Comparing the Forecasting Ability of Financial Conditions Indices: The Case of South Africa[#]

Mehmet Balcilar[a, b], Rangan Gupta [b], Reneé van Eyden[* b], Kirsten Thompson[b] and Anandamayee Majumdar[c]

[a] *Department of Economics, Eastern Mediterranean University, Famagusta, Northern Cyprus, via Mersin 10, Turkey*
[b] *Department of Economics, University of Pretoria, Pretoria 0002, South Africa*
[b] *Center for Advanced Statistics and Econometrics, Soochow University, Suzhou, China*

Highlights

- We forecast output, inflation and interest rates based on three alternative FCIs.
- FCIs are constructed using rolling-window PCA, DMA in the context of TVP-FAVAR and TVP-VAR.
- Forecasting results from BVAR, non-linear logistic VSTAR, NP and SP regressions are compared to benchmark models.
- VSTAR model performs best in forecasting output and inflation, while SP is superior in forecasting the interest rate.
- Results suggest superior predictive ability of the nonlinear models.

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 output and inflation, while a SP specification proves to be the best for forecasting the interest rate. More importantly, statistical testing for significant differences in forecast errors across models corroborates the finding of superior predictive ability of the nonlinear models.

[#] We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.
[*] Corresponding author. Email: renee.vaneyden@up.ac.za.

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

JEL Classification: C32, G01, E44, E32

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 (2015a) 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*., (2015a) 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, (2015b) 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.*, (2015b) 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*., (2015a), 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*., (2015a). More specifically, we follow Koop and Korobilis (2014), and employ time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) models. However,

---

[1] Thompson *et al.,* (2015a) 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*., (2015b).

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 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*., (2015a) 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*., (2015b). 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 (2016).

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*. (2016) 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. Unlike the parametric nonlinear VSTAR model, the NP and SP models do not specify the functional forms governing the relationship between the key macro variables with itself and the FCI, or just the FCI respectively. Here the relationship is purely data-driven, and hence, is a more general, though in some sense atheoretical, form of modelling nonlinear relationships. The benchmark pure time series models like the RW and AR, tries to capture the dynamics of these variables of interest based on the information content of their own-past, while the VAR models allow the effect of the other key variables and the FCIs on a specific macro variables to be occurring in a linear fashion. Now to judge the economic value of each of these models, i.e., what is the best way to represent the underlying data generating process of the key macroeconomic variables, and also their relationship with FCIs, we undertake a statistical, i.e., a forecasting approach. While, there is clearly, some in-sample evidence that the FCI does affect the South African economy, and most likely nonlinearly (Balcilar et al., 2016; Thompson *et al*., (2015a, 2015b), the real test is in terms of out-of-sample forecasting, if indeed it is to be considered as a real-time leading indicator for macroeconomic variables. Hence, this is what we aim to do, i.e., evaluate whether FCIs does play a leading indicator for the South African macroeconomy, controlling for known and unknown forms of nonlinearity in the relationship between the FCIs and macroeconomic variables. In addition, modelling nonlinearity also allows us to say, whether it does matter statistically over linear models in terms of out-of-sample forecasting. The emphasis on out-of-sample forecasting, rather than in-sample predictability to determine the economic value of variables and models, have been emphasized at depth by Campbell (2008), with him suggesting that "the ultimate test of any predictive model is its out-of-sample performance" (Cambell, 2008, pp. 2).

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. So, while we use South Africa as a case-study, we also add value to the existing international literature (primarily involving developed countries) by not only creating alternative FCIs, but using them to forecast macroeconomic variables for an emerging economy. In addition, to the best of our knowledge, besides relying on parametric linear and nonlinear models as in Alessandri and Mumtaz (2014), this is the first study to use nonparametric models in conducting our forecasting analysis. This is important (as our results show below), since we are able to capture unknown forms of data-driven relationship between macroeconomic variables and the FCIs, without imposing pre-specified parametric forms to the relationships. In addition, unlike the existing literature on using FCIs to just forecast output growth and inflation, we also analyze their role in forecasting the interest rate, and in the process, contribute to the huge literature on whether monetary policy should be designed to respond to financial conditions, and if so how, i.e., whether in a linear or nonlinear fashion (André et al., 2012; Sun and Tsang, 2014).

A relevant question to ask at this stage is why consider South Africa as our case-study of an emerging market. There are several reasons for it: First, we wanted to build on comprehensive existing studies dealing with FCIs in South Africa. Second, South Africa is one emerging market, when compared to other countries like Brazil, China, India and Russia, for which data is available for prolonged periods and that too at monthly frequencies for key macroeconomic variables of interest, and also financial variables used in the development of FCIs. And finally, the choice of South Africa can be motivated more generally from the perspective of the importance of the performance of BRICS (Brazil, Russia, India, China and South Africa) countries for the world economy in general. The BRICS countries have grown at a rapid pace and have become more integrated with the developed world in terms of trade and investment. They account for more than one-fourth of the world's land area, more than 40 percent of the world's population and about 15 percent of global GDP (Mensi et al., 2014). Understandably, the current and potential growth of the BRICS countries has important implications for the capitalization of their stock markets, along with their financial dependence with other stock markets. The four BRIC countries are expected to account for 41% of the world's stock market capitalization by 2030, with China overtaking the United States in equity market capitalization, to become the largest equity market in the world (Mensi et al., 2014). Recently, several studies (see for example Mensi et al., 2014; 2016 and references cited therein), have added South Africa into the BRIC group while conducting economic analyses. This is because of the fact that South Africa has also a fast-growing economy,[2] with rapid financial market development and sophistication. In addition, South Africa is also one of the world's largest exporters of some strategic commodities that include coal, chrome, gold, and iron,[3] which in turn, are vital resources to support domestic and global economic growth. Thus, the presence of South Africa in the BRICS group provides opportunities to establish a dedicated investment strategy in terms of economic diversification opportunities, and hence, deserves a separate analysis in terms of the role of domestic and international financial variables (i.e., the FCI) in determining the future path of the macroeconomy. As part of future research from a comparative perspective, it would be interesting to extend our analysis (accounting for data limitations though) to the BRIC nations.

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

---

[2] South Africa was growing over 5% during 2005 to 2007 until the global financial crisis hit the economy resulting in negative growth rates. But the economy has now revived and growing over 2%.

[3] Though, diamond and gold production may now be well down from their peaks, South Africa is still the sixth in gold production. It is the world's largest producer of chrome, manganese, platinum, vanadium and vermiculite. It is the second largest producer of ilmenite, palladium, rutile and zirconium. It is also the world's third largest coal exporter. South Africa is also a huge producer of iron ore, with it overtaking India in 2012 to become the world third biggest iron ore supplier to China - the world's largest consumer of iron ore. Further details can be found at: https://en.wikipedia.org/wiki/Mining_industry_of_South_Africa.

a set of sixteen monthly financial variables (see Table 2 in the Appendix) over the period 1966M02–2012M01. The three FCIs are estimated as follows.

The first FCI is estimated in Thompson, *et al*. (2015a) 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. Specifically, $X_t = \beta FCI1_t + U_t$, where β is a *pxm* coefficient matrix, U_t is a *px1* error vector, with $FCI1_t$ being the *mx1* vector of the financial conditions index obtained from the PCA. To make the β coefficient time-varying, i.e., the weights of different financial variables producing the FCI to have time-varying weights, we estimate the above equation using a 10 years, i.e., 120 months rolling window approach. $FCI1_t$ is furthermore purged of any endogenous feedback effects related to output, inflation and monetary policy. Thompson, *et al*. (2015b) 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.* (2015a) 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:

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

with

$$\lambda_t = \lambda_{t-1} + v_t$$
$$\beta_t = \beta_{t-1} + \eta_t \qquad (2)$$

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 $FCI2_t$.

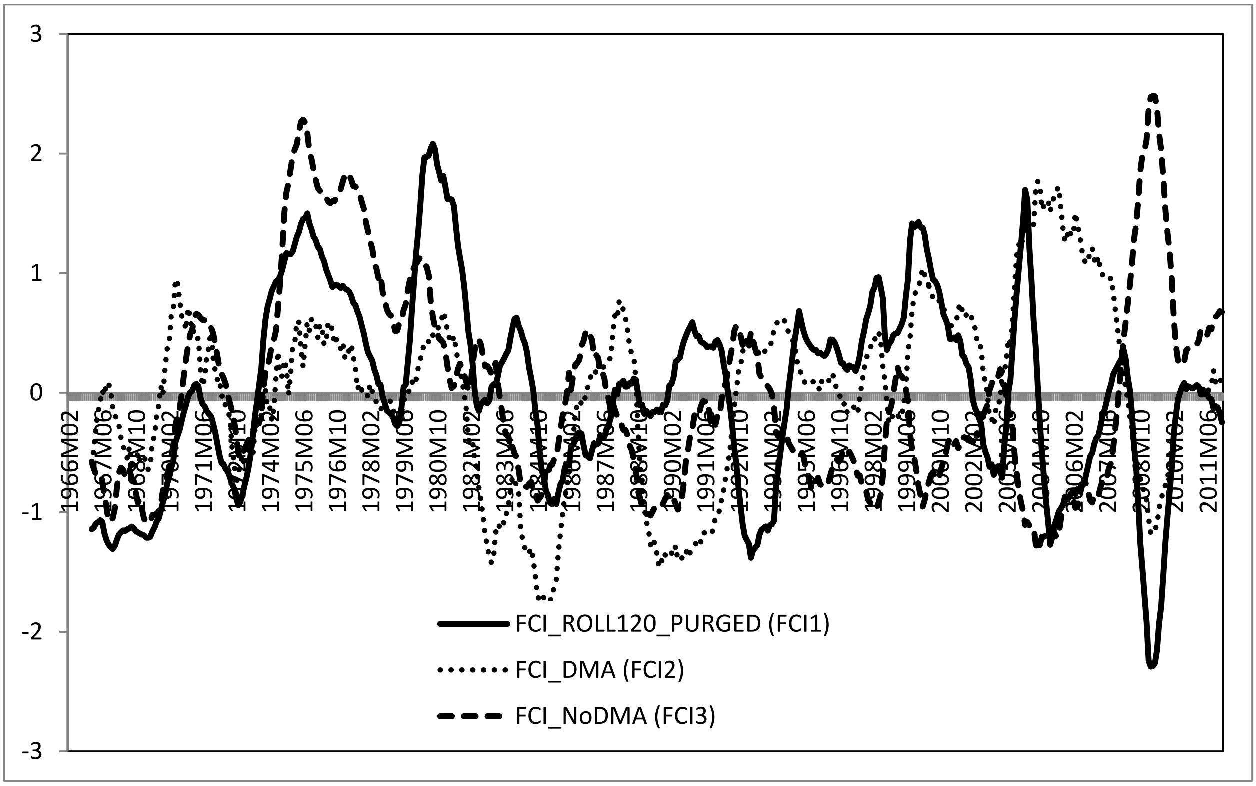
As with Koop and Korobilis (2014:12-14), the model above "allows factor loadings, regression coefficients and VAR coefficients to evolve over time according to a random walk, … and all of the error covariance matrices to be time-varying" using exponentially weighted moving average (EWMA) methods combined with Kalman filter recursions. In other words, at each point in time the model and the variables entering into the model, and their probabilities of inclusion, i.e., weights, to construct the FCI is allowed to vary.

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 12-month moving average of the three estimated FCIs exhibit similar trends – albeit at differing levels and magnitudes. The rolling-window PCA-estimated FCI ($FCI1_t$) and the no-DMA-estimated FCI ($FCI3_t$) appears to exhibit larger fluctuations than the other index at different points in time. A noticeable divergence is evident during the period of the global financial crisis (late 2000s) where $FCI3_t$ 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. The differences in the way these three FCIs behave is goverened by the underlying techniques to obtain them, while the FCI1 is based on time varying weights of the variables constructing the FCI, the FCI3 is not, i.e., it is at the other end of the spectrum. The most general form is the FCI3, which not only allows the variables to vary over time (i.e., the model), but also the weights used to construct the variables selected to derive the ultimate FCI. The importance of time-variation in the choice of the variables, but especially the weights to create the FCI is highlighted by the abilities of FCI1 and FCI3 to pick up the recent financial crisis, with FCI2 based on fixed wieghts unable to do the same. In addition, the fact that FCI1 predicts a deeper crisis relative to FCI2, is indicative of the fact that the chosen financial variables are all important with varying weights, especially in context of the recent one. This probably makes sense, given that the South African financial market has evolved over time, with it becoming more sophisticated, and hence, with all the financial variables playing important roles rather than a select few, over and above the US stock market scenario.

Figure 1. **Comparison of three estimated FCIs**



Note: FCI1: 120-Month Rolling-window PCA-estimated FCI; FCI2: DMA-estimated FCI; FCI3: No-DMA-estimated FCI. The FCIs are standardised to have zero mean and unit variance.

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.

3.1.1 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:

$$\mathrm{Y}_{t+1} = Bx_t + \varepsilon_{t+1} \tag{3}$$

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 $t = 1, \ldots, T$; 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:

$$\mathrm{Y}_{t+1} = z_t \beta + \varepsilon_{t+1} \tag{4}$$

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.

3.1.2 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.

3.1.3 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:

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

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_is 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.[4] 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 $E[f(x)]\neq f[E(x)]$.

3.1.4 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

[4] 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.

forecasting abilities. These specifications are as follows:

Model 1: Nonparametric regression model (NP model)

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

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

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

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

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

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

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

Here, $f_i(.)$ and $g_i(.)$, i=1,2 and 3, denote unknown functions that the data estimate. The ε_{it}, $i=y, r, \pi$, 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}, $i=y, r, \pi$, 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.[5]

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.

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

---

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

R-squared values.[6] 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[7]; and (b) if so, which financial variables are more relevant in the FCI construction.

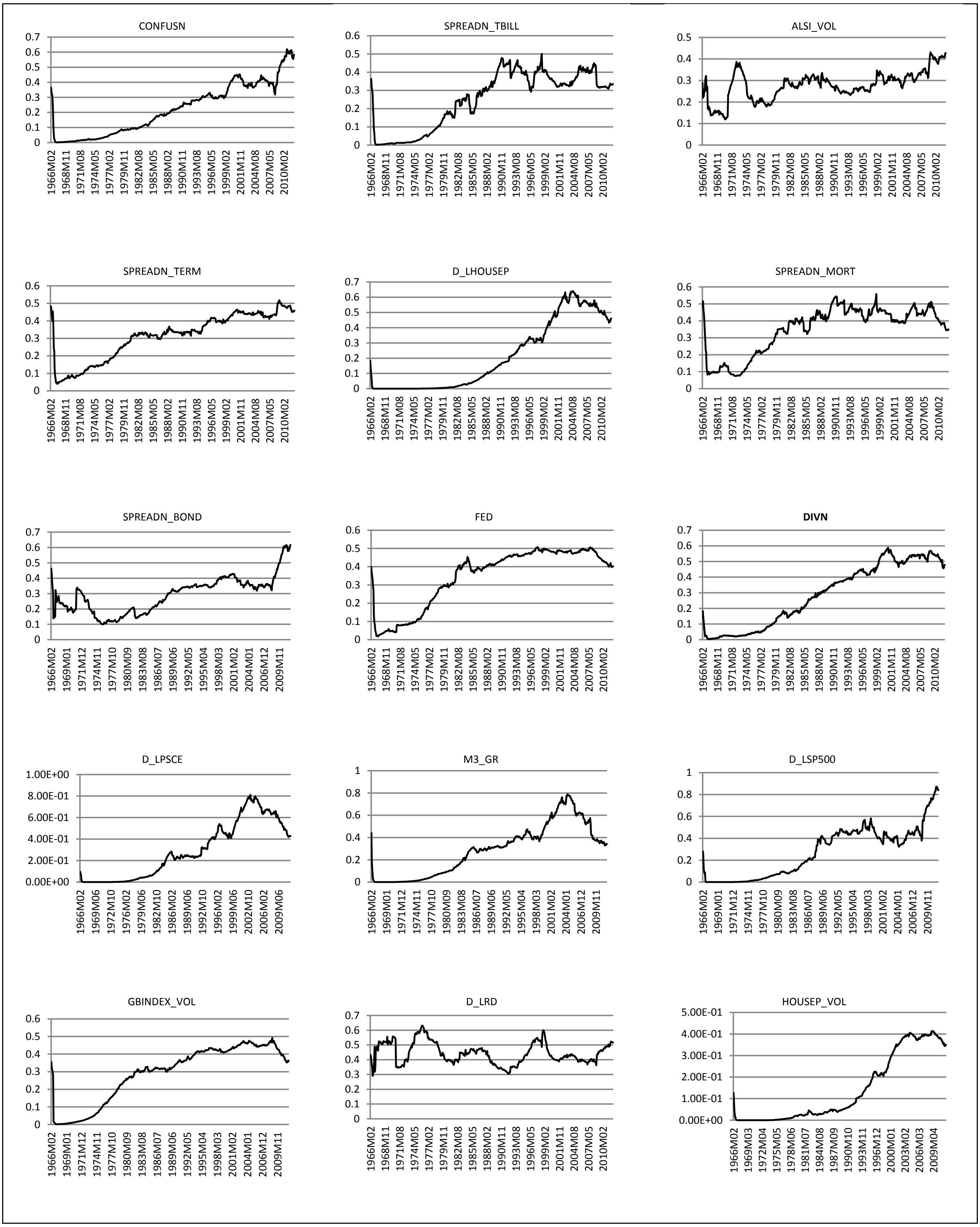
It is interesting to note that the inclusion probabilities for all of the financial variables, bar one, show, on average, an increasing trend over the sample. The exception is the Rand-Dollar exchange rate, which has a relatively stable (and significant in size) probability of between 0.3 and 0.6 throughout 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 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.

---

[6] 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.

[7] 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.

Figure 2. Posterior inclusion probabilities of financial variables under DMA



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.)

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 1986:01 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.

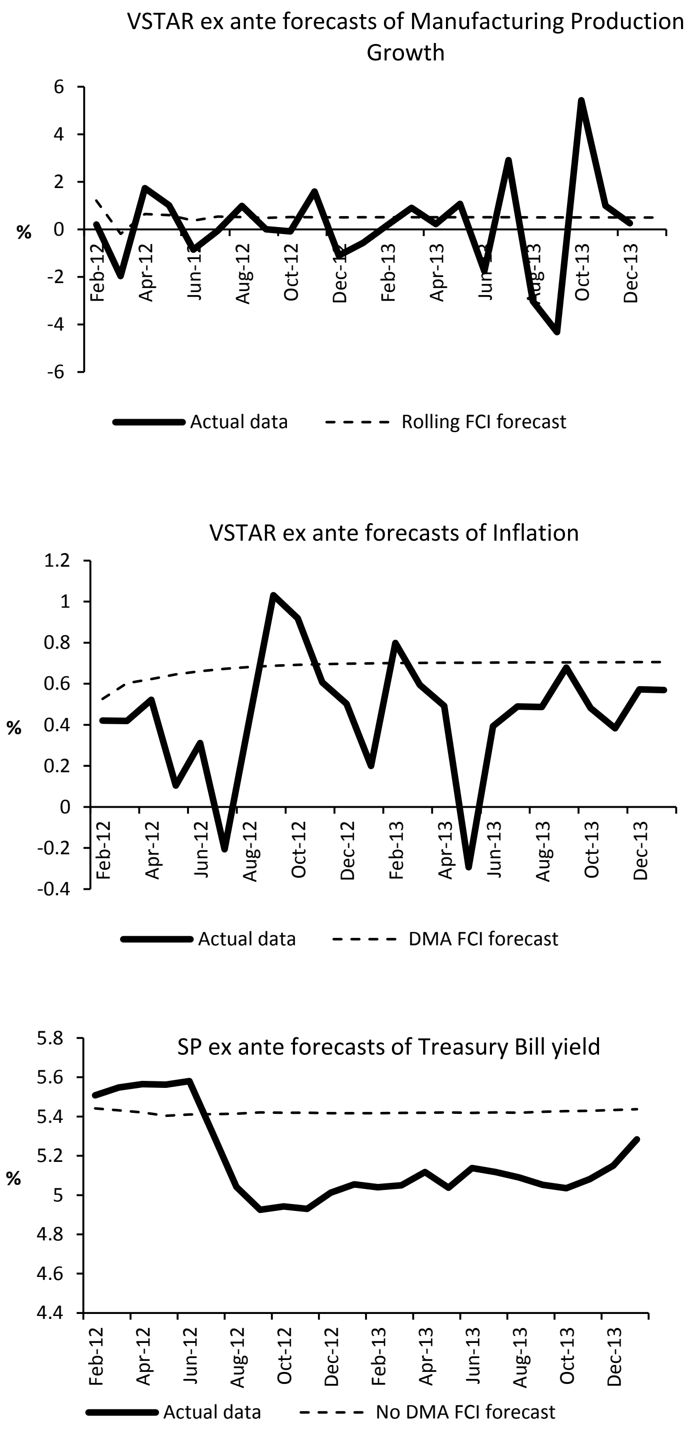
Table 1. Out-of-sample forecasting for x_t: FCI (Sample: 1986:01 – 2012:01) – RMSE statistics under differing models relative to RW model

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).

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.

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



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.

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:

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

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 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.

However, the DM-test statistic is no longer appropriate when we compare nested models, as happened to be the case in one instance (for inflation between AR and models with FCIs) for us. Given this, we use McCracken's (2007) powerful MSE-F test statistic. The MSE-F statistic tests the null hypothesis that restricted (AR) and unrestricted (models that includes the FCIs) models have equal forecasting ability. The null is tested against the one-sided alternative hypothesis that the MSE for the unrestricted model forecasts is less than the MSE for the restricted model forecasts. Formally, the statistic is given as:

$MSE\text{-}F=(T\text{-}R\text{-}h+1).\bar{d}/M\hat{S}E_1$

where T is the total sample, R is number of observations used for estimation of the model from which the first forecast is formed (i.e. the in-sample portion of the total number of observations), $M\hat{S}E_i = (T-R-h+1)^{-1}\sum_{t=R}^{T-h}(u_{i,t+1})^2$, i=1, 0, $\bar{d} = M\hat{S}E_0 - M\hat{S}E_1$, with u_i being the forecast error. A positive and significant MSE-F statistic indicates that the unrestricted model forecasts are statistically superior to those of the restricted model.

Figures 4 to 6 in the Appendix contain a graphical representation of the inflation, manufacturing production and Treasury Bill rate series used in the analysis. For each series the density of the series as well as weights used for the forecast comparison (Diebold-Mariano) test are displayed. These weights include those for the high and low inflation periods, as well as tail weights.

Tables 3 through 14 in the appendix present the results of the MMSE-F and 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 for inflation from the MMSE-F and MDM tests which compares the forecasting performance of the linear (AR) model with the NP, SP and VSTAR models, with the latter set of models nesting the former; and between the non-nested NP, SP and VSTAR models respectively, 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 one-month and six-month horizons,. 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 and 6), 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 forecast accuracy 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. So from an economic perspective, our results imply that nonlinearity matters in modelling the relationship between FCI and macroeconomic variables in South Africa. In addition, while a regime-switching known parametric model can capture the relationship between the FCIs and output growth and interest rate; the appropriate model capturing the relationship between the responses of interest rate to FCIs needs to be data-driven. So while, interest rate movements seem to be responding linearly to macroeconomic variables, the FCIs tend to affect the interest rate in a form that cannot be parametrically specified. So from the perspective of monetary policy decisions, there are economic gains to be had by incorporating the role of financial conditions in setting interest rate, but in a nonlinear way, with the underlying relationship being determined by the data generating processes of the FCIs and the interest rate, which in turn, needs to be evaluated and updated regularly as new data on the variables of interest becomes available to the policymaker.

References

Alessandri, P. and Mumtaz, H., 2014. Financial conditions and density forecasts for US Output and inflation, *Working Papers 715, Queen Mary, University of London, School of Economics and Finance*.

André C, Gupta R., and Kanda P.T, 2012. Do house prices impact consumption and interest rate?: Evidence from OECD countries using an agnostic identification procedure. *Applied Economics Quarterly* 58: 19–70.

Arora, S., Little, M. A., and McSharry, P. E., 2011. Nonlinear and nonparametric modeling approaches for probabilistic forecasting of the US Gross National Product. Available at: http://www.maxlittle.net/publications/SNDE_GNP.pdf

Banbura, M., Giannone, D., and Reichlin, L., 2010. Large Bayesian VARs. *Journal of Applied Econometrics* 25, 71-92.

Balcilar, M., Thompson, K., Gupta, R. & Van Eyden, R., 2016. Testing the Asymmetric Effects of Financial Conditions in South Africa: A Nonlinear Vector Autoregression Approach. *Journal of international Financial Markets, Institutions & Money,* Vol 43, July, 30-43.

Campbell, J.Y., 2008, Viewpoint: Estimating the Equity Premium, *Canadian Journal of Economics*, 41, 1–21.

Diebold, F.X. & Mariano, R.S., 1995. Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, 13(3), pp. 253-263.

Doan, T., Litterman, R. & Sims, A.C., 1984. Forecasting and Conditional Projection Using Realistic Prior Distributions. *Economic Reviews*, 3, pp. 1-100.

Estrella, A., and Hardouvelis, G. (1991), The term structure as a predictor of real economic activity, *Journal of Finance* 46, pp. 555-576.

Freedman, C. (1994). The use of indicators and of the monetary conditions index in Canada. In Balino, T.J.T. and Cottarelli, C. (eds), Frameworks for Monetary Stability: Policy Issues and Country Experiences, IMF, Washington, D.C.

Harvey, D.I., Leybourne, S. & Newbold, P., 1997. Testing the Equality of Prediction Mean Squared Errors. *International Journal of Forecasting*, 13, pp. 281-291.

Hatzius, J., Hooper, P., Mishkin, F.S., Schoenholtz, K.L, and Watson, M., 2010, Financial Conditions Indexes: A fresh look after the financial crisis. *Working Paper 16150, National Bureau of Economic Research.*

Jurado, K., Ludvigson, S.C. and S. Ng (2015): Measuring uncertainty, *American Economic Review* 105: 1177–1216.

Koop, G. & Korobilis, D., 2014. A New Index of Financial Conditions. *European Economic Review,* 71(C), pp. 101-116.

Lundbergh, S., and Terasvirta, T., 2002. Forecasting with smooth transition autoregressive models. In: Clements, M. P., and Hendry, D. F., (eds.). *A Companion to Economic Forecasting.* Oxford: Blackwell, 485–509.

Luukkonen, R., Saikkonen, P., and Teräsvirta, T., 1988. Testing linearity against smooth transition autoregressive models. *Biometrika* 75, 491–499.

Litterman, R.B., 1981. A Bayesian Procedure for Forecasting With Vector Autoregressions. *Federal Reserve Bank of Minneapolis Working Paper Series*, 274.

Litterman, R.B., 1986. Forecasting with Bayesian Vector Autoregression: Five Years of Experience. *Journal of Business and Economic Statistics*, 4, pp. 25-38.

McCracken, M.W. (2007): Asymptotics for out-of-sample tests of Granger causality, *Journal of Econometrics* 140, 719–752.

Mensi, W., Hammoudeh, S., Reboredo, J.C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, 19(C), 1-17.

Mensi, W., Hammoudeh, S., Yoon, S-M., & Nguyen, D. K. (2016). Asymmetric Linkages between BRICS Stock Returns and Country Risk Ratings: Evidence from Dynamic Panel Threshold Models. *Review of International Economics*, 24(1), 1–19.

Opsomer, J. D., Moisen, G. G., and Kim, J. Y., 2001. Model-assisted estimation of forest resources with generalized additive models. In: *Proceedings of the Section on Survey Research Methods*, American Statistical Association. Alexandria, VA.

Spencer, D.E., 1993. Developing a Bayesian Vector Autoregression Model. *International Journal of Forecasting*, 9, pp. 407-421.

Stock, J. and Watson, M (1989), New Indexes of Coincident and Leading Economic Indicators, in Blanchard O. and S. Fischer (eds.), *NBER Macroeconomics Annual* (Cambridge, MA: MIT), 352-94.

Sun X, and Tsang K.P., 2014. Optimal interest rate rule in a DSGE model with housing market spillovers. *Economics Letters* 125: 47–51.

Teräsvirta, T., 1998. Modelling economic relationships with smooth transition regressions. In: Ullah, A., and Giles, D. E. A., (eds.). *Handbook of Applied Economic Statistics*. New York: Marcel Dekker, 507-552.

Thompson, K., Van Eyden, R. & Gupta, R., 2015a. Identifying a Financial Conditions Index for South Africa. *Studies in Economics and Finance,* Vol 32(2), pp.256-274.

Thompson, K., Van Eyden, R. & Gupta, R., 2015b. Testing the Out-of-Sample Forecasting Ability of a Financial Conditions Index for South Africa. *Emerging Markets, Finance and Trade,* Vol 51(3), pp. 502-524.

Todd, R.M., 1984. Improving Economic Forecasting with Bayesian Vector Autoregression. *Federal Reserve Bank of Minneapolis Quarterly Review*, Fall, pp. 18-29.

Van Dijk, D. & Franses, P.H., 2003. Selecting a Nonlinear Time-series Model Using Weighted Tests of Equal Forecast Accuracy. *Oxford Bulletin of Economics and Statistics*, 65, pp. 727-744.

Appendix

Figure 4. Inflation graphs related to weights used for the forecast comparison tests (MSE-F and Diebold-Mariano)

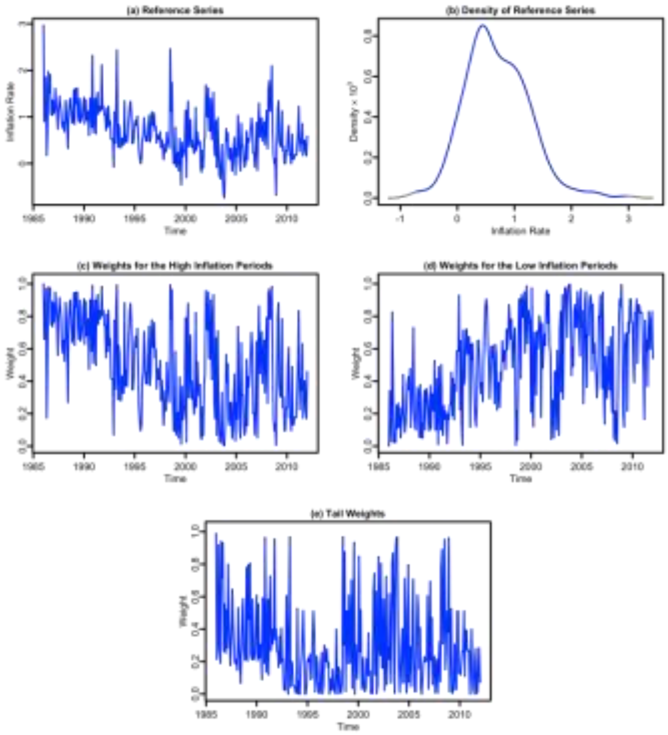


Figure 5. Manufacturing production graphs related to weights used for the forecast comparison test (Diebold-Mariano)

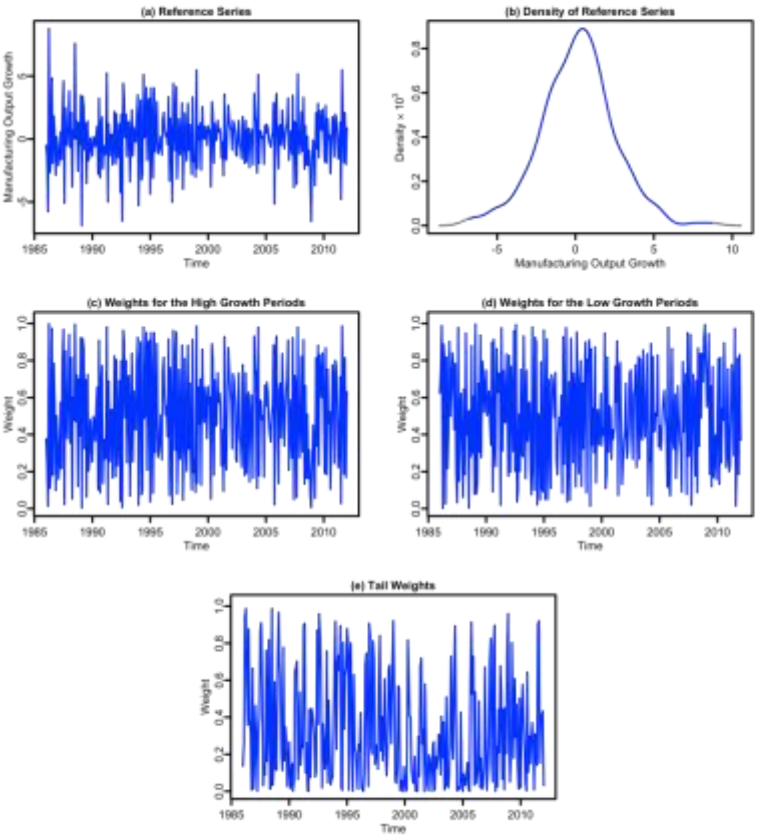


Figure 6. Treasury Bill graphs related to weights used for the forecast comaprison test (Diebold-Mariano)

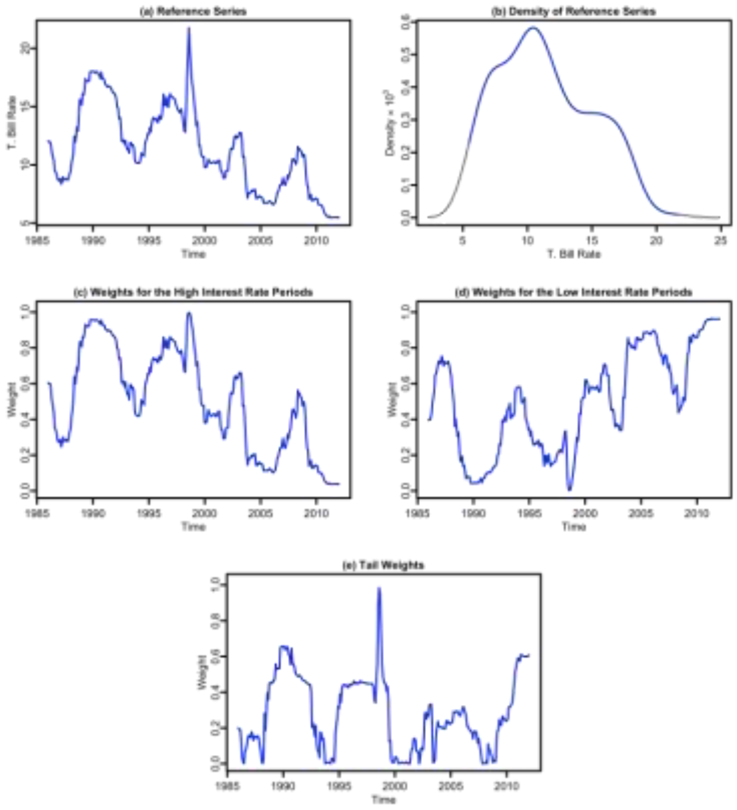


Table 2. Variables used to construct and test the FCI

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.

Table 3. Modified Diebold-Mariano and MSE-F tests 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	***31.310***		-2.12 (0.03)	-0.46 (0.65)	0	1
SP	***43.062***	2.12 (0.03)		0.61 (0.54)	2	0
VSTAR	***35.963***	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	-15.560		-1.35 (0.18)	-0.88 (0.38)	0	0
SP	-7.090	1.35 (0.18)		-0.44 (0.66)	0	0
VSTAR	**1.626**	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	-87.869		-0.93 (0.35)	-1.20 (0.23)	0	0
SP	-22.304	0.93 (0.35)		-1.18 (0.24)	0	0
VSTAR	-0.127	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	-53.626		-1.19 (0.23)	-1.80 (0.07)	0	2
SP	-28.093	1.19 (0.23)		-1.07 (0.29)	0	0
VSTAR	-6.807	1.80 (0.07)	1.07 (0.29)		1	0

Note: Comparison between NP, SP, and VSTAR model with nested linear AR model (best linear model) is based on the modified MSE-F test. Critical values for the Modified MSE-F test statistic are calculated from Table 4 of McCracken (2007) with linear interpolation. Bold indicates significance at the 5% level, while bold-italic indicates significance at the 1% level. The remainder of cases use the Modified Diebold-Mariano test with values in parentheses corresponding to the p-values of the Modified Diebold-Mariano test.

Table 4. Modified Diebold-Mariano and MSE-F tests 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	***103.007***		-0.36 (0.72)	1.20 (0.23)	1	0
SP	***104.967***	0.36 (0.72)		1.24 (0.22)	1	0
VSTAR	***71.624***	-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	***15.213***		-1.55 (0.12)	-0.59 (0.56)	0	0
SP	***41.675***	1.55 (0.12)		0.32 (0.75)	1	0
VSTAR	***30.467***	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	-83.332		-1.03 (0.30)	-1.31 (0.19)	0	0
SP	***7.996***	1.03 (0.30)		-0.32 (0.75)	0	0
VSTAR	***18.951***	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	-26.862		-2.05 (0.04)	-3.52 (<0.01)	0	3
SP	-2.462	2.05 (0.04)		-1.70 (0.09)	1	1
VSTAR	***31.665***	3.52 (<0.01)	1.70 (0.09)		3	0

Note: See Notes to Table 3.

Table 5. Modified Diebold-Mariano and MSE-F tests 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	***91.397***		-1.96 (0.05)	0.49 (0.62)	1	1
SP	***104.371***	1.96 (0.05)		1.01 (0.31)	2	0
VSTAR	***81.046***	-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	***25.482***		-1.54 (0.12)	0.87 (0.39)	0	0
SP	***42.389***	1.54 (0.12)		1.32 (0.19)	1	0
VSTAR	***9.587***	-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	-7.949		-0.93 (0.35)	-0.80 (0.43)	0	0
SP	***10.105***	0.93 (0.35)		0.36 (0.72)	0	0
VSTAR	**1.356**	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	-24.676		-2.07 (0.04)	-2.21 (0.03)	0	3
SP	-2.444	2.07 (0.04)		-0.72 (0.47)	1	0
VSTAR	***8.988***	2.21 (0.03)	0.72 (0.47)		1	0

Note: See Notes to Table 3.

Table 6. Modified Diebold-Mariano and MSE-F tests 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	***64.712***		-1.66 (0.10)	0.85 (0.40)	1	1
SP	***72.379***	1.66 (0.10)		1.32 (0.19)	2	0
VSTAR	***53.444***	-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	**2.818**		-1.60 (0.11)	-0.84 (0.40)	0	0
SP	***21.403***	1.60 (0.11)		0.10 (0.92)	0	0
VSTAR	***18.936***	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	-85.011		-1.00 (0.32)	-1.27 (0.20)	0	0
SP	-3.843	1.00 (0.32)		-0.61 (0.54)	0	0
VSTAR	***11.702***	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	-36.907		-1.91 (0.06)	-3.43 (<0.01)	0	3
SP	-11.984	1.91 (0.06)		-1.80 (0.07)	1	1
VSTAR	***17.048***	3.43 (<0.01)	1.80 (0.07)		3	0

Note: See Notes to Table 3.

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

Note: See Notes to Table 3; Best linear model is BVAR with FCI3 (i.e., FCI with no DMA).

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

Note: See Notes to Tables 3 and 4.

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

Note: See Notes to Tables 3 and 4.

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

Note: See Notes to Table 3 and 4.

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

Note: See Notes to Table 3. Best linear model is BVAR with FCI3 (i.e., FCI with no DMA).

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

Note: See Notes to Tables 3 and 11.

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

Note: See Notes to Tables 3 and 11.

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

Note: See Notes to Tables 3 and 11.