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Abstract

In this paper we test the forecasting ability of three estimated financial conditions indices (FCIs) with respect to key macroeconomic variables of output growth, inflation and interest rates. We do this by forecasting the aforementioned macroeconomic variables based on the information contained in the three alternative FCIs using a Bayesian VAR (BVAR), nonlinear logistic vector smooth transition autoregression (VSTAR) and nonparametric (NP) and semi-parametric (SP) regressions, and compare the results with the standard benchmarks of random-walk, univariate autoregressive and classical VAR models. The three FCIs are constructed using rolling-window principal component analysis (PCA), dynamic model averaging (DMA) in the context of a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, and a time-varying parameter vector autoregressive (TVP-VAR) model with constant factor loadings. Our results suggest that the VSTAR model performs best in the case of forecasting manufacturing production and inflation, while a SP specification proves to be the best for forecasting the interest rate. More importantly, statistics testing for significant differences in forecast errors across models corroborate the finding of superior predictive ability of the nonlinear models.

Keywords: Financial conditions index, dynamic model averaging, nonlinear logistic smooth transition vector autoregressive model.

JEL Classification: C32, G01, E44, E32

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1. Introduction

The global financial crisis of 2008 has sparked an interest in and demonstrated the need for better measurement of financial shocks and their impact on the macroeconomy. To this end, recent literature has explored the development of financial conditions indices (FCIs). In this regard, the reader is referred to Koop and Korobilis (2014), Alessandri and Mumtaz (2014) and Thompson, Van Eyden and Gupta (forthcoming (a)) for an overview of the recent literature on FCIs. One of the key objectives of designing an FCI is for policymakers to use it as an early-warning tool of future crises.

Given this, Thompson *et al*., (forthcoming (a)) developed a financial conditions index for South Africa based on monthly data over the period of 1966 to 2011, using a set of sixteen financial variables, which include variables that define the state of international financial markets, asset prices, interest rate spreads, stock market yields and volatility, bond market volatility and monetary aggregates. The authors explore different methodologies for constructing the FCI, and find that rolling-window principal components analysis (PCA) yields the best results in terms of in-sample predictability of output growth, inflation and the interest rate. The intuition behind the rolling-window based FCI outperforming the full-sample FCI was explained by indicating the fact that the importance of the sixteen variables included in the FCI varied considerably over ten-year sub-samples during the period 1966-2011.[1] In a different paper, Thompson, Van Eyden and Gupta, (forthcoming (b)) tested whether the rolling-window estimated FCI does better than its individual financial components in forecasting output growth, inflation and interest rates. They used the concept of forecast encompassing to examine the forecasting ability of the individual predictors and the FCI for the three key macroeceonomic variables controlling for data-mining. Thompson *et al*., (forthcoming (b)) find that the rolling-window estimated FCI has out-of-sample forecasting ability with respect to manufacturing output growth at short- to medium-horizons, but has no forecasting ability with respect to inflation and interest rates.

Against this backdrop, the objectives of the current paper are twofold: (a) Due to the fact that the weights the financial variables carry in the construction of the FCI vary over time, as indicated by Thompson *et al*., (forthcoming (a)), we look at an alternative and more sophisticated statistical approach to the rolling-window PCA method, for the construction of the FCI for South Africa based on the same set of 16 variables used by Thompson *et al*., (forthcoming (a)). More specifically, we follow Koop and Korobilis (2014), and employ time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) models. However, given that we work with a large set of TVP-FAVARs that differ in which financial variables are included in the construction of the FCI, we augment the approach with Dynamic Model Selection (DMS) and Dynamic Model Averaging (DMA) to accommodate for the large model space and the intention to allow for model change. As indicated by Koop and Korobilis (2014), these methods

[1] Thompson *et al.,* (forthcoming (a)) also developed a recursively generated FCI, but they found that this FCI performed relatively poorly in terms of serving as an early warning system for South Africa. Further details can be found in Thompson *et al.*, (forthcoming (a)).

forecast at each point in time with a single optimal model (DMS), or reduce the expected risk of the final forecast by averaging over all possible model specifications (DMA), with model selection or model averaging applied in a dynamic manner. More precisely, DMS helps in choosing different financial variables for the construction of the FCI at different points in time, while the DMA constructs a FCI by averaging over many individual FCIs constructed using different financial variables. Clearly then, the weights used in this averaging procedure vary over time.

We compare the DMS and DMA based FCI with the rolling-window PCA FCI of Thompson *et al.*, (forthcoming (a)) and a standard full-sample FCI where all sixteen variables are included at each point in time, by looking at the ability of the respective indices to predict the South African recession visually, but the formal comparison is based on an extensive out-of-sample forecasting exercise across these three alternative FCIs. Specifically, we look at the ability of the three alternative FCIs in predicting output growth, inflation and interest rate over an out-of-sample period of 1986:1-2012:1, using an in-sample period of 1966:2-1985:12. The starting point of the out-of-sample corresponds to the period of financial liberalization in South Africa and was also used by Thompson *et al.*, (forthcoming (b)). In addition to the standard benchmarks such as a random-walk (RW), univariate autoregressive (AR) models and classical VAR models, we also look at Bayesian VARs, nonlinear logistic vector smooth transition autoregression (VSTAR) models, non-parametric (NP) and semi-parametric (SP) models, which incorporate the three different FCIs along with the three key variables to be predicted. Note that in case of the VSTAR and in the nonparametric part of the semi-parametric regressions, we use the FCI as the switch variable, or rather the source of nonlinearity as in Alessandri and Mumtaz (2014). The decision to look at models that capture the nonlinear effects of FCIs on the three macroeconomic variables emanate from the recent work by Balcilar, Thompson, Gupta and Van Eyden (2014).

The nonlinear logistic VSTAR model used in this paper allows for a smooth evolution of the economy, governed by a chosen switching variable between periods of high and low financial volatility. Balcilar *et al*. (2014) found that the South African economy responds nonlinearly to financial shocks, and that manufacturing output growth and Treasury Bill rates are more affected by financial shocks during upswings. Inflation was found to respond significantly more to financial changes during recessions. In addition to the forecasting exercise conducted over the recursively estimated out-of-sample period, we also conduct an ex ante forecasting exercise, i.e., without updating the estimates of the parameters based on recursive estimation of the models. This forecasting exercise is conducted over the period 2012:2-2014:2 to gauge the ability of our best performing (over 1986:1-2012:1) FCIs and models in predicting the turning points in the three variables of concern. To the best of our knowledge this the first attempt in developing a DMS-DMA-based FCI for South Africa, and also comparing the ability of this FCI relative to the existing FCIs in the South African literature in forecasting key macroeconomic variables based on a wider set of linear and nonlinear models.

The rest of the paper is organized as follows: section 2 contains a discussion of the construction of the three different FCIs in terms of the financial and real economic variables used in the construction thereof as well as the techniques used. Section 3 discusses the methodologies used in the forecasting exercises. Section 4 contains the empirical results, while section 5 concludes.

2. Data

This paper sets out to test the forecasting ability of three FCIs which are estimated using contrasting methodologies. The variables making up each of the FCIs are the same in all three instances, and comprise a set of sixteen monthly financial variables (see Table 1~~Table 3~~ in the Appendix) over the period 1966M02–2012M01. The three FCIs are estimated as follows.

The first FCI is estimated in Thompson, *et al*. (forthcoming (a)) and is compiled using rolling-window PCA applied to the set of financial variables, where a common factor, in this case $FCI1_t$, is extracted from a group of 16 variables, X_t. $FCI1_t$ is furthermore purged of any endogenous feedback effects related to output, inflation and monetary policy. Thompson, *et al*. (forthcoming (b)) find, using a forecast encompassing approach, that $FCI1_t$ has good out-of-sample forecasting ability for the key macroeconomic variable of growth in manufacturing production. Balcilar, *et al*. (2014) find, using a nonlinear logistic VSTAR model which incorporates $FCI1_t$ that the South African economy responds nonlinearly to financial shocks. Specifically, manufacturing output growth and Treasury Bill rates are more affected by financial shocks during upswings, while inflation responds significantly more to financial changes during recessions.

The second FCI is compiled using DMA in the context of a TVP-FAVAR, which accounts for the fact that the 16 variables making up the FCI can change in importance over time (see Thompson, *et al.* (forthcoming (a)) for a discussion of the need for time-varying weights in an FCI). The process followed is similar to Koop and Korobilis (2014), and the reader is referred to their paper for a discussion on DMA, which "constructs an FCI by averaging over many individual FCIs constructed using different financial variables" (2014:3). Specifically, if X_t is again a vector of 16 financial variables used in constructing the FCI, the TVP-FAVAR can be represented as:

$$\begin{aligned} X_t &= \lambda_t^y y_t + \lambda_t^f f_t + u_t \\ \begin{bmatrix} y_t \\ f_t \end{bmatrix} &= c_t + B_t \begin{bmatrix} y_{t-1} \\ f_{t-1} \end{bmatrix} + \varepsilon_t \end{aligned} \tag{1}$$

with

$$\begin{aligned} \lambda_t &= \lambda_{t-1} + \upsilon_t \\ \beta_t &= \beta_{t-1} + \eta_t \end{aligned} \tag{2}$$

where $\lambda_t = \left((\lambda_t^y)', (\lambda_t^f)'\right)'$, $\beta_t = (c_t', vec(B_t)')'$ and f_t is a latent factor interpreted as $FCI2_t$.

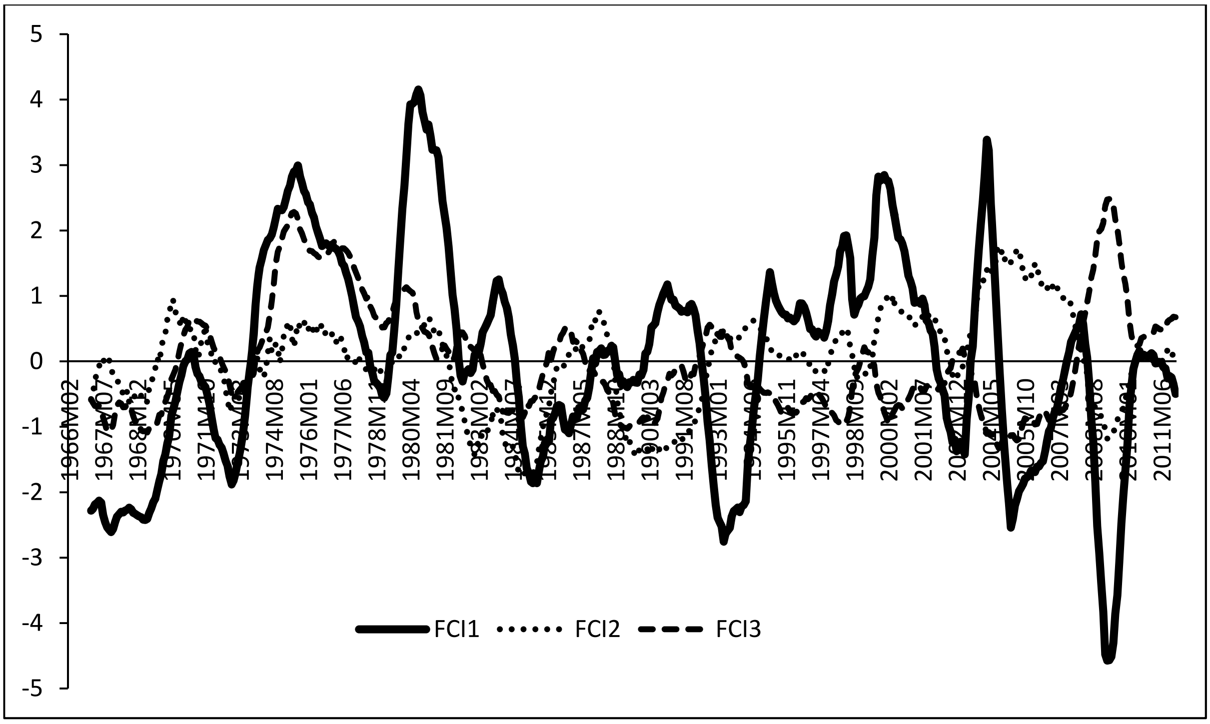
As with Koop and Korobilis (2014:12-14), the model above "allows factor loadings, regression coefficients and VAR coefficients to evolve over time according to a random walk, … and all of the error covariance matrices to be time-varying" using exponentially weighted moving average (EWMA) methods combined with Kalman filter recursions.

The third FCI is also compiled using a time-varying VAR (as with $FCI2_t$), however DMA is not used to allow varying importance of the financial variables over time. Instead, $FCI3_t$ always includes all of the 16 financial variables, and their probabilities remain the same throughout the sample – i.e. the weights in the FCI are constant. Specifically, in equation (2) a restriction is imposed such that $\lambda_t = \lambda$, which means that even though the factor equation will have constant factor loadings, the VAR component of the model will still have time-varying parameters. Koop and Korobilis (2014) refer to this restricted model as a factor-augmented TVP-VAR, or a FA-TVP-VAR.

The three FCI series are subsequently used in a forecasting exercise, where the respective indices are compared in terms of their ability to forecast manufacturing output, inflation and the Treasury Bill rate. All data is sourced from the Global Financial Database (see Table 3 in Appendix).

Figure 1 shows that the three estimated FCIs exhibit similar trends – albeit at differing levels and magnitudes. The rolling-window PCA-estimated FCI ($FCI1_t$) appears to exhibit larger fluctuations than the other two indices. A noticeable divergence is evident during the period of the global financial crisis (late 2000s) where the no-DMA-estimated FCI ($FCI3_t$) does not appear to pick up the global recession. $FCI1_t$ and the DMA-estimated FCI ($FCI2_t$), however, both capture the recession – the former to a much larger extent.

Figure 1. Comparison of three estimated FCIs



Note: The FCIs are standardised

3. Forecasting methodology

In this paper we test the forecasting ability of the three estimated FCIs with respect to the key macroeconomic variables of output growth (y) – the month-on-month rate of change in South Africa's Manufacturing Production Index; a measure of inflation (π) – the month-on-month rate of change in the consumer price index (CPI); and the 3-month Treasury Bill yield (r).

We do this by forecasting the aforementioned macroeconomic variables based on the information contained in the three alternative FCIs using a Bayesian VAR, nonlinear logistic VSTAR and nonparametric and semi-parametric regressions, and compare the results with the standard benchmarks of a random-walk, autoregressive and classical VAR, where understandably, the RW and AR models incorporate only one of the variables to be predicted, while the VAR includes all three variables chosen for prediction.

3.1 Model descriptions

This section describes the models used in our empirical analysis.

Classical Vector Autoregressive (VAR) Model

The VAR model, though 'atheoretical,' is particularly useful for forecasting purposes. VAR models suffer from an important drawback, since they require the estimation of many potentially insignificant parameters. This problem of over-parameterization, resulting in multicollinearity and loss of degrees of freedom, leads to inefficient estimates and large out-of-sample forecasting errors. One solution, often adopted, simply excludes the insignificant lags based on statistical tests. Another approach uses near VAR models, which specify unequal number of lags for the different equations.

An alternative approach to overcoming over-parameterization, as described in Litterman (1981), Doan *et al.* (1984), Todd (1984), Litterman (1986), and Spencer (1993), uses a Bayesian VAR (BVAR) model. Instead of eliminating longer lags, the Bayesian method imposes restrictions on the model's coefficients by assuming that these coefficients more likely approach zero than the coefficients on shorter lags. If strong effects from less important variables exist, the data can override this assumption. The researcher imposes restrictions by specifying normal prior distributions with zero means and small standard deviations for all coefficients with the standard deviations decreasing as the lag length increases. The researcher sets the coefficient on the first own lag of a variable equal to unity, unless the variable is mean reverting or stationary. Generally, following Litterman (1981), the constant exhibits a diffuse prior. This specification of the BVAR prior is popularly called the 'Minnesota prior' due to its development at the University of Minnesota and the Federal Reserve Bank at Minneapolis.

We can represent a reduced form VAR using following linear regression specification:

$$\mathrm{Y}_{t+1} = Bx_t + \varepsilon_{t+1} \quad (3)$$

where Y_{t+1} denotes an (*m x 1*) vector of dependent variables (i.e., output growth, inflation, the measure of short-term interest rate i.e., y_t, π_t, r_t,) from time $t = 1, ..., T$; x_t denotes a (*k x 1*) vector, which may include lags of the dependent variables, intercepts, dummies, trends, and exogenous regressors; *B* denotes an (*m x k*) vector of VAR coefficients; and $\varepsilon_t \sim N(0,\Sigma)$, where Σ denotes a (*m*×*m*) covariance matrix.

We can rewrite equation (3) as a system of seemingly unrelated regressions (SURs) as follows, where different equations in the VAR can include different explanatory variables:

$$\mathrm{Y}_{t+1} = z_t \beta + \varepsilon_{t+1} \quad (4)$$

where Y_{t+1} and ε_t are defined in equation (3); $z_t = I_m \otimes x_t'$ is a (*m x n*) matrix vector; and $\beta = vec(B)$ is an (nx1) matrix. When no parameter restrictions exist, equation (4) is an unrestricted VAR model.

Bayesian Vector Autoregressive (BVAR) Model

For the BVAR based on the Minnesota prior, the means and variances of the Minnesota prior for β take the form $\beta \sim N(b^{min}, V^{min})$ where $V_{i,l}^{min} = g_1/p^2$ and $g_3 \times s_i^2$ applying to parameters on own lags and for intercepts respectively, while $V_{i,l}^{min} = (g_2 \times s_i^2)/(s_l^2 \times p^2)$ is for parameters *j* on variable $l \neq i; l, i = 1, ..., m.$ s_i^2 is the residual variance from the *p*-lag univariate autoregression for variable *i*. Following Banbura *et al*., (2010), we set the hyperparameters of the BVAR to the following values: $g_1 = g_2 = 0.1274$, 0.1964 and 0.2111 under FCI1, FCI2 and FCI3 respectively, and $g_3 = 100$. Note that, $g_1(=g_2)$ is obtained to ensure that the average fit of the three variables of interest (output growth, inflation and the interest rate) matches that of the in-sample fit of the VAR model without the specific FCI. To be specific, the BVAR includes a specific FCI one at a time, over and above the variables to be predicted, and hence is made up of four variables rather than three as in the classical VAR. Since we transform the variable used in the forecasting exercise to induce stationarity, we set the prior mean vector b^{min} equal to zero for parameters on the lags of all variables, including the first own lag (Banbura *et al*., 2010). The forecasts from the BVAR are based on 30,000 draws from the posterior, discarding the first 2,000 draws. Also, we set the lags in these models to 2, determined by the Bayesian information criterion (BIC). Besides the VAR and BVAR, we also use the standard linear benchmarks, namely the random-walk (RW) and autoregressive (AR) model of order *p* in our forecasting exercises.

Vector Smooth Transition Autoregressive (VSTAR) Model

Next, we turn our attention to the VSTAR model used by Balcilar *et al*., (2014) to analyze the nonlinear impact of financial conditions index on key South African macroeconomic variables. Define $X_t = (x_{1t,} x_{2t}, ..., x_{nt})'$ as a $(k \times 1)$ time-series vector. In our case, X_t is defined as (4×1) time-series vector comprising of output growth, inflation, interest rate and the specific FCI (i.e., y_t, π_t, r_t, $FCI_{i,t}$). We specify the *k*-dimensional VSTAR model as follows:

$$X_t = (\Theta_{1,0} + \sum_{j=1}^{p} \Theta_{1,j} X_{t-j}) + (\Theta_{2,0} + \sum_{j=1}^{p} \Theta_{2,j} X_{t-j}) G(s_t; \gamma, c) + \varepsilon_t, \tag{5}$$

where $\Theta_{i,0}$, $i = 1,2$, are $(k \times 1)$ vectors, $\Theta_{i,j}$, $i = 1,2$, $j = 1,2,...,p$, are $(k \times k)$ matrices, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{kt})$ is a *k*-dimensional vector of white noise processes with zero mean and nonsingular covariance matrix Ω, $G(\cdot)$ is the transition function that controls smooth moves between the two regimes, and s_t is the transition variable.

The VSTAR model in equation (5) defines for two regimes, one associated with $G(s_t; \gamma, c) = 0$ and another associated with $G(s_t; \gamma, c) = 1$. The transition from one regime to the other occurs smoothly, depending on the shape of the $G(\cdot)$ function. In this paper, we consider a logistic transition function

$$G(s_t; \gamma, c) = \frac{1}{1 + \exp\{-\gamma(s_t - c)/\hat{\sigma}_s\}}, \qquad \gamma > 0, \tag{6}$$

where $\hat{\sigma}_s$ is the estimate of the standard deviation of transition variable s_t. The threshold parameter c determines the midpoint between two regimes at $G(c; \gamma, c) = 0.5$. The parameter γ determines the speed of transition between the regimes with higher values corresponding to faster transition.

To specify the VSTAR model, we follow the procedure presented in Terasvirta (1998) (see, also Lundbergh and Terasvirta, 2002; Van Dijk and Franses, 2003). First, we specify the lag order of p =2.

Second, we test linearity against the VSTAR alternative. Since the VSTAR model contains parameters not identified under the alternative, we follow the approach of Luukkonen *et al*. (1988) and replace the transition function $G(\cdot)$ with a suitable Taylor approximation to overcome the nuisance parameter problem. The testing procedure selects a logistic VSTAR model with a single threshold, which we maintain for the univariate case as well.

Third, we select the transition variable s_t. To identify the appropriate transition variable, we run the linearity tests for several candidates, $s_{1t}, s_{2t}, ..., s_{mt}$, and select the one that gives the smallest p-value for the test statistic. Here, we consider lagged values of only the *FCI*s for lags 1 to 2 as the candidate transition variable, to check whether allowing the FCI to nonlinearly affect the variables of interest improves our forecasts relative to the linear models. Let $s_t = x_{i,t-d}$, where x equals the various FCIs in turn. We test linearity with these variables for delays $d = 1,2$. We obtain the smallest p-value with $s_t = FCI_{i,t-d}$ and $d = 2$. Note that, in this regard, we follow Alessandri and Mumtaz (2014), by allowing the nonlinearity to emerge from the FCIs. Explicit analytical point formula for obtaining forecasts do not exist for non-linear (V)AR models even with a Gaussian disturbance term when $h \geq 2$, as $E[f(x)] \neq f[E(x)]$, where h is the number of steps-ahead for the forecasts.[2] That is, a nonlinear function involving a stochastic variable will arise for $h \geq 2$ and expected value of the forecast function will depend on the unknown stochastic term, since $E[f(x)] \neq f[E(x)]$.

Nonparametric (NP) and Semi-Parametric (SP) Models

We now consider nonparametric and semi-parametric regression approaches for forecasting output growth, inflation and the interest rate. We consider two competing multivariate models, and examine their forecasting abilities. These specifications are as follows:

Model 1: Nonparametric regression model (NP model)

$$y_t = f_1(y_{t-1}, y_{t-2}, r_{t-1}, r_{t-2}, \pi_{t-1}, \pi_{t-2}, \mathrm{FCI}_{i,t-1}, \mathrm{FCI}_{i,t-2}) + \varepsilon_{yt}; \quad (7)$$

$$\pi_t = f_2(y_{t-1}, y_{t-2}, r_{t-1}, r_{t-2}, \pi_{t-1}, \pi_{t-2}, \mathrm{FCI}_{i,t-1}, \mathrm{FCI}_{i,t-2}) + \varepsilon_{\pi t}; \quad (8)$$

$$r_t = f_3(y_{t-1}, y_{t-2}, r_{t-1}, r_{t-2}, \pi_{t-1}, \pi_{t-2}, \mathrm{FCI}_{i,t-1}, \mathrm{FCI}_{i,t-2}) + \varepsilon_{rt}. \quad (9)$$

Model 2: Semi-parametric regression model (SP model)

$$y_t = \alpha_{0y} + \alpha_{1y} y_{t-1} + \alpha_{2y} y_{t-2} + \alpha_{1\pi}\pi_{t-1} + \alpha_{2\pi}\pi_{t-2} + \alpha_{1r} r_{t-1} + \alpha_{2r} r_{t-2} + g_1(FCI_{i,t-1}, FCI_{i,t-2}) + \varepsilon_{yt}; \quad (10)$$

$$\pi_t = \beta_{0\pi} + \beta_{1y} y_{t-1} + \beta_{2y} y_{t-2} + \beta_{1\pi}\pi_{t-1} + \beta_{2\pi}\pi_{t-2} + \beta_{1r} r_{t-1} + \beta_{2r} r_{t-2} + g_2(FCI_{i,t-1}, FCI_{i,t-2}) + \varepsilon_{\pi t}; \quad (11)$$

$$r_t = \lambda_{0r} + \lambda_{1y} y_{t-1} + \lambda_{2y} y_{t-2} + \lambda_{1\pi}\pi_{t-1} + \lambda_{2\pi}\pi_{t-2} + \lambda_{1r} r_{t-1} + \lambda_{2r} r_{t-2} + g_3(FCI_{i,t-1}, FCI_{i,t-2}) + \varepsilon_{rt}. \quad (12)$$

Here, $f_i(.)$ and $g_i(.)$, i=1,2 and 3, denote unknown functions that the data estimate. The ε_{it}, i=y, r, π, are mean-zero errors with unchanged variance over the entire data set. The parameters α_{0i}, β_{0i}, λ_{0i}; α_{1i}, β_{1i}, λ_{1i}; and α_{2i}, β_{2i}, λ_{2i}, i=y, r, π, are constants estimated from the data. Therefore, we can also describe the semi-parametric model as a partially linear nonparametric model, with the nonlinearity coming from the lagged-values of the FCIs – as with the VSTAR, this is to check if allowing the FCIs to have a nonlinear impact on the key variables improves our forecasts.[3]

In the time-series context, nonparametric regressions can lead to issues with correlated errors (e.g., Opsomer, *et al*. 2001). For instance, the data-driven band-width selection techniques in the kernel-smoothing methodology can break down in this context. In such cases, we could use a correlation-corrected method called CDPI to yield stable results. In our case, for Models 1 and 2, two lags guarantee the absence of autocorrelation. As a result, the responses in equations (7) to (9) and (10) to (12) exhibit uncorrelated errors. Also, stationarity checks ensure constant variances in each model. Finally, we compare such models based on their prediction errors or forecast performances.

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[2] Details of the bootstrapping procedure are available upon request from the authors. We implement all computations of the STAR models with the RSTAR package (Version 0.1-1) in R developed by the one of the authors of this paper.

[3] We use the *np* package in *R* to carry out the regressions outlined above.

We check the goodness of fit using Bootstrap testing and find *p*-values close to 1 for the models used. When estimating the unknown functions $f_i(.)$ and $g_i(.)$ in case of the nonparametric models, we use a local linear regression, using AIC_c bandwidth selection criterion. In this case, we also examine all options for the choice of kernels and find that the Gaussian kernel of order 2 works the best yielding the highest R-squared values and smallest MSE. We use the optimum bandwidth chosen by the software. In case of the semi-parametric modeling, we first compute data-driven bandwidths of the kernels to use in the $f_i(.)$ and $g_i(.)$ parts of the model, since bandwidth selection for lower levels of tolerance takes an extremely long time. We use a local-linear, and not local-constant, regression type, as the local-linear type yields smaller R-squared values.[4] Again, for the $f_i(.)$ and $g_i(.)$ parts of the model, we use Gaussian kernels of order 2, because they yield the highest R-squared values and the lowest MSE. We generate the forecasts from the NP and SP models using a recursive algorithm. That is, the forecast from origin *n* is generated for period *n*+1, and forecast values for period *n*+1 is inserted for unobserved values when forecasting for period *n*+2, and so forth.

4. Empirical results

4.1 Posterior inclusion probabilities

Before considering the forecasting results, the posterior inclusion probabilities of each of the financial variables in $FCI2_t$ are presented in Figure 2. This figure enables us to determine (a) if each of the 16 financial variables is being allocated differing weights at different points in time[5]; and (b) if so, which financial variables are more relevant in the FCI construction.

It is interesting to note that the inclusion probabilities for all of the financial variables, bar one, show, on average, an increasing trend over the sample. The exception is the Rand-Dollar exchange rate, which has a relatively stable (and significant in size) probability of between 0.3 and 0.6 throughout the sample. The exchange rate has traditionally been considered a central variable of concern in the financial conditions literature. The Bank of Canada (BOC) pioneered work on broader financial condition measures in the mid-1990s, when it introduced its monetary conditions index (MCI). For the BOC, the exchange rate was the most important additional variable. Its MCI, therefore, consisted of a weighted average of its refinancing rate and the exchange rate. The weights were determined via simulations with macroeconomic models designed to quantify the relative effect of a given percentage change in each variable on GDP or final demand. In the case of Canada, a relatively open economy, the exchange rate was given a weight

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[4] The decision to use the local linear regression method instead of the kernel-smoother methods adopted by Arora *et al.* (2011) in forecasting US real GDP based on nonparametric method, emanates from the fact that the former does not suffer from the problem of biased boundary points.

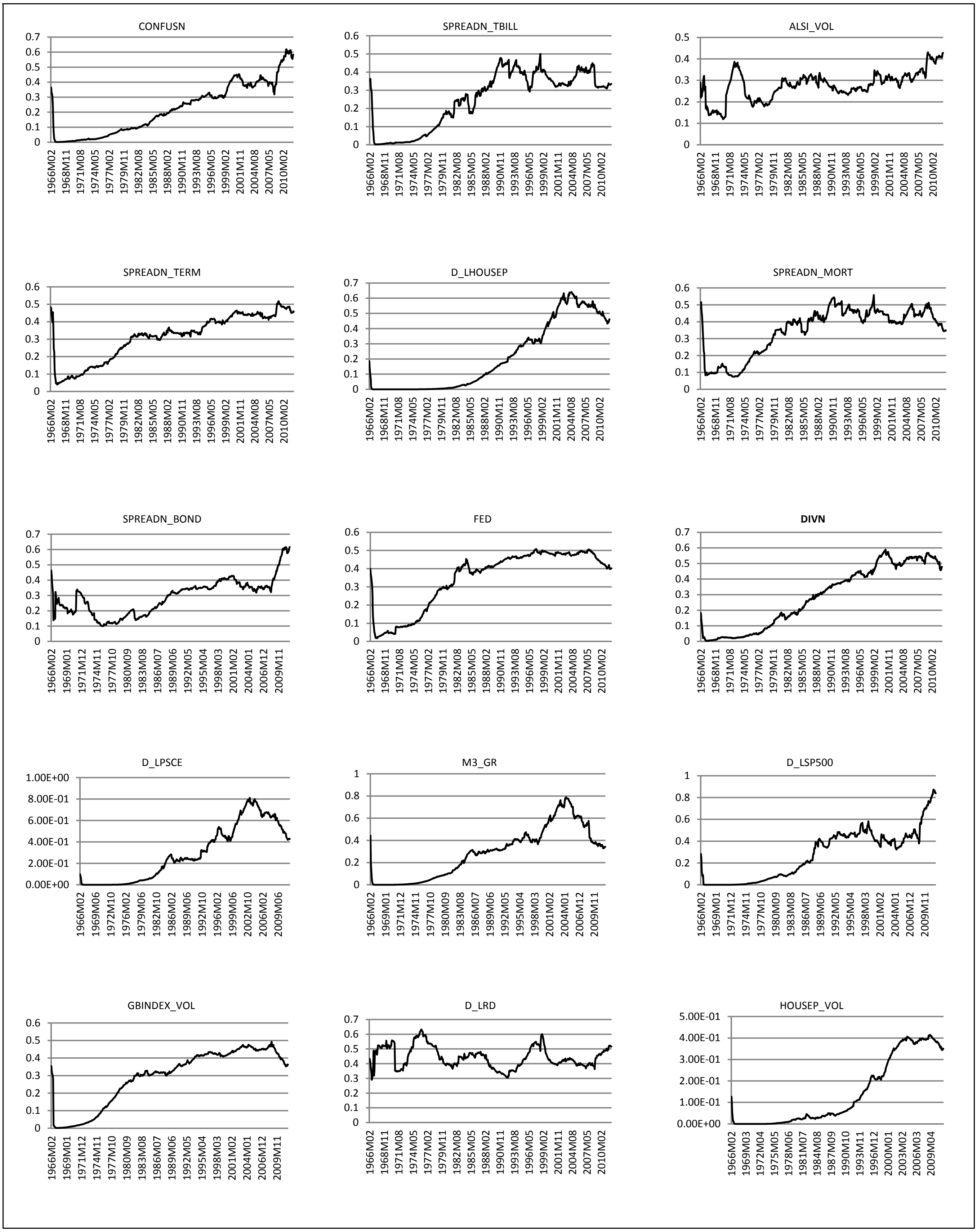
[5] It should be noted here that in order for the DMA model to compute, one of the 16 financial variables needs to remain fixed. As with Koop and Korobilis (2014), we set stock returns (D_LALSI) as fixed. Therefore, the inclusion probabilities for the remaining 15 variables indicate whether they contain information useful for forecasting beyond that which is provided by stock returns.

equal to about one-third that of the refinancing rate (Freedman, 1994). With South Africa also being a small open economy, one would likewise expect a fairly constant and significantly large weight, and therefore probability of inclusion.

The three volatility measures included in the FCI (house price volatility (HOUSEP_VOL), government bond volatility (GBINDEX_VOL) and stock return volatility (ALSI_VOL)) all exhibit rapidly rising inclusion probabilities. The four spread measures exhibit similarly increasing inclusion probabilities until approximately the mid- to late-1980s, where after they remain relatively steady. Early research on financial conditions centred on the slope of the yield curve and has been found to outperform other financial variables in terms of predicting recessions (Hatzius *et al.,* 2010), while stock market performance has been found to be a useful recession predictor as well (Stock & Watson, 1989; Estrella & Hardouvelis, 1991). The commercial paper-Treasury bill spread has been seen as a measure for credit risk, and been used as a leading indicator of output since the late 1980s (Stock and Watson, 1989). The period of stability in the probabilities of inclusion for the spread measures coincides with the era of financial liberalisation in South Africa. The political transition to a democracy during the first half of the 1990s, also contributed to greater stability in financial markets as well as the real sector of the economy.

Credit and money variables (D_LPSCE and M3_GR) show trends of decreasing inclusion probabilities in the 2000s, as do variables related to the housing market (HOUSEP_VOL and D_LHOUSEP). The decline in inclusion probabilities in credit and money variables during the 2000s can likely be attributed to the fact that South Africa introduced inflation targeting in February 2000 following a monetary-aggregate targeting framework. (Between 1960 and 1998 monetary policy frameworks included exchange rate targeting, discretionary monetary policy, monetary-aggregate targeting and an eclectic approach.) By 2000 the probability of inclusion of the house price variable exceeded 0.5. During the housing boom (from 2000 to 2006), house prices rose by an average of 20% annually. Riding on the back of an empowered middle class, house price peaked in October 2004 with 35.7% annual growth (32.5% in real terms). The probability of inclusion increased to above 0.6 during the same period. However in Q1 2008 the boom ground to a halt, following the global financial crisis. Between 2008 and 2011 house prices fell for four consecutive years by 9%, 5.4%, 1% and 5.1% in real terms, respectively. The probability of inclusion also fell back to 0.4 during this time. Only in 2012 did the housing market bounce back with house price rising by 3.2% in real terms, however, this turnaround does not reflect in the graph as our sample ends in 2012M1.)

Figure 2. Posterior inclusion probabilities of financial variables under DMA



4.2 Out-of-sample forecasting

Table 1 provides the results of the various forecasts conducted with respect to the key macroeconomic variables of output growth, inflation and interest rates. The measure of forecast performance used is the root mean squared error (RMSE) which is evaluated over the period 1987:01 to 2012:01 for h = 1, 2,…, 24 forecast horizons. The RMSE results in Table 1 are reported relative to the RW RMSE. In the case of manufacturing output growth, it is interesting to note that on average, the nonlinear methods provide superior forecasts to the linear models. In terms of the linear approaches, the BVAR using $FCI3_t$ is slightly superior to the BVAR using $FCI1_t$ (at four decimal points) in providing the best forecast. The best NP and SP forecasts are both achieved using $FCI2_t$. The best VSTAR forecast is achieved using $FCI1_t$. Overall, the best forecast of manufacturing output growth is achieved using $FCI1_t$ in a nonlinear VSTAR.

In terms of forecasting inflation – a notoriously autoregressive and persistent variable – it is unsurprising that the best linear forecast is provided by the AR model. In terms of NP and SP models, FCI2 provides the best SP forecasts. The best VSTAR forecast is achieved using $FCI2_t$, and this also represents the best inflation forecast overall.

The best linear forecast of the Treasury Bill rate is achieved by using $FCI3_t$ in the BVAR. $FCI1_t$ provides the best NP forecast, while $FCI3_t$ presents both the best SP forecast and the best VSTAR forecast. Overall, the best forecast of the Treasury Bill rate is achieved using $FCI3_t$ in a SP model.

Figure 3 contains ex-ante forecasts for the three models selected as the best performing overall for manufacturing growth, inflation and Treasury Bill rate according to RMSE measures. *Ex ante* forecasts are carried out over the period 2012:01 to 2014:01.

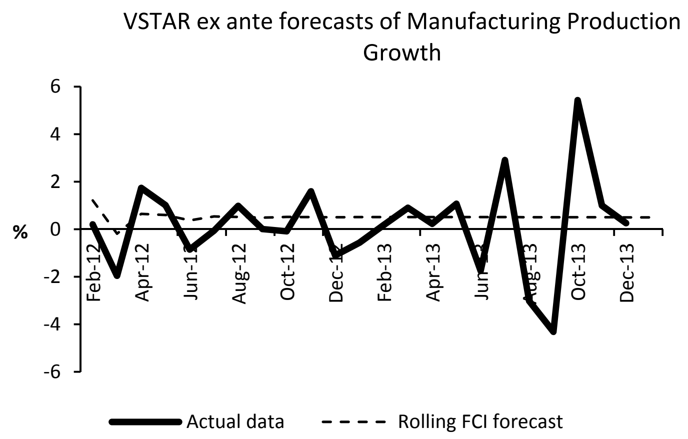
Table 1. Out-of-sample forecasting for x_t: FCI (Sample: 1986:01 – 2012:01) – RMSE statistics under differing models relative to RW model

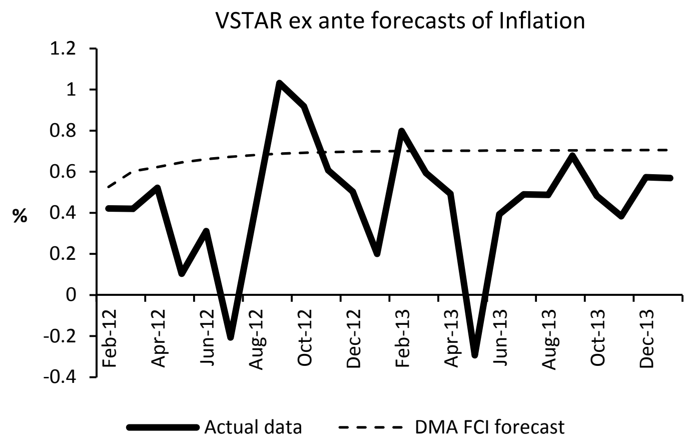
Horizon (h) months ahead:	1m	6m	12m	24m	Ave 1	Ave 2
x_t: Manufacturing production growth as dependent variable						
RW	*3.883*	*3.058*	*3.131*	*3.484*	*3.389*	*3.266*
AR	0.564	0.737	0.722	0.647	0.668	0.696
VAR	0.556	0.733	0.719	0.647	0.664	0.693
BVAR (Rolling FCI)	0.550	0.734	0.719	0.647	0.663	0.693
BVAR (DMA)	0.558	0.733	0.719	0.647	0.664	0.694
BVAR (no DMA)	0.548	0.733	0.719	0.647	0.662	0.693
NP (Rolling FCI)	0.493	0.745	0.787	0.671	0.674	0.744
NP (DMA)	0.523	0.740	0.721	0.653	0.659	0.700
NP (no DMA)	0.505	4.533	0.876	0.843	1.689	1.167
SP (Rolling FCI)	0.489	0.739	0.735	0.657	0.655	0.704
SP (DMA)	0.522	0.743	0.713	0.649	0.657	0.697
SP (no DMA)	0.494	0.748	0.757	0.650	0.662	0.697
VSTAR (Rolling FCI)	0.523	0.735	0.721	0.646	0.656	0.692
VSTAR (DMA)	0.536	0.735	0.720	0.647	0.660	0.693
VSTAR (no DMA)	0.517	0.738	0.723	0.647	0.656	0.693
x_t: Inflation as dependent variable						
RW	*0.565*	*0.623*	*0.622*	*0.606*	*0.604*	*0.654*
AR	0.841	0.854	0.865	0.906	0.867	0.817
VAR	0.846	0.884	0.894	0.959	0.896	0.847
BVAR (Rolling FCI)	0.850	0.886	0.894	0.959	0.897	0.848
BVAR (DMA)	0.827	0.873	0.892	0.957	0.887	0.841

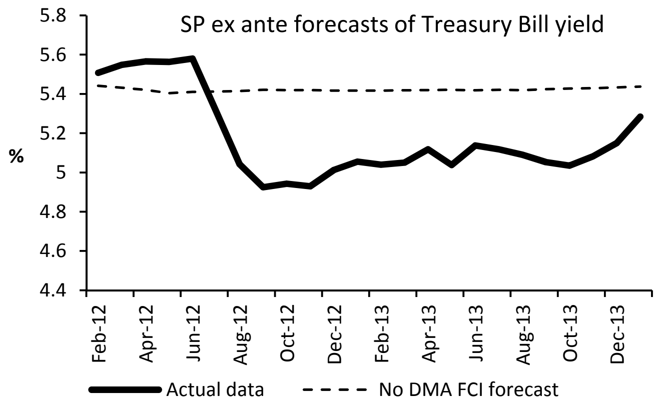
BVAR (no DMA)	0.832	0.883	0.897	0.957	0.892	0.846
NP (Rolling FCI)	0.768	0.859	0.902	1.005	0.884	0.852
NP (DMA)	0.773	1.591	0.857	0.913	1.034	0.841
NP (no DMA)	0.770	1.144	0.915	1.040	0.967	0.935
SP (Rolling FCI)	0.761	0.835	0.876	0.932	0.851	0.849
SP (DMA)	0.768	0.844	0.859	0.911	0.846	0.841
SP (no DMA)	0.754	0.886	1.105	0.924	0.917	0.876
VSTAR (Rolling FCI)	0.777	0.854	0.878	0.949	0.865	0.820
VSTAR (DMA)	0.781	0.835	0.854	0.886	0.839	0.797
VSTAR (no DMA)	0.788	0.846	0.876	0.941	0.863	0.824
x_t: Treasury Bill as dependent variable						
RW	*0.520*	*1.790*	*2.722*	*3.911*	*2.236*	*2.598*
AR	0.938	0.972	0.973	0.964	0.962	0.968
VAR	0.948	0.956	0.961	0.987	0.963	0.967
BVAR (Rolling FCI)	0.952	0.960	0.964	0.989	0.966	0.971
BVAR (DMA)	0.948	0.975	0.972	0.965	0.965	0.970
BVAR (no DMA)	0.931	0.926	0.919	0.923	0.925	0.923
NP (Rolling FCI)	0.637	1.091	0.965	1.089	0.946	0.954
NP (DMA)	0.635	1.182	1.065	0.962	0.961	1.013
NP (no DMA)	0.604	1.295	1.170	1.159	1.057	1.202
SP (Rolling FCI)	0.631	0.818	0.854	0.986	0.822	0.894
SP (DMA)	0.644	0.891	0.880	0.900	0.829	0.883
SP (no DMA)	0.600	0.870	0.813	0.854	0.784	0.842
VSTAR (Rolling FCI)	0.894	0.926	0.902	0.909	0.908	0.910
VSTAR (DMA)	0.902	0.947	0.931	0.886	0.917	0.922
VSTAR (no DMA)	0.865	0.837	0.825	0.831	0.840	0.833

Notes: Entries corresponding to RW is the absolute RMSEs for the model, rest of the entries are relative to the RW. Ave 1 refers to the average over the columns in this table. Ave 2 refers to the average RMSE over all forecast horizons (including those not reflected in the table).

Figure 3. *Ex ante* forecasts of manufacturing production growth, inflation and Treasury Bill yields







4.3 Weighted Diebold-Mariano (DM) Tests

To further assess the forecast accuracy of the various models above, we conduct pairwise Diebold and Mariano (1995) tests. Specifically, we use a modified version of this test developed by Harvey, Leybourne and Newbold (1997). This modified DM test is based on a weighted loss function, and basically compares the loss differences between a pair of models to determine if the average is significantly different from zero. Under the null hypothesis of equal forecast performance between a benchmark model, 0, and an alternative model, i, the expected loss differential, $d_{i,t}$, is given by:

$$E[d_{i,t}] = E[\mathcal{L}_{0,t}^{\omega} - \mathcal{L}_{i,t}^{\omega}] = 0$$

where the weighted loss function is $\mathcal{L}_{i,t}^{\omega} = \omega_t e_{i,t}^2$. Van Dijk *et al.*, (2003) assign heavier weights to extreme events, such that:

- $\omega_{left,t} = 1 - \hat{F}(y_t)$ where $F(\cdot)$ represents the cumulative distribution of the variable being forecasted, y_t, so as to impose heavier weights on the left tail of the distribution.
- $\omega_{right,t} = \hat{F}(y_t)$ where heavier weights are imposed on the right tail of the distribution.
- $\omega_{tail,t} = \frac{1-\hat{F}(y_t)}{\max(\hat{F}(y_t))}$ where $F(\cdot)$ represents the density of y_t, so as to impose heavier weights on both tails.

The modified DM-test statistic (*MDM*) from Harvey, *et al.* (1997) is used to "ascertain whether empirical loss differences between two contending models are statistically significant, … (i.e.) compares the forecast accuracy of two models at a time" (Bahramian, *et al.*, 2014:5) and is given as:

$$MDM = \left(\frac{P + 1 - 2h + P^{-1}h(h-1)}{P}\right)^{\frac{1}{2}} \hat{V}(\bar{d}_i)^{-\frac{1}{2}}\bar{d}_i$$

where h is the forecast horizon and $\hat{V}(\bar{d}_i)$ is the variance of $d_{i,t}$, and the *MDM* is compared to a t-distribution with $P - 1$ degrees of freedom.

0~~Table~~s 3 through 14 in the appendix present the results of the MDM tests of the best performing linear, NP, SP and VSTAR models for inflation, manufacturing production growth and the Treasury Bill rate respectively, under boom, recession, uniform and tail weighting schemes. Based on the RMSE results contained in Table 1, the best linear model for inflation is the simple AR model, while the BVAR model using $FCI3_t$ (no DMA) is the best model for both manufacturing output growth and Treasury Bill rate. (For manufacturing output growth, the forecasting performance for the BVAR with rolling-window FCI and no DMA FCI is virtually the same, but BVAR with no DMA FCI has a marginally lower RMSE when considering more decimal digits.)

Tables 3, 4, 5 and 6 report results from the MDM test which compares the forecasting performance of the linear, NP, SP and VSTAR models of inflation based on different weighting schemes and across different forecasting horizons. Under boom weights and at a short horizon (h=1), SP models significantly outperform linear and NP models, while at longer horizons (h=24) NP models are outclassed by both linear and VSTAR models. When using recession weights, NP, SP and VSTAR models outperform the linear model at a one-month horizon, while the linear model is also outperformed by SP and VSTAR models at the 6-month horizon. At longer horizons (h=24), NP models are outperformed by all rival models. At this horizon the VSTAR model also displays better forecasting abilities when compared to linear and SP models. Similar results are found when a tail or uniform weighting scheme is employed – at short horizons, (h=1), all models are significantly better than the linear model while at long horizons NP is outperformed by other models. For the uniform weighting scheme, the VSTAR model outperforms all rival models at a 24-mont horizon. These results are supportive of the out-of-sample forecasting results reported in section 4.2, where the VSTAR model is reported to have the best inflation forecast overall.

Tables 7, 8, 9 and 10 repeat the comparative analysis for manufacturing output growth. Under boom weights, the VSTAR model significantly outperforms all other models at a horizon of 24 months. At a 12-month horizon, it also outperforms all rival models, although the null is only rejected at a 10 per cent level of significance for the linear model. The same holds true for a 6-month horizon, with a rejection of the null for the NP model. The same holds true when a tail weighting scheme is employed, namely that the VSTAR model significantly outperforms all other models, in this case for a short forecasting horizon. When using recession weights, all models outclass the linear model at short horizons (h=1). Under a uniform weighting scheme there are no significant differences between models' forecasting ability, except for the linear model being outperformed by other models at a one-month horizon. Once again, results support the finding in section 4.2 that the VSTAR model has the best overall forecast for manufacturing output growth.

Lastly, tables 11, 12, 13 and 14 report the MDM results, comparing different models for the Treasury Bill rate, again using different weighting schemes and different horizons. Under boom weights at short horizons (h=1), both linear and VSTAR models are significantly outperformed by SP and NP models. The SP model in turn outperforms the NP model. At longer horizons (h=6, 12 and 24), the null is only significantly rejected for the linear model as benchmark and VSTAR as alternative model, with VSTAR outperforming the linear model. With a recession weighting scheme, the SP model performs significantly better than linear and VSTAR models at short (h=1) horizons. It also outperforms the linear model at a 6-month horizon and the NP model at a 12-month horizon. At short horizons the NP model significantly outperforms the linear and VSTAR model, whereas the VSTAR displays significantly better forecasting performance at medium to longer (h=12, 24) horizons. When using tail weights, only SP model displays better forecasting performance than other models at short horizons (h=1), while linear models are outperformed by VSTAR models at longer horizons (h=12, 24). For a uniform weighting scheme, once again SP models significantly outperform all rival models at a short forecasting horizon (h=1), with VSTAR showing a significantly better performance than linear models at longer horizons. Out-of-sample forecasting analysis suggested that the SP model achieves the best results, which result is supported by the MDM tests for the Treasury bill rate.

5 Conclusions

In this paper we set out to compare the forecasting ability of three estimated financial conditions indices (FCIs) with respect to key macroeconomic variables of output growth, inflation and interest rates. We do this by forecasting the aforementioned macroeconomic variables based on the information contained in the three alternative FCIs using a Bayesian VAR, nonlinear logistic VSTAR and nonparametric and semi-parametric regressions, and compare the results with the standard benchmarks of random-walk, univariate autoregressive and classical VAR models.

The three FCIs are constructed using rolling-window principal component analysis (PCA), dynamic model averaging (DMA) in the context of a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, and a time-varying parameter vector autoregressive (TVP-VAR) model with constant factor loadings.

Using RMSE as model selection criteria our out-of-sample forecasting results suggest that the VSTAR model performs best in the case of forecasting manufacturing production and inflation, while a SP specification proves to be the best for forecasting the interest rate. Weighted Diebold-Mariano test results lend support to these findings. Overall, our results point to the importance of allowing nonlinear effects of the FCI on macroeconomic variables in order to produce more accurate forecasts relative to linear models.

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Appendix

Table 1. Variables used to construct and test the FCI

Name	Description	Transformation(s)
FCI construction		
ALSI_VOL	Stock exchange volatility (South Africa)	Square of the first log difference of the All-Share Index
CONFUSN	University of Michigan US Consumer Sentiment Index	N/A
D_LALSI	FTSE/JSE All-Share Index (South Africa)	Seasonally adjusted, deflated by South African CPI, first log difference
D_LHOUSEP	Absa House Price Index (medium house size $141m^2$–$220m^2$) (South Africa)	Deflated by South African CPI, first log difference
D_LPSCE	Credit extended to domestic private sector (South Africa)	Deflated by South African CPI, first log difference
D_LRD	Rand-US Dollar exchange rate	Seasonally adjusted, deflated by relative US-SA CPI, first log difference
D_LSP500	S&P500 Composite Price Index	Seasonally adjusted, deflated by US CPI, first log difference
DIVN	Johannesburg Stock Exchange dividend yield (South Africa)	Seasonally adjusted
FED	US Federal Funds market rate	Deflated by US CPI
GBINDEX_VOL	Government bond volatility (South Africa)	Square of the first log difference of Government Bond Return Index
HOUSEP_VOL	House price volatility (South Africa)	Square of the first log difference of House Price Index
M3_GR	Month-on-month growth in M3 money supply (South Africa)	Seasonally adjusted, deflated, month-on-month rate of change
SPREADN_BOND	Long-term bond spread between Eskom Corporate Bond yield and 10-year Government Bond yield (South Africa)	N/A
SPREADN_MORT	Mortgage spread between mortgage loan borrowing rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TBILL	Short-term spread between prime overdraft rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TERM	Term spread between 10-year Government Bond yield and 3-month Treasury Bill yield (South Africa)	N/A
FCI forecasting		
π	Month-on-month growth in CPI (South Africa)	Seasonally adjusted, month-on-month rate of change
y	Month-on-month growth in Manufacturing Production Index (South Africa)	Month-on-month rate of change
r	3-month Treasury Bill Yield (South Africa)	N/A

Notes: All data is extracted from the Global Financial Database (https://www.globalfinancialdata.com). The US Census X-12 procedure is used to seasonally adjust the data for series not already seasonally adjusted. Unit roots are tested for using the Ng-Perron (2001) procedure, and non-stationary series are differenced to be made stationary. All data series are standardised.

Figure 4. Inflation graphs

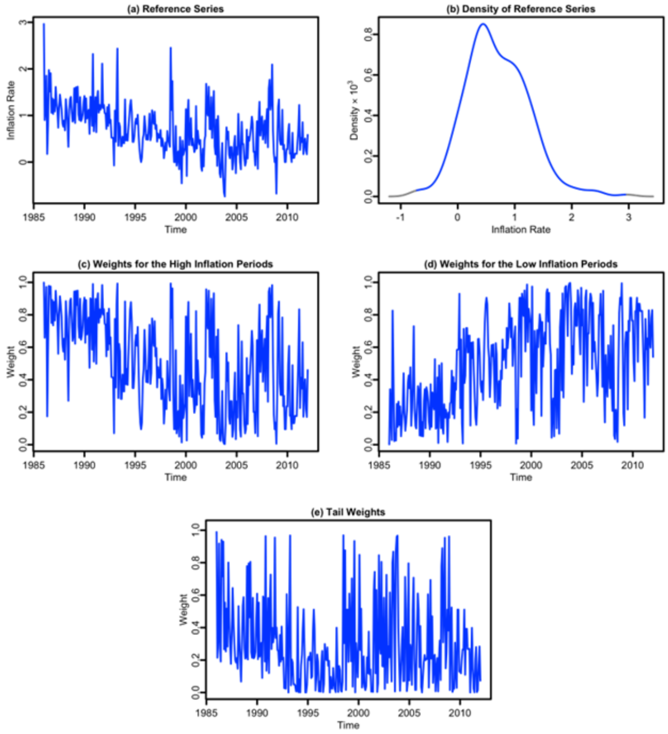

Figure 5. Manufacturing production graphs

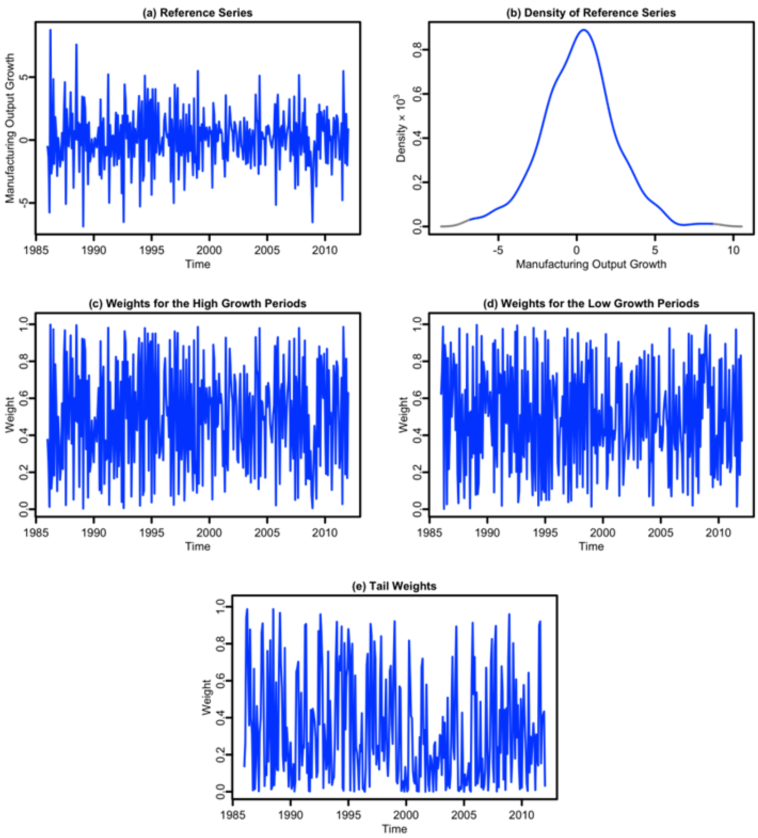

Figure 6. Treasury Bill graphs

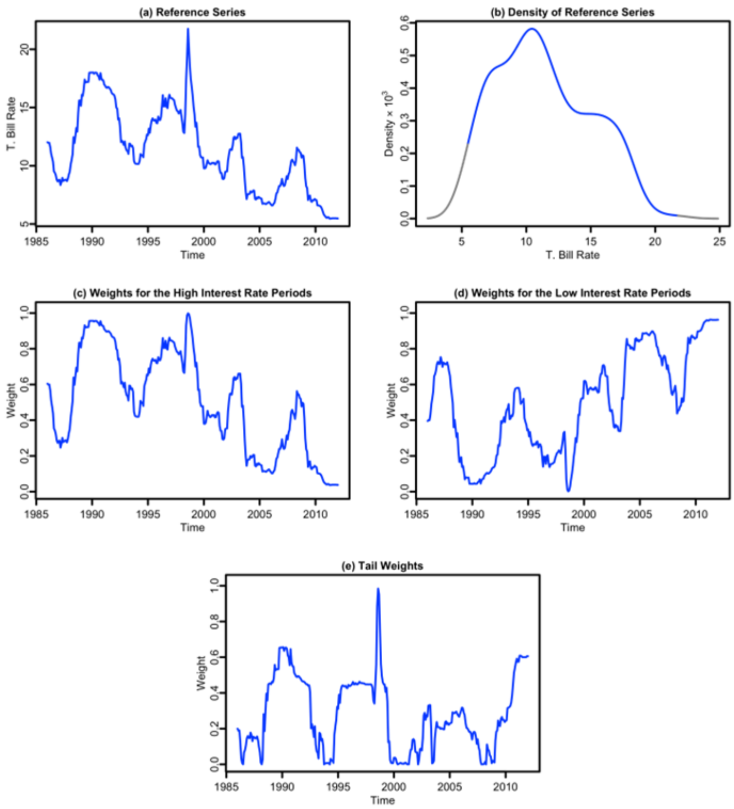

Table 3. Modified Diebold-Mariano test for inflation under boom weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-1.48 (0.14)	-2.05 (0.04)	-1.50 (0.13)	0	1
NP	1.48 (0.14)		-2.12 (0.03)	-0.46 (0.65)	0	1
SP	2.05 (0.04)	2.12 (0.03)		0.61 (0.54)	2	0
VSTAR	1.50 (0.13)	0.46 (0.65)	-0.61 (0.54)		0	0
h=6						
Linear		0.84 (0.40)	0.40 (0.69)	-0.13 (0.89)	0	0
NP	-0.84 (0.40)		-1.35 (0.18)	-0.88 (0.38)	0	0
SP	-0.40 (0.69)	1.35 (0.18)		-0.44 (0.66)	0	0
VSTAR	0.13 (0.89)	0.88 (0.38)	0.44 (0.66)		0	0
h=12						
Linear		1.18 (0.24)	1.24 (0.22)	0.02 (0.99)	0	0
NP	-1.18 (0.24)		-0.93 (0.35)	-1.20 (0.23)	0	0
SP	-1.24 (0.22)	0.93 (0.35)		-1.18 (0.24)	0	0
VSTAR	-0.02 (0.99)	1.20 (0.23)	1.18 (0.24)		0	0
h=24						
Linear		2.02 (0.04)	1.39 (0.16)	1.01 (0.31)	1	0
NP	-2.02 (0.04)		-1.19 (0.23)	-1.80 (0.07)	0	2
SP	-1.39 (0.16)	1.19 (0.23)		-1.07 (0.29)	0	0
VSTAR	-1.01 (0.31)	1.80 (0.07)	1.07 (0.29)		1	0

Table 4. Modified Diebold-Mariano test for inflation under recession weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-3.58 (<0.01)	-3.60 (<0.01)	-3.10 (<0.01)	0	3
NP	3.58 (<0.01)		-0.36 (0.72)	1.20 (0.23)	1	0
SP	3.60 (<0.01)	0.36 (0.72)		1.24 (0.22)	1	0
VSTAR	3.10 (<0.01)	-1.20 (0.23)	-1.24 (0.22)		1	0
h=6						
Linear		-0.69 (0.49)	-1.68 (0.09)	-2.18 (0.03)	0	2
NP	0.69 (0.49)		-1.55 (0.12)	-0.59 (0.56)	0	0
SP	1.68 (0.09)	1.55 (0.12)		0.32 (0.75)	1	0
VSTAR	2.18 (0.03)	0.59 (0.56)	-0.32 (0.75)		1	0
h=12						
Linear		1.06 (0.29)	-0.31 (0.75)	-1.62 (0.11)	0	0
NP	-1.06 (0.29)		-1.03 (0.30)	-1.31 (0.19)	0	0
SP	0.31 (0.75)	1.03 (0.30)		-0.32 (0.75)	0	0
VSTAR	1.62 (0.11)	1.31 (0.19)	0.32 (0.75)		0	0
h=24						
Linear		2.04 (0.04)	0.15 (0.88)	-4.40 (<0.01)	1	1
NP	-2.04 (0.04)		-2.05 (0.04)	-3.52 (<0.01)	0	3
SP	-0.15 (0.88)	2.05 (0.04)		-1.70 (0.09)	1	1
VSTAR	4.40 (<0.01)	3.52 (<0.01)	1.70 (0.09)		3	0

Table 5. Modified Diebold-Mariano test under inflation for tail weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-3.16 (<0.01)	-3.62 (<0.01)	-2.70 (0.01)	0	3
NP	3.16 (<0.01)		-1.96 (0.05)	0.49 (0.62)	1	1
SP	3.62 (<0.01)	1.96 (0.05)		1.01 (0.31)	2	0
VSTAR	2.70 (0.01)	-0.49 (0.62)	-1.01 (0.31)		1	0
h=6						
Linear		-1.39 (0.16)	-1.98 (0.05)	-0.85 (0.40)	0	1
NP	1.39 (0.16)		-1.54 (0.12)	0.87 (0.39)	0	0
SP	1.98 (0.05)	1.54 (0.12)		1.32 (0.19)	1	0
VSTAR	0.85 (0.40)	-0.87 (0.39)	-1.32 (0.19)		0	0
h=12						
Linear		0.62 (0.54)	-0.57 (0.57)	-0.15 (0.88)	0	0
NP	-0.62 (0.54)		-0.93 (0.35)	-0.80 (0.43)	0	0
SP	0.57 (0.57)	0.93 (0.35)		0.36 (0.72)	0	0
VSTAR	0.15 (0.88)	0.80 (0.43)	-0.36 (0.72)		0	0
h=24						
Linear		1.82 (0.07)	0.17 (0.86)	-1.43 (0.15)	1	0
NP	-1.82 (0.07)		-2.07 (0.04)	-2.21 (0.03)	0	3
SP	-0.17 (0.86)	2.07 (0.04)		-0.72 (0.47)	1	0
VSTAR	1.43 (0.15)	2.21 (0.03)	0.72 (0.47)		1	0

Table 6. Modified Diebold-Mariano test for inflation under uniform weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-3.62 (<0.01)	-4.08 (<0.01)	-3.35 (<0.01)	0	3
NP	3.62 (<0.01)		-1.66 (0.10)	0.85 (0.40)	1	1
SP	4.08 (<0.01)	1.66 (0.10)		1.32 (0.19)	2	0
VSTAR	3.35 (<0.01)	-0.85 (0.40)	-1.32 (0.19)		1	0
h=6						
Linear		-0.17 (0.86)	-1.23 (0.22)	-1.78 (0.07)	0	1
NP	0.17 (0.86)		-1.60 (0.11)	-0.84 (0.40)	0	0
SP	1.23 (0.22)	1.60 (0.11)		0.10 (0.92)	0	0
VSTAR	1.78 (0.07)	0.84 (0.40)	-0.10 (0.92)		1	0
h=12						
Linear		1.10 (0.27)	0.19 (0.85)	-1.34 (0.18)	0	0
NP	-1.10 (0.27)		-1.00 (0.32)	-1.27 (0.20)	0	0
SP	-0.19 (0.85)	1.00 (0.32)		-0.61 (0.54)	0	0
VSTAR	1.34 (0.18)	1.27 (0.20)	0.61 (0.54)		0	0
h=24						
Linear		2.64 (0.01)	0.83 (0.41)	-2.78 (0.01)	1	1
NP	-2.64 (0.01)		-1.91 (0.06)	-3.43 (<0.01)	0	3
SP	-0.83 (0.41)	1.91 (0.06)		-1.80 (0.07)	1	1
VSTAR	2.78 (0.01)	3.43 (<0.01)	1.80 (0.07)		3	0

Table 7. Modified Diebold-Mariano test for manufacturing production growth under boom weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-0.21 (0.84)	0.27 (0.79)	0.20 (0.84)	0	0
NP	0.21 (0.84)		1.34 (0.18)	0.36 (0.72)	0	0
SP	-0.27 (0.79)	-1.34 (0.18)		-0.05 (0.96)	0	0
VSTAR	-0.20 (0.84)	-0.36 (0.72)	0.05 (0.96)		0	0
h=6						
Linear		1.59 (0.11)	0.32 (0.75)	-0.57 (0.57)	0	0
NP	-1.59 (0.11)		-0.23 (0.81)	-2.03 (0.04)	0	1
SP	-0.32 (0.75)	0.23 (0.81)		-0.48 (0.63)	0	0
VSTAR	0.57 (0.57)	2.03 (0.04)	0.48 (0.63)		1	0
h=12						
Linear		1.13 (0.26)	-0.00 (1.00)	-2.28 (0.02)	0	1
NP	-1.13 (0.26)		-0.88 (0.38)	-1.31 (0.19)	0	0
SP	0.00 (1.00)	0.88 (0.38)		-0.29 (0.77)	0	0
VSTAR	2.28 (0.02)	1.31 (0.19)	0.29 (0.77)		1	0
h=24						
Linear		0.73 (0.47)	0.96 (0.34)	-4.50 (<0.01)	0	1
NP	-0.73 (0.47)		0.31 (0.75)	-2.26 (0.02)	0	1
SP	-0.96 (0.34)	-0.31 (0.75)		-2.42 (0.02)	0	1
VSTAR	4.50 (<0.01)	2.26 (0.02)	2.42 (0.02)		3	0

Table 8. Modified Diebold-Mariano test for manufacturing production growth under recession weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-3.19 (<0.01)	-3.33 (<0.01)	-2.59 (0.01)	0	3
NP	3.19 (<0.01)		-0.18 (0.86)	0.44 (0.66)	1	0
SP	3.33 (<0.01)	0.18 (0.86)		0.51 (0.61)	1	0
VSTAR	2.59 (0.01)	-0.44 (0.66)	-0.51 (0.61)		1	0
h=6						
Linear		-0.66 (0.51)	0.82 (0.41)	0.81 (0.42)	0	0
NP	0.66 (0.51)		1.17 (0.24)	1.17 (0.24)	0	0
SP	-0.82 (0.41)	-1.17 (0.24)		-0.54 (0.59)	0	0
VSTAR	-0.81 (0.42)	-1.17 (0.24)	0.54 (0.59)		0	0
h=12						
Linear		0.29 (0.77)	-1.69 (0.09)	3.20 (<0.01)	1	1
NP	-0.29 (0.77)		-1.05 (0.29)	0.04 (0.97)	0	0
SP	1.69 (0.09)	1.05 (0.29)		2.31 (0.02)	2	0
VSTAR	-3.20 (<0.01)	-0.04 (0.97)	-2.31 (0.02)		0	2
h=24						
Linear		-0.10 (0.92)	-0.27 (0.79)	4.23 (<0.01)	1	0
NP	0.10 (0.92)		-0.25 (0.81)	1.89 (0.06)	1	0
SP	0.27 (0.79)	0.25 (0.81)		0.55 (0.58)	0	0
VSTAR	-4.23 (<0.01)	-1.89 (0.06)	-0.55 (0.58)		0	2

Table 9. Modified Diebold-Mariano test for manufacturing production growth under tail weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		0.87 (0.39)	1.04 (0.30)	-1.12 (0.26)	0	0
NP	-0.87 (0.39)		0.85 (0.40)	-2.14 (0.03)	0	1
SP	-1.04 (0.30)	-0.85 (0.40)		-2.23 (0.03)	0	1
VSTAR	1.12 (0.26)	2.14 (0.03)	2.23 (0.03)		2	0
h=6						
Linear		1.11 (0.27)	-0.26 (0.80)	0.26 (0.80)	0	0
NP	-1.11 (0.27)		-0.60 (0.55)	-1.00 (0.32)	0	0
SP	0.26 (0.80)	0.60 (0.55)		0.33 (0.74)	0	0
VSTAR	-0.26 (0.80)	1.00 (0.32)	-0.33 (0.74)		0	0
h=12						
Linear		-1.50 (0.13)	-1.20 (0.23)	1.21 (0.22)	0	0
NP	1.50 (0.13)		-0.85 (0.39)	1.70 (0.09)	1	0
SP	1.20 (0.23)	0.85 (0.39)		1.32 (0.19)	0	0
VSTAR	-1.21 (0.22)	-1.70 (0.09)	-1.32 (0.19)		0	1
h=24						
Linear		0.24 (0.81)	-0.54 (0.59)	0.02 (0.98)	0	0
NP	-0.24 (0.81)		-0.59 (0.56)	-0.23 (0.81)	0	0
SP	0.54 (0.59)	0.59 (0.56)		0.53 (0.60)	0	0
VSTAR	-0.02 (0.98)	0.23 (0.81)	-0.53 (0.60)		0	0

Table 10. Modified Diebold-Mariano test for manufacturing production growth under uniform weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-2.14 (0.03)	-1.95 (0.05)	-1.60 (0.11)	0	2
NP	2.14 (0.03)		0.85 (0.40)	0.48 (0.63)	1	0
SP	1.95 (0.05)	-0.85 (0.40)		0.26 (0.80)	1	0
VSTAR	1.60 (0.11)	-0.48 (0.63)	-0.26 (0.80)		0	0
h=6						
Linear		0.78 (0.43)	0.54 (0.59)	0.03 (0.98)	0	0
NP	-0.78 (0.43)		0.26 (0.79)	-0.87 (0.39)	0	0
SP	-0.54 (0.59)	-0.26 (0.79)		-0.57 (0.57)	0	0
VSTAR	-0.03 (0.98)	0.87 (0.39)	0.57 (0.57)		0	0
h=12						
Linear		0.76 (0.45)	-0.80 (0.42)	0.84 (0.40)	0	0
NP	-0.76 (0.45)		-0.98 (0.33)	-0.71 (0.48)	0	0
SP	0.80 (0.42)	0.98 (0.33)		0.90 (0.37)	0	0
VSTAR	-0.84 (0.40)	0.71 (0.48)	-0.90 (0.37)		0	0
h=24						
Linear		0.46 (0.65)	-0.05 (0.96)	-0.70 (0.49)	0	0
NP	-0.46 (0.65)		-0.18 (0.86)	-0.60 (0.55)	0	0
SP	0.05 (0.96)	0.18 (0.86)		0.01 (0.99)	0	0
VSTAR	0.70 (0.49)	0.60 (0.55)	-0.01 (0.99)		0	0

Table 11. Modified Diebold-Mariano test for Treasury Bill under boom weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-1.90 (0.06)	-2.02 (0.04)	-1.05 (0.29)	0	2
NP	1.90 (0.06)		-2.07 (0.04)	2.20 (0.03)	2	1
SP	2.02 (0.04)	2.07 (0.04)		2.33 (0.02)	3	0
VSTAR	1.05 (0.29)	-2.20 (0.03)	-2.33 (0.02)		0	2
h=6						
Linear		1.02 (0.31)	-0.24 (0.81)	-1.92 (0.06)	0	1
NP	-1.02 (0.31)		-0.90 (0.37)	-1.19 (0.23)	0	0
SP	0.24 (0.81)	0.90 (0.37)		-0.39 (0.70)	0	0
VSTAR	1.92 (0.06)	1.19 (0.23)	0.39 (0.70)		1	0
h=12						
Linear		-1.12 (0.26)	-1.55 (0.12)	-2.46 (0.01)	0	1
NP	1.12 (0.26)		-1.06 (0.29)	-0.63 (0.53)	0	0
SP	1.55 (0.12)	1.06 (0.29)		0.73 (0.46)	0	0
VSTAR	2.46 (0.01)	0.63 (0.53)	-0.73 (0.46)		1	0
h=24						
Linear		-1.28 (0.20)	-1.40 (0.16)	-2.71 (0.01)	0	1
NP	1.28 (0.20)		-0.88 (0.38)	-0.65 (0.52)	0	0
SP	1.40 (0.16)	0.88 (0.38)		0.43 (0.66)	0	0
VSTAR	2.71 (0.01)	0.65 (0.52)	-0.43 (0.66)		1	0

Table 12. Modified Diebold-Mariano test for Treasury Bill under recession weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-3.94 (<0.01)	-4.52 (<0.01)	0.65 (0.52)	0	2
NP	3.94 (<0.01)		-1.21 (0.23)	4.21 (<0.01)	2	0
SP	4.52 (<0.01)	1.21 (0.23)		4.83 (<0.01)	2	0
VSTAR	-0.65 (0.52)	-4.21 (<0.01)	-4.83 (<0.01)		0	2
h=6						
Linear		0.28 (0.78)	-1.52 (0.13)	-2.84 (<0.01)	0	1
NP	-0.28 (0.78)		-0.94 (0.35)	-1.02 (0.31)	0	0
SP	1.52 (0.13)	0.94 (0.35)		0.14 (0.89)	0	0
VSTAR	2.84 (<0.01)	1.02 (0.31)	-0.14 (0.89)		1	0
h=12						
Linear		1.15 (0.25)	-0.62 (0.53)	-2.81 (<0.01)	0	1
NP	-1.15 (0.25)		-1.67 (0.09)	-1.70 (0.09)	0	2
SP	0.62 (0.53)	1.67 (0.09)		-0.41 (0.68)	1	0
VSTAR	2.81 (<0.01)	1.70 (0.09)	0.41 (0.68)		2	0
h=24						
Linear		1.71 (0.09)	0.71 (0.48)	-2.43 (0.01)	1	1
NP	-1.71 (0.09)		-1.42 (0.16)	-2.19 (0.03)	0	2
SP	-0.71 (0.48)	1.42 (0.16)		-1.63 (0.10)	0	0
VSTAR	2.43 (0.01)	2.19 (0.03)	1.63 (0.10)		2	0

Table 13. Modified Diebold-Mariano test for Treasury Bill under tail weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-1.55 (0.12)	-1.64 (0.10)	-1.05 (0.30)	0	0
NP	1.55 (0.12)		-1.97 (0.05)	1.75 (0.08)	1	1
SP	1.64 (0.10)	1.97 (0.05)		1.86 (0.06)	2	0
VSTAR	1.05 (0.30)	-1.75 (0.08)	-1.86 (0.06)		0	2
h=6						
Linear		1.06 (0.29)	-0.38 (0.70)	-1.54 (0.12)	0	0
NP	-1.06 (0.29)		-0.94 (0.35)	-1.19 (0.23)	0	0
SP	0.38 (0.70)	0.94 (0.35)		-0.02 (0.98)	0	0
VSTAR	1.54 (0.12)	1.19 (0.23)	0.02 (0.98)		0	0
h=12						
Linear		-0.48 (0.63)	-1.47 (0.14)	-2.36 (0.02)	0	1
NP	0.48 (0.63)		-1.20 (0.23)	-0.67 (0.50)	0	0
SP	1.47 (0.14)	1.20 (0.23)		0.44 (0.66)	0	0
VSTAR	2.36 (0.02)	0.67 (0.50)	-0.44 (0.66)		1	0
h=24						
Linear		0.32 (0.75)	-0.72 (0.47)	-1.95 (0.05)	0	1
NP	-0.32 (0.75)		-1.25 (0.21)	-1.34 (0.18)	0	0
SP	0.72 (0.47)	1.25 (0.21)		-0.18 (0.86)	0	0
VSTAR	1.95 (0.05)	1.34 (0.18)	0.18 (0.86)		1	0

Table 14. Modified Diebold-Mariano test for Treasury Bill under uniform weights

	Linear	NP	SP	VSTAR	+	-
h=1						
Linear		-2.33 (0.02)	-2.45 (0.01)	-0.95 (0.34)	0	2
NP	2.33 (0.02)		-1.88 (0.06)	2.82 (<0.01)	2	1
SP	2.45 (0.01)	1.88 (0.06)		2.91 (<0.01)	3	0
VSTAR	0.95 (0.34)	-2.82 (<0.01)	-2.91 (<0.01)		0	2
h=6						
Linear		0.95 (0.34)	-0.51 (0.61)	-2.28 (0.02)	0	1
NP	-0.95 (0.34)		-0.92 (0.36)	-1.19 (0.23)	0	0
SP	0.51 (0.61)	0.92 (0.36)		-0.33 (0.74)	0	0
VSTAR	2.28 (0.02)	1.19 (0.23)	0.33 (0.74)		1	0
h=12						
Linear		0.34 (0.73)	-1.23 (0.22)	-2.83 (<0.01)	0	1
NP	-0.34 (0.73)		-1.54 (0.12)	-1.51 (0.13)	0	0
SP	1.23 (0.22)	1.54 (0.12)		0.23 (0.81)	0	0
VSTAR	2.83 (<0.01)	1.51 (0.13)	-0.23 (0.81)		1	0
h=24						
Linear		0.80 (0.42)	-0.46 (0.64)	-3.03 (<0.01)	0	1
NP	-0.80 (0.42)		-1.42 (0.16)	-2.01 (0.04)	0	1
SP	0.46 (0.64)	1.42 (0.16)		-0.68 (0.50)	0	0
VSTAR	3.03 (<0.01)	2.01 (0.04)	0.68 (0.50)		2	0