2011 | 04

Working Paper

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ISSN 1502-8143 (online)
ISBN 978-82-7553-602-8 (online)

Forecasting Macroeconomic Variables using Disaggregate Survey Data*

Kjetil Martinsen[†], Francesco Ravazzolo[‡], and Fredrik Wulfsberg[§]

Norges Bank

April 7, 2011

Abstract

We assess the forecast ability of Norges Bank's regional survey for inflation, GDP growth and the unemployment rate in Norway. We propose several factor models based on regional and sectoral information given by the survey. The analysis identifies which information extracted from the ten sectors and the seven regions performs particularly well at forecasting different variables and horizons. Results show that several factor models beat an autoregressive benchmark in forecasting inflation and unemployment rate. However, the factor models are most successful in forecasting GDP growth. Forecast combinations based on past performance give in most cases more accurate forecasts than the benchmark, but they never give the most accurate forecasts.

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

JEL Categories: C53; C80.

*We thank Knut Are Aastveit, Raffaella Giacomini, James Mitchell, Christian Kascha, Shaun Vahey and seminar participants at Norges Bank for helpful comments. The views expressed in this paper are our own and do not necessarily reflect those of Norges Bank.

[†]Contact: Norges Bank, Bankplassen 2, P.O. Box 1179 Sentrum, 0107 Oslo, Norway, Phone No: +47 22 31 61 88, e-mail: kjetil.martinsen@norges-bank.no

[‡]Contact: Norges Bank, Bankplassen 2, P.O. Box 1179 Sentrum, 0107 Oslo, Norway, Phone No: +47 22 31 61 72, e-mail: francesco.ravazzolo@norges-bank.no

[§]Contact: Norges Bank, Bankplassen 2, P.O. Box 1179 Sentrum, 0107 Oslo, Norway, Phone No: +47 22 31 61 62, e-mail: fredrik.wulfsberg@norges-bank.no

Several central banks conduct surveys yielding regional and sectoral information on the general economic outlook. Following the Federal Reserve's Beige Book which has been conducted since 1970, and the Bank of England's Agents which started out 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 rather than quantitative like the well-known Livingston survey, the Michigan survey or the Survey of Professional Forecasters.[1] While it is well documented that quantitative survey information have 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 qualitative surveys (see for example Hansson and Löf (2005), Abberger (2007), Claveria, Pons, and Ramos (2007), Lui, Mitchell, and Weale (2010a) and Lui, Mitchell, and Weale (2010b)).

This paper attempts to investigate the forecast ability of the qualitative information from the Norges Bank regional survey on key macroeconomic variables: Gross domestic product (GDP) growth; consumer price inflation and the unemployment rate. Norges Bank regional survey consists of both backward and forward looking questions. Survey participants possibly respond to questions with this in mind and therefore all the information in the survey should be used in the evaluation of its forecasting ability. Our approach differs from Abberger (2007), Claveria et al. (2007), Lui et al. (2010a,b) who focus on specific questions for individual macroeconomic variables. We construct sector and region specific indices for the questions in the survey by evaluating the qualitative conjectures for an increase or a decrease in the particular economic activity. Then, following Stock and Watson (2002), we apply a static factor model for each region and each sector using the principal component analysis.[2] Region and sector factors should contain the most relevant information for regions and sectors from where they are extracted.

[1]The Michigan survey is based on interviews with households, whereas both the Livingston survey is based on forecasts made by professional economists as the Survey of Professional Forecasters. All of these surveys have been conducted for more than 40 years on a regular basis, see Thomas (1999) for supplementary information about the surveys. In qualitative survey, interviewers are asked a range of questions to which they provide categorical answers; for example, they are asked whether the output has fallen, stayed the same or risen but not by how much it has changed.

[2]We denote the method of Stock and Watson (2002) as "static" and the method of Forni, Hallin, Lippi, and Reichlin (2000) as "dynamic" as is common in the literature (see for instance Boivin and Ng, 2005, p. 2).

We investigate both a model with only one factor and a model with up to four factors. We address the issue of small common components (see the discussion in Boivin and Ng (2005)) by computing the average indices with common characteristics, and use this new dataset to perform the same analysis.

A similar study is Hansson and Löf (2005) who apply a dynamic factor model (as defined in footnote 2) based on net balance indices[3] from the Swedish Business Tendency Survey to forecast the Swedish GDP. They find that their factor models outperform popular alternatives as VAR models and other indicators of economic activities in most cases. We extend their analysis in at least three directions. First, we consider a more comprehensive survey in terms of sectors and regions of the economy of interest, following the claims in Beck, Hubrich, and Marcellino (2009) that highly disaggregate regional and sectorial information is important in explaining aggregate Euro area and US inflation rates. Our results identify which of ten sectors and seven regions that perform particularly well at forecasting different variables and horizons. Second, we mitigate the uncertainties in the construction of factors, the number of the factors and the relation to the variable of interest by investigating four different classes of factor models where factors are extracted from the full dataset or by averaging questions and the number of factors is fixed *a priori* (denoted model A) or estimated via a selection criterion (model B). Finally, we apply forecast combinations to cope with 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 variable of interest. Averaging these forecasts thus combines information from different datasets.

We find that the factor models based on several regions and sector systematically beat the benchmark in forecasting inflation and unemployment rate. Unemployment, however, seems to be the most difficult variable to forecast and only using the factors estimated from the full dataset outperform the benchmark. When forecasting inflation, the preferred factor estimation approach is to combine model A with the average dataset. When forecasting GDP growth, all factor models perform well. Forecast combinations

[3]Net balance indices represent differences between the shares of firms that have specified an increase and a decrease of a particular economic activity.

based on past performances provide more accurate forecasts than the benchmark for all variables, but they are never more accurate than the best regional or sectoral model. However, they provide an insurance against selecting inappropriate models.

The paper continues as follows: Section 1 describes the data; Section 2 outlines the static factor model used in our analysis; Section 3 presents the full-sample results while Section 4 explains the forecasting models and discusses the forecasting results. Finally, Section 5 concludes.

1 The Norges Bank Regional Survey

In 2002, Norges Bank established a regional network of enterprizes, organizations and local authorities throughout Norway. By interviews with its contacts, Norges Bank gets 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 sectorial dividing the country into $R = 7$ regions: Inland, Mid-Norway, North, North-West, South, South-West and East, and $S = 10$ sectors: building and construction, manufacturing (including the subsectors of domestically-oriented manufacturing, export industry and suppliers to the oil industry), public sector, services (with the subsectors: household services (B2C) and corporate services (B2B)) and retail trade.[4] All sectors and subsectors are represented in each region apart from the suppliers to the oil industry, which is not represented in the Inland and North regions.

The interviews consist of $Q = 11$ questions in total, see Table 1. However, all questions are not addressed to all sectors, see Table 2. Note in particular that the manufacturing sector is asked different questions than its subsectors of domestically-oriented manufacturing, export industry and suppliers to the oil industry, and similarly for services and its subsectors B2C and B2B. In total there are 60 combinations of questions and sectors. Some questions are backward looking and some are forward looking.

For each question, Norges Bank maps the responses on a scale which ranges from -5 to $+5$, where $+1$ corresponds to an annualized quarterly growth of 1–3 percent, and $+5$

[4] 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 network only concentrate on the developments and activities for the mainland economy, while the primary industries are strongly regulated and do not necessarily reflect the developments of the business cycle.

Table 1: 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 2: 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	×	×	×	×	×	×	×	×	×	×	×

corresponds to a growth of more than nine 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 next twelve months, are conducted in a different manner. For the question concerning labor supply, the survey asks whether the firm or contact thinks the labor supply will be a limiting factor for production or turnover if there is a rise in demand. We compute the difference between the number of contacts who answer 'yes' and 'no' as a fraction. Contacts are also asked about the 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 rise in demand. We calculate 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 total contacts within each sector and region. Finally, the last variable to be calculated, concerns the retail prices over the past and the next 12 months. The contacts are asked whether they did change and think 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 for 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 ($r = 1, \ldots, 7$), 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 2) apart from regions Inland and North which have 54 variables due to the absence of the suppliers to the oil industry. For each sector the number of variables varies between 77 for retail trade (11 questions $\times$ 7 regions) and 20 for suppliers to the oil industry (4 questions $\times$ 5 regions).[5]

The asymptotic theory of principal components assumes that the cross-correlation of the series is not too large, and that the common component is not too small. If a set of

[5]Grouping all the information in a unique dataset results in 777 variables. In this case, estimation uncertainty is very large and information whether some regions or sectors are leading economy is lost. This provides less accurate forecasts as we show in section 4.1.

series correlates between them, but do not correlate with other series or sets of series, a grouping of the regional network questions might be favorable for the forecasting performance, see for example discussion in (Boivin and Ng, 2006). Examining the results from the questions on a weighted national level, there is a high correlation among a number of series.[6] Studying the correlations between series, we thus create new datasets, $(\bar{X}^r, \bar{X}^s)$, with only two questions ($\bar{Q}_1$ and $\bar{Q}_2$) where $\bar{Q}_1$ is the average of the questions about output, market prospects, capacity utilization, investments, labor supply and profitability, and $\bar{Q}_2$ is the average of employment over the past three months, employment over the next three months, annual wage growth, product prices over the past twelve months and product prices over the next twelve months. The total number of variables in $\bar{X}^r$ is now 20 (= 2 questions $\times$ 10 sectors) for each region and in $\bar{X}^s$ there are 14 (= 2 questions $\times$ 7 regions) variables for each sector.[7] The forecasts using the different datasets are evaluated against each other.

Since the start in 2002, there have been between four to six rounds of interviews each year. In total, our data is based on 41 interview rounds, with the last round carried out in November 2010. 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 34 quarters, from 2002Q3 to 2010Q4. 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 24 observations for each sector and region.

[6] Martinsen and Wulfsberg (2009) created a dynamic set of weights to optimally aggregate the regional and sectoral results of the regional survey.

[7] A different approach would be similarly to Lui et al. (2010a) to test whether each variable in the region or sector of the regional survey provides signal or noise to the macroeconomic variable to be forecasted and average only variables with positive information. The shortness of our sample does not allow first to test properly the assumption and then produce in a pseudo real-time exercise forecasts.

2 A Static Factor Model

More available information on economic activity and more disaggregated information make factor models a very attractive approach of 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 estimation errors resulting on more accurate forecasts.

In the literature on macroeconomic forecasting using large datasets, there are two factor models which are most commonly used: the static model of Stock and Watson (2002) and the dynamic model of Forni et al. (2000). Among others, Artis, Banerjee, and Marcellino (2005), Matheson (2006) and Cheung and Demers (2007) find that the static model performs as good as, or better than, more elaborate models. Forni et al. (2000) point out that the model of Stock and Watson (2002) only focus on contemporaneous covariances in datasets, and thus that it "[...] fails to exploit the potentially crucial information contained in the leading-lagging relations between the elements of the panel" (Forni et al., 2000, p. 2).[8] However, as Forni et al. (2000) also report, it is difficult to establish *a priori* a measure of any empirical relative performance between the two models and there is no clear-cut strategy of which factor model to choose. We decide to apply the static model of Stock and Watson (2002) which is easier to implement and estimation errors in the dynamic factor increase substantially with a short dataset like ours. The advantage of the static representation of the approximate factor model is that the factors can be estimated using principal components and are thus easy to compute.

Let X_t^j be an N-dimensional multiple time series of variables from region or sector j, observed for $t = 1, \dots, T$. X_{it}^j is the observation for variable i at time t. X_t^j then admits a static linear factor representation with $\overline{\rho}$ common factors, f_t^j, if:

$$X_{it}^j = \lambda_i(L) f_t^j + e_{it}^j \tag{1}$$

for $i = 1, \dots, N$, where $e_t^j = (e_{1t}^j, \dots, e_{Nt}^j)'$ is the $N \times 1$ idiosyncratic disturbance term

[8] Banerjee, Marcellino, and Masten (2003); Giacomini and White (2006); Kapetanios and Marcellino (2004); Schumacher and Dreger (2004); Schumacher (2007); Eickmeier and Ziegler (2008) support this conclusion.

and $\lambda_i(L)$ is a lag polynomial in nonnegative powers of L. An important modification of the model can be made by assuming that the lag polynomial $\lambda_i(L)$ is modeled as having finite orders of at most q. The finite lag assumption allows us to rewrite the model as:

$$X_t^j = \Lambda F_t^j + e_t^j, \tag{2}$$

where $F_t^j = (f_{1t}^j, \ldots, f_{\rho t}^j)'$ is $\rho \times 1$, and where $\rho \leq (q+1)\overline{\rho}$. 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. Because F_t^j and e_t^j are uncorrelated for all lags and leads, Σ_{XX}^j is simply a sum of two parts, one part from the common factors, and one part from the idiosyncratic errors: $\Sigma_{XX}^j = \Lambda \Sigma_{FF}^j \Lambda' + \Sigma_{ee}^j$, where Σ_{FF}^j and Σ_{ee^j} are the variance matrices of F_t^j and e_t^j, respectively. Under sufficient assumptions on the variance matrices and the $\rho \times \rho$ matrix, $\Lambda'\Lambda$, the first ρ principal components of X^j can be treated as estimators of Λ. Thus, in the sample, $\hat{\Lambda}$ is set to be the first ρ eigenvectors of $\hat{\Sigma}_{XX}^j$, and the factors can then be estimated as $\hat{F}_t^j = \hat{\Lambda}' X_t^j$, which is the vector of the first ρ principal components of X_t^j, see (Stock and Watson, 2006). Reasoning in the same manner, the factors from the averaged dataset can be estimated as: $\hat{\bar{F}}_t^j = \hat{\Lambda}' \bar{X}_t^j$.

When estimating the factor model we must take account of the four questions which were not available until 2005Q1 (see above). To handle this issue the factors are first estimated from 2002Q3 to 2004Q3 using the available series, and then a new estimation of the factors for the time span 2004Q4 to 2010Q4 using all variables included in X^j.[9] The factors are then concatenated to series ranging over the full sample, i.e. from 2002Q3 to 2010Q4.[10]

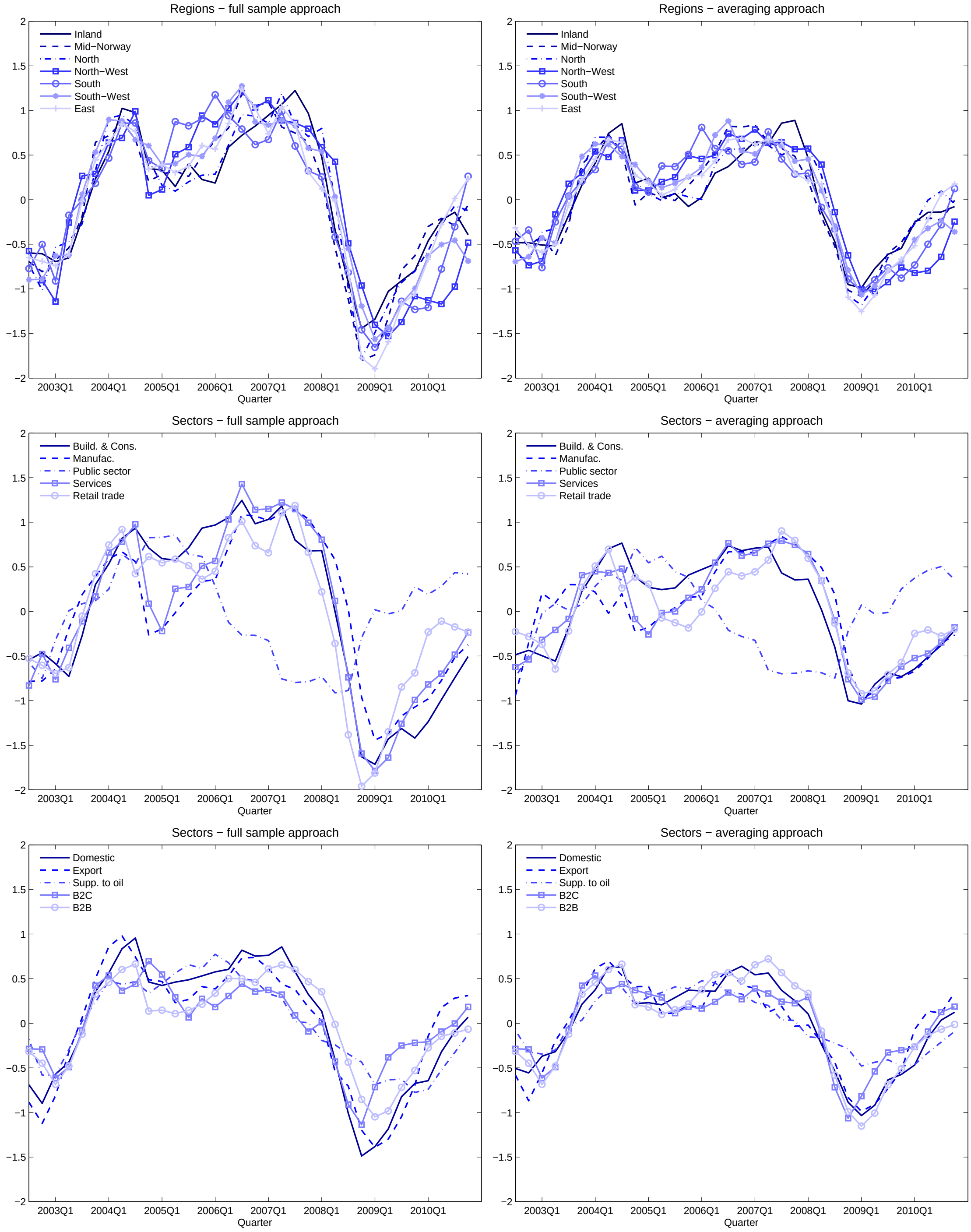
3 The Regional and Sectoral Factors

For each region or sector we can extract up to ρ factors, where ρ is fixed *a priori*. For both datasets, (X^r, X^s) and $(\bar{X}^r, \bar{X}^s)$, the first factor seems to explain on average about 60 percent of the variation in the datasets. The marginal contribution of the second factor

[9] The reason why the sample is split after 2004Q3, is because the results of the first interview round in 2005 is given a weight of 2/3 when calculating the results of the fourth quarter of 2004.

[10] An alternative way would be an unbalanced estimation approach in dynamic factor models as in Banbura and Modugno (2010).

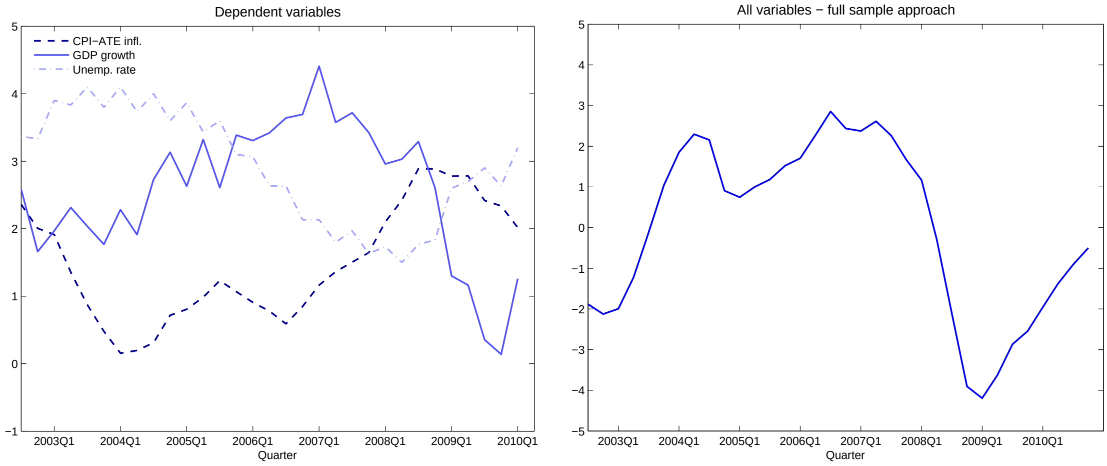
Figure 1: Plots of the first factor for all regions and sectors, for both the full dataset (left column) and the dataset with averaged dataset (right column).



is around 15 percent. When we include five factors, these explain almost 80 percent. There is little variation between the different sectors and regions in this respect.

Figure 1 displays plots of the first factor for each region and sector for both datasets, f_{1t}^{j} in the left panel and $\bar{f}_{1t}^{j}$ in the right. The regional factors (top panel) show the same

Figure 2: CPI-ATE inflation, GDP growth and the unemployment rate (left), and the first factor derived from all variables (right).



pattern for all the seven regions. The factors estimated from the dataset with averaged questions ($\bar{f}^r_{1t}$) seem to vary somewhat less over time than f^r_{1t}. The middle and bottom panels in Figure 1 show the first factors for each sector (f^s_{1t} and $\bar{f}^s_{1t}$). There is more variation between the sectorial factors than the regional ones because the former are based on different variables within each sector, see Table 2. The factors for building and construction, manufacturing, public sector, services and retail trade plotted in the middle panel are based on a larger set of variables. The public sector differs from the other ones surging sharply during the recent financial crises while the factors for the other sectors decline. The factors for the subsectors in manufacturing and services which are plotted in the bottom panel, are based on a smaller set of variables, see Table 2, and show less variation. Common for all factors are that there is less variation over time for $\bar{f}^s_{1t}$ than for f^s_{1t}.

Figure 2 plots the three variables we aim to forecast in the left panel: year-on-year logarithmic CPI-ATE inflation, year-on-year logarithmic GDP growth and unemployment rate. CPI-ATE is the consumer price index adjusted for taxes and energy prices. Norway was in expansion from end of 2002 to 2007 with increasing GDP growth and decreasing unemployment rate after 2006. From the start of the Great Recession in 2008 we notice an increase in the unemployment rate and a sharp decrease in GDP growth. Inflation decreased to almost zero percent during the initial two years of the sample, but then increased to around two percent. GDP growth is the most volatile variable. The right

Table 3: Correlations in absolute values between the dependent variables and the regional first factors from the full dataset, X^r, and from the dataset with averaged questions, $\bar{X}^r$.

	Inflation		GDP *growth*		*Unemployment*	
Region	f^r	$\bar{f}^r$	f^r	$\bar{f}^r$	f^r	$\bar{f}^r$
1 Inland	0.74	0.70	0.66	0.63	0.03	0.09
2 Mid-Norway	0.83	0.76	0.63	0.66	0.08	0.05
3 North	0.77	0.73	0.65	0.62	0.02	0.08
4 North-West	0.68	0.66	0.78	0.77	0.08	0.12
5 South	0.82	0.78	0.72	0.73	0.13	0.03
6 South-West	0.77	0.76	0.72	0.70	0.01	0.03
7 East	0.83	0.79	0.70	0.71	0.06	0.02
Regional average	0.78	0.74	0.69	0.69	0.06	0.06

panel shows the first factor derived from all variables which summarizes all the regional and sectoral factors. We recognize the pattern from Figure 1 and the strong correlation with the business cycle is striking.

Table 3 reports (absolute) correlation coefficients between the regional factors (f^r_{1t} and $\bar{f}^r_{1t}$) and the macro variables. On average, the factors estimated from the full datasets have a correlation of .78 with inflation, .69 with GDP growth and .06 with the unemployment rate. The factors estimated from the datasets with averaged questions, are on average slightly less correlated.

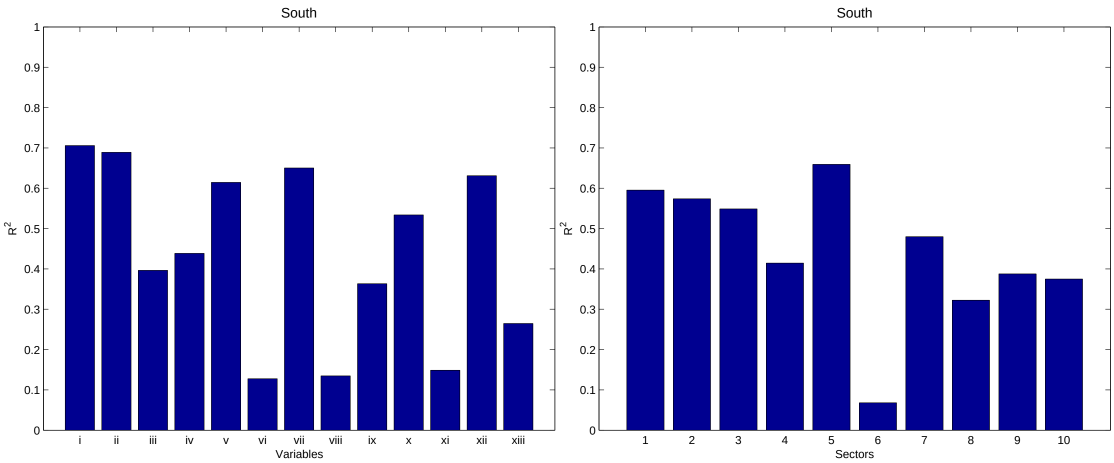
As expected from Figure 1 there is much more variation in the similar correlation coefficients among the sectors than among the regions, see Table 4. The factor for the export industry has a correlation coefficient with inflation of .91, while the public sector has a correlation coefficient of .52. Services – B2C has a correlation coefficient .77 with GDP growth while the public sector has a correlation coefficient of .20, and the factors are generally uncorrelated with unemployment apart from the public sector which shows strong correlation with unemployment. The fiscal stimulus implemented by the Norwegian government during the recent crises may explain this correlation.

To extract more information from the composition of each factor, we can analyze which variables, within each sector or region, contribute most to each factor. We regress each variable, X^j_{it} ($\bar{X}^j_{it}$) on a constant and the first factor, f^j_{1t} ($\bar{f}^j_{1t}$). A significant t-statistic and correspondingly high R^2 indicates that the variable is an important component of the

Table 4: Correlations in absolute values between the dependent variables and the first factor of sectors from the full dataset, X^s, and from the dataset with averaged questions, $\bar{X}^s$.

	Inflation		GDP *growth*		*Unemployment*	
Sector	f^s	$\bar{f}^s$	f^s	$\bar{f}^s$	f^s	$\bar{f}^s$
1 Building and cons.	0.73	0.76	0.77	0.72	0.01	0.00
2 Manufacturing	0.59	0.47	0.77	0.74	0.24	0.28
3 Domestically-oriented manuf.	0.87	0.86	0.65	0.68	0.14	0.09
4 Export industries	0.91	0.90	0.57	0.55	0.19	0.21
5 Suppliers to oil ind.	0.79	0.78	0.68	0.69	0.21	0.18
6 Public sector	0.52	0.48	0.20	0.28	0.70	0.69
7 Services	0.71	0.61	0.75	0.74	0.11	0.23
8 Services – B2C	0.87	0.84	0.40	0.50	0.33	0.17
9 Services – B2B	0.77	0.79	0.69	0.67	0.04	0.00
10 Retail trade	0.81	0.57	0.60	0.65	0.11	0.20
Sectoral average	0.76	0.71	0.61	0.62	0.21	0.21

Figure 3: R^2 of regression of X^5 (resp. $\bar{X}^5$) on a constant and f_1^5 (resp. $\bar{f}_1^5$) for each 10 sectors in region South. The corresponding plots for the other regions are displayed in Figure A1 and A2 in the appendix.



factor, and can thus be interpreted as a driving force of that factor (Stock and Watson, 1998). A significance level of 1% implies a critical value of .189 for the R^2 when there are 34 observations as in our case.[11] Figure 3 presents R^2 for the region South as an example. We see in the left panel that the R^2 for variables vi, viii, and xi are insignificant, and in

[11]The 1% critical value of the t-statistic and R^2 with 24 observations is 2.80 and .262, which is relevant for variables v, ix, x, and xi. We 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 .218; manufacturing .226; domestically-oriented manufacturing .203; export industry .203, suppliers to the oil industry .189; public sector .218; services .216; B2C .213; B2B .213; and retail trade .215.

Table 5: The upper panel summarizes the results for the regions in Figure 3 and A1 and the lower panel reports the results for the sectors in Figure 3 and A3. A "Y" indicates that the factor loads significantly, "N" indicates that the factor does not load significantly, and "-" indicates that the factor is not relevant for the region or sector. Critical value for R^2 at the 1% level with 34 observations is 0.189.

	Loads sectors										*Loads variables**										
Region	1	2	3	4	5	6	7	8	9	10	i	ii	iii	iv	v	vi	vii	viii	ix	x	xi
1 Inland	Y	Y	Y	Y	-	N	Y	Y	Y	Y	Y	Y	N	Y	Y	N	Y	Y	Y	Y	N
2 Mid-Norway	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N
3 North	Y	Y	Y	Y	-	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N
4 North-West	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
5 South	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y	Y	N
6 South-West	Y	Y	Y	Y	Y	N	Y	N	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N
7 East	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N

	Loads regions							*Loads variables*										
Sector	1	2	3	4	5	6	7	i	ii	iii	iv	v	vi	vii	viii	ix	x	xi
1 Building & const.	Y	Y	Y	Y	Y	Y	Y	Y	Y	-	Y	Y	Y	Y	Y	Y	Y	N
2 Manufacturing	Y	Y	Y	Y	Y	Y	Y	-	-	Y	Y	Y	Y	-	-	Y	Y	-
3 Dom. oriented manuf.	Y	Y	Y	Y	Y	Y	Y	Y	Y	-	-	-	-	Y	N	-	-	N
4 Export industry	Y	Y	Y	Y	Y	Y	Y	Y	Y	-	-	-	-	Y	Y	-	-	N
5 Supp. to oil industry	-	Y	-	Y	Y	Y	Y	Y	Y	-	-	-	-	Y	-	-	-	-
6 Public sector	Y	Y	Y	Y	N	Y	Y	-	-	N	N	N	Y	-	-	Y	-	-
7 Services	Y	Y	Y	Y	Y	Y	Y	-	Y	Y	Y	Y	N	Y	-	Y	Y	-
8 Services – B2C	Y	Y	Y	Y	Y	N	Y	Y	-	-	-	-	-	-	N	-	-	N
9 Services – B2B	Y	Y	Y	Y	Y	Y	Y	Y	-	-	-	-	-	-	N	-	-	N
10 Retail trade	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	N	N	N

Note: * See Table 1.

the right panel we see that the R^2 for the public sector is insignificant.

Figures A1–A4 in appendix A plot R^2 for each of the other regions and all sectors. Table 5 gives an overview of which sectors and questions are important for the regional factors (top panel), and which regions and questions are important for the sectorial factors (bottom panel). Likewise, the lower panel reports which regions and variables in each sector yield a significant R^2 at the 1% level. From the top panel of Table 5 we see that all regions load sectors 1–5, 7, 9 and 10, and that only North-West loads the public sector (sector 6). Furthermore, we see that all regions load questions i, ii, iv, v, vii, ix, and x. Only North-West loads variables vi (wage growth) and no region loads variable xi (product price next 12 months). From Figure A1 we see that variable i (output) and ii (market prospects) generally have R^2s between .50–.70 in all regions, while vii (profitability), ix (labor supply), v (employment over the next three months), and x (capacity utilization) also score high R^2s in most regions.

Turning to the bottom half of Table 5 we see that all regions affect the first factor for all sectors apart from South for the public sector and South-West for services – B2C. The public sector loads only variables vi (wage growth) and ix (labor supply). No sector loads variable xi (product price next 12 months). Building and construction, manufacturing and services seem to be the sectors that, overall, have the highest R^2s, see Figure A3 and A4 in the appendix. Also, the subsectors of manufacturing: domestic-oriented, export, and suppliers to the oil industry report high R^2s for all regions, and the available variables (see Table 2). As was the case for regional factors output, market prospects, profitability, labor supply, employment over the next three months, and capacity utilization score R^2s around 0.70 in most cases.

4 Forecasting

The final aim of this paper is to forecast CPI-ATE inflation, GDP growth and the unemployment rate up to four quarters ahead using the regional survey. CPI-ATE is the consumer price index adjusted for taxes and energy prices. The series is seasonally adjusted by X-12-ARIMA, and is transformed into quarterly frequency before we calculate the logarithmic yearly growth rate. GDP is the adjusted basic values of mainland Norway and is made stationary by calculating the yearly logarithmic growth, as is the CPI-ATE. For unemployment, we use register based unemployment by the end of the month (in percent), transformed into a quarterly series. All data are collected from the Statbank of Statistics Norway.[12] We split the sample in two periods. The period 2002Q3 to 2006Q4 is used as in-sample period, and the period 2007Q1 to 2010Q4 is our forecasting period. Our experiments are pseudo real-time exercise as we do not consider real-time data for CPI-ATE inflation, GDP and unemployment but use the 2011Q1 vintage of data.

We produce nowcast of the current quarter in addition to one, two, three, and four quarter ahead forecasts. Regional survey data is available at the end of the second month of the quarter and we use them in nowcasting and forecasting, see equations (4)–(5).[13]

[12] http://statbank.ssb.no/

[13] The shortness of our dataset constraints the number of forecasts. Testing statical difference seems

We compare two different factor models with a benchmark, which is an autoregressive forecast model excluding any factors. We denote the h-step-ahead forecast of the dependent variable y^h_{t+h}, where $h = 0, \ldots, 4$. The lag length of the dependent variable is chosen by the Schwartz's Bayesian Information Criterion (BIC) and is restricted to be between zero and four:

$$y_{t+h} = \gamma_0 + \gamma_1(L)y_{t-1} + \varepsilon_{t+h}. \tag{3}$$

Thus, the largest model includes a constant and four lags of the dependent variable, while the smallest only includes a constant. The BIC selects 3, 1, and 2 lags respectively for CPI-ATE inflation, GDP and unemployment. All the forecasts are based on h-step-ahead direct linear projections. Marcellino, Stock, and Watson (2006) compare direct versus iterative forecasts and Patton and Timmermann (2010) propose tests for rationality on multi-horizon forecasts.

The first factor model, *Model A*, includes the first factor in addition to lags of the dependent variable:

$$y^A_{t+h} = \alpha_0 + \alpha_1 \tilde{f}_{j,t} + \alpha_2(L)y_{t-1} + \varepsilon^A_{j,t+h}. \tag{4}$$

where $\tilde{f}_{j,t}$ is the first factor for region or sector j from the full sample, $f_{j,t}$ or from the averaged sample, $\bar{f}_{j,t}$. We restrict the model to have between zero and four lags of the first factor, and zero and four lags of the dependent variable as in the benchmark. We choose the lag structure by minimizing the BIC criterion.

The second and more general factor model, *Model B*, includes from one to five contemporaneous factors in addition to lags of the dependent variable:

$$y^B_{t+h} = \beta_0 + \beta_1\tilde{F}_{j,t} + \beta_2(L)\, y_{t-1} + \varepsilon^B_{j,t+h}. \tag{5}$$

β_B is a $1 \times \rho$ vector, and $\tilde{F}_{j,t}$ is a $\rho \times 1$ vector of factors for region or sector j, either based on the full sample, $\tilde{F}_{j,t} = F_{j,t}$, or the averaged sample, $\tilde{F}_{j,t} = \bar{F}_{j,t}$. The number of factors, ρ, and the lags of the AR-term are again determined by BIC, where the smallest model only consists of a constant and the first factor and the largest model includes four

also uninformative with such a short out-of-sample period.

lags of y_t and five contemporaneous factors.

To summarize, for each dependent variable (inflation, GDP growth, and unemployment) at each point in time, we produce 17 sets of h-step-ahead forecasts for each model A and B, using both the full and averaged sample, i.e. 17 (regions and sectors) $\times$ 2 (models) $\times$ 2 (datasets) $\times$ 5 (horizons) $=$ 340 different sets of forecasts in addition to the benchmark forecasts. When forecasting the same variable using different information sets and forecasting models, it is possible to combine them in order to extract all the available information on the variable to be predicted in order to possibly produce a better forecast. Timmermann (2006), and references therein, give several reasons for why a combination of individual forecasts may be favorable. The most relevant arguments for this paper, aside from the portfolio diversification argument, are that individual forecasts might be differently affected by structural breaks, and thus a combination of the forecasts will outperform the individual ones. Also, forecasting models might be subject to an unknown misspecification bias (for example, related to the region or sector individual models are constructed), and a combination of the forecasts can be seen as more robust method against such biases. In empirical studies, forecast combinations have been found to outperform individual forecasts, even when the combinations are based on more simple rules for pooling the individual forecasts (again see Timmermann, 2006, and the references therein). Bjørnland, Gerdrup, Jore, Smith, and Thorsrud (2009) find that model combination outperforms Norges Banks own point forecast for Norwegian inflation.

Instead of considering factor models and forecast combinations as competitive methods in forecasting, we propose to unite these approaches. For each class of models (A and B) and of factors (from the full sample or the average sample factors), we combine forecasts from the 17 region and sector different models at time t for horizon h as

$$\tilde{y}^i_{j,t+h} = \sum_{j=1}^{17} w_{j,t+h} y^i_{j,t+h} \tag{6}$$

where $i = A$, B. We consider two different weight schemes to investigate the advantages of the forecast combinations. The first, and also the simplest way of combining forecasts, is to assign equal weights to the individual forecasts, $w_{j,t+h} = 1/17$, 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 forecasts sum of prediction squared errors:

$$w_{j,t+h} = \frac{1/\text{MSPE}^h_{j,t}}{\sum_{i=1}^{17}\left(1/\text{MSPE}^h_{i,t}\right)} \tag{7}$$

where $\text{MSPE}^h_{j,t}$ is the mean squared prediction error for region or sector j for forecast up to time t and horizon h. Forecasts that have relatively low MSPEs are thus assigned a higher weight in the combination than forecasts with relatively high MSPE's. We denote this forecast combination method as FC-MSPE.

4.1 Forecasting Results

We evaluate forecasting performance by comparing the root mean squared prediction error (RMSPE) from each factor model with the RMSPE from the benchmark model. Tables C2–C7 in the appendix report the RMSPE of all the factor models relative to the RMSPE of the benchmark model for the three dependent variables. Also, the results of both forecast combination methods, FC-EW and FC-MSPE, are reported at the bottom of each table. Before proceeding, we should note that due to the extremely small out-of-sample sample size (which is maximum 17 observations for h=0) we make no attempts to test for statistical significance across prediction errors. Tests for statistical significance across prediction errors are often based on asymptotic assumptions which are not relevant for our sample. Instead we investigate systematic patterns in how often and by how much the factor based forecasts outperform the benchmark model. The volatility of the three variables is different, see Figure 2. Therefore, relative gains cannot be compared among the three variables to forecast.

One of the clear benefits of having disaggregated data, is that it is possible to isolate which regions and sectors that forecast the dependent variables well. Table 6 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, horizons, and datasets, and the success rate defined as the fraction of times a factor based forecast beats the benchmark, by regions and sectors as reported in Tables C2–C7. For example,

Table 6: The median relative RMSPE and the success rate of factor models relative to benchmark by regions and sectors. The number of factor based relative RMSPEs for each region and sector is 20.

	Inflation		GDP growth		Unemployment	
Region	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
1 Inland	0.96	0.55	0.95	0.65	1.08	0.30
2 Mid-Norway	0.95	0.60	0.80	0.85	0.86	0.70
3 North	1.02	0.40	0.89	0.65	1.10	0.30
4 North-West	0.96	0.60	0.85	0.80	1.21	0.20
5 South	0.96	0.60	0.80	1.00	1.02	0.30
6 South-West	0.99	0.50	0.80	0.85	0.99	0.50
7 East	1.05	0.30	0.78	0.85	0.94	0.50
Sector						
1 Building and construction	0.99	0.55	0.78	0.95	0.99	0.55
2 Manufacturing	1.06	0.30	1.06	0.40	1.19	0.20
3 Domestically-oriented manuf.	0.97	0.55	0.74	0.90	0.89	0.65
4 Export industry	0.97	0.50	0.78	0.90	1.36	0.20
5 Suppliers to the oil industry	1.08	0.30	0.85	1.00	1.16	0.05
6 Public sector	0.96	0.55	0.97	0.70	1.06	0.25
7 Services	1.07	0.40	0.88	0.60	1.06	0.45
8 Services–B2C	1.10	0.05	0.86	0.75	1.16	0.40
9 Services–B2B	0.94	0.65	0.82	0.80	0.98	0.50
10 Retail trade	1.00	0.55	0.91	0.65	1.04	0.50

55 percent of the factor model forecasts for the Inland region beat the benchmark in forecasting inflation. The median RMSPE is .96 implying that, on average, the gain from forecasting inflation using factors from the Inland region is 4 percent relative to the benchmark. Furthermore, we see that the factor model forecasts for Mid-Norway outperform the benchmark in more than 60 percent of the cases, for all three variables. All regions and sectors (apart from manufacturing) outperform the benchmark when forecasting GDP growth. Several regions and sectors provide more accurate forecasts for inflation than the benchmark with service – B2B the most accurate. However, the gains are generally smaller than for GDP growth. The finding is consistent with the fact that no factors load product-price next 12 months and only North-West loads wage growth (see Table 5). Mid-Norway is the only region and domestically-oriented manufacturing is the only sector which factor based forecasts for unemployment systematically outperform the benchmark model with success rates of .70 and .65. The factor for public sector performs

Table 7: The median relative RMSPE and the success rate of factor based forecasts relative to the benchmark by model A and B, dataset (X^j and $\bar{X}^j$), and horizons ($h = 0 - h = 4$). The number of relative RMSPEs for each model and dataset is 170 and for each horizon is 68.

	Inflation		GDP growth		Unemployment		All variables	
	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
A	0.97	0.62	0.85	0.75	1.05	0.40	0.96	0.59
B	1.05	0.32	0.85	0.82	1.07	0.37	0.99	0.50
X^j	1.04	0.35	0.83	0.83	1.04	0.45	0.97	0.54
$\bar{X}^j$	0.98	0.58	0.87	0.74	1.09	0.32	0.98	0.55
h=0	0.96	0.63	0.84	0.94	0.91	0.78	0.90	0.78
h=1	1.02	0.47	0.78	1.00	0.92	0.66	0.90	0.71
h=2	1.04	0.44	0.79	0.88	1.08	0.32	0.97	0.55
h=3	1.08	0.38	0.85	0.78	1.20	0.09	1.04	0.42
h=4	1.09	0.41	1.05	0.31	1.27	0.07	1.13	0.26

poorly despite the high correlation it has with unemployment (Table 4), suggesting it lags the real economy. A high contemporaneous correlation does not provide information whether the public sector forecasts unemployment accurately.

Table 7 reports how models A and B, as well as the two datasets (X^j and $\bar{X}^j$) perform relative to the benchmark at all horizons. Overall, the model A forecasts beat the benchmark about 59 percent of the time while Model B outperforms the benchmark 50 percent of the time. Model A and B give the highest gain when forecasting GDP growth with a success rate of 75 and 82 percent and a gain in RMSPE of 15 percent; while model A performs well in forecasting inflation with a success rate of 62 percent and a gain of 3 percent relative to the benchmark. The full and average dataset approaches perform slightly better than the benchmark overall. They are both significantly better when forecasting GDP growth while only the average approach is better than the benchmark in forecasting inflation, however, the gain is modest (2 percent). When forecasting unemployment the factor models outperform the benchmark only at shorter horizons (h=0 and h=1), confirming evidence in Zaher (2007) that factor models based on large information sets do not provide accurate long horizon forecasts for this variable. For inflation, the factor models are only better when nowcasting, while for GDP growth the factor models are better for $h = 0 - 3$. Looking at the more detailed results reported in Table B1 in the appendix reveals that factor forecasts using model A and the average data approach

Table 8: Median relative RMSPE and success rate of the forecast combinations FC-EW and FC-MSPE by variable, models, and dataset. The number of factor based relative RMSPEs for each variable is 20 and for each model and dataset is 15.

	FC-EW		FC-MSPE	
	RMSPE	S-rate	RMSPE	S-rate
Inflation	0.89	0.90	0.83	0.95
GDP growth	0.82	0.85	0.80	0.95
Unemployment	0.94	0.55	0.88	0.65
Model A	0.84	0.77	0.82	0.80
Model B	0.90	0.77	0.86	0.90
Full dataset	0.90	0.80	0.84	0.90
Average dataset	0.89	0.73	0.85	0.80

outperform the benchmark when forecasting inflation at all horizons with a success rate of .79 even at h=4.

The performance of the forecast combinations FC-EW and FC-MSPE are summarized in Table 8. The weighted forecast combinations (FC-MSPE) do systematically better than the benchmark when forecasting all variables. The gain is largest when forecasting GDP growth with a median relative RMSPE of .80. The equal weighted forecast combination (FC-EW) does significantly better than the benchmark for inflation and GDP growth. Model A and B outperform the benchmark for both forecast combinations. Furthermore, both forecast combinations using the full and average dataset outperforms the benchmark. However, comparing the performance of the forecast combinations to the performance of regional and sectoral forecasts in Table 6 we see that several of the individual forecasts seems to do better, even if there is not a superior factor model for all horizons and variables. Therefore, forecast combinations mitigate model uncertainty and provide insurance against selecting inappropriate models.[14]

Finally, we also investigate models where factors are constructed from a unique dataset which groups all the region and sector information. The bottom rows in Tables C2–C7, labeled "All", reports the associated RMSPE results. Forecasts based on these factors are never more accurate than the best individual factor model, and in only

[14]It would be interesting to compare *ex-ante* selection of the best model against model combination. Our short sample size limits interpretation of results from a similar exercise and we leave it for future research.

9 cases over 60 their RMSPEs are marginally smaller than those provided by the weighted forecast combinations (FC-MSPE). Therefore, grouping all the information in our dataset and discarding regional and sector information does not seem the direction to follow to maximize forecast accuracy, confirming preliminary evidence in Figure 1.

5 Concluding Remarks

This paper propose a factor model approach to forecast macroeconomic variables using information from large qualitative surveys where questions can be very different and refer to disaggregate information of the variables of interest. We apply our methodology to Norges Bank regional survey data. We find several interesting results. First, regarding the factor estimation based on the approximate factor model of Stock and Watson (2002), the first factor usually explain around 60 percent of the variation in the datasets. Including as much as five factors, these explain on average approximately 80 percent of the variation. Therefore, the factor model approach seems to be an effective way of handling the dimensional issue of the regional survey and the differences in its questions.

Secondly, it is indeed possible to isolate which regions and sectors that perform well, and show that it is feasible to exploit the disaggregate information that is contained in the survey-based network. The type of factor model which should be used, based on the full dataset approach or averaging approach depends on the specific variable of interest, but only using model A in combination with the factors estimated from the average dataset outperform the benchmark for inflation at longer horizons. Forecast combinations yield accurate forecasts, but they are never more accurate than the best regional or sectoral model. However, they provide an insurance against selecting inappropriate models.

The out-of-sample forecasting exercises are conducted using a relatively short sample of data. As the regional network interview rounds are carried out four times a year, it will be interesting to follow the development of the forecast results in the future.

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Appendix A: Additional Figures

Figure A1: Average R^2 of regressions of X^r (resp. $\bar{X}^r$) on a constant and f_1^r (resp. $\bar{f}_1^r$) for regions except South (see Figure 3) by variable. Critical value for R^2 at 1% level with 34 observations is 0.189.

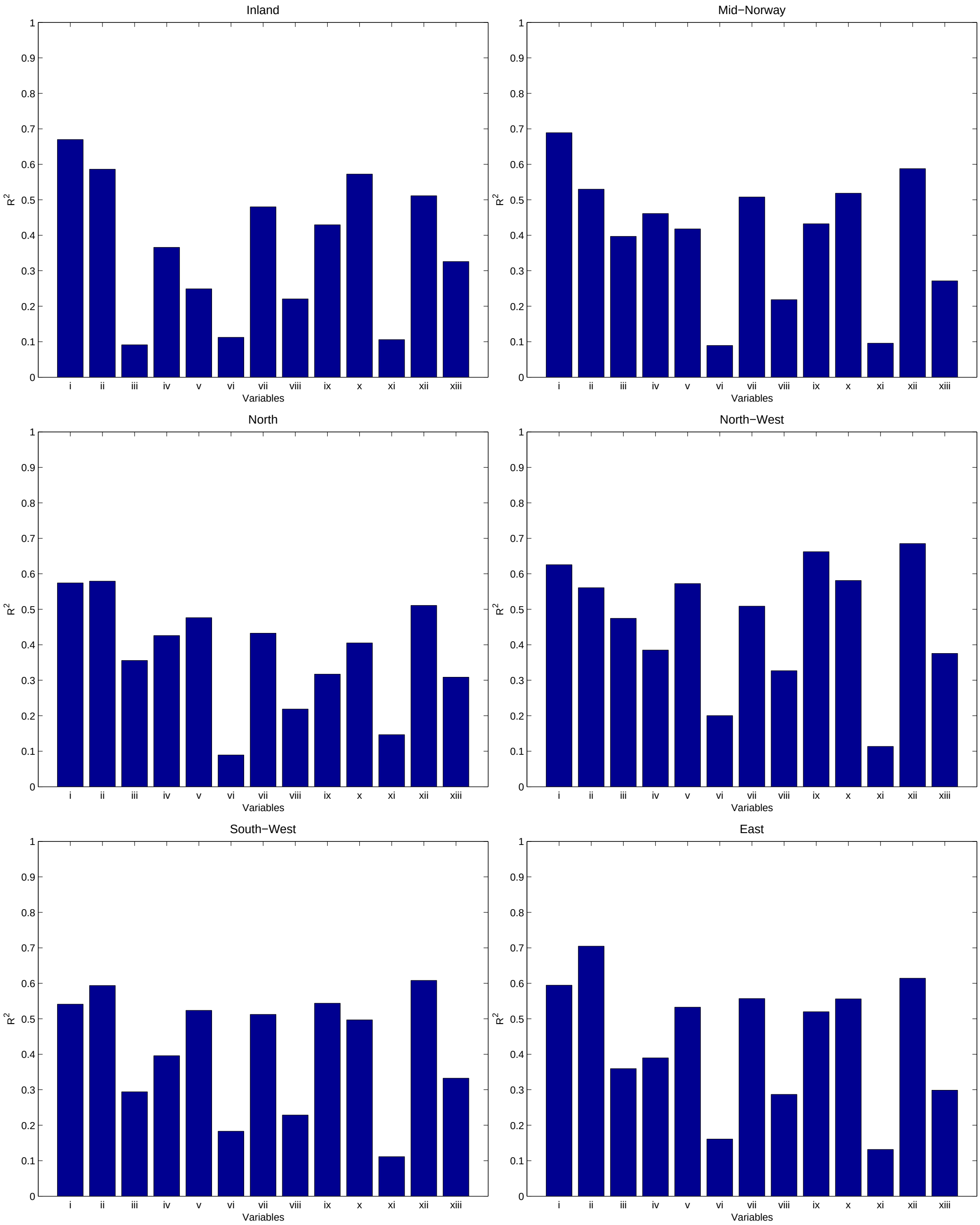


Figure A2: Average R^2 of regressions of X^r (resp. $\bar{X}^r$) on a constant and f_1^r (resp. $\bar{f}_1^r$) for regions except South (see Figure 3) by sector. Critical value for R^2 at 1% level with 34 observations is 0.189. When data is not available $R^2 = 0$.

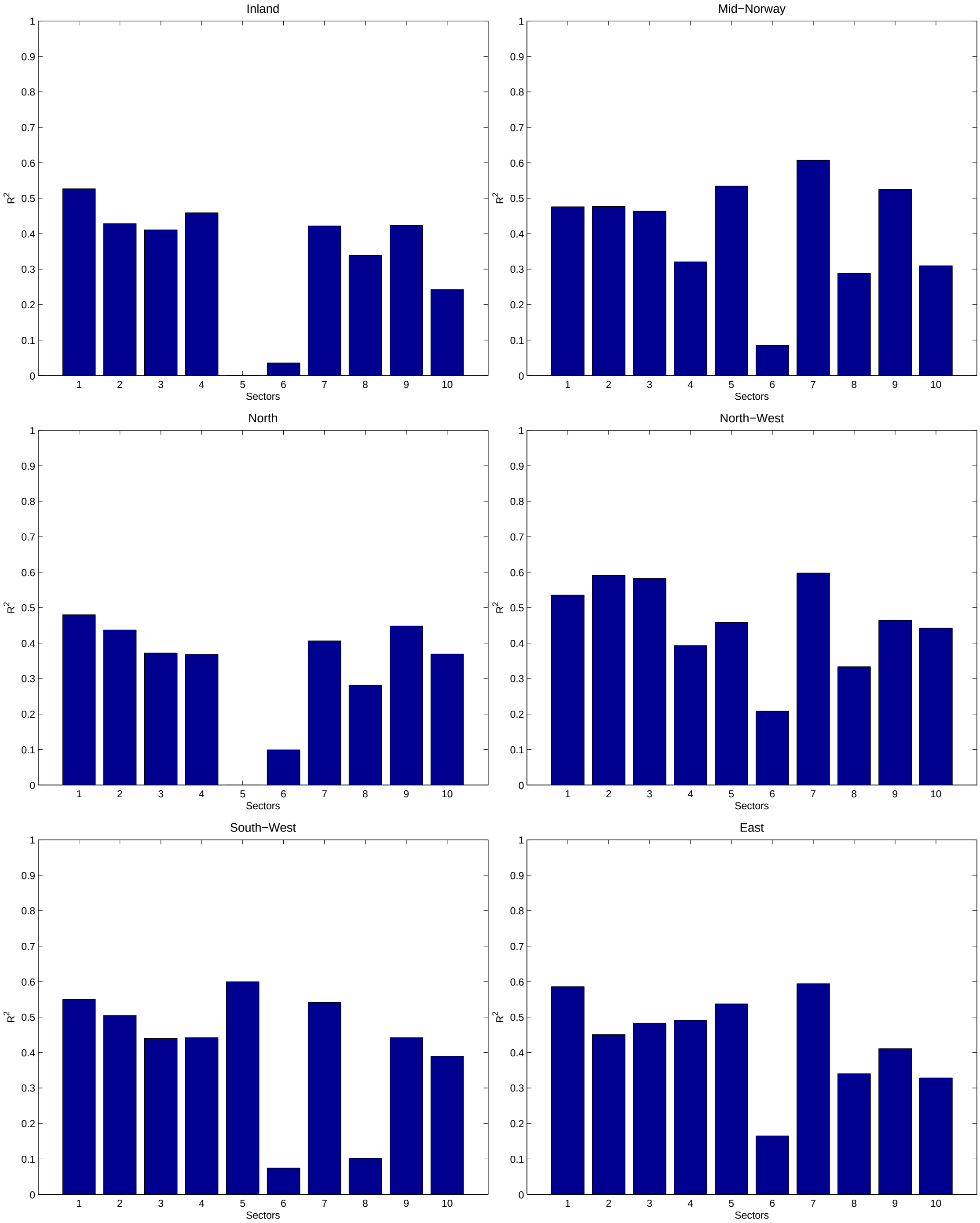
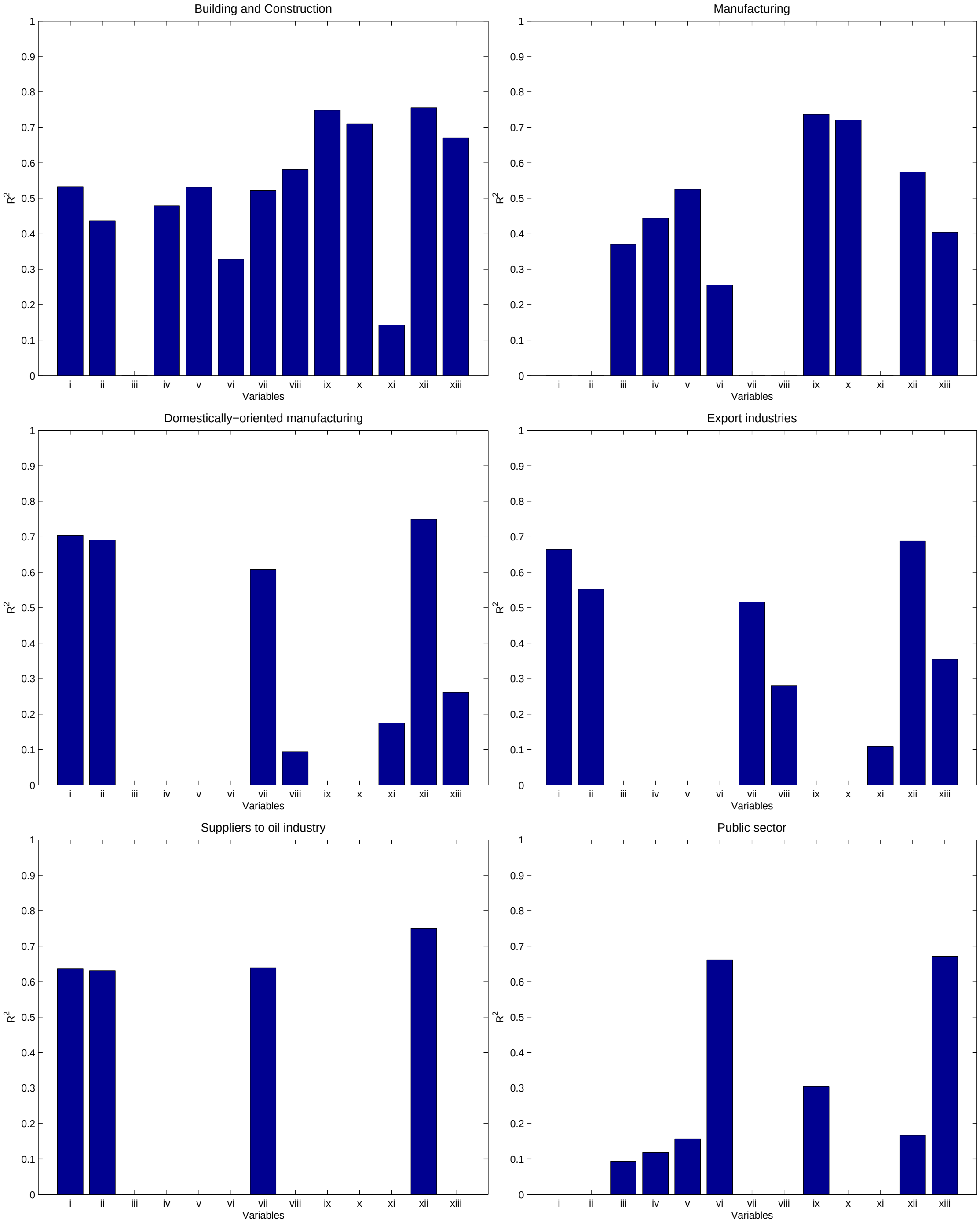


Figure A3: Average R^2 of regression of X^s (resp. $\bar{X}^s$) on a constant and f_1^s (resp. $\bar{f}_1^s$) for sectors by variable. Critical value for R^2 at 1% level with 34 observations is 0.189. When data is not available $R^2 = 0$.



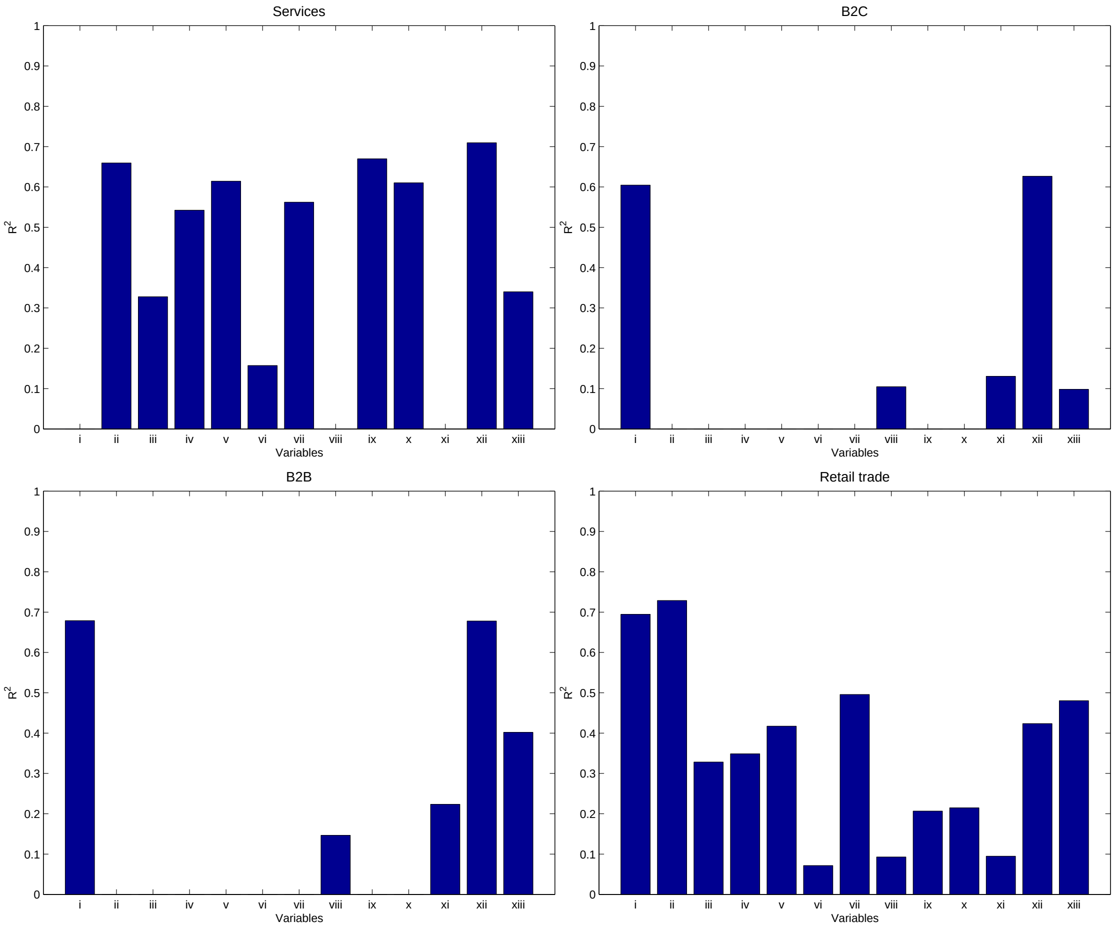
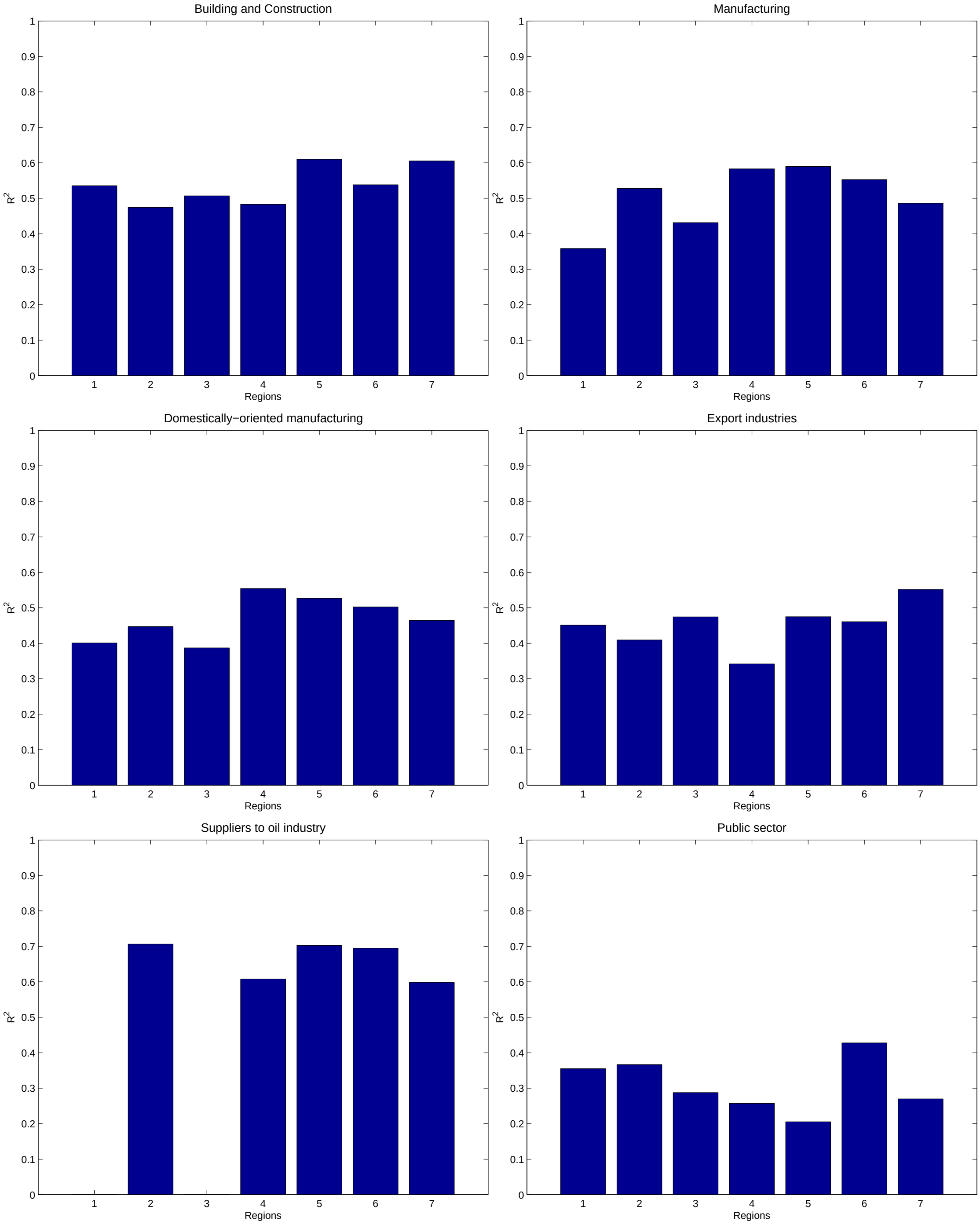
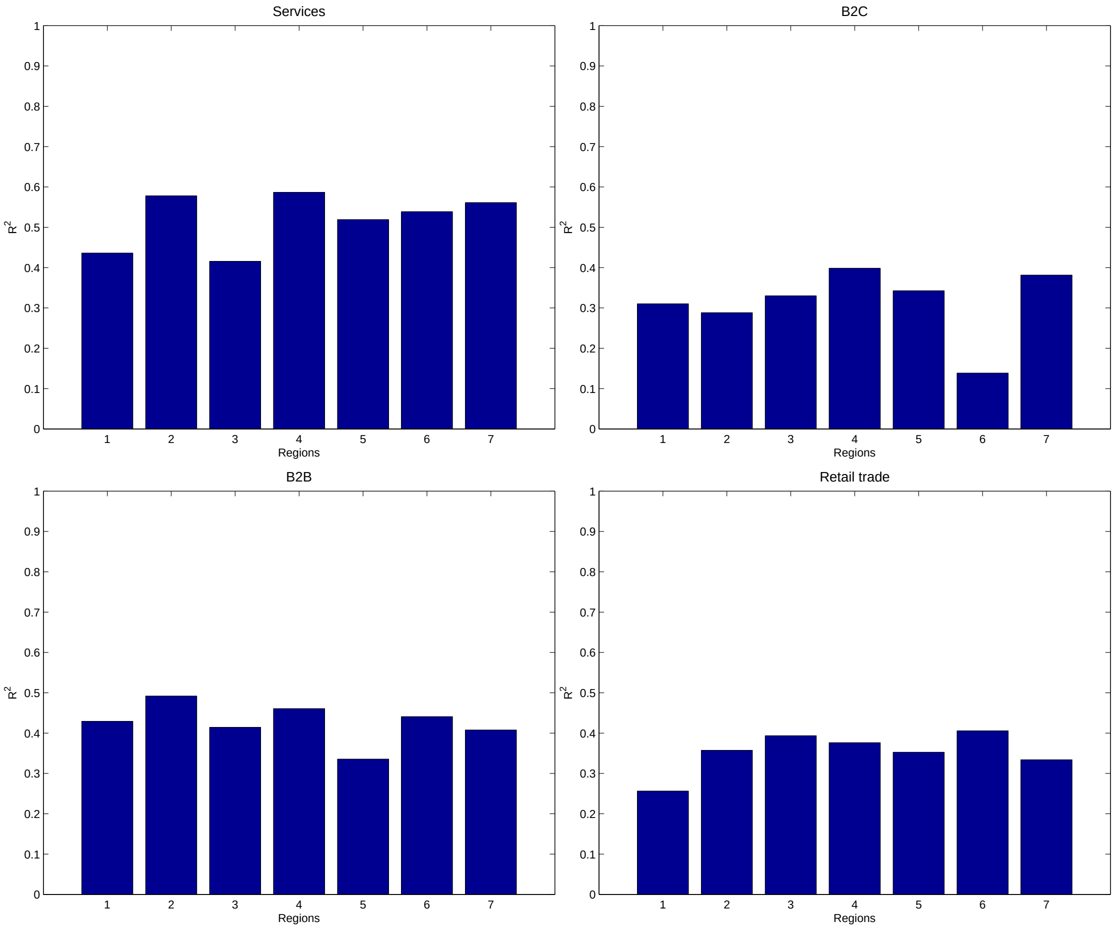

Services
B2C
B2B
Retail trade
R^2
Variables
i
ii
iii
iv
v
vi
vii
viii
ix
x
xi
xii
xiii
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Figure A4: Average R^2 of regressions of X^s (resp. $\bar{X}^s$) on a constant and f_1^s (resp. $\bar{f}_1^s$) for sectors by region. Critical value for R^2 at 1% level with 34 observations is 0.189. When data is not available $R^2 = 0$.





Services
B2C
B2B
Retail trade
R^2
Regions
1
2
3
4
5
6
7
0
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0.8
0.9
1

Appendix B: Forecasting performance of models, datasets and horizons

Table B1: The median relative RMSPE and the success rate of factor based forecasts relative to the benchmark by model A and B, dataset (X^j and $\bar{X}^j$), and horizons ($h = 0 - h = 4$). The number of relative RMSPEs for each model and dataset at each horizon is 19.

	Inflation				GDP growth				Unemployment			
	X^j		$\bar{X}^j$		X^j		$\bar{X}^j$		X^j		$\bar{X}^j$	
	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate	RMSPE	S-rate
							h=0					
A	0.96	0.79	0.91	0.84	0.83	0.95	0.84	0.95	0.88	0.84	0.89	0.89
B	1.01	0.42	0.95	0.32	0.86	0.95	0.83	0.95	0.90	0.74	0.89	0.47
							h=1					
A	1.01	0.47	0.95	0.79	0.77	1.00	0.79	1.00	0.89	0.84	0.96	0.58
B	1.05	0.37	1.01	0.47	0.74	1.00	0.78	1.00	0.82	0.74	0.96	0.63
							h=2					
A	1.04	0.42	0.94	0.74	0.71	0.95	0.83	0.84	0.96	0.58	1.11	0.16
B	1.07	0.32	0.98	0.53	0.74	0.95	0.84	0.84	1.00	0.47	1.16	0.21
							h=3					
A	1.00	0.47	0.87	0.74	0.82	0.84	0.88	0.74	1.11	0.11	1.18	0.00
B	1.17	0.16	1.12	0.37	0.78	0.95	0.88	0.68	1.16	0.26	1.23	0.05
							h=4					
A	0.97	0.53	0.83	0.79	1.04	0.21	1.14	0.11	1.20	0.05	1.15	0.05
B	1.22	0.37	1.12	0.37	0.95	0.63	1.05	0.37	1.24	0.16	1.27	0.05
							All horizons					
A	0.99	0.54	0.92	0.78	0.82	0.79	0.86	0.73	1.01	0.48	1.08	0.34
B	1.07	0.27	1.01	0.47	0.83	0.89	0.86	0.77	1.02	0.47	1.09	0.34

Appendix C: Relative RMSPE Tables

Table C2: Relative RMSPE of Model A and the benchmark for CPI-ATE inflation over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.96	1.05	1.13	1.09	0.96	0.94	0.95	0.91	0.83	0.66
Mid-Norway	0.99	1.06	1.08	1.06	1.11	0.90	0.92	0.92	0.87	0.77
North	1.03	1.04	0.99	0.98	0.80	0.97	0.97	0.86	0.71	0.53
North-West	0.80	0.93	0.89	0.84	0.93	0.88	0.95	0.96	0.95	0.98
South	1.01	1.03	1.08	1.20	1.38	0.93	0.96	0.89	0.93	0.96
South-West	0.84	0.87	0.87	0.96	0.96	0.82	0.82	0.79	0.82	0.76
East	0.99	1.06	1.01	0.99	1.12	1.02	0.96	0.95	0.81	0.76
Build. & Cons.	1.07	1.21	1.17	1.19	1.21	0.94	0.95	0.97	0.98	0.99
Manufac.	0.97	0.87	0.77	0.66	0.51	1.04	1.20	1.46	1.62	1.67
Domestic	0.82	0.96	1.08	1.17	1.30	0.82	0.93	1.06	1.12	1.17
Export	0.83	0.71	0.82	0.91	0.91	0.91	0.92	0.87	0.86	0.83
Supp. To Oil	0.86	0.95	1.07	1.28	1.43	0.90	1.01	1.09	1.21	1.32
Public sector	0.96	1.01	1.04	1.00	0.86	0.95	1.02	1.05	1.04	0.87
Services	0.85	1.03	1.16	1.18	1.19	0.89	0.86	0.75	0.60	0.48
Services–B2C	1.10	1.09	1.07	1.15	1.25	1.02	1.10	1.18	1.15	1.14
Services–B2B	0.89	0.88	0.90	0.83	0.78	0.93	0.95	0.96	0.90	0.88
Retail trade	0.99	1.16	1.42	1.57	1.52	0.90	0.89	0.93	0.69	0.73
FC-EW	0.83	0.84	0.90	0.95	0.96	0.83	0.80	0.82	0.81	0.77
FC-MSPE	0.81	0.81	0.86	0.87	0.81	0.82	0.79	0.78	0.73	0.63
All	0.87	0.84	0.89	0.95	1.04	0.89	0.81	0.81	0.81	0.80

Note: A value less than 1 indicates that the factor model forecast beats the benchmark.

Table C3: Relative RMSPE of Model A and the benchmark for GDP growth over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.94	0.86	0.96	1.01	1.25	0.86	0.89	0.99	1.06	1.20
Mid-Norway	0.78	0.55	0.44	0.65	1.04	0.83	0.75	0.83	0.94	1.16
North	0.82	0.80	0.84	1.04	1.31	0.86	0.86	0.96	1.04	1.32
North-West	0.84	0.79	0.83	0.83	1.02	0.83	0.85	0.94	0.97	1.12
South	0.91	0.78	0.71	0.68	0.81	0.87	0.81	0.79	0.80	0.92
South-West	0.74	0.78	0.78	0.93	1.30	0.82	0.75	0.78	0.88	1.05
East	0.72	0.63	0.64	0.78	1.03	0.78	0.71	0.79	0.92	1.14
Build. & Cons.	0.89	0.73	0.68	0.69	0.89	0.84	0.76	0.77	0.84	1.05
Manufac.	0.81	0.86	1.01	1.12	1.29	0.84	0.97	1.19	1.30	1.47
Domestic	0.77	0.71	0.64	0.71	1.00	0.76	0.68	0.68	0.80	1.03
Export	0.89	0.74	0.73	0.82	1.08	0.90	0.73	0.75	0.83	1.11
Supp. To Oil	0.93	0.89	0.89	0.79	0.77	0.92	0.85	0.84	0.75	0.77
Public sector	1.06	0.89	0.69	0.85	1.48	1.12	1.00	0.68	0.83	1.79
Services	0.83	0.72	0.75	0.89	1.14	0.83	0.87	1.01	1.15	1.34
Services–B2C	0.86	0.72	0.66	0.76	1.03	0.81	0.77	0.83	0.87	1.22
Services–B2B	0.83	0.77	0.89	0.89	1.16	0.82	0.73	0.82	0.84	1.14
Retail trade	0.79	0.80	0.62	0.96	1.02	0.89	0.93	1.05	1.14	1.24
FC-EW	0.77	0.71	0.70	0.78	1.05	0.82	0.79	0.83	0.89	1.14
FC-MSPE	0.76	0.69	0.64	0.75	0.99	0.81	0.77	0.79	0.85	1.08
All	0.79	0.71	0.69	0.74	1.07	0.84	0.80	0.87	0.92	1.17

Note: see footnote in Table C2.

Table C4: Relative RMSPE of Model A and the benchmark for the unemployment rate over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.88	0.96	1.15	1.24	1.20	0.92	1.01	1.16	1.18	1.08
Mid-Norway	0.76	0.52	0.65	0.98	1.15	0.84	0.92	1.11	1.20	1.15
North	0.83	0.95	1.19	1.25	1.14	0.89	1.05	1.22	1.17	1.01
North-West	0.98	1.02	1.17	1.27	1.31	0.99	1.08	1.25	1.34	1.36
South	1.02	0.92	0.94	1.00	0.96	1.02	0.96	1.01	1.09	1.08
South-West	0.87	0.83	0.96	1.22	1.35	0.87	0.87	1.02	1.32	1.46
East	0.84	0.73	0.86	1.11	1.24	0.84	0.82	1.02	1.28	1.36
Build. & Cons.	1.00	0.89	0.97	1.06	1.06	0.88	0.81	0.93	1.09	1.12
Manufac.	0.91	0.98	1.11	1.14	1.09	0.96	1.24	1.37	1.41	1.26
Domestic	0.85	0.73	0.84	1.10	1.23	0.81	0.76	0.91	1.13	1.21
Export	0.96	0.93	1.05	1.44	1.60	1.13	1.09	1.58	1.67	1.72
Supp. To Oil	1.04	1.21	1.44	1.42	1.24	0.99	1.10	1.17	1.21	1.19
Public sector	1.00	1.03	0.92	1.05	1.07	0.95	0.96	1.06	1.08	1.07
Services	0.83	0.71	0.85	1.08	1.12	0.92	1.05	1.24	1.25	1.13
Services–B2C	0.92	0.91	1.16	1.52	1.73	0.85	0.86	1.17	1.32	1.55
Services–B2B	0.84	0.83	1.01	1.25	1.32	0.79	0.75	0.92	1.18	1.27
Retail trade	0.90	0.72	0.77	1.10	1.28	0.97	1.09	1.17	1.09	0.92
FC-EW	0.79	0.75	0.87	1.07	1.15	0.83	0.89	1.05	1.14	1.15
FC-MSPE	0.78	0.70	0.82	1.04	1.10	0.82	0.85	1.01	1.11	1.09
All	0.86	0.76	0.90	1.17	1.30	0.87	0.84	1.05	1.32	1.42

Note: see footnote in Table C2.

Table C5: Relative RMSPE of Model B and the benchmark for CPI-ATE inflation over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	1.00	1.01	0.91	1.03	1.14	0.95	0.96	0.82	1.12	1.21
Mid-Norway	0.97	1.07	1.23	1.46	1.45	0.73	0.67	0.57	0.93	0.81
North	1.05	1.08	1.25	1.25	1.15	1.01	1.04	1.19	1.14	1.02
North-West	0.88	0.92	1.08	1.32	1.36	1.05	1.26	1.51	1.67	1.66
South	1.06	0.86	0.72	0.58	0.76	0.95	0.93	0.98	1.09	1.15
South-West	1.01	1.13	1.23	1.37	1.23	1.01	1.17	1.12	1.13	1.30
East	1.08	1.29	1.32	1.52	1.55	1.01	1.05	1.17	1.20	1.12
Build. & Cons.	1.01	0.96	0.98	1.16	1.13	0.89	1.03	0.92	0.95	0.84
Manufac.	0.93	1.20	1.01	1.07	1.00	1.06	1.29	1.24	1.35	1.28
Domestic	0.93	0.83	0.83	1.01	1.22	0.92	1.10	0.91	0.98	0.93
Export	1.03	1.05	1.12	1.22	1.23	1.02	1.04	1.08	1.15	1.15
Supp. To Oil	0.86	0.95	1.07	1.28	1.43	0.90	1.01	1.09	1.21	1.32
Public sector	0.91	1.04	1.02	0.96	0.97	0.82	0.72	0.55	0.86	1.14
Services	1.04	1.24	1.19	1.21	1.23	0.94	0.89	1.09	1.24	1.11
Services–B2C	1.10	1.09	1.07	1.15	1.25	0.88	1.02	1.09	1.20	1.16
Services–B2B	1.13	1.07	1.02	1.17	1.14	1.06	0.85	0.97	1.06	0.93
Retail trade	1.07	1.37	1.40	1.51	1.64	0.99	1.00	0.92	0.83	0.76
FC-EW	0.89	0.91	0.93	1.05	1.11	0.86	0.88	0.88	0.99	0.97
FC-MSPE	0.88	0.87	0.87	0.94	1.05	0.84	0.82	0.77	0.94	0.91
All	0.97	1.23	0.87	0.80	0.95	0.92	1.14	1.08	0.91	0.93

Note: see footnote in Table C2.

Table C6: Relative RMSPE of Model B and the benchmark for GDP growth over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.87	0.82	0.88	0.93	1.11	0.86	0.89	0.99	1.06	1.20
Mid-Norway	0.85	0.70	0.62	0.65	0.94	0.82	0.73	0.78	0.88	1.13
North	0.88	0.79	0.83	0.95	1.14	0.81	0.78	0.89	1.02	1.21
North-West	0.84	0.79	0.83	0.83	1.02	0.83	0.85	0.94	0.97	1.12
South	0.91	0.78	0.71	0.68	0.81	0.87	0.81	0.79	0.80	0.92
South-West	0.82	0.70	0.68	0.77	0.97	0.82	0.75	0.78	0.88	1.05
East	0.81	0.60	0.62	0.72	0.94	0.78	0.65	0.76	0.87	1.06
Build. & Cons.	0.89	0.73	0.68	0.69	0.89	0.85	0.75	0.75	0.80	0.99
Manufac.	0.81	0.86	1.01	1.12	1.29	0.84	0.97	1.19	1.30	1.47
Domestic	0.88	0.72	0.68	0.69	0.88	0.83	0.67	0.69	0.76	0.95
Export	0.78	0.68	0.72	0.78	0.95	0.76	0.67	0.74	0.81	0.97
Supp. To Oil	0.93	0.89	0.89	0.79	0.77	0.92	0.85	0.84	0.75	0.77
Public sector	1.01	0.98	0.99	0.96	0.81	1.01	0.97	0.96	0.94	0.81
Services	0.83	0.72	0.75	0.89	1.14	0.83	0.87	1.01	1.15	1.34
Services–B2C	0.89	0.85	0.79	0.88	1.07	0.90	0.79	0.84	1.02	1.15
Services–B2B	0.81	0.72	0.79	0.86	1.07	0.82	0.70	0.73	0.80	1.03
Retail trade	0.90	0.74	0.63	0.67	0.85	0.89	0.93	1.05	1.14	1.24
FC-EW	0.84	0.75	0.74	0.77	0.95	0.82	0.78	0.84	0.90	1.05
FC-MSPE	0.84	0.73	0.71	0.74	0.91	0.82	0.76	0.81	0.86	1.00
All	0.84	0.70	0.69	0.74	0.97	0.81	0.74	0.82	0.90	1.09

Note: see footnote in Table C2.

Table C7: Relative RMSPE of Model B and the benchmark for the unemployment rate over five horizons. Left panel reports the results using the factors from the full datasets, X_t^j, while the right panel reports results using the factors estimated from the averaged datasets, $\bar{X}_t^j$.

	X^j					$\bar{X}^j$				
	h=0	*h=1*	*h=2*	*h=3*	*h=4*	*h=0*	*h=1*	*h=2*	*h=3*	*h=4*
Inland	0.91	0.77	1.07	1.24	1.48	0.92	1.01	1.16	1.18	1.08
Mid-Norway	0.76	0.52	0.65	0.98	1.15	1.03	0.88	0.73	0.75	0.70
North	0.83	0.95	1.19	1.25	1.14	0.89	1.05	1.22	1.17	1.01
North-West	0.98	1.02	1.17	1.27	1.31	0.99	1.08	1.25	1.34	1.36
South	1.06	1.15	1.03	1.39	1.11	1.02	0.96	1.01	1.09	1.08
South-West	0.87	0.83	0.96	1.22	1.35	0.87	0.87	1.02	1.32	1.46
East	0.84	0.73	0.86	1.11	1.24	0.84	0.82	1.02	1.28	1.36
Build. & Cons.	0.93	0.87	1.00	1.14	1.09	0.88	0.81	0.93	1.09	1.12
Manufac.	1.00	0.94	1.11	1.40	1.45	1.12	1.35	1.66	1.82	1.81
Domestic	0.87	0.56	0.67	0.98	1.31	0.81	0.76	0.91	1.13	1.21
Export	1.12	1.27	1.82	2.22	2.01	0.83	0.98	1.22	1.49	1.66
Supp. To Oil	1.18	1.18	1.24	1.15	1.11	1.10	1.08	1.13	1.09	1.09
Public sector	1.18	1.29	1.19	1.04	0.98	0.99	1.15	1.20	1.23	1.19
Services	0.84	0.61	0.60	0.67	0.74	1.07	1.15	1.56	1.86	2.05
Services–B2C	0.90	0.82	1.03	1.19	1.42	0.85	0.86	1.17	1.32	1.55
Services–B2B	0.82	0.76	0.96	1.28	1.44	0.83	0.93	1.19	1.45	1.61
Retail trade	0.90	0.72	0.77	1.10	1.28	0.94	0.98	1.24	1.35	1.83
FC-EW	0.79	0.68	0.78	1.00	1.09	0.84	0.89	1.05	1.20	1.27
FC-MSPE	0.78	0.61	0.69	0.91	0.99	0.82	0.85	0.97	1.08	1.06
All	0.86	0.76	0.90	1.17	1.30	0.87	0.84	1.05	1.32	1.42

Note: see footnote in Table C2.