Forecasting Macroeconomic Variables using Disaggregate Survey Data*

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Abstract

We construct factor models based on disaggregate survey data to forecast 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 information extracted from the individual regions in Norges Bank's survey and the sectors for both 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 in forecasting GDP growth. Forecast combinations using the past performance of regional and sectoral factor models in the majority of the cases yield the most accurate forecasts.

Keywords: Factor models; macroeconomic forecasting; qualitative survey data.

JEL Categories: C53; C80.

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Many central banks conduct surveys yielding 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 like the Bank of Canada, Norges Bank, Sveriges Riksbank, and the Swiss National Bank have initiated their own surveys. The information provided by these surveys is typically anecdotal and qualitative, unlike than 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 information obtained from quantitative surveys has high forecasting power for macroeconomic variables (see for example Thomas (1999), Mehra (2002), Fama and Gibbons (1984), and Ang, Bekaert, and Wei (2007)), there is less evidence of the forecasting power of information obtained from qualitative surveys.

This paper investigates the ability of the Norges Bank's regional survey and the Swedish Business Tendency Survey to forecast 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 Abberger (2007), Claveria, Pons, and Ramos (2007) and Lui, Mitchell, and Weale (2010a,b) focus on examining specific survey questions for predicting individual macroeconomic variables. Our approach differs and applies 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 regions and sectors from where they are extracted.

Our approach is similar to Hansson, Jansson, and Löf (2005) who apply a dynamic factor model (based on net balance indices, representing differences between the share of firms that have specified an increase and a decrease for a particular economic activity) from the Swedish Business Tendency Survey to forecast the Swedish GDP. Hansson et al. (2005) find that in most cases their factor model outperforms popular alternatives such as econometric VAR models. 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 in Beck, Hubrich, and Marcellino (2009) that highly disaggregate 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 factors, the number of the factors, and the relation to 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 apply 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. In several cases forecast combinations of the regional and sectoral models based on past performance are more accurate than the best regional or sectoral model and in almost all the cases provide more accurate forecasts than the benchmark model. Furthermore, we empirically find that aggregating the survey data either by pooling all the Norwegian regional and sectoral survey information in a single factor model or aggregating individual question-based forecasts via model combinations to account for the heterogeneity of individual survey questions results in less accurate forecasts compared to 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 1 outlines methodological aspects of our dynamic factor model and Section 2 explains the forecasting models. Section 3 describes Norges Bank's regional survey data, presents the factors and discusses the forecasting results. Section 4 reports results using the Sweden Business Tendency survey. Finally, Section 5 concludes.

1 A Dynamic Factor Model

The increasing availability of information on economic activities and their disaggregate components make 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 more parsimonious models 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:

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

$$F_t^j = A F_{t-1}^j + B u_t^j, \tag{2}$$

where $e_t^j = (e_{1t}^j, \ldots, e_{Nt}^j)'$ is the $N \times 1$ idiosyncratic disturbance term, which has zero expectation and a covariance matrix Σ_{ee}^j (see Forni, Giannone, Lippi, and 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, and 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 at capturing the lead and lag relations along the business cycle.

Equations (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.

2 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 in addition to one-, two-, three-, and four-quarter ahead forecasts for a total of five horizons. Survey data are 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, $t = 1+h, \dots, \tau - 1$, $h = 0, \dots, 4$, and $\tau = \underline{t}, \dots, \bar{t}$ with $\underline{t}$ and $\bar{t}$ the first and last quarter to be forecasted. Thus, the largest model includes a constant and four lags of the dependent variable, while the smallest model only includes a constant and one lag.[1] We denote the h-step-ahead forecast of the dependent variable as $\hat{y}_{\tau+h}$. All the forecasts are based on h-step-ahead direct linear projections.

The first factor model, *Model A*, includes the first factor for a region or sector j, $f^j_{1,t}$, in addition to lags of the dependent variable as chosen in the benchmark model:

$$y_t = \alpha_0 + \alpha_1(L)f^j_{1,t-h} + \alpha_2(L)y_{t-1-h} + \varepsilon^A_t. \tag{4}$$

Model A restricts both the first factor and the dependent variable to having between one and four lags, the same limits as in the benchmark model. We choose the lag structure by minimizing the BIC criterion. We denote direct forecasts from Model A using factors from region or sector j as

$$\hat{y}^A_{j,\tau+h} = \hat{\alpha}^h_0 + \hat{\alpha}^h_1(L)f^j_{1,\tau} + \hat{\alpha}^h_2(L)y_{\tau-1}. \tag{5}$$

The second and more general factor model, *Model B*, includes from one to five con-

[1] The BIC selects three, one, and two lags respectively for inflation, GDP growth and unemployment for Norway and one, three, and two for Sweden.

temporaneous factors in addition to the lags of the dependent variable chosen in equation (3):

$$y_t = \beta_0 + \beta_1 F_t^j + \beta_2(L) y_{t-1-h} + \varepsilon_t^B. \tag{6}$$

β_1 is a $1 \times \rho$ vector, and F_t^j is a $\rho \times 1$ vector of factors for region or sector j. The number of factors, ρ, and the autoregressive lags are again determined by the BIC, where the smallest model only consists of a constant and the first factor and the largest model includes four lags of y_t and five contemporaneous factors. We denote forecasts from Model B using factors from region or sector j as

$$\hat{y}_{j,\tau+h}^B = \hat{\beta}_0^h + \hat{\beta}_1^h F_\tau^j + \hat{\beta}_2^h(L) y_{\tau-1}. \tag{7}$$

When forecasting the same variable using different information sets and forecasting models, combining all of them might produce a better forecast. Timmermann (2006) (and references therein) gives several reasons for why a combination of individual forecasts may be favorable. The two most relevant arguments for this paper are that firstly individual forecasts might be affected differently by structural breaks, and thus a combination of forecasts will outperform the individual ones. Secondly, forecasting models might be subject to an unknown misspecification bias (for example, related to how the region or sector individual models are constructed), and using a combination of models can be seen as a more robust method to guard against such biases. In empirical studies, forecast combinations have been found to outperform individual forecasts (again see Timmermann (2006) and the references therein). Specifically for one of the paper's variables of interest, Bjørnland, Gerdrup, Jore, Smith, and Thorsrud (2009) find that forecast combinations outperform the Norges Bank's own point forecast for Norwegian inflation.

Instead of considering factor models and forecast combinations as competing forecasting methods, we propose a merger of the two approaches. For each class of models (A and B), we combine forecasts from the different (regional and sectoral) models at time t for horizon h as a weighted average,

$$\tilde{y}_{\tau+h}^i = \sum_{j=1}^{J} w_{j,\tau+h}^i \hat{y}_{j,\tau+h}^i, \tag{8}$$

where $w^i_{j,\tau+h}$ are the weights, J is the number of regions and sectors, and $i = A, B$. We consider two different weighting schemes. The first and the simplest way of combining forecasts is to assign equal weights to the individual forecasts, $w^i_{j,\tau+h} = 1/J$, denoted as FC-EW. For point forecasting, equally weighted combinations have been found to be surprisingly effective (Clemen, 1989). The second combination scheme, originally proposed by Bates and Granger (1969), is to assign weights according to the region's or sector's relative prediction squared errors:

$$w^i_{j,\tau+h} = \frac{1/\text{MSPE}^{h,i}_{j,\tau-1}}{\sum_{m=1}^{J}\left(1/\text{MSPE}^{h,i}_{m,\tau-1}\right)} \tag{9}$$

where $\text{MSPE}^{h,i}_{j,\tau-1}$ is the forecast's mean squared prediction error (MSPE) for region or sector j for up to time $\tau - 1$ and horizon h. Forecasts that have relatively low MSPEs are thus assigned a higher weight in the combination than forecasts with relatively high MSPEs. We denote this forecast combination method as FC-MSPE.

3 The Norges Bank's Regional Survey

In 2002, Norges Bank established regional networks of enterprizes, organizations, and local authorities throughout Norway. By conducting interviews with its contacts, Norges Bank obtains information concerning their current economic situation and their plans for the coming months. The survey reflects the production side of the economy both geographically and sectorally by dividing the country into $R = 7$ regions: Inland, Mid-Norway, North, North-West, South, South-West and East, and $S = 10$ sectors: 1) building and construction, 2) manufacturing (including the subsectors of 3) domestically oriented manufacturing, 4) export industry, and 5) oil industry suppliers), 6) public sector, 7) services (with the subsectors: 8) household services (B2C) and 9) corporate services (B2B)) and 10) retail trade. Sectors that are not represented include the oil industry, overseas shipping, agriculture, and other primary industries. The oil industry and overseas shipping are excluded because the regional networks only concentrate on the developments and activities pertaining to the mainland economy. The primary industries are strongly regulated and do not necessarily reflect developments in the business cycle. All sectors and subsectors in the survey are represented in each region, with the exception of the oil industry suppliers, which are not represented in the Inland and North regions.

The interviews consist of 11 questions in total (see Table A1 in the Appendix for these specific questions). However, all 11 questions are not posed to all sectors (see Table A2 in the Appendix). In particular, the manufacturing sector has different questions than the subsector of domestically oriented manufacturing, the export industry, and oil industry suppliers. The same holds for the service industry and its subsectors B2C and B2B. In total there are 60 combinations of questions and sectors. Questions I, IV, VII, and VIII are backward-looking, questions II, III, V, and XI are forward-looking, while timing is not specified for the other questions.

For each question, Norges Bank maps the responses on a scale that ranges from −5 to +5, where +1 corresponds to an annualized quarterly growth rate of 1–3 percent, and +5 corresponds to a growth of more than 9 percent. An annualized quarterly decrease of 1–3 percent is reported as −1, whereas a decrease of nine percent or more corresponds to −5 on the regional network scale (Brekke and Halvorsen, 2009).

The questions related to capacity utilization, labor supply, and retail prices for next twelve months are conducted in a different manner. For the question concerning labor supply, the survey asks whether the firm or industry contact thinks the labor supply will be a limiting factor for production or turnover if there is a rise in demand. Norges Bank computes the difference between the number of contacts who answer "yes" and "no" as a fraction of the total number of responses. The firms are also asked about capacity utilization and whether the firm will find it difficult to meet a rise in demand. The possible answers are "no" problems, "some" and "considerable" problems to meet the potential rise in demand. Norges Bank calculates a diffusion index as the difference between the number of contacts answering "considerable" or "some" problems within a given region and sector as a fraction of the total contacts within each sector and region.[2] Finally, the last variable calculated concerns retail prices over the previous and the coming 12-month period. The contacts are asked whether they did change prices over the previous period

[2]Unfortunately, we do not have access to results on the firm level, but only have results aggregated up to the regional and sectoral level. Norges Bank's regional survey analysts perform the aggregation from the firm level to the regional and sectoral level based on the firm's size, and general tendencies in the regions and sectors. All of these values are estimated by using discretionary judgement and are not publicly available.

and they expect that their own retail prices will be "higher", stay "unchanged" or be "lower". Again, we calculate a diffusion index as the difference between those contacts expecting higher and lower prices over the next 12 months as a fraction of total answers within each sector and region.

In order to make the regional survey dataset ready for factor estimation, we group and split the dataset into the following dimensions: for each region R ($R = A, \ldots, G$), we make a panel dataset of all variables for all sectors denoted X^R. Likewise, for each sector S ($S = 1, \ldots, 10$), we create a panel dataset of all variables for all regions denoted by X^S. For each region the number of variables, N, is 60 (the number of combinations of sectors and questions in Table A2) apart from Inland and North regions which each has 54 variables due to the absence of oil industry suppliers. For each sector the number of variables ranges between 77 for retail trade (11 questions $\times$ 7 regions) and 20 for suppliers to the oil industry suppliers (4 questions $\times$ 5 regions). Grouping all the information into a unique dataset results in 777 variables.

Since the Norges Bank's regional survey began in 2002, each year there have been between four to six rounds of interviews. In total, our data is based on 47 interview rounds, with the last round conducted in May 2012. The results from these rounds are then transformed into quarterly data to match the frequency of the dependent variables we want to forecast. The frequency transformation is a weighted average of data from one or more interview rounds, depending on which months the different interviews took place. We thus end up with a panel dataset of observations for ten sectors in seven regions over 40 quarters, from 2002:Q3 to 2012:Q2. However, four of the questions (no. V employment next 3 months, no. IX labor supply, no. X capacity utilization, and no. XI product prices next 12 months) were not available until the first interview round of 2005. For these questions we have thus 27 observations for each sector and region.

The Norges Bank's regional survey is conducted each quarter during the first and the second month , and this timing poses various possibilities regarding what horizon to forecast. Lui et al. (2010b) discriminate among questions and just focus on those which provide information on the previous three months and the coming three months. By comparing answers to quantitative survey data, Lui et al. (2010b) investigate whether qualitative projections are formed "rationally"; see also Pesaran and Weale (2006). Such questions pertaining to short-run quarterly results and projections could be considered as natural choices for nowcasting macroeconomic variables. Hansson et al. (2005) extend the set of questions and work with backward- and forward-looking questions. Their analysis uses each set separately, constructs factors from each of the two groups, and makes forecasts up to eight-quarters ahead. We do not apply such timing separation and instead when computing regional and sectoral factors combine all the questions in the dataset, as in Matheson, Mitchell, and Silverstone (2010) and focus both on nowcasting and on forecasting macroeconomic variables. Therefore, we do not investigate whether some questions are more "rational" for specific horizons. There are several justifications for this decision. First, the Norges Bank's regional survey was originally conducted more frequently, up to six rounds of interviews each year, and this frequency might have created issues with survey agents allocating the proper timing information to each question. See Bertrand and Mullainathan (2001) for a general discussion of the fact that respondents do not always mean what they say when subjectively replying to surveys. Second, several questions are not posed to all the sectors (see Table A2) and therefore we might miss data for some sectors.

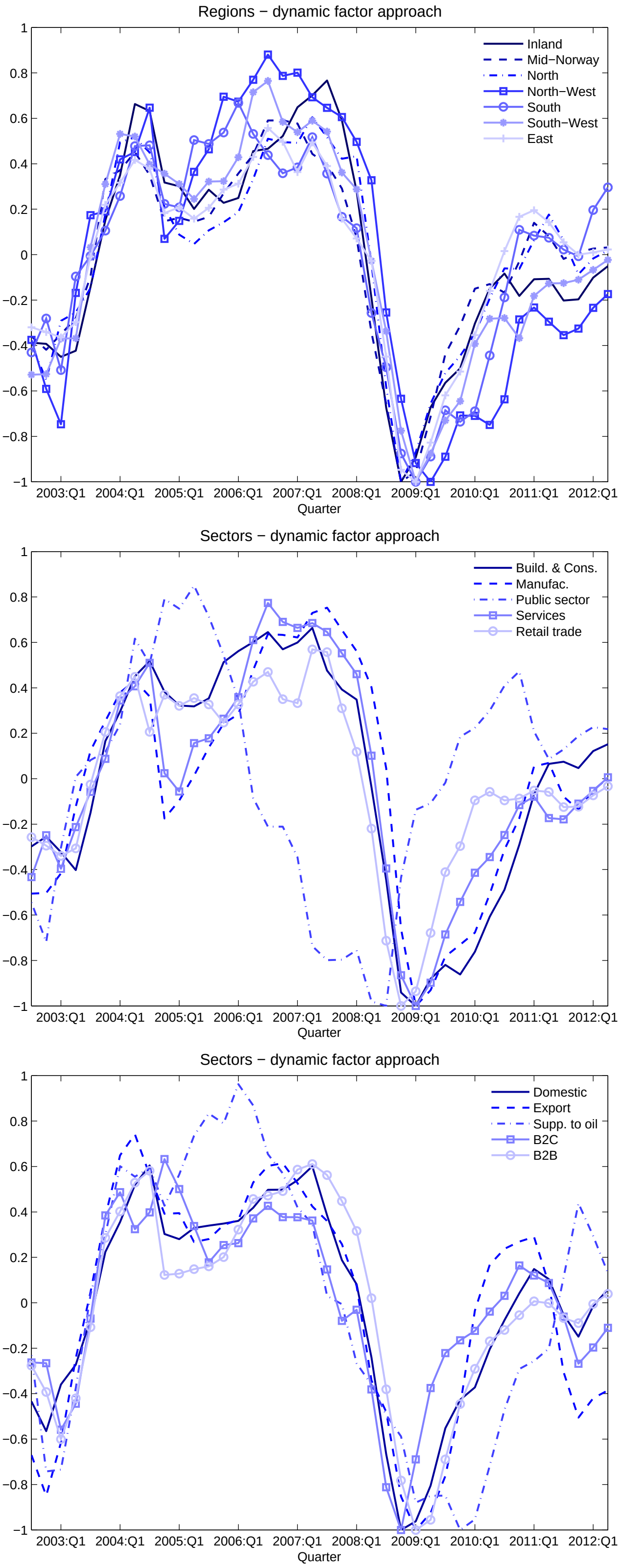
3.1 The Regional and Sectoral Factors

For each region or sector we can extract up to ρ factors, where ρ is fixed *a priori*. The first factor seems to explain, on average, about 53 percent of the variation in the datasets. The marginal contribution of the second factor is around 21 percent. When we include five factors, together these explain almost 93 percent of the variation among the datasets. There is little variation between the different sectors and regions in this respect.

When estimating the factor model we must take account of the four questions which were not available until 2005:Q1 (see above). To handle this issue the factors are first estimated from 2002:Q3 to 2004:Q3 using the available series, and then a new estimation of the factors for the time span 2004:Q4 to 2012:Q2 using all variables included in X^j.[3] The factors are then concatenated to series ranging over the full sample, i.e. from 2002:Q3 to 2012:Q2.

[3]The reason why the sample is split after 2004:Q3, is because the results of the first interview round in 2005 is given a weight of two-thirds when calculating the results for 2004:Q4.

Figure 1: Plots of the first factor for all regions, f_{1t}^{R}, in the top panel, and the first factor for all sectors, f_{1t}^{S}, in the middle and bottom panels.



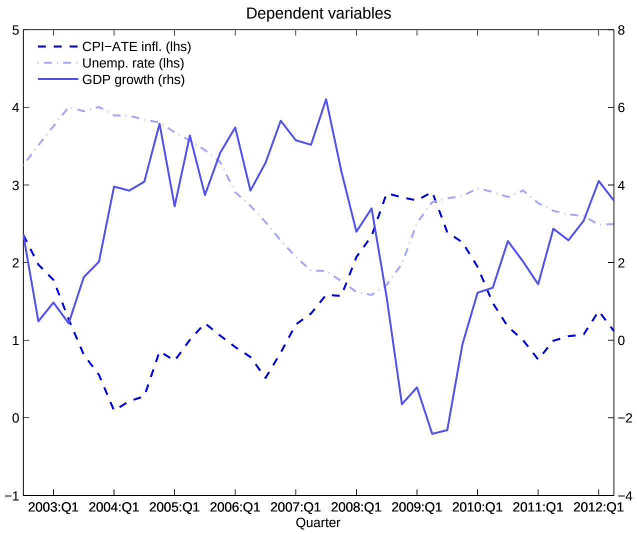
Source: Norges Bank

Figure 1 displays plots of the first factor for each region, f_{1t}^{R}, in the top panel and each sector, f_{1t}^{S} in the middle and bottom panels. The factors are standardized by dividing them by the largest absolute value of each (regional or sectoral) factor, and thus vary between −1 and 1. The regional factors show very similar patterns for all the seven regions, meaning that they initially surged from a low level. When the financial crises hit in 2008:Q3 the regional factors all fell rapidly before picking up over the last two years, 2011-1012. The middle and bottom panels in Figure 1 show each sector's first factors. There is more variation between the sectoral factors than the regional ones. The public sector factor differs most from the others declining from 2005 to 2008 while the other sectors increased. When the financial crises hit in 2008, the public sector factor surged sharply while the first factors for the other sectors declined. The factors in the bottom panel are based on a smaller set of variables than the factors in the middle panel (see Table A2). We see that the factor for oil industry suppliers remained higher than the other sectoral factors during 2005–2007.

Figure 2 plots the three variables we aim to forecast: year-on-year logarithmic CPI-ATE inflation, year-on-year logarithmic GDP growth, and the unemployment rate. CPI-ATE is the consumer price index adjusted for taxes and energy prices. Norway's economy expended from the end of 2002:Q4 to 2008:Q2, with increasing GDP growth and a decreasing unemployment rate after 2006. From the start of the Great Recession in 2008:Q3 we see an increase in the unemployment rate and a sharp decrease in GDP growth. Inflation fell to almost zero percent during the initial two years of the sample, but then increased to around 2 percent. GDP growth is the most volatile variable.

Table 1 reports correlation coefficients between the first factors and the macro variables. There is a strong correlation between all first factors and the business cycle. The regional factors have a correlation between 0.59 (North-West) and 0.84 (East) with inflation, close to 0.9 with GDP growth for all regions, but only between 0.02 and 0.13 (South) with the unemployment rate. The sectoral factors are also more correlated with GDP growth and inflation than with unemployment, but there is much more variation in the similar correlation coefficients among the sectors than among the regions. As already noted, the public sector is the outlier with correlation coefficients of 0.67 for unemployment and only 0.14 for GDP growth.

Figure 2: CPI-ATE inflation, GDP growth and the unemployment rate.



Source: Statistics Norway

Table 1: Correlations coefficients between the dependent variables and the first factors.

Region/Sector	*Inflation*	GDP *growth*	*Unemployment*
A Inland	0.72	0.87	0.03
B Mid-Norway	0.83	0.85	0.10
C North	0.76	0.85	0.02
D North-West	0.59	0.83	0.08
E South	0.81	0.88	0.13
F South-West	0.74	0.88	0.02
G East	0.84	0.89	0.08
1 Building and cons.	0.71	0.91	0.01
2 Manufacturing	0.58	0.81	0.22
3 Domestically oriented manuf.	0.84	0.87	0.14
4 Export industries	0.82	0.76	0.17
5 Suppliers to oil ind.	0.75	0.81	0.20
6 Public sector	0.57	0.14	0.67
7 Services	0.66	0.87	0.11
8 Services – B2C	0.82	0.72	0.32
9 Services – B2B	0.74	0.89	0.05
10 Retail trade	0.77	0.87	0.15

To extract information from the composition of each factor, we analyze which variables, within each sector or region, contribute most to each factor. We regress each first factor, f^j_{1t} on a constant and on each variable, X^j_{it}. A significant R^2 indicates that the variable is an important component of the factor, and can thus be interpreted as a driving force of that factor (Stock and Watson, 1998). The top panel of Table A3 in the Appendix reports R^2 for all regions and sectors, and gives an overview of which of the variables load the regional and sectoral factors. We see that all regions and sectors load questions I, II, and VII. Only building and construction and the public sector load variable VI (wage growth). No sector or region load the forward-looking variable XI (product prices next 12 months). The public sector loads only variable VI (wage growth) in addition to IX (labor supply).

Likewise, the middle panel shows which regions are important for the sectoral factors. We see that all regions affect the first factor for all the sectors, apart the public sector for South and services – B2C for South-West. The factor for building and construction is particularly important for the region South and East, while manufacturing is important for North-West and South. Surprisingly, the factor for oil industry is not important for South-West. From the reverse perspective, we see from the bottom panel that all regions load sectors 1–5, 7, 9 and 10. The services sector is particularly important for Mid-Norway, North-West and East.

3.2 Forecasting Results

In this section we forecast CPI-ATE inflation, GDP growth, and the unemployment rate for Norway using the factors and forecast models derived above. CPI-ATE is the CPI adjusted for taxes and energy prices, GDP is the adjusted basic value for mainland Norway and is made stationary by calculating the yearly logarithmic growth, as is the CPI-ATE. For unemployment, we use register-based unemployment at the end of the month (in percent), transformed into a quarterly series. The series is seasonally adjusted by X-12-ARIMA, and is transformed into quarterly frequency before we calculate the logarithmic yearly growth rate. All data are collected from the Statbank of Statistics Norway. We divide the sample into two periods: 2002:Q3–2006:Q4 is used as in-sample period, and 2007:Q1–2012:Q2 is our forecasting period (22 quarters). Our experiments are pseudo real-time exercise as we do not consider real-time data for GDP growth, but rather use the 2012:Q3 vintage of data.

To summarize, for each dependent variable (inflation, GDP growth, and unemployment) at each point in time, we produce 17 (regions and sectors) $\times$ 2 (models) $\times$ 5 (horizons) = 170 different factor model forecasts in addition to the benchmark forecasts.

We evaluate the forecasting performance by comparing the root mean squared prediction error (RMSPE) from each factor model with the RMSPE from the benchmark model. Tables A4 and A5 in the Appendix report the RMSPE of all the factor models relative to the RMSPE of the benchmark model for the three dependent variables. The results of both forecast combination methods, FC-EW and FC-MSPE, are reported at the bottom of each table. Following Clark and McCracken (2012) (and Groen, Paap, and Ravazzolo (2012) for density forecasting) we test the null of equal finite sample forecast accuracy, based on square prediction errors. This result is compared to the alternative that a model outperformed the AR benchmark by using the Harvey, Leybourne, and Newbold (1997) small sample correction of the Diebold and Mariano (1995) and West (1996) statistic--to-standard normal critical values.

One of the clear benefits of having disaggregate data is that it is possible to isolate the regions and sectors that are good predictors of the dependent variables. Table 2 summarizes the forecasting performance using factors from the regions and the sectors. For each dependent variable the table shows the median relative RMSPE across models and horizons. The success rate (S-rate) is defined as the fraction of number of times a factor based forecast beats the benchmark, by regions and sectors as reported in Tables A4 and A5. For example, 70 percent of the factor model forecasts beat the benchmark forecast for GDP growth when using factors for the Inland region. The median RMSPE is 0.87 implying that, on average, the gain from forecasting GDP growth using factors from the Inland region is 13 percent relative to the benchmark forecast.

When forecasting inflation, among the regional factor models only the South outperforms the benchmark, albeit with modest gains (9 percent). Among the sectoral models few specifications systematically outperform the benchmark model when forecasting inflation; Services–B2B has the lowest RMSPE at 0.92. This finding is consistent with the fact that only Services–B2B loads variable XI, product-price next 12 months. Studying numbers in Table A4 shows that the forecasts are more accurate for all the five horizons we consider. However, when forecasting GDP growth, we see that all the regional factor models outperform the benchmark model forecast, and the gains are fairly large, in particular for Mid-Norway and East. All the sectoral factor models outperform the benchmark when forecasting GDP growth. Again, the gains are larger than when forecasting inflation

Table 2: The median relative RMSPE and the success rate of factor models relative to benchmark by regions and sectors. There are 10 factor-based relative RMSPEs for each region and sector.

	Inflation		GDP growth		Unemployment	
Region/Sector	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
A Inland	1.03	0.40	0.87	0.70	1.08	0.40
B Mid-Norway	1.08	0.30	0.72	1.00	0.91	0.60
C North	1.11	0.20	0.96	0.60	1.11	0.40
D North-West	1.17	0.10	0.86	1.00	1.01	0.50
E South	0.91	0.60	0.73	1.00	0.97	0.50
F South-West	1.02	0.50	0.80	1.00	1.09	0.40
G East	1.01	0.40	0.81	1.00	0.89	0.60
1 Building and construction	1.19	0.10	0.73	1.00	0.94	0.70
2 Manufacturing	1.00	0.50	0.92	0.70	0.88	0.70
3 Domestically-oriented manuf.	1.06	0.40	0.68	0.90	0.94	0.50
4 Export industry	1.03	0.50	0.82	1.00	1.02	0.50
5 Suppliers to the oil industry	0.95	0.60	0.84	1.00	1.22	0.00
6 Public sector	0.95	0.90	0.97	0.60	1.05	0.30
7 Services	1.05	0.10	0.84	0.80	0.83	0.70
8 Services–B2C	1.06	0.00	0.68	1.00	1.01	0.50
9 Services–B2B	0.91	0.80	0.79	0.80	0.94	0.60
10 Retail trade	0.98	0.50	0.74	0.60	1.07	0.40

and stars in Tables A4–A5 show they are often statistically significant at 5 percent.

The services and manufacturing sectors give the most accurate forecasts for unemployment relative to the benchmark. The factor for the public sector performs poorly despite the high correlation it has with unemployment (Table 1), which suggests that it lags the real economy. A high contemporaneous correlation does not provide information on whether the public sector forecasts unemployment accurately.

Table 3 reports how models A and B perform relative to the benchmark at all horizons. Models A and B give the highest gains when forecasting GDP growth, with a success rate of 81 and 92 percent respectively, and a gain in RMSPE of more than 20 percent. Neither model A nor B systematically outperform the benchmark model when forecasting inflation; yet model B performs better in forecasting unemployment. The factor models outperform the benchmark model for unemployment only at short horizons (h=0 and h=1) and for inflation at nowcasting, confirming evidence in Zaher (2007) that factor models based on large information sets do not generally provide accurate long horizon forecasts for inflation and might call for an analysis with just forward-looking survey

Table 3: The median relative RMSPE and the success rate of factor based forecasts relative to the benchmark by model A and B and horizons ($h = 0, \ldots, 4$). The number of relative RMSPEs for each model is 85 and for each horizon is 34.

	Inflation		GDP growth		Unemployment	
	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
Model A	1.01	0.42	0.83	0.81	1.08	0.39
Model B	1.05	0.39	0.79	0.92	0.92	0.59
h=0	0.98	0.68	0.79	0.97	0.89	0.88
h=1	1.06	0.26	0.67	0.97	0.85	0.85
h=2	1.03	0.41	0.80	0.97	1.04	0.38
h=3	1.11	0.32	0.83	0.79	1.18	0.15
h=4	1.08	0.35	0.95	0.62	1.23	0.18

Table 4: Median relative RMSPE and success rate of the forecast combinations FC-EW and FC-MSPE by variable and models. There are 10 factor-based relative RMSPEs for each variable, and 15 for each model.

	FC-EW		FC-MSPE	
	RMSPE	S-rate	RMSPE	S-rate
Inflation	0.87	1.00	0.83	1.00
GDP growth	0.71	1.00	0.70	1.00
Unemployment	0.86	0.80	0.82	0.80
Model A	0.83	0.87	0.82	0.87
Model B	0.84	1.00	0.79	1.00

questions. For GDP growth the factor models, on contrary, perform better for all horizons. The regional and sectoral factor models are very accurate both in predicting the start of the 2008 recession and the subsequent recovery. Following Aastveit and Trovik (2011), who find that unemployment, industrial production, and stock markets are crucial to producing accurate forecasts of Norwegian GDP, we compare our forecasts for GDP to combinations of several dynamic factor models based on a large set of macroeconomic variables using Norges Bank's system of averaging models (see Aastveit, Gerdrup, Jore, and Thorsrud (2011)). Using Aastveit et al. (2011)'s framework we select the block data when the regional network is available. Our best regional and sectoral models (and the FC-MSPE combination) provide more accurate forecasts at horizons $h = 0, 1, 2$.[4]

The performance of the forecast combinations FC-EW and FC-MSPE are summarized

[4]Norges Bank's system of averaging models gives the lowest RMSPE for inflation at any horizon, but it is not used to forecast unemployment.

in Table 4. When forecasting all variables, both forecast combinations do systematically (and often statistically, see Tables A4–A5) better than the benchmark model forecast. However, FC-MSPE performs better than FC-EW for all instances. The largest gain relative to the benchmark occurs when forecasting GDP growth. FC-MSPE has a relative MSPE of 0.70 and FC-EW of 0.71. Comparing the performance of the forecast combinations to the performance of all regional and sectoral forecasts reported in Table 2, there are few individual forecasts which seem to do marginally better. Those are, however, not produced from the same model for all horizons and variables. Forecast combinations are the best for forecasting short term inflation. Therefore, forecast combinations mitigate model uncertainty, provide accurate forecasts, and offer insurance against selecting inappropriate models.[5] Figure A1 plots the $h = 0, ..., 4$ step-ahead GDP growth forecasts based on FC-MSPE and model B, and shows that the forecast is quite accurate both at the start of the 2008 recession and also at the recovery, in particular for the shorter horizons $h = 0, 1$.

Finally, in our exercises, we also investigate whether the use of disaggregate data in regional and sectoral factor models and the forecast combinations is optimal, in terms of forecast accuracy compared to 1) a dynamic factor model applied to the full survey database (meaning no disaggregation) such as in Hansson et al. (2005), and 2) to a question-level approach which ignores regional and sectoral factors. In the former approach we apply dynamic factor models as in equation (4) and (6), where the factors are constructed by the full database X_t accordingly to equations (1)–(2). The results, ALL are provided in Table A4 and A5. In the latter approach, we construct forecasts based on the variables/questions directly from

$$y_t = \delta_0 + \delta_1 X_{i,t-h} + \delta_2(L)\, y_{t-1-h} + \varepsilon_t^D. \tag{10}$$

Then we aggregate the forecasts $\hat{y}^D_{i,\tau+h}$ using the MSPE weights described in equation (9). The results, FC-D-MSPE, are provided in the bottom rows of both Tables A4 and A5. These two alternatives never provide lower RMSPE than our methodology. FC-D-MSPE forecasts are more accurate than ALL forecasts, and, interestingly, FC-D-MSPE forecasts for

[5]It would be interesting to compare the *ex-ante* selection of the best model against the combined model. We think this exercise is out of the scope of this paper and we leave it for future research.

inflation are statistically significant for many horizons. When studying the combination weights to compute $\hat{y}^{D}_{i,\tau+h}$, we find that the XI forward looking price question has larger weights than other questions.

4 The Swedish Business Tendency Survey

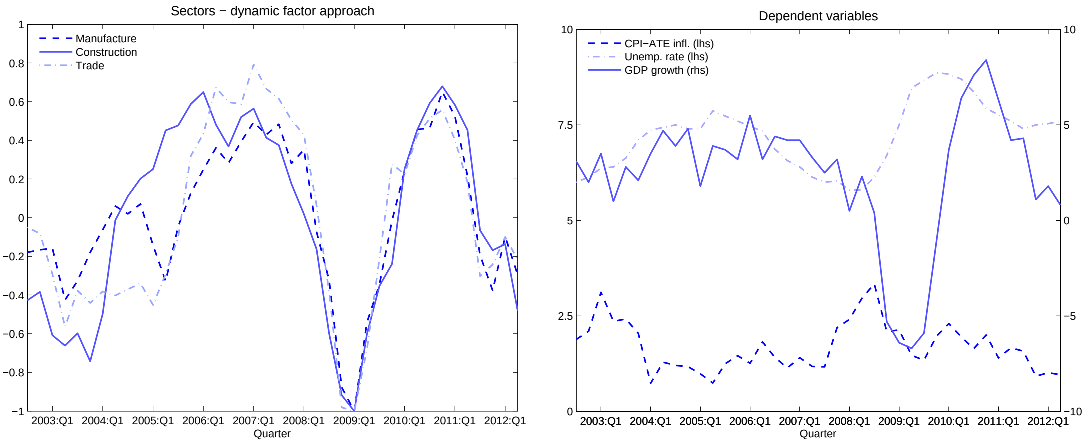
The Swedish Business Tendency Survey (SBTS) provides fast and accurate information on developments in the Swedish economy. Each month, Sweden National Institute of Economic Research asks a large number of businesses for their assessment of the current economic situation. Among the questions, the firms are asked their view on output, new orders, employment, and prices. The SBTS's aim is to produce timely information on the economy's current situation and provide short-term forecasts for important macroeconomic variables such as GDP.

Hansson et al. (2005) find that a dynamic factor model based on the SBTS is an attractive way of handling data for forecasting Swedish macroeconomic variables and that this type of model outperforms alternative models in most cases. Besides updating the dataset to 2012:Q2, we are able to extend their analysis in three directions. First, we extend the dataset to include one more sector, the trade sector. Second, we empirically investigate what is the most accurate way to aggregate information, as we did with the Norges Bank's regional survey. Third, we directly compare the results with the results obtained from the Norwegian survey.

Our analysis of the SBTS on three sectors: manufacturing, construction and trade. Beginning in 2003:Q1 the SBTS also covers the private service sector, but since this sector is shorter than the Norges Bank's regional survey, we omit it from our analysis. We only include the questions from the survey that are net balance indices, which gives us a total of 24 questions for manufacturing, 10 questions for construction, and 12 questions for the trade sector. To compare results to the Norwegian example, we consider all questions, not just coincident and forward-looking ones, as both are defined in Hansson et al. (2005).

In the analysis, we use the same sample length as Norges Bank's regional survey, namely 2002:Q3 – 2012:Q2. In this way we are able to compare the SBTS results directly

Figure 3: Plots of the first factor for all sectors for the dynamic factor model.



Sources: NIER, Statistics Sweden and Norges Bank

to the Norges Bank's regional survey results.[6]

The left panel of Figure 3 displays plots of the first factor for each of the three sectors; the right panel plots Sweden's its year-on-year logarithmic CPI-ATE inflation, its year-on-year logarithmic GDP growth, and its unemployment rate. As for Norway, we recognize a strong correlation between the factors and the business cycle.

Using the same approach as with the Norges Bank's regional survey data, we report the forecasting results in Tables 5 and 6 (the details are shown in Tables A6 and A7 in the Appendix). Forecasts using factors from the trade sector provide the most accurate information for GDP growth, with an accuracy gain of 26 percent relative to the benchmark model and a success rate of 0.8. In contrast to the Norwegian example, all sectors outperform the benchmark when forecasting unemployment, with gains up to 25 percent and a success rate of 1.0. However, it performs poorly when forecasting inflation; no sector outperforms the benchmark. Model B seems to be more accurate, especially when forecasting GDP growth. The two models perform similarly to forecasting unemployment and inflation, but neither one is better than the benchmark for inflation forecasting at any horizon.

The forecast combination results in Table 6 are based on averaging the three sector forecasts using equation (8). The weighted forecast combinations overall do better than

[6]The SBTS sample made available to us starts in 1996:Q2. When extending the sample size but keeping the same out-of-sample evaluation period 2007:Q1–2012:Q2, model B applied to sectoral factors gives the most accurate forecasts.

Table 5: The median relative RMSPE and the success rate of factor models relative to benchmark by sectors. There are 10 factor-based relative RMSPEs for each sector.

	Inflation		GDP growth		Unemployment	
Sector	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
Manufacturing	1.14	0.00	1.02	0.40	0.75	0.80
Construction	1.06	0.00	0.93	0.60	0.75	1.00
Trade	1.03	0.30	0.74	0.80	0.88	0.90
Model A	1.06	0.13	0.93	0.53	0.85	0.87
Model B	1.06	0.07	0.86	0.67	0.75	0.93

Table 6: Median relative RMSPE and success rate of the forecast combinations FC-EW and FC-MSPE by variable and models. The number of factor based relative RMSPEs for each variable is 10, and 15 for each model.

	FC-EW		FC-MSPE	
	RMSPE	S-rate	RMSPE	S-rate
Inflation	1.04	0.30	1.04	0.30
GDP growth	0.84	0.70	0.69	0.90
Unemployment	0.68	1.00	0.63	1.00

the benchmark model when forecasting GDP growth and unemployment. The weighted forecast combination achieves slightly higher gains than the unweighted forecast combinations.

When comparing different levels of disaggregation, evidence in Tables A6–A7 is similar to the Norges Bank's regional survey example with an important exception: our combinations based on sectoral factor models give more accurate forecasts than pooling all the information or combining forecasts that are implied by single questions for GDP growth and unemployment (see equation (10)). But for inflation, aggregating the forecasts statistically beats the benchmark forecast and our model when nowcasting and one-step ahead forecasting. As for the Norges Bank's regional survey exercise, this method gives higher weights to forecasts based on the current and near future price developments. This finding seems to suggest that survey agents accurately respond to precise and timing-specific questions for inflation, but, information for GDP growth and unemployment must be extracted from a larger set of questions.

5 Concluding Remarks

This paper proposes a factor model approach to forecast macroeconomic variables using information from large qualitative surveys, where the questions used to collect information can be very different and refer to disaggregate information for the variables of interest. We apply our methodology to the Norges Bank's regional survey and to the Swedish Business Tendency Survey. We find several interesting results. First, regarding the factor estimation based on a dynamic factor model, the first factor usually explains around 53 percent of the variation in the Norwegian datasets and around 65 percent of the Swedish datasets. Including as many as five factors, these explain on average approximately 93 percent of the variation in the Norwegian datasets. For the Swedish datasets, the number is 96 percent. Therefore, the factor model approach seems to be an effective way of handling the dimensional issue of the regional survey and the differences among its questions.

Second, it is indeed possible to isolate which regions and sectors perform well, and to show that it is feasible to exploit the disaggregate information contained in the survey-based network. There is some uncertainty on which type of factor model should be used, based on the model structure and specific variable of interest, and averaging the set of models with forecast combinations yields accurate forecasts that statistically outperform autoregressive benchmarks and insures against selecting inappropriate models.

Finally, discarding the regional and sectoral structure of the surveys and working at the question level or pooling all regions and sectors in a single factor reduces forecast accuracy.

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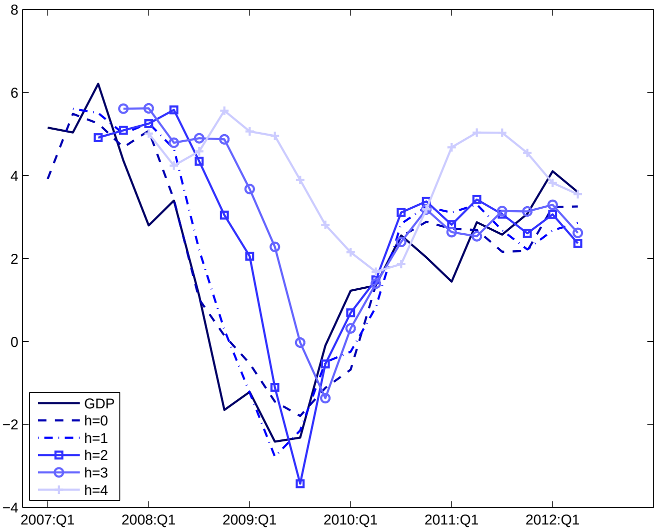
Appendix A: Figures and tables

Figure A1: Plots of the GDP growth forecasts based on FC-MSPE and model B.



Sources: Statistics Norway and Norges Bank

Table A1: The regional survey questions.

I	Output	Developments in demand/production over the past three months (seasonally adjusted)
II	Market prospects	Market prospects for the next six months
III	Investments	Investments made, and plans for the next six to twelve months
IV	Employment past 3 months	Change in number of person-years worked in the past three months
V	Employment next 3 months	Planned change in employment the next three months
VI	Annual wage growth	Annual wage growth for the current calendar year
VII	Profitability	Developments in profitability (operating profits) over the past three months
VIII	Product prices past 12 months	Changes in retail prices over the past twelve months
IX	Labor supply	The difference between the number of enterprizes which report that labor supply will be a limiting factor on production and those who not
X	Capacity utilization	Diffusion index for enterprizes who will have some or considerable problems meeting a rise in demand
XI	Product prices next 12 months	Diffusion index for enterprizes expecting increased vs. reduced prices over the next 12 months

Table A2: Overview of the questions asked to each sector. A × indicates that a question is addressed to the sector.

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
1 Building and construction	×	×		×	×	×	×	×	×	×	×
2 Manufacturing			×	×	×	×			×	×	
3 Domestically-oriented manu.	×	×					×	×			×
4 Export industry	×	×					×	×			×
5 Suppliers to the oil industry	×	×					×	×			
6 Public sector			×	×	×	×			×		
7 Services		×	×	×	×	×	×		×	×	
8 Services – B2C	×							×			×
9 Services – B2B	×							×			×
10 Retail trade	×	×	×	×	×	×	×	×	×	×	×

Table A3: Average R^2 of regressions of f_{1t}^j on a constant and X_{it}^j. Insignificant R^2s in italics.

	Load variable										
Region/Sector	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
A Inland	60.8	55.0	*5.7*	29.4	23.8	*9.9*	44.0	*18.7*	35.9	49.7	*10.9*
B Mid-Norway	59.3	52.2	29.2	38.1	39.5	*7.9*	39.8	*18.7*	38.7	45.6	*9.1*
C North	52.9	51.4	26.2	39.0	40.0	*9.0*	38.9	*18.6*	28.2	35.7	*12.2*
D North-West	61.0	59.1	47.0	36.3	57.1	17.4	46.1	28.8	60.3	56.7	*8.5*
E South	61.7	62.5	33.5	36.7	58.4	*9.2*	58.8	*12.1*	29.7	44.9	*13.0*
F South-West	49.5	56.4	25.4	37.1	47.2	16.2	51.6	*20.2*	49.0	42.1	*8.4*
G East	52.2	68.3	30.3	35.5	50.8	*13.9*	49.3	25.5	46.0	49.5	*12.7*
1 Build & const	51.2	43.7	-	43.2	47.4	30.7	48.9	57.0	68.8	62.7	*12.6*
2 Manufacturing	-	-	32.4	40.9	49.1	*12.6*	-	-	66.7	66.7	-
3 Dom manuf	55.0	60.6	-	-	-	-	48.8	*7.6*	-	-	*15.5*
4 Export industry	56.2	53.9	-	-	-	-	46.1	28.4	-	-	*7.9*
5 Supp to oil ind	49.5	54.0	-	-	-	-	52.4	-	-	-	-
6 Public sector	-	-	*7.7*	*11.7*	*14.3*	66.4	-	-	23.6	-	-
7 Services	-	58.9	28.9	50.9	58.3	*8.1*	56.5	-	64.2	57.4	-
8 Services - B2C	48.7	-	-	-	-	-	-	*7.9*	-	-	*12.4*
9 Services - B2B	62.0	-	-	-	-	-	-	*12.4*	-	-	*19.2*
10 Retail trade	65.0	71.8	28.9	30.5	39.6	*5.1*	43.7	*7.7*	*16.7*	*17.8*	*7.5*

	Load region						
Sector	A	B	C	D	E	F	G
1 Building & const.	44.9	41.3	42.3	44.2	51.1	48.4	54.2
2 Manufacturing	31.3	44.9	36.7	53.0	54.6	49.3	43.4
3 Dom.oriented manuf.	35.5	33.9	32.8	44.3	43.7	35.2	37.2
4 Export industry	38.5	36.6	44.2	31.0	39.3	34.8	45.1
5 Supp. to oil industry	-	51.4	-	47.5	48.9	62.7	48.1
6 Public sector	30.7	27.8	23.1	19.8	*16.7*	31.0	24.0
7 Services	40.3	53.6	37.4	56.3	47.7	48.3	51.7
8 Services - B2C	20.4	19.1	24.1	29.0	22.2	*14.3*	31.8
9 Services - B2B	33.5	33.0	31.6	38.0	22.6	30.1	29.6
10 Retail trade	20.7	32.4	33.1	31.1	29.8	35.5	30.1

	Load sector									
Region	1	2	3	4	5	6	7	8	9	10
A Inland	42.5	37.2	36.1	40.1	-	*5.3*	36.1	24.5	34.3	21.2
B Mid-Norway	37.9	38.6	37.3	29.7	43.4	*10.1*	55.2	20.2	37.5	28.5
C North	37.2	38.9	32.4	31.6	-	*14.8*	36.0	21.6	32.9	30.1
D North-West	47.8	57.2	49.4	38.1	42.9	*13.2*	57.6	26.2	38.2	40.4
E South	47.0	50.2	50.3	44.3	48.8	*4.8*	42.4	24.7	31.7	33.7
F South-West	50.9	43.8	31.0	39.0	51.2	*6.6*	47.3	*10.1*	30.2	34.1
G East	50.8	42.1	42.1	45.6	47.8	*16.0*	54.0	28.1	33.5	28.0

Note: The 1% critical value of the R^2 with 40 observations is 16.1, which is relevant for variables I–IV, and VI–VIII in the top panel. For the variables V, IX–XI the critical value of the R^2 with 27 observations is 20.6. To average across sectors we compute the average critical value of R^2 because the number of observations for the relevant questions varies between sectors. The critical values for R^2 by sector at the 1% level are: building and construction 17.9; manufacturing 18.4; domestically-oriented manufacturing 17.0; export industry 17.0, suppliers to the oil industry 16.1; public sector 17.9; services 17.8; B2C 17.6; B2B 17.6; and retail trade 17.8.

Table A4: Relative RMSPE of Model A using the factors estimated from dynamic factor models over five horizons for Norges Bank's regional survey.

	CPI-ATE inflation					GDP growth					Unemployment				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	1.01	1.16	1.27	1.21	1.04	0.83	0.78*	0.95	1.04	1.21	0.89**	0.92	1.11	1.21	1.21
Mid-Norway	0.95	1.01	1.14	1.11	1.22	0.72*	0.48**	0.72**	0.80**	0.77**	0.75**	0.65**	0.91*	1.14	1.17
North	0.98	1.11	1.09	1.11	0.97	0.84	0.79**	0.96	1.04	1.19	0.82**	0.91*	1.15	1.22	1.11
North-West	0.90	1.13	1.22	1.12	1.16	0.79*	0.74*	0.88	0.86**	0.98*	0.99	1.02	1.17	1.28	1.30
South	0.96	1.03	1.08	1.16	1.30	0.80	0.68**	0.70**	0.73**	0.88**	0.95	0.94	1.04	1.14	1.20
South-West	0.90	0.91	0.90	1.00	0.98	0.73*	0.67**	0.80*	0.84**	0.89**	0.90	0.93	1.09	1.26	1.33
East	1.07	1.25	1.14	0.86	1.00	0.71*	0.67**	0.81**	0.82**	0.92**	0.79**	0.78*	0.99	1.19	1.31
Build. & Cons.	1.00	1.06	1.08	1.16	1.23	0.80	0.53**	0.63**	0.83**	0.78**	0.96	0.94	1.12	1.26	1.29
Manufac.	0.99	1.01	1.00	0.96	0.91	0.92*	0.96	1.07	1.14	1.28	0.89	0.94	1.08	1.09	1.03
Domestic	0.95	1.11	1.19	1.29	1.41	0.71	0.51**	0.62**	0.69**	1.01	0.81**	0.81*	1.04	1.20	1.28
Export	0.99	0.78	0.82	0.82	0.83	0.89	0.89	0.88	0.79*	0.90**	0.91	0.94	1.08	1.23	1.34
Supp. To Oil	0.84*	0.80*	0.78	1.00	1.15	0.94	0.84	0.84*	0.73**	0.91*	1.15	1.15	1.22	1.24	1.25
Public sector	0.97	0.99	0.98	0.90	0.74	1.00	1.03	0.98	1.07	1.00	1.04	1.09	1.01	1.05	0.97*
Services	0.85	1.00	1.02	1.06	1.00	0.78**	0.78**	0.93**	1.00*	1.14	0.84**	0.86	1.05	1.21	1.23
Services–B2C	1.05	1.06	1.03	1.14	1.25	0.87	0.66**	0.68**	0.64**	0.82**	0.88	0.81*	1.00	1.16	1.41
Services–B2B	0.89	0.93	0.89	0.81	0.81	0.76**	0.76**	0.96	0.98*	1.19	0.85**	0.93	1.11	1.20	1.17
Retail trade	1.02	1.10	1.32	1.55	1.62	0.73*	0.57**	0.74**	1.04	1.05	0.91	0.85	1.07	1.31	1.55
FC-EW	0.82**	0.82*	0.86	0.89	0.91	0.72**	0.63**	0.77**	0.81**	0.93**	0.83**	0.83*	1.00	1.14	1.19
FC-MSPE	0.81**	0.79*	0.82*	0.84	0.83	0.70**	0.57**	0.73**	0.77**	0.89**	0.82**	0.81**	0.99	1.13	1.16
ALL	0.92	0.91	0.88	0.90	0.94	0.69*	0.57**	0.76**	0.80**	0.98*	0.84*	0.81	1.03	1.23	1.30
FC-D-MSPE	0.91**	0.94**	0.96**	0.94**	0.96**	0.86**	0.89**	0.86**	0.90**	0.96**	0.89**	0.89**	0.99	1.05	1.02

Note: One * and two ** indicate that the null of equal finite sample forecast accuracy, based on square prediction errors, *versus* the alternative that a model outperformed the AR benchmark using the Harvey et al. (1997) small sample correction of the Diebold and Mariano (1995) and West (1996) statistic is rejected at 10% and 5% respectively.

Table A5: Relative RMSPE of Model B using the factors estimated from dynamic factor models over five horizons for Norges Bank's regional survey.

	CPI-ATE inflation					GDP growth					Unemployment				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.97	1.06	0.86	0.95	0.98	0.90	0.61**	0.61**	0.64**	1.19	0.92	0.78*	1.04	1.20	1.42
Mid-Norway	0.93	1.19	0.81	1.41	1.05	0.71**	0.49**	0.71**	0.78**	0.98*	0.75**	0.65**	0.91*	1.14	1.17
North	1.08	1.14	1.26	1.24	1.14	0.84	0.79**	0.96	1.04	1.19	0.82**	0.91*	1.15	1.22	1.11
North-West	1.05	1.18	1.23	1.40	1.64	0.79*	0.74*	0.88	0.86**	0.98*	0.95	0.83*	0.88	1.09	1.00
South	0.86	0.78	0.75	0.77	0.86	0.80	0.68**	0.70**	0.73**	0.88**	0.91	0.79	0.82	1.00	1.01
South-West	1.05	1.29	1.35	1.48	1.47	0.73*	0.67**	0.80*	0.84**	0.89**	0.90	0.93	1.09	1.26	1.33
East	0.93	1.01	0.88	1.09	0.90*	0.71*	0.67**	0.81**	0.82**	0.92**	0.79*	0.62*	0.78	1.00	1.23
Build. & Cons.	1.02	1.22	1.23	1.45	1.56	0.73	0.54**	0.67**	0.73**	0.84**	0.94	0.77	0.81	0.87	0.88**
Manufac.	0.99	1.13	1.10	1.11	1.11	0.8*	0.61**	0.59**	0.91	0.92*	0.87*	0.71**	0.63*	0.70*	0.76*
Domestic	0.91	0.92	0.85	1.10	1.02	0.75	0.50**	0.63**	0.68**	1.00	0.78**	0.65**	0.84	1.05	1.24
Export	1.10	1.31	1.13	1.07	1.28	0.79	0.63**	0.79*	0.73**	0.84**	0.86	0.72*	0.96	1.09	1.26
Supp. To Oil	0.89*	0.90*	0.99	1.15	1.26	0.94	0.84	0.84*	0.73**	0.91*	1.15	1.15	1.22	1.24	1.25
Public sector	0.93	1.01	0.97	0.90	0.85	0.97	0.81*	0.82*	0.88	0.79**	1.15	1.17	1.07	0.93	0.86
Services	1.04	1.15	1.14	1.15	1.16	0.78*	0.55**	0.75*	0.89	1.51	0.82**	0.60**	0.51**	0.60**	0.65**
Services–B2C	1.05	1.06	1.03	1.14	1.25	0.87	0.66**	0.68**	0.64**	0.82**	0.88*	0.89	1.02	1.10	1.29
Services–B2B	1.00	1.09	1.01	0.97	0.82	0.71*	0.65*	0.57**	0.82*	1.17	0.76**	0.68**	0.84	0.96	1.03
Retail trade	0.90	0.94	0.81	0.94	0.78*	0.73*	0.57**	0.74**	1.04	1.05	0.91	0.85	1.07	1.31	1.55
FC-EW	0.89	0.86	0.84	0.98	0.97	0.71**	0.54**	0.66**	0.69**	0.88**	0.80**	0.67**	0.76*	0.89**	0.99*
FC-MSPE	0.88	0.82	0.79	0.92	0.89	0.70**	0.52**	0.63**	0.66**	0.86**	0.79**	0.63**	0.68**	0.80**	0.87**
ALL	1.06	1.33	1.32	1.43	1.53	0.69*	0.57**	0.76**	0.8**	0.98*	0.85*	0.63**	0.74	0.95	1.03
FC-D-MSPE	0.91**	0.94**	0.96**	0.94**	0.96**	0.86**	0.89**	0.86**	0.90**	0.96**	0.89**	0.89**	0.99	1.05	1.02

Note: See note in Table A4.

Table A6: Relative RMSPE of Model A using the factors estimated from dynamic factor models over five horizons for Swedish Business Tendency Survey.

	CPI-ATE inflation					GDP growth					Unemployment				
	h=0	h=1	h=2	h=3	h=4	h=0	h=1	h=2	h=3	h=4	h=0	h=1	h=2	h=3	h=4
Manufacture	1.01	1.04	1.14	1.31	1.57	0.86*	0.79*	1.02	1.33	1.66	0.72**	0.62**	0.67**	0.81**	1.05
Construction	1.05	1.05	1.06	1.09	1.18	0.91	0.69*	0.93	1.11	1.32	0.85**	0.75**	0.71**	0.73**	0.87
Trade	0.98	0.97	1.03	1.13	1.23	1.04	0.68*	0.62*	0.78*	1.13	0.88	0.90	0.93	0.98	1.03
FC-EW	1.00	1.01	1.06	1.16	1.32	0.90	0.66*	0.79*	1.03	1.28	0.72**	0.63**	0.65**	0.76**	0.92**
FC-MSPE	1.00	1.01	1.06	1.14	1.28	0.89	0.65*	0.70*	0.92*	1.22	0.71**	0.60**	0.62**	0.74**	0.91**
ALL	1.01	1.01	1.08	1.21	1.33	0.96	0.73*	0.81	1.14	1.65	0.70**	0.68**	0.70**	0.76**	0.93
FC-D-MSPE	0.96**	0.97*	1.02	1.07	1.15	0.83*	0.64*	0.69*	0.84*	1.01	0.71**	0.58**	0.59**	0.70**	0.85**

Note: See note in Table A4.

Table A7: Relative RMSPE of Model B using the factors estimated from dynamic factor models over five horizons for Swedish Business Tendency Survey.

	CPI-ATE inflation					GDP growth					Unemployment				
	h=0	h=1	h=2	h=3	h=4	h=0	h=1	h=2	h=3	h=4	h=0	h=1	h=2	h=3	h=4
Manufacture	1.01	1.04	1.14	1.31	1.57	0.86*	0.79*	1.02	1.33	1.66	0.78**	0.58**	0.63**	0.80**	1.04
Construction	1.05	1.05	1.06	1.09	1.18	0.91	0.69*	0.93	1.11	1.32	0.85**	0.75**	0.71**	0.73**	0.87
Trade	1.03	1.00	1.02	1.09	1.67	0.78	0.83	0.62	0.60	0.71*	0.88*	0.72**	0.71**	0.85	0.59**
FC-EW	0.97	0.99	1.02	1.12	1.44	0.70**	0.63*	0.71	0.91	1.12	0.77**	0.57**	0.56**	0.64**	0.70**
FC-MSPE	0.97	0.99	1.02	1.10	1.38	0.68**	0.63*	0.60	0.68	0.85*	0.77**	0.54**	0.56**	0.64**	0.59**
ALL	1.01	1.01	1.08	1.21	1.33	0.99	0.93	0.65*	1.05	1.59	0.79*	0.64**	0.63**	0.74**	0.93*
FC-D-MSPE	0.96**	0.97*	1.02	1.07	1.15	0.83*	0.64*	0.69*	0.84*	1.01	0.71**	0.58**	0.59**	0.70**	0.85**

Note: See note in Table A4.