Comparing the forecasting ability of financial conditions indices: The case of South Africa

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\textbf{A R T I C L E   I N F O}

\textbf{Article history:}
Available online xxx

\textbf{JEL classification:}
C32
G01
E44
E32

\textbf{Keywords:}
Financial conditions index
Dynamic model averaging
Nonlinear logistic smooth transition vector autoregressive model

\textbf{A B S T R A C T}

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.

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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 (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 1966–2011, 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.\textsuperscript{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 macroeconomic variables controlling for data-mining. Thompson et al. (2015b) find that the rolling-window

\textsuperscript{1} We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

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\textsuperscript{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).

https://doi.org/10.1016/j.jref.2018.03.012
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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, 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 Muntz (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, Thompson et al., 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” (Campbell, 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 Muntz (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, Gupta, & Kanda, 2012; Sun & 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
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