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ScienceDirect
International Journal of Forecasting 23 (2007) 679–693
www.elsevier.com/locate/ijforecast

Evaluating factor forecasts for the UK: The role of asset prices

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Abstract

This paper applies a large data set, consisting of 167 monthly time series for the UK, both economic and financial, to simulate out-of-sample predictions of industrial production, inflation, 3-month Treasury Bills, and other variables. Fifteen dynamic factor models that allow forecasting based on large panels of time series are considered. The performances of these factor models are then compared to the following competing models: a simple univariate autoregressive, a vector autoregressive, a leading indicator, and a Phillips curve models. The results show that the best dynamic factor models outperform the competing models in forecasting at 6-, 12-, and 24-month horizons. Thus, the financial markets may have predictive power for the economic activity. This can be a useful tool for central banks and financial institutions, which may use the factor models to construct leading indicators of the economic conditions. In addition, researchers can see a strategic application of factor models.

Keywords: Time series; Econometric models; Factor models; Inflation forecasting; Interest rate forecasting; Finance

1. Introduction

The role of financial markets has increased in recent decades. For that reason, stock and interest rate returns might be informative for predicting the evolution of inflation and economic growth. Indeed, previous empirical works have found links between the term structure of interest rates, monetary policy, economic growth and inflation (see e.g. Estrella & Hardouvelis, 1991; Mishkin, 1990b; Stock & Watson, 2003). This body of literature adopts both univariate and multivariate approaches, such as (vector) autoregressive and leading indicator approaches. However, the empirical evidence is mixed and the results are not robust with respect to model specification, sample choice, or forecast horizons. This is clearly a puzzle for empirical research that is worth investigating.

This paper explores a large panel of monthly time series for the UK, containing financial variables, industrial production, prices, money aggregates and a variety of potentially leading indicators. The key idea of the paper is to evaluate whether, by pooling information from a broad group of financial variables, we can obtain good predictions for industrial production, inflation and other variables. In other words, instead of evaluating the predictive content of a single

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doi:10.1016/j.ijforecast.2007.03.002

financial variable, I evaluate the predictive content of suitably selected averages of many such variables. The forecasting performances of the full sample, subsamples, and different time horizons are evaluated through an out-of-sample simulation exercise.

The model of reference is the dynamic factor model, which is conceived as an alternative approach to the autoregressive and leading indicator models for evaluating the role of asset prices in economic activity. It is based on the model developed by Stock and Watson (2002a,b), which is specifically designed to handle large panels of dynamically related time series. Stock and Watson conduct forecasting exercises on industrial production and price inflation, as well as other variables for the US. Marcellino, Stock, and Watson (2003) apply the model to the Euro-area. Banerjee, Marcellino, and Masten (2004) made forecasts about the accession of eight Central and Eastern European countries into the European Union. Earlier applications of factor models include Engle and Watson (1981), Stock and Watson (1991), Geweke (1977), and Sargent and Sims (1977). However, to complement the large number of macroeconomic variables used by Stock and Watson, I include a wide range of financial variables.

As a further extension of the estimation of the factor model, I use an intercept correction and second-differencing approach. These methods aim to adjust for potentially unknown structural breaks in the data. The purpose of intercept correction is to add the most recent residual to the forecasts at all of the horizons, while the second-differencing approach treats the forecasted variables as if they are integrated of order two. These two methods, according to Clements and Hendry (1996, 1998a,b, 1999) and Artis, Banerjee, and Marcellino (2005), provide robust forecasts in the presence of structural breaks. For the UK, I suspect that financial crises and economic regime shifts during recent decades have caused structural breaks in the data. In addition, the Diebold and Mariano (1995) test is used to test for equal forecast accuracy between two competing models.

The results show that the best forecast of the factor models at a 12-months horizon outperforms most of the competing approaches, especially for the price variables. However, the median performances of the factor models have a limited success. Nevertheless, for some areas such as industrial production, unemployment and interest rates, the intercept-corrected forecasts of the factor models outperform the competing approaches. The forecasts vary considerably for different subsamples, as well as forecast horizons such as 6-months and 24-months. The factors that are estimated using financial data seem to have predictive power for some of the economic activity. For example, the dynamic factor models, which rely solely on large-scale financial variables, outperform other dynamic factor models that include both financial and macroeconomic variables. The best predictions are for industrial production, consumer and producer prices. In other words, the dynamic factor model can forecast better than other models, despite some weaknesses that might be explained by redundant information included in the estimation of the factors.

The paper proceeds as follows: Section 2 provides an overview of the dynamic factor models and the forecasting methods. Section 3 discusses the intercept correction method. Sections 4 and 5 describe the data set and the estimation of the factors. Sections 6 and 7 contain the empirical results of different samples and forecast horizons. Section 8 concludes this paper.

2. Forecast framework

This part includes some alternative models that are used to perform the forecast. For each series, several forecasting models are compared at the 3-, 6-, 12-, and 24-month forecasting horizons. All of the forecasting models are specified and estimated as linear projections of an h-step ahead transformed variable, y_{t+h}, onto t-dated predictors. The h-step ahead projection, also called dynamic estimation, differs from the standard approach to estimating a 1-step ahead model. Indeed, it iterates the model forward to obtain h-step ahead forecasts. This forecasting method has two advantages. First, additional equations for simultaneously forecasting y_t, e.g. using a vector autoregressive model, are not needed. Second, the potential impact of specification errors in the 1-step ahead model can be reduced by using the same horizon for estimation as for forecasting.

The out-of-sample forecasting exercise for the full sample (1986:1–2003:4) is performed as follows:

(i) The models are first estimated using data from 1986:1 to 1994:12, which corresponds to 108 months.