International Journal of Forecasting 30 (2014) 65–77

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting macroeconomic variables using disaggregate survey data

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ARTICLE INFO

Keywords:
Factor models
Macroeconomic forecasting
Qualitative survey data

ABSTRACT

We construct factor models based on disaggregate survey data for forecasting national aggregate macroeconomic variables. Our methodology applies regional and sectoral factor models to Norges Bank's regional survey and to the Swedish Business Tendency Survey. The analysis identifies which of the pieces of information extracted from the individual regions in Norges Bank's survey and the sectors for the two surveys perform particularly well at forecasting different variables at various horizons. The results show that several factor models beat an autoregressive benchmark in forecasting inflation and the unemployment rate. However, the factor models are most successful at forecasting GDP growth. Forecast combinations using the past performances of regional and sectoral factor models yield the most accurate forecasts in the majority of the cases.

1. Introduction

Many central banks conduct surveys which yield regional and sectoral information on the general economic outlook. Following the example of the Federal Reserve's Beige Book, which was implemented in 1970, and the Bank of England's Agents survey, which begun in 1997, other central banks such as the Bank of Canada, Norges Bank, Sveriges Riksbank, and the Swiss National Bank have also initiated their own surveys. The information provided by these surveys is typically anecdotal and qualitative, unlike the well-known, quantitative Livingston survey, the Michigan survey, or the Survey of Professional Forecasters (see Thomas, 1999 for supplementary information about these surveys). While it is well-documented that the information obtained from quantitative surveys has strong forecasting power for macroeconomic variables (see for example Ang, Bekaert, & Wei, 2007; Fama & Gibbons, 1984; Mehra, 2002; and Thomas, 1999), there is less evidence of the forecasting power of information obtained from qualitative surveys.

This paper investigates the abilities of the Norges Bank's regional survey and the Swedish Business Tendency Survey to forecast the gross domestic product (GDP) growth, consumer price inflation, and the unemployment rate for Norway and Sweden. Each survey consists of both backward- and forward-looking qualitative information. Studies such as those of Abberger (2007), Claveria, Pons, and Ramos (2007) and Lui, Mitchell, and Weale (2011a,b) focus on examining specific survey questions in order to predict individual macroeconomic variables. Our approach is different, applying a dynamic factor model to the full database in order to construct regional and sectoral factors. These factors should contain the most relevant information for the regions and sectors from which they are extracted.

Our approach is similar to that of Hansson, Jansson, and Löf (2005), who use a dynamic factor model (based on net balance indices, representing differences between the shares of firms that have specified increases and decreases

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0169-2070/$ – see front matter
http://dx.doi.org/10.1016/j.ijforecast.2013.02.003

for a particular economic activity) from the Swedish Business Tendency Survey to forecast the Swedish GDP. Hansson et al. (2005) find that their factor model outperforms popular alternatives such as econometric VAR models in most cases. We extend their analysis in at least four directions. First, we consider the Norges Bank's regional survey, which is more comprehensive in terms of sectors and regions of the economy. Our choice follows the claims made by Beck, Hubrich, and Marcellino (2009) that highly disaggregated regional and sectoral information is important in explaining aggregate Euro area and US inflation rates. Second, we work at a higher level of disaggregation and construct regional and sectoral factor models from the surveys. Out of ten sectors and seven regions for the Norwegian economy, and three sectors for the Swedish economy, our results identify which ones perform particularly well at forecasting different variables at various horizons. Third, we mitigate the uncertainties in the construction of the factors, the numbers of factors, and the relationships with the variable of interest by investigating two different classes of factor models where the number of factors is fixed *a priori* (denoted as model A) or estimated via a selection criterion (model B). Finally, we use forecast combinations to address the model uncertainty created by the use of several factors constructed by different datasets (regions or sectors). Each factor model is used to extract information and produce forecasts from a given dataset (regions or sectors) for the particular variable of interest.

We find that factor models based on several regions and sectors systematically beat the nowcasts and one-quarter-ahead forecasts of Norwegian inflation and unemployment rate given by the benchmark model. However, the factor models are most successful in nowcasting and forecasting GDP growth. Forecast combinations of the regional and sectoral models based on past performances are more accurate than the best regional or sectoral model in several cases, and provide more accurate forecasts than the benchmark model in almost all cases. Furthermore, we empirically find that aggregating the survey data either by pooling all of the Norwegian regional and sectoral survey information in a single factor model or by aggregating individual question-based forecasts via model combinations, to account for the heterogeneity in individual survey questions, results in less accurate forecasts than our regional and sector factor models. This finding is qualitatively similar when we use the Swedish Business Tendency Survey.

The paper proceeds as follows: Section 2 outlines the methodological aspects of our dynamic factor model, and Section 3 explains the forecasting models. Section 4 describes Norges Bank's regional survey data, presents the factors and discusses the forecasting results. Section 5 reports results using the Sweden Business Tendency survey. Finally, Section 6 concludes.

2. A dynamic factor model

The increasing availability of information on economic activities and their disaggregate components makes factor models a very attractive approach for handling macroeconomic data. Applying a factor model to a large dataset of possibly correlated variables reduces the dimension of the dataset while retaining as much of the variation in the data as possible. This reduced form can be useful for forecasting, since models which are more parsimonious reduce the estimation errors and may yield more accurate forecasts.

We apply the approximate dynamic factor model of Doz, Giannone, and Reichlin (2011), which is a two-step estimator based on the Kalman filter. Let X_t^j be an N-dimensional multiple time series of variables (survey questions) from a region or a sector j, observed for $t = 1, \ldots, T$. X_{it}^j is the observation for variable i at time t, where $i = 1, \ldots, N$. X_t^j could then be described as an approximate dynamic factor model:

$$X_t^j = \chi_t^j + e_t^j = \Lambda F_t^j + e_t^j, \tag{1}$$

$$F_t^j = AF_{t-1}^j + Bu_t^j, \tag{2}$$

where $e_t^j = (e_{1t}^j, \ldots, e_{Nt}^j)'$ is the $N \times 1$ idiosyncratic disturbance term, which has a zero expectation and a covariance matrix Σ_{ee}^j (see Forni, Giannone, Lippi, & Reichlin, 2009, for details). $F_t^j = (f_{1t}^j, \ldots, f_{\rho t}^j)'$ is $\rho \times 1$, where ρ is the number of estimated common factors. Λ is the $N \times \rho$ factor loading matrix, which consists of eigenvectors corresponding to the ρ largest eigenvalues of the sample variance–covariance matrix of X_t^j, Σ_{XX}^j. B is a $\rho \times q$ matrix of full rank q, and q is the number of common shocks in the economy. A is a $\rho \times \rho$ matrix, and all roots of $\det(I_\rho - Az)$ lie outside the unit circle; while u_t^j is the shock to the common factors and is a white-noise process. When ρ is large relative to q, this model aims to capture the lead and lag relationships along the business cycle.

Eqs. (1) and (2) are estimated by a two-step procedure. First, the parameters are estimated by ordinary least squares on principal components extracted from the full dataset. Second, the parameters are replaced with their consistent estimates obtained from the first step, and the factors are estimated recursively using Kalman filtering techniques.

3. Forecasting

This paper's ultimate goal is to forecast inflation, GDP growth, and the unemployment rate for Norway and Sweden using the factors derived from the surveys. We produce nowcasts of the current quarter, as well as one-, two-, three-, and four-quarter-ahead forecasts for a total of five horizons. Survey data become available at the end of the second month of the current quarter, and we use this information in nowcasting and forecasting.

We compare two different factor models with an autoregressive benchmark model. The lag length of the dependent variable, y_t, is chosen by the Bayesian information criterion (BIC), and is restricted to be between one and four:

$$y_t = \gamma_0 + \gamma_1(L)y_{t-1-h} + \varepsilon_t, \tag{3}$$

where L is the lag operator, $t = 1 + h, \ldots, \tau - 1$, $h = 0, \ldots, 4$, and $\tau = \underline{t}, \ldots, \overline{t}$, with $\underline{t}$ and $\overline{t}$ being the first and last quarter to be forecast, respectively. Thus, the largest model includes a constant and four lags of the dependent variable, while the smallest model only includes a constant