Forecasting Portuguese GDP with factor models[1]

Francisco Dias[2] | Maximiano Pinheiro[3] | António Rua[2]

ABSTRACT

In this article, we assess the relative performance of factor models to forecast GDP growth in Portugal. A large dataset is compiled for the Portuguese economy and its usefulness for nowcasting and short-term forecasting is investigated. Since, in practice, one has to cope with different publication lags and unbalanced data, we also address the real-time performance of such models.

1. Introduction

With the widespread development of the statistical systems, the information set available to policymakers has become progressively larger. Naturally, this poses methodological challenges in terms of how to take on board all the available data, which can involve hundreds of series.

For forecasting purposes, the use of factor models to forecast macroeconomic variables in a data rich environment has become increasingly popular in the literature and among practitioners at central banks and international institutions. See, for example, Stock and Watson (1998, 2002a, 2002b) and Giannone *et al.* (2008) for the United States, Marcellino *et al.* (2003) and Angelini *et al.* (2011) for the euro area, Artis *et al.* (2005) for the UK, Schumacher (2007, 2010, 2011) and Schumacher and Breitung (2008) for Germany, Barhoumi *et al.* (2010) for France, de Winter (2011) and den Reijer (2013) for the Netherlands, and for a cross-country study encompassing several European countries see Rünstler *et al.* (2009).

Factor models allow circumventing the curse of dimensionality when dealing with large datasets by reducing the dimension of the number of series to a manageable scale, which is particularly useful in the case of forecasting. In fact, these models allow one to summarize the information contained in large databases in a set of a handful of unobserved common factors that drive a sizeable fraction of the overall comovement amongst the whole set of variables in the dataset. However, since it ignores entirely the information content other than the one conveyed by this small set of factors, it may potentially disregard data that can be useful for the variable to be forecasted or the forecast horizon under consideration.

Dias, Pinheiro and Rua (2010) suggest an alternative procedure to overcome this shortfall. In particular, a tailor made targeted diffusion index (TDI) dependent on the variable to be forecasted and the forecast horizon is proposed. This index is simply a weighted average of all the factors of the dataset that take into account both the explanatory power of each factor for the variable to be forecasted and the relative importance of the factor in capturing the total variation of the series. For the US case, such an approach outperformed the standard factor model in forecasting several macroeconomic variables.

Herein, we focus on the Portuguese case which was one of the hardest hit economies as from the latest economic and financial crisis. In particular, we assess the performance of several alternative factor models to forecast GDP growth using a large dataset compiled for Portugal, which encompasses 126 monthly series as from 1995.

By considering a relatively long out-of-sample period, from 2002 up to 2013, we can assess the relative performance of the different models during the pre-crisis period and during the latest years where pronounced GDP downturns and upswings were observed. This can be particularly useful to assess the robustness of the forecasting performance of factor models in periods of significant economic stress.

Since forecasting in real-time typically involves missing observations for some of the variables due to different release lags, we also address how to overcome this issue and evaluate the corresponding pseudo real-time forecasting performance.

The article is organised as follows. In section 2, an introductory overview of the factor models considered in subsequent analysis is provided. In section 3, we describe the dataset for Portugal whereas in section 4 the estimated common factors are discussed. In section 5, we assess the out-of-sample forecasting performance with balanced data. In section 6, the issue of how to deal with unbalanced data is addressed whereas in section 7 the pseudo real-time performance is evaluated. Finally, section 8 concludes.

2. Factor models

Formally, the static factor model assumes that each and every variable in the data set can be specified as a combination of two terms: one component driven by a small set of latent unobserved static factors common to all variables and an idiosyncratic component specific to each variable, that is

$$X_t = \Lambda F_t + e_t$$

where X_t is the N-dimensional vector time series in the panel for period t, Λ is an (Nxr) matrix of factor loadings, F_t is the vector of r unobserved common factors and e_t is the N-dimensional vector of idiosyncratic terms. The unobserved factors can be estimated relying on the principal components technique which is shown to provide a consistent estimator of the factor space under fairly general conditions.

Dynamic factor models, on the other hand, were originally developed by Geweke (1977), Sargent and Sims (1977), Geweke and Singleton (1981) and Watson and Engle (1983) and applied in the context of a limited number of variables. This type of model has been extended to handle the information conveyed by large data sets. The dynamic factor model has an equivalent static factor model representation, where the r-dimensional static factors comprise both current and lagged values of the q dynamic factors. When the number of static and dynamic factors are the same, that is, r = q, there is no difference between the static and dynamic forms (see Stock and Watson (2005)). Moreover, as pointed out by Bai and Ng (2007), not much is expected to be gained from the distinction between the static factors and the dynamic factors for forecasting purposes.

Typically, the first few top-ranked principal components capture a sizeable share of the comovent amongst the series in the dataset. Once the number of factors is determined, the variable to be forecasted y is projected on the set of the r estimated factors and possibly on lags of the dependent variable. This results in the following forecasting model

$$y_{t+h} = \beta_0 + \sum_{i=1}^{r} \beta_i \hat{F}_{t,i} + \sum_{j=0}^{p} \delta_j y_{t-j} + v_{t+h}$$

where h refers to the forecast horizon, y_{t-j} are the autoregressive components of the regression and v_{t+h} denotes the forecast error. Such an approach corresponds to the so-called diffusion index (DI) model proposed by Stock and Watson (1998, 2002a, 2002b).

In practice, the above discussed factor model requires a priori the determination of the number of factors and the space spanned by those factors relies on the principal components method. In fact, the factors reflect the top-ranked principal components, that is, the ones that encompass the largest share of the common comovement in the dataset. All other lower-ranked factors are entirely disregarded independently of their possible informational content for forecasting the variable of interest. This can result in an important shortcoming for the forecasting purposes as such an approach does not take into account neither the specific variable to be forecasted nor the forecast horizon. This shortfall was circumvented in Dias, Pinheiro and Rua (2010), where the authors propose a targeted diffusion index (TDI), which reconciles both the spirit of the Stock and Watson approach and the targeting principle discussed by Bai and Ng (2008). Basically, the suggested procedure considers in the forecasting model a synthetic regressor which is computed as a linear combination of all the factors of the dataset, that is

$$\begin{aligned}
y_{t+h} &= \beta_0 + \beta_1 F^{\circ}_{(h)t} + \sum_{j=0}^{p} \delta_j y_{t-j} + v_{t+h} \\
F^{\circ}_{(h)t} &= \sum_{n=1}^{N} \left(\frac{\omega_{(h)n}}{\sum_{i=1}^{N} \omega_{(h)i}} \right) \hat{F}_{(h)t,n} \\
\omega_{(h)n} &= \left(\frac{1}{T-h} \sum_{t=1}^{T-h} \hat{F}_{(h)t,n} y_{t+h} \right) \left(\frac{\varphi_{(h)n}}{\varphi_{(h)1}} \right)
\end{aligned}$$

The first equation is the same as in the case of the DI approach but where the top-ranked principal components, *i.e.*, the common factors, are replaced by the synthetic composite indicator. This targeted diffusion index is the convex linear combination of all the factors derived from the database, where the weights attached to each factor take into account both the relative size of the of the overall variation captured by each factor $\left(\frac{\varphi_{(h)n}}{\varphi_{(h)1}} \right)$ and its correlation with the variable of interest at the relevant forecast horizon $\left(\frac{1}{T-h} \sum_{t=1}^{T-h} \hat{F}_{(h)t,n} y_{t+h} \right)$. The weights attached to each factor are naturally dependent not only on the relative importance of the factor but also on the specific series to be forecasted and corresponding forecast horizon. This modelling strategy avoids discarding potentially relevant information contained in the dataset and it is designed to obtain a better match between the available data and the variable to be forecasted. As shown in Dias, Pinheiro and Rua (2010), this approach proved to be quite promising *vis-à-vis* the diffusion index model, improving considerably the forecast performance for several US macroeconomic variables.

3. Dataset

The monthly dataset compiled for the Portuguese economy comprises 126 series and it includes both hard and soft data. It covers business and consumers surveys (43 series), retail sales (4 series), industrial production (7 series), turnover in industry and services (20 series), employment, hours worked and wage indices in industry and services (24 series), tourism nights spent in Portugal (3 series), car sales (3 series), cement sales, vacancies and registered unemployment (5 series), energy consumption (3 series), goods exports and imports (10 series), real effective exchange rate, Portuguese stock market index and ATM/POS series (see the Appendix for a detailed list of series and corresponding source).

Although most series are provided on a seasonally adjusted basis, for those variables that are not, but which present a seasonal pattern, a seasonal adjustment was conducted resorting to X12-ARIMA. The sample period runs from the beginning of 1995 up to the end of 2013 (T=228 monthly observations). Since for some variables the series start later than 1995, we resort to the Expectation-Maximization (EM) algorithm suggested by Stock and Watson (2002a) to balance the dataset at the beginning of the sample period.

Regarding GDP, the series in real terms is available from the Portuguese National Statistics Office (INE) as from the first quarter of 1995 up to the fourth quarter of 2013 on a seasonally adjusted basis.

With the exception of survey data, all series are taken in logarithms. The series are then differenced to obtain stationarity. For GDP we took the first-difference of the quarterly series, which corresponds to the quarter-on-quarter growth rate. For the monthly series we compute a 3-month difference, that is, the change in one month as against three months earlier.[4]

Additionally, for the estimation of the common factors, we use outlier-adjusted series, as in Stock and Watson (2005). The outlier adjustment corresponds to replacing observations of the transformed series with absolute deviations exceeding six times the interquartile range by the median value of the preceding five observations.

4. Common factors

In the case of the diffusion index model approach one has to determine the number of factors to consider for the forecasting purposes. Based on the IC_2 criterion suggested by Bai and Ng (2002), we find the number of static factors to be four. As a whole these four factors explain 41 per cent of the total variation in the monthly dataset over the entire sample with the first factor accounting for 21 per cent, the second 9 per cent, the third 6 per cent and the fourth 5 per cent. In the case of the United States and using the same criterion, Bai and Ng (2007) show that the common factors (which were determined to be seven) explain as a whole 46 per cent of the variation in the dataset compiled by Stock and Watson (2005) which comprises 132 monthly series.[5]

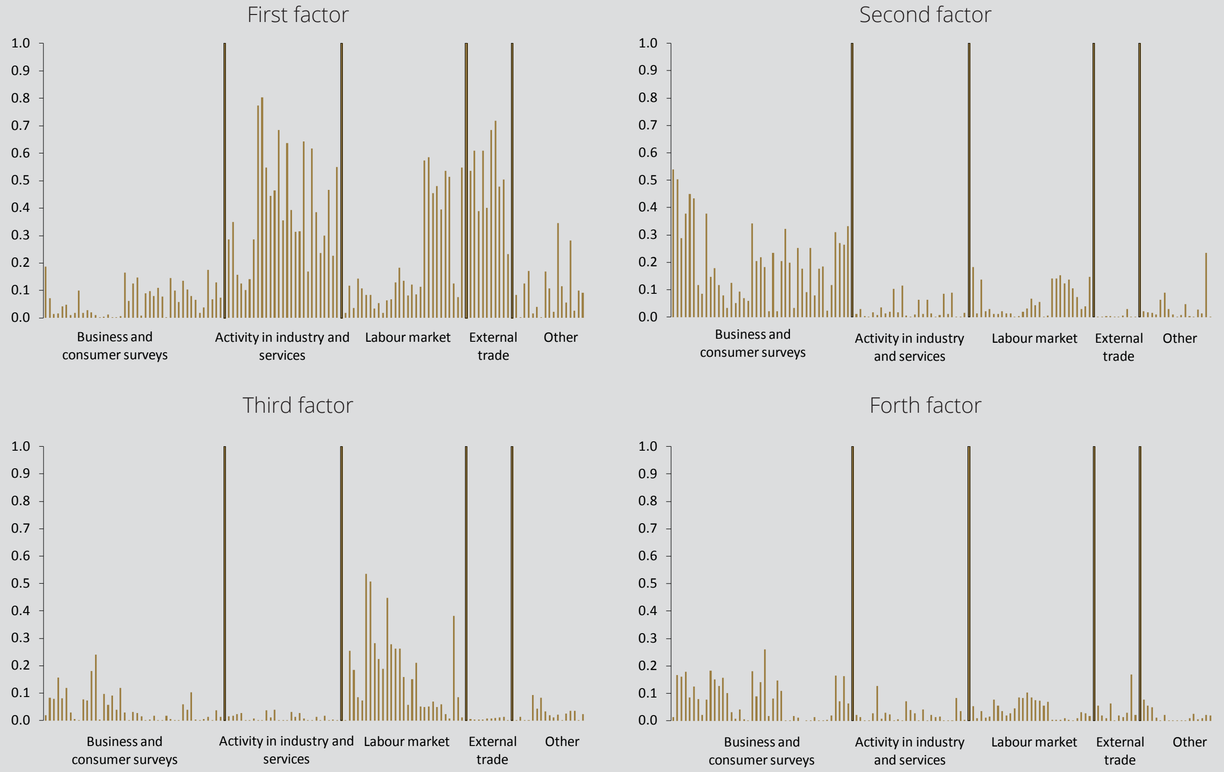
As is Stock and Watson (2002a), to characterize the factors we present in chart 4.1 the R^2 of the regressions of the 126 individual series on each of the four factors over the entire sample period. We find that the first factor is related with industrial and services activity and external trade and some labour market series namely hours worked in industry. The second factor reflects to a large extent business and consumer confidence while the third factor is related with labour market developments namely employment. Finally, the fourth factor seems to be spread out meaning that is not representative of any particular type of series.

Given the number of static factors, one can determine the number of primitive or dynamic factors, that is, the factors that are dynamically distinct. In this respect, Bai and Ng (2007) propose two criteria, q_3 and q_4, to estimate the number of dynamic factors with the former having better properties for samples with small N or T. In our case, the first criterion points to the presence of four dynamic factors whereas the second suggests the existence of three. This is in line with the results of Bai and Ng (2007) who found, for the United States, the number of dynamic factors to be the same or close to the number of static factors when the number of static factors is relatively small.

To assess the robustness of the above results to the sample period, we conduct the following exercise. Starting with the sample period up to the end of 2001, we compute the above criteria. Then, we expand the sample period by one month and compute again the criteria. This is done in each and every month until we reach the end of 2013, that is, the full sample. The resulting number of factors is presented in chart 4.2. Regarding the number of static factors, the criterion always points to the existence of four static factors. Concerning the number of dynamic factors, q_3 suggests almost always the presence of four dynamic factors whereas the results based on q_4 are more unstable changing basically between three and four dynamic factors. Overall, the above evidence reinforces the finding of four static factors which essentially coincide with the number of dynamic factors.

A similar recursive exercise has been conducted to assess the stability of the degree of the communality over time. In chart 4.3, we plot the variation in the dataset explained by the space spanned by the set of common factors as a whole as well as for each factor individually. Until the end of 2008, the results suggest a slightly increase in the case of the first factor whereas the other factors present a very mild downward trend. However, in late 2008 and early 2009, there is a sizeable increase in the communality. This is mainly evident the case of the first two factors. In fact, with the Great recession there was a significant increase in the comovement in the series which resulted in a larger variance captured by these two factors. Thereafter, there seems to be a slight overall reversal.

Chart 4.1 • R^2 between the individual series and the factors



Source: Authors' calculations.

5. Out-of-sample forecasting exercise

In this section, we present results for an out-of-sample forecasting exercise to assess the relative performance of the above mentioned models to forecast Portuguese real GDP growth.

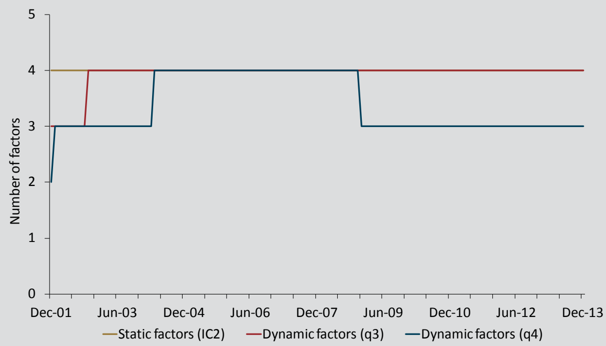
The out-of-sample forecast evaluation period runs from the first quarter of 2002 up to the fourth quarter of 2013, which corresponds to two thirds of the sample period. On the one hand, such a long out-of sample period allows for a better assessment of the relative forecasting performance of the models. On the other hand, it provides room for a sub-sample analysis which can be particularly useful given the economic features of the Portuguese economy over the last decade. In particular, we split the out-of-sample period in two sub-samples namely from 2002 Q1 up to 2007 Q4 and from 2008 Q1 up to 2013 Q4. The latter covers the period in which Portugal has been under stress with pronounced economic activity changes while the former sub-sample captures the pre-crisis period. Such an analysis will enable us to assess if the forecasting performance during a more stable period differs from the one recorded during a clearly more challenging period.

We focus on the nowcasting performance of the models (denoting this forecast horizon as h=0) as well as on forecasting up to 4-quarters ahead (h=1,...,4). In particular, the nowcast exercise involves forecasting GDP growth for a given quarter assuming that all the observations for the monthly series are available up to the end of that quarter. This corresponds to the so-called balanced data case.

As is usual in this type of exercises, we consider as a benchmark a univariate autoregressive model for GDP with the lag order determined by standard BIC criteria in each round of the recursive exercise. We have also considered for both the diffusion index and TDI models the corresponding models augmented with GDP lags. However, augmenting the regression with lags of the dependent variable does not improve on GDP forecasting performance. Hence, to save space, we present only the results for the factor models without GDP lags in the regression.

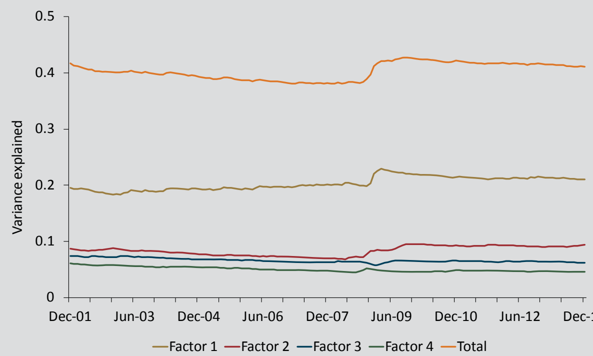
The results in terms of the Mean Squared Error (MSE) and the relative MSE *vis-à-vis* the benchmark model are presented in Table 5.1. For the forecast evaluation period as a whole, the TDI model outperforms the other models for all the forecast horizons considered. However, one should note that factor models do not seem to improve substantially on the univariate

Chart 4.2 • Number of static and dynamic factors



Source: Authors' calculations.

Chart 4.3 • Variation in the dataset explained by the common factors



Source: Authors' calculations.

autoregressive model for more distant forecast horizons. Giannone *et al*. (2008) for the United States and Runstler *et al*. (2009) for several European countries also found that the forecasting gains of using factor-augmented models disappear when the forecast horizon increases. In particular, the forecasting gains are noteworthy for nowcasting and forecasting one-period ahead, to a lesser extent for two-quarters ahead and relatively negligible for higher horizons. To assess the statistical significance of the gains in terms of GDP forecast accuracy of the factor models relative to the benchmark we computed the Diebold and Mariano (1995) test. The test results are also presented in Table 5.1 and basically support the previous finding. *Vis-à-vis* the DI approach, the TDI model presents a gain of more than 20 per cent for the shorter horizons.

To assess the robustness of the forecasting performance of the models over time we conducted a sub-sample analysis. One can see that all the models for all forecast horizons present a higher MSE in the second part of the out-of-sample period than in the first sub-sample. This results support the a priori that that the second sub-sample is a much more challenging period. In terms of the relative performance of the models, the previous findings remain unchanged for both sub-samples. In addition, one should mention that the gains of the TDI approach against the DI model for shorter horizons are less striking for the second sub-sample period.

We also computed the Mean Absolute Error as an alternative to the MSE. The results are presented in Table 5.2. One can see that all the main conclusions are robust to the forecast error measure considered.

6. Jagged edge data

As mentioned above, the exercise conducted in the previous section assumes that all the series are available up to the end of the quarter. In a real-time context, due to different release lags, one is often confronted with incomplete data for several series when the forecasting exercise is performed. This results in an unbalanced dataset at the end of the sample, the so called jagged edge

Table 5.1 • MSE and relative MSE for GDP forecasts

	Mean Squared Error					**Relative Mean Squared Error**				
Forecast horizon	**h = 0**	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 0**	**h = 1**	**h = 2**	**h = 3**	**h = 4**
Out-of-sample period: 2002Q1-2013Q4										
Autoregressive model	0.0099	0.0109	0.0116	0.0108	0.0107	1.00	1.00	1.00	1.00	1.00
DI model	0.0042	0.0089	0.0105	0.0109	0.0118	0.43 ***	0.82	0.90	1.02	1.10
TDI model	**0.0033**	**0.0071**	**0.0095**	**0.0097**	**0.0104**	0.33 ***	0.65 ***	0.82	0.90	0.98
Out-of-sample period: 2002Q1-2007Q4										
Autoregressive model	0.0090	0.0081	0.0096	0.0083	0.0084	1.00	1.00	1.00	1.00	1.00
DI model	0.0042	0.0076	0.0072	0.0095	0.0090	0.47 **	0.93	0.75	1.15	1.06
TDI model	**0.0025**	**0.0058**	**0.0064**	**0.0063**	**0.0070**	0.28 **	0.71 *	0.66	0.76	0.82
Out-of-sample period: 2008Q1-2013Q4										
Autoregressive model	0.0108	0.0137	0.0136	0.0132	**0.0129**	1.00	1.00	1.00	1.00	1.00
DI model	0.0043	0.0103	0.0137	**0.0123**	0.0146	0.40 *	0.75	1.00	0.93	1.13
TDI model	**0.0040**	**0.0085**	**0.0126**	0.0130	0.0139	0.37 **	0.62 **	0.92	0.98	1.08

Source: Authors' calculations.
Notes: Bold format denotes the best performing model for each forecast horizon. Asterisks *,**,*** denote rejection of the null hypothesis of equal forecast accuracy at 10%, 5% and 1% significance level, respectively.

data. To avoid discarding the most recent information for forecasting purposes, one has to fill in the missing data. Suppose that one is interested in updating the GDP forecast every month and that the forecasting exercise is conducted around mid-month. In chart 6.1, we provide a stylized description of the information set available at each point in time.

Chart 6.1 should be read in the following way. In the middle of the second month of the quarter, say mid-February, a subset of the series – N_1 series – are available up to January whereas for the remaining series there is no available information for any of the months of the first quarter. In mid-March, the former subset is now available up to February while the other series are available up to January. In April, only the latter series are not available up to the end of the first quarter. For the Portuguese case, taking into account the corresponding release calendar, the set of series more timely represent around 45 per cent of the total number of series in the monthly dataset.

To take on board the latest available information and to cope with the incomplete data, one has to fill in the missing observations. Hence, we assess the relative performance of the previously discussed models also to forecast the monthly series.[6] As highlighted in chart 6.1, we have to consider forecasts up to 3-months ahead. Based on the MSE criterion, we determine the number of series for which each model performs best (chart 6.2). For the entire out-of-sample period the univariate autoregressive model seems to perform best for most series and such evidence seems to be more marked for longer horizons. Qualitatively similar results are obtained for both sub-samples.

Furthermore, based on the distribution of the relative MSE of the several models *vis-à-vis* the autoregressive model (see chart 6.3), one can conclude that even when the autoregressive model does not outperform the other models, the losses are relatively small. In particular, for the series where the relative MSE is less than one, the losses are, on average, smaller than 4 per cent for all horizons (and around 5 per cent *vis-à-vis* the best performing model). In contrast, the gains of the autoregressive model against the remaining models are, on average, above 14 per cent for the one-month ahead forecasts, more than 12 per cent for two-months ahead and close to 8 per cent for the three-months ahead horizon. In summary, the parsimonious univariate autoregressive

Table 5.2 • MAE and relative MAE for GDP forecasts

	Mean Absolute Error					Relative Mean Absolute Error				
Forecast horizon	h = 0	h = 1	h = 2	h = 3	h = 4	h = 0	h = 1	h = 2	h = 3	h = 4
Out-of-sample period: 2002Q1-2013Q4										
Autoregressive model	0.80	0.87	0.91	0.85	0.84	1.00	1.00	1.00	1.00	1.00
DI model	0.54	0.75	0.80	0.83	0.89	0.67 ***	0.86 *	0.88	0.97	1.05
TDI model	**0.48**	**0.71**	**0.76**	**0.78**	**0.84**	0.60 ***	0.81 ***	0.84	0.91	0.99
Out-of-sample period: 2002Q1-2007Q4										
Autoregressive model	0.78	0.77	0.83	0.77	0.78	1.00	1.00	1.00	1.00	1.00
DI model	0.51	0.70	0.66	0.79	0.78	0.65 ***	0.91	0.80	1.03	0.99
TDI model	**0.43**	**0.64**	**0.65**	**0.66**	**0.67**	0.55 ***	0.82 *	0.78	0.85	0.86
Out-of-sample period: 2008Q1-2013Q4										
Autoregressive model	0.81	0.97	0.98	0.93	**0.90**	1.00	1.00	1.00	1.00	1.00
DI model	0.57	0.80	0.93	**0.86**	1.00	0.70 *	0.83	0.95	0.92	1.11
TDI model	**0.52**	**0.77**	**0.88**	0.90	1.00	0.65 *	0.80 *	0.90	0.96	1.11

Source: Authors' calculations.
Notes: A bold format denotes the best performing model for each forecast horizon. Asterisks *,**,*** denote rejection of the null hypothesis of equal forecast accuracy at 10%, 5% and 1% significance level, respectively.

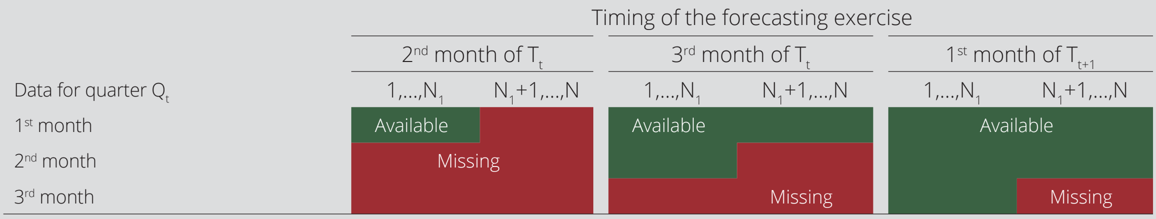
model seems to be a suitable choice for balancing the dataset whenever required. This is also in line with the results of Runstler *et al.* (2009) who found the univariate autoregressive model to work best for coping with jagged edge data when forecasting with the above factor models.

7. Pseudo real-time forecasting exercise

Drawing on the autoregressive model to fill in the missing monthly data whenever required, we now assess how the forecasting performance of the TDI approach deteriorates *vis-à-vis* the balanced data case addressed in section 5.[7] As expected, the jagged edge data issue is much more relevant for the nowcasting purposes than for longer horizons. Since for all the horizons other than the nowcast the impact is marginal, we only present the results for the nowcasting case. We assess both the MSE and the MAE for the TDI model for each of the timings discussed in the previous section.[8] Moreover, we also display the results for the balanced data case (see section 5), which corresponds to nowcasting GDP growth for quarter t in the 2nd month of quarter $t+1$. For instance, in mid-May all the monthly information is available concerning the 1st quarter of the year.

From chart 7.1, one can see that less information implies a worsening of the forecasting performance, whatever the forecast measure considered. This seems particularly striking in the worst case scenario considered, with the MSE being twice as large as the balanced data case. Moreover, as the available information for quarter t in the 2nd month of that quarter is quite scarce, the nowcasting performance is not much different from forecasting one-quarter ahead. When considering the sub-samples, one can conclude that the deterioration in absolute terms is more

Chart 6.1 • Stylized calendar and data availability



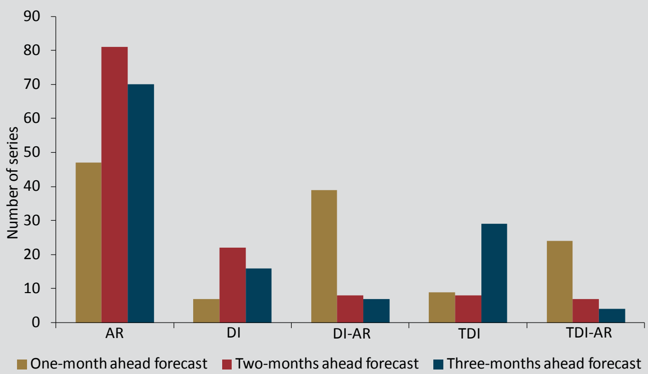


Chart 6.2 • Best performing model for the monthly series

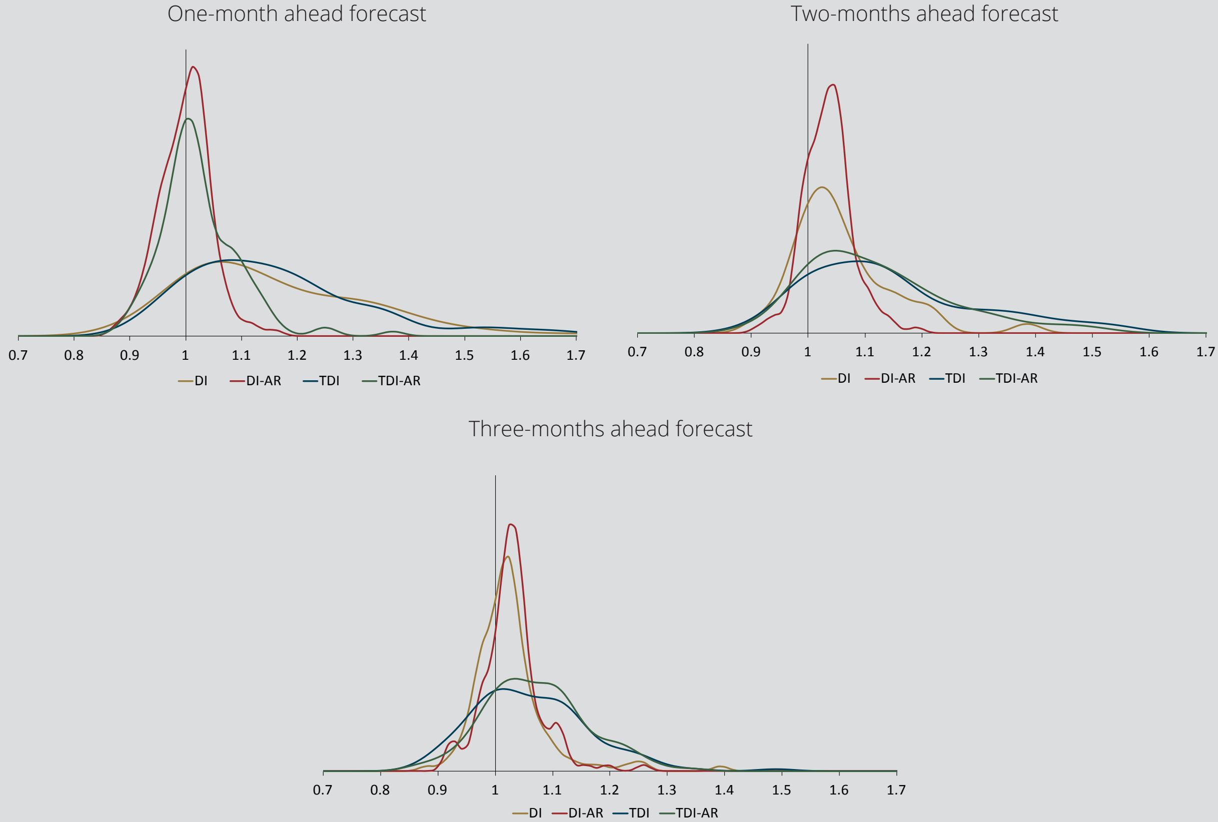
Source: Authors' calculations.

marked in the second half of the out-of-sample period. In fact, in a sample period with pronounced changes the availability of information becomes even more important to assess ongoing developments.

8. Conclusions

In this article, we assessed the relative performance of several factor models to forecast GDP growth using a large monthly dataset compiled for the Portuguese economy. We find that factor models outperform significantly the univariate autoregressive model for nowcasting and one-quarter ahead forecasting while for longer forecast horizons the gains are substantially reduced. Among the factor models, the TDI approach developed by Dias, Pinheiro and Rua (2010) clearly improves on the diffusion index model.

Chart 6.3 • Distribution of relative MSE for the monthly series

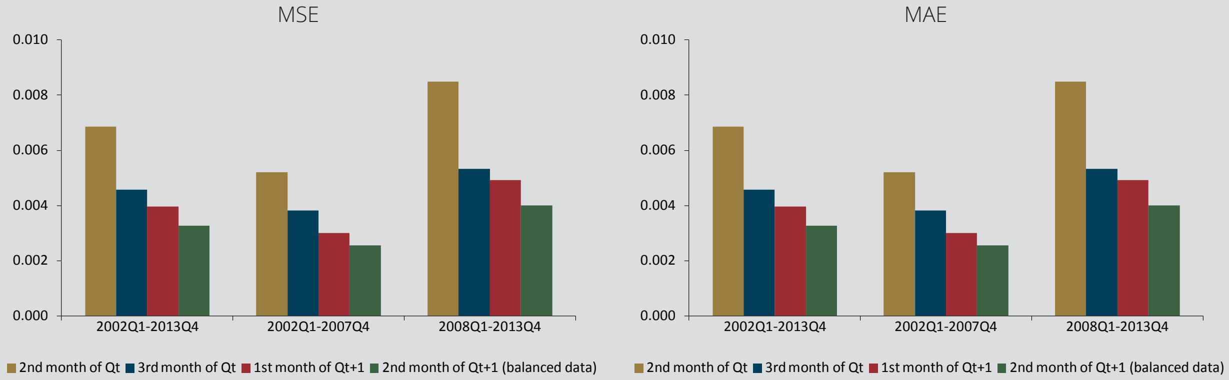


Source: Authors' calculations.

To gain further insights on the relative performance of the models, we considered a relatively long out-of-sample period namely from the first quarter of 2002 up to the fourth quarter of 2013. By splitting it in two, we could assess the forecasting performance over a pre-crisis period and as from the latest economic and financial crisis onwards. Although the forecast errors are larger in the latter period, the main findings in terms of the relative performance still hold in such a challenging period.

Since in real-time one has to deal with jagged-edge data so to take on board the latest available information, we also investigated the forecasting performance of the same models to fill in the missing data for the monthly series. Overall, the parsimonious autoregressive model seems to perform fairly well *vis-à-vis* the other models. Having established this, we assessed the impact of coping with jagged-edge data on the forecasting performance of the TDI approach. As expected, less available information leads to larger forecast errors.

Chart 7.1 • MSE and MAE for GDP nowcasting with jagged edge data



Source: Authors' calculations.

References

Angelini, E., **Camba-Mendez**, G., **Giannone**, D., **Reichlin**, L. and G. **Rünstler** (2011) "Short-term forecasts of euro area GDP growth", *Econometrics Journal*, 14(1), C25-C44.

Artis, M.J., A. **Banerjee** and M. **Marcellino** (2005) "Factor forecasts for the UK", *Journal of Forecasting*, 24, 279-298.

Bai, J. and Ng, S. (2002) "Determining the number of factors in approximate factor models", *Econometrica*, 70, 191-221.

Bai, J. and Ng, S. (2007) "Determining the number of primitive shocks in factor models", *Journal of Business and Economic Statistics*, 25, 52-60.

Bai, J. and Ng, S. (2008) "Forecasting economic time series using targeted predictors", *Journal of Econometrics*, 146(2), 304-317.

Barhoumi K., **Darné** O. and **Ferrara** L. (2010) "Are disaggregate data useful for factor analysis in forecasting French GDP?", *Journal of Forecasting*, 29(1-2), 132–144.

de **Winter**, J. (2011) "Forecasting GDP growth in times of crisis: private sector forecasts versus statistical models", DNB Working Papers 320, Netherlands Central Bank.

Dias, F., **Pinheiro**, M. and **Rua**, A. (2010) "Forecasting using targeted diffusion indexes", *Journal of Forecasting*, 29(3), 341-352.

Diebold, F. and **Mariano**, R. (1995) "Comparing predictive accuracy", *Journal of Business and Economic Statistics*, 13, 253-263.

Geweke, J. (1977) "The dynamic factor analysis of economic time series", in D. Aigner and A. Goldberger (eds), Latent Variables in Socio-Economic Models, North-Holland.

Geweke, J. and **Singleton** K. (1977) "Maximum likelihood 'confirmatory' factor analysis of economic time series", *International Economic Review*, 22, 37-54.

Giannone, D., **Reichlin**, L. and D. **Small** (2008) "Nowcasting: The real-time informational content of macroeconomic data", *Journal of Monetary Economics*, 55(4), 665-676.

Marcellino, M., **Stock**, J.H. and M. **Watson** (2003) "Macroeconomic forecasting in the euro area: country specific versus euro wide information", *European Economic Review*, 47, 1-18.

den **Reijer**, A. (2013) "Forecasting Dutch GDP and inflation using alternative factor model specifications based on large and small datasets", *Empirical Economics*, 44, 435–453.

Pinheiro, M., **Rua**, A. and **Dias**, F. (2013) "Dynamic factor models with jagged edge panel data: Taking on board the dynamics of the idiosyncratic components", *Oxford Bulletin of Economics and Statistics*, 75(1), 80-102.

Rünstler, G., K. **Barhoumi**, S. Benk, R. **Cristadoro**, A. **Den Reijer**, A. **Jakaitiene**, P. Jelonek, K. Ruth, C. Van Nieuwenhuyze (2009) "Short-term forecasting of GDP using large datasets: A pseudo real-time forecast evaluation exercise", *Journal of Forecasting*, 28(7), 595-611.

Sargent, T. and **Sims** C. (1981) "Business cycle modelling without pretending to have too much a priori economic theory" in Christopher A. Sims (ed.), New Methods in Business Research, Federal Reserve Bank of Minneapolis.

Schumacher, C. (2007) "Forecasting German GDP using alternative factor models based on large datasets", *Journal of Forecasting*, 26(4), 271-302.

Schumacher, C. (2010) "Factor forecasting using international targeted predictors: The case of German GDP", *Economics Letters*, 107(2), 95-98.

Schumacher, C. (2011) "Forecasting with Factor Models Estimated on Large Datasets: A Review of the Recent Literature and Evidence for German GDP", *Journal of Economics and Statistics*, 231(1), 28-49.

Schumacher, C. and **Breitung**, J. (2008) "Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data", International *Journal of Forecasting*, 24(3), 386-398.

Stock, J.H. and M. **Watson** (1998) "Diffusion Indexes", *Working Paper no. 6702*, National Bureau of Economic Research.

Stock, J.H. and M. **Watson** (2002a) "Macroeconomic forecasting using diffusion indices", *Journal of Business and Economics Statistics*, 20, 147-162.

Stock, J.H. and M. **Watson** (2002b) "Forecasting using principal components from a large number of predictors", *Journal of the American Statistical Association*, 97, 1167-1179.

Stock, J. H. and M. **Watson** (2005) "Implications of dynamic factor models for VAR analysis", *Working Paper no. 11467*, National Bureau of Economic Research.

Watson, M. and **Engle** R. (1983) "Alternative algorithms for the estimation of dynamic factors, MIMIC, and varying coefficient regression models", *Journal of Econometrics*, 23, 385-400.

Notes

1. The opinions expressed in the article are those of the authors and do not necessarily coincide with those of Banco de Portugal or the Eurosystem. Any errors and omissions are the sole responsibility of the authors.

2. Banco de Portugal, Economic Research Department.

3. Banco de Portugal, Advisor to the Board.

4. We also assessed the forecasting performance with alternative transformations of the monthly data, namely month-on-month and year-on-year changes. We find that forecasting quarter-on-quarter GDP growth with the 3-month difference transformation outperforms the variant with the month-on--month transformation (see also Runstler *et al*. (2009)) and that forecasting the year-on-year growth does not improve on the results.

5. For comparison, the first four common static factors explain around 35 per cent of the variation in that US dataset.

6. For a more precise modelling of the dynamics, we focus on the month-on-month changes of the monthly series.

7. As is standard in the literature, this is called a pseudo real-time exercise since data revisions are not taken into account.

8. Concerning the case addressed in the last column of chart 6.1, we also assessed the forecasting performance when the EM algorithm suggested by Stock and Watson (2002a) is used to balance the dataset as well as its extension proposed by Pinheiro, Rua and Dias (2013). We find the former to perform worse whereas the latter delivers similar results *vis-à-vis* the AR case.

Appendix

Series	Source
Economic Sentiment Indicator	European Commission
Consumer Confidence Indicator	European Commission - Consumers survey
Financial situation over last 12 months	European Commission - Consumers survey
Financial situation over next 12 months	European Commission - Consumers survey
General economic situation over last 12 months	European Commission - Consumers survey
General economic situation over next 12 months	European Commission - Consumers survey
Major purchases at present	European Commission - Consumers survey
Major purchases over next 12 months	European Commission - Consumers survey
Unemployment expectations over next 12 months	European Commission - Consumers survey
Savings at present	European Commission - Consumers survey
Savings over next 12 months	European Commission - Consumers survey
Price trends over last 12 months	European Commission - Consumers survey
Price trends over next 12 months	European Commission - Consumers survey
Statement on financial situation of household	European Commission - Consumers survey
Construction Confidence Indicator	European Commission - Construction survey
Building activity development over the past 3 months	European Commission - Construction survey
Assessment of order books	European Commission - Construction survey
Employment expectations over the next 3 months	European Commission - Construction survey
Prices expectations over the next 3 months	European Commission - Construction survey
Industrial Confidence Indicator	European Commission - Manufacturing survey
Production trend observed in recent months	European Commission - Manufacturing survey
Assessment of order-book levels	European Commission - Manufacturing survey
Assessment of export order-book levels	European Commission - Manufacturing survey
Assessment of stocks of finished products	European Commission - Manufacturing survey
Production expectations for the months ahead	European Commission - Manufacturing survey
Selling price expectations for the months ahead	European Commission - Manufacturing survey
Employment expectations for the months ahead	European Commission - Manufacturing survey
Retail trade Confidence Indicator	European Commission - Retail trade survey
Business activity over recent months	European Commission - Retail trade survey
Assessment of stocks	European Commission - Retail trade survey
Expected business activity	European Commission - Retail trade survey
Orders placed with suppliers	European Commission - Retail trade survey
Employment expectations	European Commission - Retail trade survey
Services confidence indicator	European Commission - Services survey
Business situation development over the past 3 months	European Commission - Services survey
Evolution of the demand over the past 3 months	European Commission - Services survey
Expectation of the demand over the next 3 months	European Commission - Services survey
Evolution of the employment over the past 3 months	European Commission - Services survey
Expectations of the employment over the next 3 months	European Commission - Services survey
Economic Sentiment Indicator - Germany	European Commission
Economic Sentiment Indicator - Spain	European Commission
Economic Sentiment Indicator - France	European Commission
Economic Sentiment Indicator - UK	European Commission
Industrial Production Index - Total	Instituto Nacional de Estatística
Industrial Production Index - Manufacturing	Instituto Nacional de Estatística

Industrial Production Index - Consumer goods	Instituto Nacional de Estatística
Industrial Production Index - Consumer goods non-durable	Instituto Nacional de Estatística
Industrial Production Index - Consumer goods durable	Instituto Nacional de Estatística
Industrial Production Index - Investment goods	Instituto Nacional de Estatística
Industrial Production Index - Intermediate goods	Instituto Nacional de Estatística
Industrial turnover index - Total	Instituto Nacional de Estatística
Industrial turnover index - Manufacturing	Instituto Nacional de Estatística
Industrial turnover index - Consumer goods	Instituto Nacional de Estatística
Industrial turnover index - Consumer goods durable	Instituto Nacional de Estatística
Industrial turnover index - Consumer goods non-durable	Instituto Nacional de Estatística
Industrial turnover index - Intermediate goods	Instituto Nacional de Estatística
Industrial turnover index - Investment goods	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Total	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Consumer goods	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Consumer goods durable	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Consumer goods non-durable	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Intermediate goods	Instituto Nacional de Estatística
Industrial turnover index - Domestic market - Investment goods	Instituto Nacional de Estatística
Industrial turnover index - External market - Total	Instituto Nacional de Estatística
Industrial turnover index - External market - Consumer goods	Instituto Nacional de Estatística
Industrial turnover index - External market - Consumer goods durable	Instituto Nacional de Estatística
Industrial turnover index - External market - Consumer goods non-durable	Instituto Nacional de Estatística
Industrial turnover index - External market - Intermediate goods	Instituto Nacional de Estatística
Industrial turnover index - External market - Investment goods	Instituto Nacional de Estatística
Services turnover index - Total	Instituto Nacional de Estatística
Vacancies	Instituto de Emprego e Formação Profissional
Unemployment	Instituto de Emprego e Formação Profissional
New applications for employment by the unemployed	Instituto de Emprego e Formação Profissional
New job vacancies	Instituto de Emprego e Formação Profissional
New occupied jobs	Instituto de Emprego e Formação Profissional
Industrial employment index - Total	Instituto Nacional de Estatística
Industrial employment index - Manufacturing	Instituto Nacional de Estatística
Industrial employment index - Consumer goods	Instituto Nacional de Estatística
Industrial employment index - Consumer goods durables	Instituto Nacional de Estatística
Industrial employment index - Consumer goods non-durables	Instituto Nacional de Estatística
Industrial employment index - Intermediate goods	Instituto Nacional de Estatística
Industrial employment index - Investment goods	Instituto Nacional de Estatística
Industrial wages index - Total	Instituto Nacional de Estatística
Industrial wages index - Manufacturing	Instituto Nacional de Estatística
Industrial wages index - Consumer goods	Instituto Nacional de Estatística
Industrial wages index - Consumer goods durables	Instituto Nacional de Estatística
Industrial wages index - Consumer goods non-durables	Instituto Nacional de Estatística
Industrial wages index - Intermediate goods	Instituto Nacional de Estatística
Industrial wages index - Investment goods	Instituto Nacional de Estatística
Hours worked index - Total industry	Instituto Nacional de Estatística
Hours worked index - Manufacturing	Instituto Nacional de Estatística
Hours worked index - Consumer goods	Instituto Nacional de Estatística
Hours worked index - Consumer goods durables	Instituto Nacional de Estatística
Hours worked index - Consumer goods non-durables	Instituto Nacional de Estatística
Hours worked index - Intermediate goods	Instituto Nacional de Estatística

Hours worked index - Investment goods	Instituto Nacional de Estatística
Services employment index - Total	Instituto Nacional de Estatística
Services wages index - Total	Instituto Nacional de Estatística
Hours worked index - Total services	Instituto Nacional de Estatística
Merchandise imports - Total	Instituto Nacional de Estatística
Merchandise imports - Total exc. Fuels	Instituto Nacional de Estatística
Merchandise imports - Consumer goods	Instituto Nacional de Estatística
Merchandise imports - Intermediate goods	Instituto Nacional de Estatística
Merchandise imports - Investment goods	Instituto Nacional de Estatística
Merchandise exports - Total	Instituto Nacional de Estatística
Merchandise exports - Total exc. Fuels	Instituto Nacional de Estatística
Merchandise exports - Consumer goods	Instituto Nacional de Estatística
Merchandise exports - Intermediate goods	Instituto Nacional de Estatística
Merchandise exports - Investment goods	Instituto Nacional de Estatística
Retail trade turnover index - Total	Instituto Nacional de Estatística
Retail trade turnover index - Food	Instituto Nacional de Estatística
Retail trade turnover index - Non-Durable Non-Food	Instituto Nacional de Estatística
Retail trade turnover index - Durable goods	Instituto Nacional de Estatística
Tourism - Number of nights spent in Portugal	Instituto Nacional de Estatística
Tourism - Number of nights spent in Portugal by residents	Instituto Nacional de Estatística
Tourism - Number of nights spent in Portugal by non-residents	Instituto Nacional de Estatística
Light passenger vehicle sales	ACAP - Associação Automóvel de Portugal
Light commercial vehicle sales	ACAP - Associação Automóvel de Portugal
Heavy commercial vehicle sales	ACAP - Associação Automóvel de Portugal
Cement sales	CIMPOR, SECIL
Consumption of electricity	Rede Eléctrica Nacional
Consumption of gasoline	Direção Geral de Energia
Consumption of diesel	Direção Geral de Energia
Real effective exchange rate index	Banco de Portugal
PSI-20	Euronext Lisboa
ATM/POS	Banco de Portugal