform VARs with homoscedastic errors. We also find that models with $\lambda = 0.99$ perform better than models where the forgetting factors are allowed to change over time. Overall, our results imply that additional information on the GDP growth rate and interest rate is sufficient to forecast core inflation accurately, but the relationship between these three variables needs to be modeled in a time-varying (nonlinear) fashion.

Camba-Mendez and Kapetanios (2005) used disaggregated price indices to forecast core inflation by employing factor models. In light of this, future research could be aimed at forecasting South African core inflation using disaggregated price indices based on time-varying models, to see if such disaggregated information on price can produce more accurate forecasts than those obtained from GDP growth rate and interest rates. At the same time, an issue that we have ignored in this paper is that of persistence in the (core) inflation rate (Kouretas and Wohar (2012)), and hence, modeling and forecasting of the same using long-memory models accounting for nonlinearity, breaks and seasonality, as stressed and shown to exist for South African (and African) inflation rates by, for example, Gil-alana (2010), Gil-Alana (2011), Gil-Alana et al. (2014), and Boateng et al. (2018), could be an area of further research as well.

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Table 1: Data series used in the small, medium and large VARs

Variable	Transformation*	Description	VAR*
RGDP	Log first diff.	Gross domestic product at market prices (GDP)	S,M,L
CORE	Log first diff.	Headline CPI less interest on mortgages, food, petrol and electricity	S,M,L
TB3	Levels	Treasury bills: 91 days tender rate	S,M,L
NEER	Log first diff.	Nominal effective exchange rate of the rand: Average for the period - 15 trading partners	M,L
OIL	Log first diff.	Brent crude oil spot price (USD)	M,L
FORPRD	Log first diff.	Foreign wholesale price index (trade weighted) (own calculation)	M,L
ULC	Log first diff.	Manufacturing: Unit labour costs	M,L
PCE	Log first diff.	Final consumption expenditure by households: Total	L
GFCF	Log first diff.	Gross fixed capital formation (Investment)	L
JSE	Log first diff.	Johannesburg Stock Exchange (JSE) All Share index	L
M3	Log first diff.	Money supply: M3	L
CREDIT	Log first diff.	All monetary institutions: Total domestic credit extension	L
LEAD_FOR	Log first diff.	Leading indicator of all the main trading partner countries	L
RETAIL	Log first diff.	Retail sales	L
WAGES	Log first diff.	Total salaries and wages in the manufacturing sector	L
EMPL_PVT	Log first diff.	Employment in private sector (own calculation)	L
INCOME	Log first diff.	Disposable income of households	L
IP	Log first diff.	Industrial production (own calculation)	L
UTIL	Levels	Manufacturing: Utilisation of production capacity - Total	L
PPI	Log first diff.	Manufacturing Producer Price Index	L
COM_NENG	Log first diff.	World bank commodity price index: non-energy (USD)	L

*Log first diff=logged and the first difference was used, S=Small VAR, M=Medium VAR, L=Large VAR

Table 2: MSFE relative to the random walk model for core inflation

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Full Model								
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} = \beta_T$	0.66	0.48	0.43	0.43	0.40	0.43	0.50	0.55
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} \sim RW$	0.93	0.63	0.52	0.52	0.47	0.54	0.60	0.62
TVP-AR								
TVP-AR, λ=0.99, $\beta_{T+h} = \beta_T$	0.80	0.57	0.45	0.41	0.40	0.44	0.50	0.50
TVP-AR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.85	0.67	0.54	0.48	0.47	0.52	0.58	0.60
TVP-AR, λ=0.99, $\beta_{T+h} \sim RW$	0.79	0.55	0.45	0.42	0.40	0.43	0.49	0.50
TVP-AR, λ= λ_t, $\beta_{T+h} \sim RW$	0.86	0.67	0.54	0.48	0.48	0.52	0.58	0.60
Small VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.72	0.47	0.38	0.35	0.35	0.38	0.44	0.45
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.77	0.55	0.45	0.41	0.41	0.46	0.51	0.54
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	0.72	0.46	0.39	0.35	0.35	0.39	0.44	0.45
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.75	0.55	0.45	0.41	0.42	0.46	0.51	0.54
VAR, Heteroscedastic	0.78	0.58	0.48	0.43	0.43	0.48	0.54	0.57
VAR, Homoscedastic	0.83	0.71	0.59	0.53	0.53	0.60	0.64	0.71
Medium VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.86	0.51	0.41	0.41	0.39	0.43	0.48	0.52
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.91	0.64	0.52	0.49	0.48	0.53	0.58	0.63
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	0.86	0.50	0.41	0.41	0.39	0.43	0.48	0.51
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.92	0.64	0.51	0.50	0.47	0.53	0.57	0.63
VAR, Heteroscedastic	0.93	0.68	0.55	0.53	0.51	0.57	0.61	0.67
VAR, Homoscedastic	2.33	1.64	1.31	1.15	1.10	1.24	1.26	1.38
Large VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	1.07	0.96	0.80	0.75	0.72	0.79	0.85	0.93
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	1.22	1.22	1.01	0.91	0.87	0.96	1.00	1.12
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	1.04	0.96	0.82	0.75	0.72	0.80	0.84	0.94
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	1.22	1.22	1.00	0.90	0.88	0.95	1.00	1.11
VAR, Heteroscedastic	1.30	1.31	1.07	0.97	0.92	1.03	1.07	1.19
VAR, Homoscedastic	1.55	1.00	0.80	0.69	0.68	0.75	0.77	0.80
FAVAR								
TVP-FAVAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.94	0.65	0.50	0.48	0.48	0.52	0.59	0.57
TVP-FAVAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.97	0.78	0.61	0.56	0.56	0.62	0.68	0.69
TVP-FAVAR, λ=0.99, $\beta_{T+h} \sim RW$	0.92	0.64	0.51	0.47	0.48	0.52	0.58	0.56
TVP-FAVAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.97	0.78	0.61	0.56	0.56	0.62	0.69	0.69
FAVAR, Heteroscedastic	0.99	0.83	0.66	0.59	0.59	0.66	0.71	0.74
FAVAR, Homoscedastic	2.07	2.27	1.83	1.57	1.53	1.71	1.74	1.93
Benchmark Models								
Random Walk	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Small VAR OLS	1.00	1.01	0.99	0.96	0.99	1.14	1.18	1.26
AR(1) OLS	1.03	1.06	1.07	1.03	1.08	1.25	1.28	1.37
AR(1) Structural Breaks	1.68	1.18	0.96	0.87	0.85	0.91	0.90	0.94
Average performance								
Excluding benchmark models	1.01	0.80	0.65	0.60	0.58	0.64	0.69	0.74
Including benchmark models	1.01	0.82	0.68	0.63	0.61	0.68	0.73	0.78

Table 3: Sum of log predictive likelihoods relative to the random walk model for core inflation

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Full Model								
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} = \beta_T$	87.7	70.4	62.8	59.4	56.8	53.6	49.7	49.7
TVP-VAR-DDS, λ= 0.99, $\beta_{T+h} \sim RW$	82.3	63.1	58.1	52.2	49.4	47.9	44.7	45.8
TVP-AR								
TVP-AR, λ=0.99, $\beta_{T+h} = \beta_T$	82.3	67.3	61.5	55.6	53.4	53.2	48.6	49.0
TVP-AR, λ= λ_t, $\beta_{T+h} = \beta_T$	80.6	63.5	57.7	51.9	49.8	49.1	45.2	45.2
TVP-AR, λ=0.99, $\beta_{T+h} \sim RW$	81.9	67.5	61.0	54.9	53.7	52.9	48.9	49.2
TVP-AR, λ= λ_t, $\beta_{T+h} \sim RW$	80.5	63.6	57.3	51.8	49.8	49.1	45.5	45.3
Small VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	86.3	71.7	65.0	59.4	56.8	55.6	51.2	51.6
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	84.6	68.5	61.7	56.1	53.6	52.2	48.4	47.8
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	85.8	71.6	64.4	59.1	55.9	55.5	51.1	50.7
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	84.6	68.5	61.4	56.0	52.9	52.2	49.1	47.8
VAR, Heteroscedastic	84.1	67.3	60.7	54.8	52.3	51.1	47.4	46.6
VAR, Homoscedastic	86.1	61.8	59.0	49.8	45.0	46.4	36.6	28.3
Medium VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	85.7	68.5	62.8	55.3	53.4	52.6	49.6	48.2
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	82.4	64.3	58.5	51.5	49.4	48.3	45.5	44.1
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	85.3	68.6	62.4	55.4	53.1	52.2	48.7	47.9
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	82.8	64.9	58.3	51.0	49.7	48.3	45.4	43.9
VAR, Heteroscedastic	81.5	63.1	56.9	49.6	47.7	46.7	43.7	42.7
VAR, Homoscedastic	52.0	36.1	31.5	27.1	26.3	24.5	22.0	21.5
Large VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	78.7	55.1	48.1	42.4	40.5	39.1	36.4	35.8
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	74.9	48.3	41.5	36.1	34.6	33.7	31.5	30.4
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	79.4	55.0	47.3	42.1	40.4	39.0	36.8	35.5
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	74.9	48.4	41.7	36.4	34.9	34.0	32.0	31.0
VAR, Heteroscedastic	73.0	46.0	39.5	33.8	32.8	31.6	29.8	28.4
VAR, Homoscedastic	57.5	44.7	41.7	34.3	31.9	31.9	30.5	35.1
FAVAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	84.0	63.3	58.1	51.3	49.3	48.3	45.0	46.0
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	82.0	59.0	54.0	47.8	45.8	44.1	40.6	41.7
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	84.2	63.7	57.9	51.6	49.7	48.2	45.4	46.4
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	82.1	58.9	53.9	47.2	45.6	44.0	40.6	41.8
VAR, Heteroscedastic	81.3	57.6	52.2	46.6	44.4	42.9	39.6	40.1
VAR, Homoscedastic	56.7	24.9	20.5	15.1	15.5	14.6	12.4	11.5
Benchmark Models								
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Random Walk	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Small VAR OLS	-1.5	-3.6	-5.4	-7.4	-9.3	-10.6	-13.0	-15.8
AR(1)	-0.7	-2.2	-3.5	-5.1	-6.8	-8.0	-10.5	-13.4
AR(1) Structural Breaks	-34.1	-7.8	6.1	12.0	17.1	20.3	24.1	27.0
Average performance								
Excluding benchmark models	79.6	59.9	53.9	47.8	45.8	44.8	41.4	41.0
Including benchmark models	73.4	55.1	49.5	43.8	41.9	40.8	37.6	37.1

Table 4: MSFE relative to the TVP-VAR ($\lambda = 0.99$, $\beta_T + h = \beta_T$) model for core inflation

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Full Model								
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} = \beta_T$	0.92	1.02	1.13	1.23	1.14	1.13	1.14	1.22
TVP-AR								
TVP-AR, λ=0.99, $\beta_{T+h} \sim RW$	1.10	1.17	1.18	1.20	1.14	1.13	1.11	1.11
Medium VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	1.19	1.06	1.08	1.17	1.11	1.13	1.09	1.13
Large VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	1.49	2.04	2.11	2.14	2.06	2.08	1.93	2.07
FAVAR								
TVP-FAVAR, λ=0.99, $\beta_{T+h} \sim RW$	1.28	1.36	1.34	1.34	1.37	1.37	1.32	1.24
Benchmark Models								
Random Walk	1.39	2.13	2.63	2.86	2.86	2.63	2.27	2.22

Table 5: Sum of log predictive likelihoods relative to the TVP-VAR ($\lambda = 0.99$, $\beta_T + h = \beta_T$) model for core inflation

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Full Model								
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} = \beta_T$	1.3	-1.3	-2.2	0.0	0.0	-2.1	-1.5	-1.9
TVP-AR								
TVP-AR, λ=0.99,$\beta_{T+h} = \beta_T$	-4.5	-4.2	-4.0	-4.5	-3.1	-2.8	-2.3	-2.4
Medium VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	-1.0	-3.1	-2.6	-4.0	-3.7	-3.5	-2.5	-3.6
Large VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	-7.6	-16.6	-16.9	-17.0	-16.3	-16.5	-14.9	-15.7
FAVAR								
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	-2.1	-7.9	-7.1	-7.8	-7.1	-7.5	-5.9	-5.2
Benchmark Models								
AR(1) Structural Breaks	-120.4	-79.5	-58.9	-47.4	-39.7	-35.3	-27.1	-24.6

Appendices

A Forecasting performance with p = 4

Table A1: MSFE relative to the random walk model for core inflation

	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Full Model								
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} = \beta_T$	0.78	0.61	0.64	0.75	0.64	0.61	0.68	0.78
TVP-VAR-DDS, λ=0.99, $\beta_{T+h} \sim RW$	0.77	0.65	0.68	0.78	0.63	0.60	0.72	0.78
TVP-AR								
TVP-AR, λ=0.99, $\beta_{T+h} = \beta_T$	0.66	0.43	0.36	0.31	0.26	0.31	0.38	0.42
TVP-AR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.67	0.44	0.37	0.32	0.28	0.33	0.40	0.44
TVP-AR, λ=0.99, $\beta_{T+h} \sim RW$	0.67	0.43	0.36	0.31	0.26	0.31	0.38	0.42
TVP-AR, λ= λ_t, $\beta_{T+h} \sim RW$	0.67	0.45	0.38	0.33	0.29	0.33	0.40	0.44
Small VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.67	0.44	0.36	0.31	0.27	0.31	0.37	0.41
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.66	0.43	0.35	0.31	0.27	0.31	0.36	0.42
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	0.67	0.44	0.36	0.32	0.27	0.31	0.37	0.41
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.66	0.43	0.35	0.30	0.27	0.31	0.37	0.41
VAR, Heteroscedastic	0.65	0.43	0.35	0.30	0.27	0.31	0.36	0.41
VAR, Homoscedastic	0.73	0.56	0.56	0.55	0.56	0.65	0.72	0.83
Medium VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.73	0.41	0.36	0.34	0.27	0.31	0.37	0.43
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.69	0.39	0.35	0.34	0.26	0.30	0.37	0.43
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	0.76	0.41	0.35	0.35	0.27	0.30	0.37	0.43
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.70	0.39	0.36	0.33	0.26	0.30	0.37	0.43
VAR, Heteroscedastic	0.69	0.39	0.35	0.34	0.26	0.30	0.37	0.44
VAR, Homoscedastic	2.00	1.83	1.76	1.70	1.81	2.02	2.09	2.32
Large VAR								
TVP-VAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.89	0.53	0.49	0.45	0.41	0.46	0.56	0.66
TVP-VAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.78	0.52	0.46	0.43	0.38	0.42	0.49	0.56
TVP-VAR, λ=0.99, $\beta_{T+h} \sim RW$	0.87	0.55	0.49	0.46	0.41	0.46	0.57	0.67
TVP-VAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.77	0.53	0.46	0.43	0.38	0.42	0.50	0.57
VAR, Heteroscedastic	0.79	0.54	0.48	0.45	0.40	0.45	0.51	0.59
VAR, Homoscedastic	3.04	2.27	1.89	1.72	1.75	1.97	2.02	2.27
FAVAR								
TVP-FAVAR, λ=0.99, $\beta_{T+h} = \beta_T$	0.81	0.50	0.41	0.36	0.31	0.37	0.43	0.45
TVP-FAVAR, λ= λ_t, $\beta_{T+h} = \beta_T$	0.76	0.50	0.41	0.35	0.30	0.36	0.42	0.44
TVP-FAVAR, λ=0.99, $\beta_{T+h} \sim RW$	0.82	0.51	0.41	0.36	0.31	0.38	0.43	0.46
TVP-FAVAR, λ= λ_t, $\beta_{T+h} \sim RW$	0.77	0.50	0.40	0.36	0.30	0.36	0.42	0.45
FAVAR, Heteroscedastic	0.75	0.50	0.41	0.35	0.30	0.37	0.42	0.45
FAVAR, Homoscedastic	1.61	1.47	1.44	1.42	1.34	1.52	1.59	1.78
Benchmark Models								
Random Walk	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Small VAR OLS	1.01	1.05	1.07	1.09	1.11	1.13	1.16	1.18
AR(1) OLS	1.02	1.05	1.08	1.11	1.15	1.18	1.21	1.23
AR(1) Structural Breaks	1.73	1.26	1.02	0.91	0.87	0.89	0.87	0.89
Average performance								
Excluding benchmark models	0.88	0.62	0.55	0.51	0.47	0.53	0.59	0.67
Including benchmark models	0.92	0.67	0.61	0.57	0.53	0.59	0.65	0.71