

A SHORT-TERM SECTORAL-BASED ANTICIPATORY SYSTEM FOR LABOUR MARKET TRENDS AND SKILL NEEDS

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Introduction & Motivation

- Labour markets are a key component of modern economies and welfare systems
- CEDEFOP has an elaborate methodology for anticipating the long term evolution of labour market trends, based on structural modelling
- A shorter term perspective provides a useful complement, with a view to anticipating and possibly smoothing cyclical fluctuations in labour related variables

Introduction & Motivation

- The short term forecasting literature is generally focused on macroeconomic indicators, such as GDP or inflation.
- A small number of studies is concerned with forecasting labour market variables.
- Even in these few studies, the focus is in general on “policy & implication scenarios” rather than “econometric forecasting & policy making”. Moreover, typically a sectoral and cross-country evaluation is missing

Introduction & Motivation

- We select well established methods from the short term macroeconomic forecasting literature and apply them to a very large set of EU labour market (employment) series, disaggregated by sectors and countries.
- First, univariate methods that exploit the persistence in the dynamic evolution of each variable. The most common approaches are:
 - Autoregressive (AR) models
 - ARMA models.
- Simple, robust and generally well performing. But other information can be useful -> multivariate approaches.

Introduction & Motivation

- To summarize the macroeconomic info to be used in the employment forecasting models, we employ three variable reduction methods:
 - Static Principal Components Analysis (PC),
 - Partial Least Squares (PLS),
 - Bayesian Shrinkage Regression (BR).
- Related literature on variable reduction methods in macroeconomic forecasting: Stock and Watson (2002a,b), Marcellino, Stock and Watson (2003), Bruggerman et al. (2003), Forni et al. (2005), De Mol et al. (2006), Alvarez et al. (2012), Kapetanios et al. (2012a,b,c) etc.

Introduction & Motivation

- Forecasting exercise using the direct (projection) method. More robust in the presence of misspecification (Marcellino, Stock and Watson (2006))
- Data sample 1998-2012. Forecast horizons: from 1- to 4-quarter ahead.
- A set of macroeconomic variables comparable across countries is used in the multivariate models, in combination with the variable reduction methods.
- Role of seasonal dummies is also assessed.

Methodology: PC

- The assumption is that the co-movements across the many macro indicators can be captured by a factor model, where each variable is driven by few unobservable common factors and an idiosyncratic term.
- The factors can be estimated by principal components (PC), and inserted in the forecasting equations for employment (Stock and Watson (2002a)).
- Dynamic PC are an alternative (Forni et al. (2000)) but static PC is a more effective and robust technique.
- Settings: 1, 2, 3 and 4 factors.

Methodology: PLS

- Similar to PC: factors are used, instead of the original variables, as regressors, Wold (1982).
- Factors are linear combinations of the original regression variables.
- Difference between PC and PLS: in PLS the relationship between dependent and independent variables is considered in constructing the factors.

Estimation: PLS

- PLS regression not explicitly considered for data sets with a very large number of series, while it could be useful.
- Conceptual definition: The PLS factors are those linear combinations of regressors that give maximum covariance between the regressand and the full set of regressors while being orthogonal to each other.
- In analogy to PC factors, an identification assumption is needed in the usual form of a normalisation.

Estimation: PLS

- In a simplified version of the algorithm the vector of loadings is determined by computing the individual covariances.
- Then, the linear combination of the above and the target construct the PLS factors.
- This is repeated by taking residuals of both the regressors and the target in a regression with the new PLS factor.
- Settings: 1, 2, 3 and 4 factors.

Estimation: BR

- Obtain a posterior distribution for the model parameters using standard Bayesian analysis, Del Mol et al. (2006).
- BR forecasts by projecting the regressand on a weighted sum of all N principal components of the set of regressors, with decaying weights, instead of projecting it on a limited number of principal components with equal weights as in PC and PLS.
- Settings: $0.5N$, N and $2N$ are used as shrinkage parameters.

A note on multivariate models

- The described data reduction techniques could be also applied directly to the large set of employment series, rather than only to the macro explanatory variables.
- For example, each employment series could be explained with EU, country and sectoral factors, plus an idiosyncratic component (and possibly the macro factors).
- However, the resulting model is very large and computationally demanding, and the interpretation of the associated forecasts can be complex. Hence, we only use the reduction techniques for the macro variables, and keep single equation models for the employment series.

Data Description

- Data for each of the EU-27 countries and some EU aggregates.
- The dependent variables are sectoral (in general 3 digit) employment series.
- Employment also disaggregated into males and females, and into four age groups: 15-24, 25-49, 50-64 and 65+.
- A medium to large set of general macroeconomic variables for each country, fed into the variable reduction techniques.

Data Description

- The macro variables include the following categories:

1) the volumes of imports and exports,	6) the general unemployment level and hours worked,
2) the volumes of the private investment and consumption,	7) the unit labour cost,
3) the volume of GDP, the GDP deflator,	8) consumer surveys and economic sentiment indicators,
4) the government deficit as a percentage of the GDP,	9) stock price and volatility indexes and long term interest rates.
5) the agricultural, construction, wholesale, communication, insurance, estates, services etc. indexes,	

Data Description

- For the majority of the above variables we use their percentage growth (period-to-period) unless they are expressed as percentages by definition (e.g. surveys, interest rates etc.).
- For different countries we use: (i) the above general aggregate variables for the EU economy and (ii) the specific variables of the economy under consideration.

Data Description

- The frequency of the above series is generally quarterly. However, we also include relevant monthly variables (e.g. surveys, stock market variables, interest and exchange rates etc.).
- The use of monthly indicators permits a monthly updating of the quarterly forecasts, if required. However, it creates an unbalancedness problem.
- We cope with this unbalancedness problem by transforming the monthly series to quarters with the following techniques.

Data Description

- Tr.1. Using the quarters averages, i.e. averaging out the three months in the same quarter.
- Tr.2. Using the last month in each quarter only.
- Tr.3. dividing each variable in three sets. Each set contains the first, second and third month in all quarters across the period. This approach is in the spirit of the UMIDAS regressions introduced in Foroni, Marcellino and Schumacher (2011).

Forecasting Algorithm & Evaluation

- Recursive looping approach is used.
- One- to four-quarter ahead are forecasted.
- We use 16 evaluation periods (quarters), except for CY, MT, LU and RO where 12 periods are used due to estimation issues.
- We use the Mean Absolute Error (MAE), Root Mean Squared Forecast Error (RMSFE) and the Sign Success Ratio (SSR) for forecast evaluation and comparison.

Forecasting Algorithm & Evaluation

- We compare the following models:
 - AR(p) with two lag values, $p=\{1,4\}$,
 - ARMA(p,q) with $(p,q)=(1,1)$ and $(p,q)=(4,4)$,
 - PC(f) with $f=\{1,2,3,4\}$ factors and including or excluding an AR(p),
 - PLS(f) with $f=\{1,2,3,4\}$ factors and including or excluding an AR(p),
 - BR(wN) with shrinkage parameters $w=\{0.5,1,2\}$ and including or excluding an AR(p).

Forecasting Algorithm & Evaluation

- Furthermore, we distinguish the following choices regarding the constant and the dummy variables:
 - No constant and dummy variables
 - Only the constant is included
 - Only the dummy variables are included (4xT, receiving 1 for the specific quarter and 0 otherwise).
- All the listed specifications lead to a comparison of 120 models (for each of the several hundreds of employment variables).

Forecasting Algorithm & Evaluation

- For each group of series we compute and report:
 - The model that has the min. average RMSFE value across the underlying universe of dependent variables,
 - The model that has been counted to have the min. RMSFE most of the times (i.e. maximum success rate) across the underlying series,
 - The model that has the min. average MAE value across the underlying universe of dependent variables.

Forecasting Algorithm & Evaluation

- For each group of series we also report:
 - The model that has been counted to have the min. MAE most of the times (i.e. maximum success rate) across the underlying series,
 - The model that has the max. average SSR value across the underlying universe of dependent variables,
 - The model that has been counted to have the max. SSR most of the times (i.e. max. success rate) across the underlying series.

Forecasting Algorithm & Evaluation

- Given the high volume of different labour series across each gender and age group per country we have to use some sort of aggregation in order to evaluate which model is the "best" to be used.
- We follow two approaches: (i) an equally weighted average and (ii) a weighted average where the weights are allocated given the contribution of each series in the general labour/employment level.
- A fair use of (ii) above is on the transformed level of the series
$$(x_t - x_{min}) / (x_{max} - x_{min})$$

Summary of the main results

- It is obvious that depending on the evaluation criterion and group of variables under analysis, different (or slightly different) models are obtained.
- We generally obtain that the AR(1), ARMA(1,1), PC(1), BR(2N) including an AR(4) and the dummy variable and PLS(1) with AR(1) or AR(4) have the lowest average MAE and RMSFE values and the highest sign success ratio.

Summary of the main results

- However, the models most often with minimum MAE (i.e. Max. Success MAE) on average are generally the standard AR and ARMA models.
- The variable reduction methods seem to work better in forecasting the employment variables for the economies of CY, CZ, DE, EL, ES, IE, IT, LU, PT, SE and SK.
- Generally, one could argue that when the variable reduction methods provide the best model, then this is much better compared to an AR(1).

Summary of the main results

- Comparing the equally weighted average and the suggested weighting scheme, we find little differences.
- For example: Comparing Tables 3 and 7 we see that the 'best' models highlighted by the min. MAE, Max. Success MAE, max. Success RMSFE and max. Success SSR statistics are the same.
- However, looking at the min. RMSFE we find slight differences (e.g. for CZ we have PLS(1) using equal weights and PLS(1) with an AR(1) using the weighting scheme.

Summary of the main results

- In order to provide a general summary of the forecasting exercise we can look at Tables 7 – 10 where we report the ‘best’ model across all genders and age groups (weighting scheme).
- In $h=1$ step ahead, variable reduction methods are selected in:
 - [using min. MAE] 13/27 countries,
 - [using max. Success MAE] 0/27 countries,
 - [using min. RMSFE] 9/27 countries,
 - [using max. Success RMSFE] 0/27 countries,
 - [using max. SSR] 5/27 countries,
 - [using max. Success SSR] 4/27 countries.

Summary of the main results

- In $h=2$ steps ahead, variable reduction methods are selected in:
 - [using min. MAE] 10/27 countries,
 - [using max. Success MAE] 1/27 countries,
 - [using min. RMSFE] 8/27 countries,
 - [using max. Success RMSFE] 0/27 countries,
 - [using max. SSR] 12/27 countries,
 - [using max. Success SSR] 3/27 countries.

Summary of the main results

- In $h=3$ steps ahead, variable reduction methods are selected in:
 - [using min. MAE] 9/27 countries,
 - [using max. Success MAE] 1/27 countries,
 - [using min. RMSFE] 6/27 countries,
 - [using max. Success RMSFE] 0/27 countries,
 - [using max. SSR] 18/27 countries,
 - [using max. Success SSR] 0/27 countries.

Summary of the main results

- In $h=4$ steps ahead, variable reduction methods are selected in:
 - [using min. MAE] 6/27 countries,
 - [using max. Success MAE] 1/27 countries,
 - [using min. RMSFE] 7/27 countries,
 - [using max. Success RMSFE] 0/27 countries,
 - [using max. SSR] 19/27 countries,
 - [using max. Success SSR] 1/27 countries.

Conclusions and next steps

- The research project is so far concerned with short term forecasting of employment series at the sectoral level for all the EU27 countries.
- We compare 120 model variations, including univariate and multivariate specifications, with or without seasonal dummies, and with different variable reduction techniques (PC, PLS, BR).
- Standard AR and ARMA models provide generally smaller forecast error (in terms of max. success MAE and max. success RMSFE) and variable reduction methods have better sign performance (in terms of SSR).

Conclusions and next steps

- Variable reduction methods also return smaller values in terms of average MAE and MSFE for some countries.
- We need to assess whether the results are affected by structural breaks. Difficult to do in this very large evaluation context, but rolling estimation could provide some indications and help robustifying the forecasts.
- If some specific conditioning variables are of interest (e.g., DG ECFIN forecasts), they can be easily included in the models.

Conclusions and next steps

- Once, a forecasting method is selected, either best for each variable or (better) more robust across groups of variables, short term employment forecasts can be transformed into occupation and skill forecasts.
- Similar approach as in long term forecasts, i.e., use employment/occupation and occupation/skills matrices
- Info and data very welcome!