Forecasting in a rich-data environment

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1 Introduction

Due to a growing amount of macroeconomic data over the last years, there has been a great deal of research on forecasting using many predictors. The currently available methods include *inter alia* forecast combining, model selection, dynamic factor models (DFM henceforth), Bayesian model averaging, empirical Bayesian methods and bagging; see Stock and Watson (2006).

The consensus over dominance of any of these methods has not been found so far, neither on a theoretical, nor on empirical level. The difficulty in comparing these methods theoretically results from different modeling assumptions of each method. It is not always clear what the models actually do when applied in settings in which the assumptions do not hold.

An attempt to assess these methods empirically was taken by Stock and Watson (2006), who compared their predictive power forecasting the US macroeconomic time series over a 30-year out-of-sample period. Their findings showed that the most accurate forecasts were produced by a DFM and that a large predictor dataset can be well summarized by a small number of factors, at least for a short-run macroeconomic forecasting purpose.

Besides, recent research points at more advantages of the factor models, eg. eliminating the idiosyncratic movement (including eg. measurement error) and independence from strict assumptions which are usually base of structural models (Breitung and Eickmeier, 2005).

Dynamic factor models are broadly used to perform forecasting tasks especially for inflation and output (eg. see Stock and Watson (1999), den Reijer (2013), Caggiano et al. (2011)). The empirical literature provides evidence that DFMs perform reasonably well, especially when forecasts combining is implemented (Watson and Stock, 2004).

This paper attempts to utilize the dynamic factor approach to forecast GDP growth rates in Spain for the four quarters of 2013. After the prescreening of the data set consisting of over 70 economic indicators and initial selection of the regressors in section 2 we proceed to the estimation of a DFM model we assess its in-sample predictive power comparing it to a simple ARMA benchmark and produce the out-of-sample forecast in section 3. Section 4 concludes.

2 Data

Our initial dataset comprised 71 economic indicators downloaded from the OECD Economic Outlook for Spain spanning from the first quarter of 1970 to the fourth quarter of 2012. Given the possible redundancy of some of the variables, the first step of our analysis was a thorough investigation of the data. Specifically, we needed to define the dependent variable and choose one of the three definitions of the Gross Domestic Product available in our dataset. Secondly, some of the potential predictors were by definition almost perfectly correlated with other ones and therefore were seen as potential sources of multicollinearity. Finally, for some variables that contained too many missing values, we decided that the loss of information connected with excluding them from the set is less severe than the result of excessive trimming of the estimation sample. The following subsections provide a concise documentation of the modifications we performed on the data to achieve a more parsimonous set of potential predictors.

2.1 Dependent variable

Our goal was to forecast the quarterly growth rates of real GDP in Spain. Therefore, from the three GDP-related variables (GDP, $GDPV$ and $GDPVD$) available in the data set, we consider the differences of logs of $GDPV$ (GDP volume) to be the best proxy for the true output growth in the economy. Naturally, we drop the remaining two variables from the data set.

2.2 Pre-selection of predictors

To avoid including variables that are of no predictive value, we scanned the set of potential predictors looking for potentially redundant economic indicators. The exclusion of some of them was straightforward, as some of them were either linear combinations of other variables in the set (eg. total employment according to the National Accounts ET_NA was the sum of dependent employment EE and total self-employment ET) or their simple transformations ($EXCHUD = 1/EXCH$), so leaving them in the data set would lead to perfect multicollinearity and render the estimation impossible.

As for other variables, in general we dropped the real variables expressed as values in favour of volumes, and for the international trade variables, we chose the ones that were expressed in USD. As the definitions of many variables were very similar and the difference was only in unit of measurement, this also allowed us to potentially reduce the consequences of collinearity without loss of information. Another criterion that determined the selection process of our variables was the proportion of missing values. Though we consider the information on the situation of the housing market in Spain to be of great importance, we were forced to drop the IHV variable, as the data on that were being collected starting from the year 2000. We also faced missing values from 2012 in $CPIDR$ (2 quarters) and HRS (4 quarters) and extrapolated them using simple ARIMA models fitted to these two series.

For the sake of brevity we refrain from documenting our futher considerations regarding the preselection of the predictors. Eventually, we ended up with 41 potential predictors (see the appendix for a list of them) which corresponds closely to the findings of Boivin and Ng (2006) and Caggiano et al. (2011), who find that dynamic factor models estimated with around 40 explanatory variables can yield equally good or even better results than using the full data set that has not been prescreened for potential problems.

2.3 Variable transformations

To avoid issues connected with nonstationarity and common stochastic trends in the variables, we decided to first-difference variables that originally could take negative values (for instance the CA balance and all the net values) and variables that were expressed as rates (eg. the nominal interest rates) and first-difference the logarithms of all real variables (following the ideas of Stock and Watson (2006) who perform similar transformations on the variables they include in their DFM models).

Due to time constraints we did not perform formal tests for unit roots in the variables but looking at the plots of the transformed variables we concluded that they are stationary. 39 variable shad means around 0 and just two of them, ΔCBD and $\Delta FBGSD$ had means substantially lower than 0. However, we decided to follow the ideas presented in (Breitung and Eickmeier, 2005) and standardized all of the regressors. With more time we would have also considered seasonally adjusting the data using the TRAMO/SEATS procedure but given our constraints we decided to tackle seasonality with quarterly dummies.

3 Forecasts

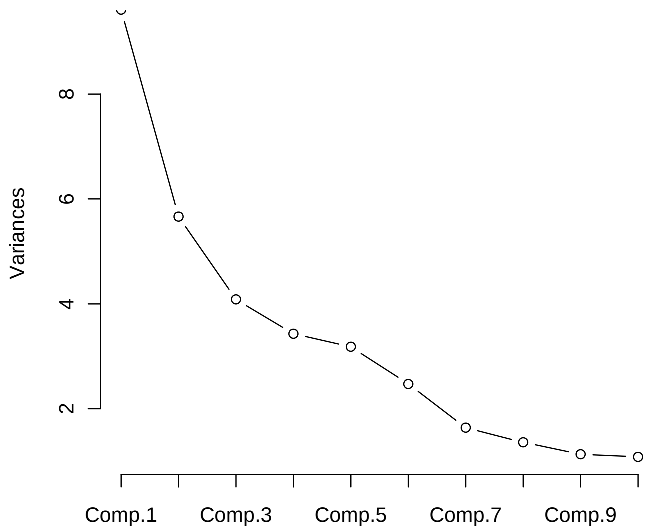
3.1 The DFM model

To estimate the DFM model we used our 41 regressors to construct factors. The number of the factors was chosen basing on the scree plot rule of the thumb approach (see figure 1). We concluded that 4 factors are enough and explain over 56% of the variance. In the usual cross-sectional settings this number might seem small but according to Breitung and Eickmeier (2005), with time series even 40% is sufficient. The addition of more factors and their lags would result in a loss of degrees of freedom. Having tested different specifications, the best DFM model we were able to come with (judging on information criteria) is as follows:

$$y_{t+h} = \sum_{p=0}^{4} \alpha_p y_{t-p} + \sum_{i=1}^{4} \sum_{q=0}^{1} \beta_{i,q} f_{i,t-q} + \sum_{r=1}^{3} \gamma_r Q_r + u_t, \tag{1}$$

that is we include four lags of the dependent variable, four factors with one lag each and three quarterly dummies.

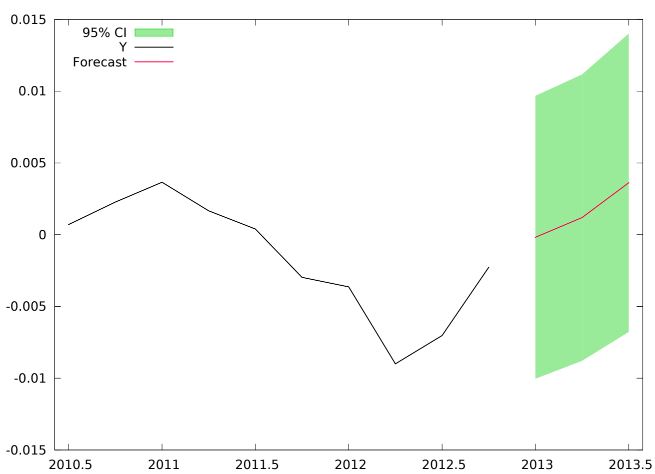
Figure 1: Scree plot for the number of factors.



3.2 Out-of-sample forecast for 2013

Figure 2 depicts our forecast of the GDP growth in spain using a DFM model with four lags on the dependent variable, one lag on each of the factors and three seasonal dummies. That was the best specification we experimented with. According to the point forecast, the GDP should fall in the first quarter by 0.2%, though the subsequent quarters suggest more optimism – in the third quarter of 2013 we should expect an increase of 3.6%. The confidence bands for these forecasts are unfortunately quite wide, so our initial optimism might in fact turn out to be a recession.

Figure 2: DFM forecast of GDP growth for 2013.



3.3 Comparison of in-sample predictive power with ARMA benchmark

In order to assess the predictive power of our DFM model and the plausibility of our forecast for 2013 we compare its in-sample forecasting ability with a benchmark ARMA model. Having experimented with various lag orders we chose an ARMA(3,1) to be the benchmark given the lowest RMSE among the relatively parsimonious lag specfications.

The in-sample recursive forecasts obtained from the DFM and ARMA model are displayed in figures 3 and 4, respecitvely. As one can observe, the ARMA model tends to oversmooth the forecast compared to the DFM. On the other hand, the 2009 recession seems to have been overestimated by the DFM model.

Figure 3: DFM in-sample 2003q1-2012q4 recursive forecast (red) of GDP growth and observed series (black).

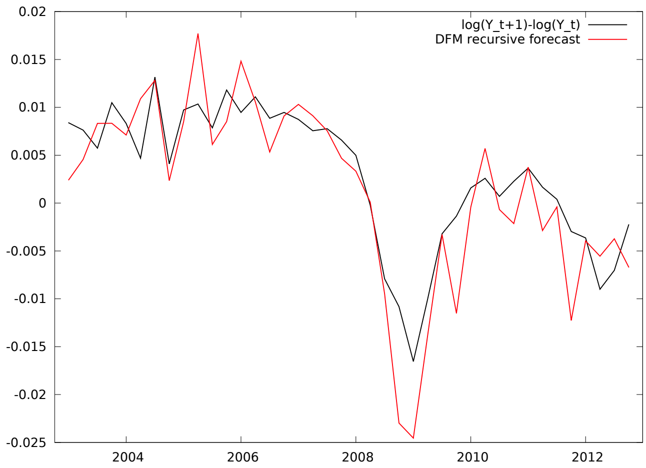


Figure 4: ARMA(3,1) in-sample 2003q1-2012q4 recursive forecast (red) of GDP growth and observed series (black).

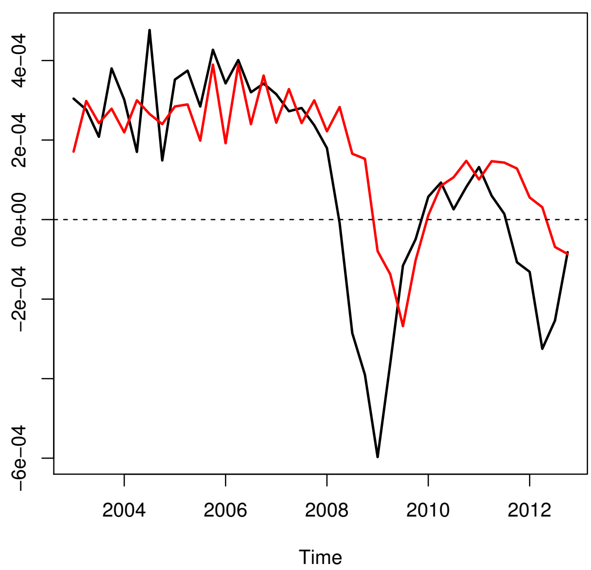


Table 1 compares the mean prediction errors of the two models. One can observe that the DFM slightly outperforms the benchmark, naive model. Assuming a quadratic or cubic loss function and using the Newey-West correction in the Diebold and Mariano (1995) test we, however, could not reject the null that the forecasts do not exhibit a significant difference.

Table 1: Comparison of DFM and ARMA forecasting ability

Model	ME	MAE	RMSE
DFM	**0.14%**	**0.31%**	**0.43%**
ARMA(3,1)	**0.16%**	**0.34%**	**0.47%**

4 Conclusions

In this paper we attempted to forecast quarterly growth rates of real GDP in Spain in 2013. In order to exploit a large dataset containing many macroeconomic time series a dynamic factor model has been specified. This approach allowed us to improve the predictions obtained with a baseline model - ARMA(3,1). However, lack of seasonal adjustment in the ARMA model specification may negatively influence our results. Moreover, more accurate prediction could be achieved should additional time series relating to finance and SME be provided.

According to our findings, Spanish economy is likely to recover this year which may be the consequence of the fiscal austerity measures taken by the Spanish government.

References

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A Appendix

A.1 Pre-selected regressors

Table 2: Regressors used to construct the factors

Variable	Description
CBD	Current account balance, value in USD
CBGDPR	Current account balance, as a percentage of GDP
CPIDR	Competitiveness indicator, relative consumer prices (CPI), overall weights
EXCH	Exchange rate, USD per National currency
EXCHEB	Nominal effective exchange rate, chain-linked, overall weights
MGSD	Imports of goods and services, value, National Accounts basis, USD
NTRD	Net current international transfers, value, balance of payments basis
PMGSX	Price of non- commodity imports of goods and services
PMNW	Price of commodity imports
PXGSX	Price of non- commodity exports of goods and services
PXNW	Price of commodity exports
RPMGS	Relative price of imported goods and services
RPXGS	Relative price of exported goods and services
SHTGSVD	Share of country's trade expressed in USD volume (2005 prices) in the world trade
XGSD	Exports of goods and services, value, National Accounts basis, USD
XMKT	Export market for goods and services, volume, USD, 2005 prices
XPERF	Export performance for goods and services, volume
CGV	Government final consumption expenditure, volume
CPV	Private final consumption expenditure, volume
FDDV	Final domestic expenditure, volume
IBGV	Private non-residential and government fixed capital formation, volume
ITISKV	Gross capital formation, total, volume
ITV	Gross fixed capital formation, total, volume
MGSV	of goods and services, volume, National Accounts basis
TDDV	Total domestic expenditure, volume
TEV	Total expenditure, volume
XGSV	Exports of goods and services, volume, National Accounts basis
PCG	Government final consumption expenditure, deflator
PCP	Private final consumption expenditure, deflator
PFDD	Final domestic expenditure, deflator
PGDP	Gross domestic product, deflator, market prices
PIT	Gross total fixed capital formation, deflator
PITISK	Gross capital formation, deflator
PTDD	Total domestic expenditure, deflator
ES	Total self-employed
ET_NA	Total employment, National Accounts basis
HRS	Hours worked per employee, total economy
LF	Labour force
UNR	Unemployment rate
IRL	Long-term interest rate on government bonds
IRS	Short-term interest rate

A.2 Different ARMA lag specification and in-sample recursive forecast performance

Table 3: Naive ARMA forecast performance for 2003q1 to 2012q4

p	q	ME	MAE	RMSE
0	0	0.45%	0.59%	0.82%
1	0	0.33%	0.46%	0.65%
2	0	0.19%	0.35%	0.50%
3	0	0.17%	0.36%	0.52%
4	0	0.18%	0.34%	0.49%
0	1	0.39%	0.53%	0.74%
1	1	0.19%	0.35%	0.53%
2	1	0.17%	0.36%	0.52%
3	**1**	**0.16%**	**0.34%**	**0.47%**
4	1	0.16%	0.34%	0.48%
0	2	0.28%	0.39%	0.56%
1	2	0.22%	0.34%	0.50%
2	2	0.19%	0.34%	0.49%
3	2	0.19%	0.34%	0.48%
4	2	0.13%	0.34%	0.46%
0	3	0.26%	0.37%	0.53%
1	3	0.18%	0.32%	0.48%
2	3	0.24%	0.37%	0.51%
3	3	0.17%	0.31%	0.47%
4	3	0.14%	0.34%	0.49%
0	4	0.25%	0.37%	0.53%
1	4	0.17%	0.33%	0.49%
2	4	0.17%	0.30%	0.45%
3	4	0.16%	0.31%	0.46%
4	4	0.11%	0.37%	0.50%