SHORT-TERM FORECASTING FOR THE PORTUGUESE ECONOMY: A METHODOLOGICAL OVERVIEW*

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ABSTRACT

The aim of this article is to provide a stylised, concise description of the methodology underlying the short-term forecasting exercise for the economic activity regularly conducted at Banco de Portugal. As in the case of other central banks, it is useful to share the experience acquired in the development of tools aimed at obtaining short-term forecasts for the Portuguese economy. The rationale underlying the methodology is discussed intuitively and its corresponding presentation should be considered merely illustrative due to the dynamics of the process. This approach may potentially change, due to the continuous search for additional indicators and use of alternative econometric models. The article also presents an overview of analogous experiences at other central banks, namely within the Eurosystem.

1. Introduction

A timely evaluation of the current economic situation as well as a correct perception of its near term evolution are key inputs for economic policymaking, as the actions to be taken may be crucially dependent upon the quality of such an assessment.

In this context, a set of tools has been developed at Banco de Portugal to predict economic behaviour in the current quarter as well as in the several of the immediately subsequent quarters (commonly referred to in the literature as nowcasting and short-term forecasting, respectively). This article summarises the current approach. It should be noted that the current procedure results from a process evolving over time and influenced by the developments in the national statistics system. Concerning the latter point, reference should be made to the improvements made by the National Statistics Institute (INE) in terms of its compilation and release of the national accounts, both annual and quarterly, with a more regular compilation and earlier release dates. In this respect, it should be noted that there is a current time lag of 70 days in the release of the Quarterly National Accounts as opposed to 120 days up to the end of 2002.[1] Based on the results of Cardoso and Rua (2011) and José (2004), real-time reliability has also improved.

The methodological developments concerning short-term forecasting were also influenced by more demanding requirements associated with Portuguese membership of the euro area. After a long period in which estimates for the current and previous years were only published annually, Banco de Portugal started to publish regular projections for the Portuguese economy in its December 2000 Economic Bulletin,

1 In the first quarter of 2007, *INE* started to release a flash estimate for the GDP growth rate 45 days after the reference period.

one month after the European Central Bank began to publish projections for the euro area based on the forecasts reported by the central banks belonging to the Eurosystem. In this context, there was a more pressing need for quarterly macroeconomic scenarios. Despite the volatility of the quarterly figures, this development facilitates the assimilation of the effects of the intra-annual profile of the previous year on the annual projections as well as reflecting the most recent economic data available.[2]

The aim of this article is to describe the general guidelines underlying the current approach to conducting short-term macroeconomic forecasts. A concise description of the methodology currently in place is therefore provided containing information on its organization from a conceptual point of view while illustrating the different stages involved. This description should be considered merely illustrative due to the evolving nature of the process.

The article is organized as follows. In section 2, the main features of the approach to short-term forecasting for the Portuguese economy are discussed. In section 3, the practice at other central banks is reviewed. The conclusion is given in section 4.

2. Methodological overview

The forecast horizon of the short-term forecasting exercise is updated quarterly, with the first forecast for each quarter being conducted two quarters ahead of its publication by *INE*. For example, in June of a given year, one takes on board *INE*'s latest release of the Quarterly National Accounts for the period up to the first quarter of the said year, while continuing to forecast the second quarter (which started being forecasted in March) and forecasts for the first time the third quarter. The projections for the following quarters are obtained from a structural macroeconometric model. It should be noted that models of the latter type do not aim to capture very short-run behaviour and do not take into account the short-term economic indicators that become available. This process is illustrated in Chart 1.

Chart 1

FORECASTING EXERCISE
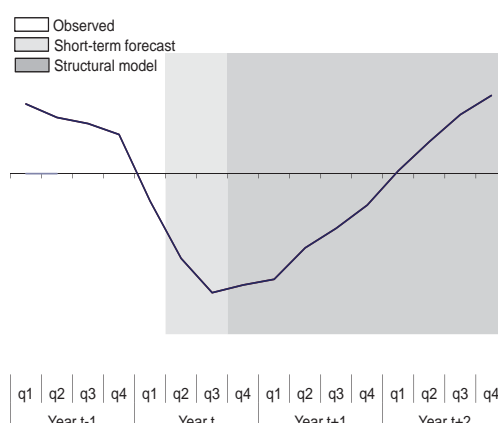
Source: Authors' calculations.

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2 In this context, Banco de Portugal, in 2004, started to regularly disclose a dataset covering the period since 1977 (see Castro and Esteves (2004)) while Amador and Dias (2004) provided the first formal contribution to the development of a procedure for the short-term forecasting of the main variables of the Quarterly National Accounts.

2.1. Main features

The short-term forecasting procedure is characterized by several special features. Firstly, GDP forecasting follows a bottom-up approach. *i.e.*, a forecast for each of the demand side components is obtained, which after taking the national accounts identities into account gives an implicit GDP forecast. This is the standard practice among institutions that report short-term forecasts, whose reasons for their choice are quite easy to understand.[3] The elaboration and presentation of a macroeconomic scenario makes it necessary to justify the GDP growth forecast. The projection of the various GDP components therefore facilitates the interpretation of the resulting GDP forecast and, accordingly, disciplines the construction of macroeconomic scenarios. In addition, the use of a bottom-up approach also facilitates the inclusion of judgment in the forecasting exercise.

The level of disaggregation considered in the bottom-up approach is conditional on the quality and availability of the data as well as on the ability to forecast the different variables. A stylised presentation of the disaggregation level considered at Banco de Portugal is given in Chart 2. Reference should be made to the use of certain specifications for forecasting purposes in the case of several variables. In addition to making it possible to forecast such variables, the use of such rules can also affect the correlation structure of the forecast errors between the different variables which can lead to an improvement of the forecasting performance of the bottom-up approach. For example, import forecasts are usually based on the behaviour of global demand weighted by the imported content while the change in inventories is modelled through a positive relationship with imports. In both cases, such *a priori* rules result in an increase of the correlation between the forecast errors of the several demand side components and imports, making it possible to reduce GDP forecast errors.

Concerning data transformation issues, the focus is, in general, on forecasting the year-on-year growth rate. This choice can be motivated by several reasons: i) the lack of chained external trade deflators indices, which makes it harder to interpret the quarter-on-quarter growth rates of the deflators and corresponding real changes; ii) the high volatility present in the quarter-on-quarter growth rates; iii) the strong seasonal pattern in some economic indicators; iv) the higher resemblance between variables measured in year-on-year terms and the evolution of some qualitative indicators.

Chart 2

BOTTOM-UP APPROACH
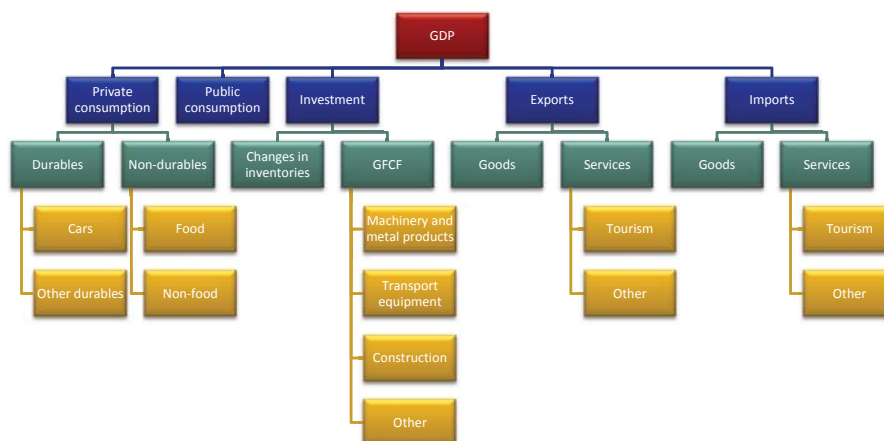
Source: Authors' calculations.

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3   See, for example, Esteves (2011) for a discussion regarding the issue of a direct forecast of GDP or resorting to a bottom-up approach in which a GDP forecast is obtained by aggregation of the projections to the corresponding demand side components.

Another feature of short-term forecasting is its eclectic nature to the extent that it includes both quantitative and qualitative available data, along with econometric models and judgment whenever required.

Regarding judgment, Pagan and Robertson (2002) are clear about its role on forecasting: "One thing that is clear, however, is that monetary policy institutions rarely, if ever, rely solely on mechanical model--based forecasts. If the science of forecasting is the model, then the art of forecasting is the judgment that is applied by the individuals involved".

Finally, in terms of econometric modelling, it should be acknowledged that there is a wide range of possible models, including a simple recursive historical average, univariate autoregressive models, vector autoregressive models, bridge models, factor models that take on board many time series, etc. As in the case of many other central banks and international institutions, bridge models have been the preferred modelling tool.

2.2. Forecasting with bridge models

As already mentioned, the current approach draws heavily on a set of bridge models that use comprehensive economic data available for Portugal to forecast the behaviour of demand side components. The fact that such types of models generally compare relatively well with other alternative short-term forecasting models in conjunction with their simplicity and tractability, has made them very popular among central banks and international institutions. Applications of bridge models can be found, for example, in Ingenito and Trehan (1996) for the United States, Zheng and Rossiter (2006) for Canada, Parigi and Schlitzer (1995) and Golinelli and Parigi (2005) for Italy, Barhoumi *et al.* (2011) for France, Grasmann and Keereman (2001), Rünstler and Sédillot (2003) and Diron (2006) for the euro area, Baffigi *et al.* (2004) for Germany, France, Italy and the euro area and Sédillot and Pain (2003) for several OECD countries.

A stylised presentation of the underlying idea is given in Chart 3, in which two monthly economic indicators are used to forecast a quarterly macroeconomic variable. As mentioned above, the idea is to exploit the informational content of the various economic indicators that are regularly released in order to obtain short-term forecasts for the main macroeconomic variables. Although conceptually straightforward, the practical implementation of this procedure involves the need to address several problems. Firstly, the economic indicators to be used for forecasting each variable must be selected. Secondly, the use of such information in real-time generally also involves the need to forecast the short-run evolution of the referred to economic indicators. In this respect, reference should be made to the fact that the economic indicators are usually available on a monthly basis whereas the variables to be forecasted are quarterly. This means that establishing a macroeconomic projection based on forecasting economic indicators enables the transparency of the exercise, by facilitating the monitoring thereof over time with the inclusion of additional monthly information. Thirdly, a bridge between the referred to economic indicators and the variable to be forecasted must be established. In particular, this is done by resorting to bridge models.

2.2.1. Choosing the economic indicators

The following should be taken into account when selecting the economic indicators. On the one hand, the indicators should be related, in economic terms, with the macroeconomic variable of interest. On the other hand, there should be a significant in-sample statistical relationship between the indicators and the variable to be forecasted.

Among the selected indicators it is important to distinguish two types of indicators. The first includes what are referred to as direct indicators, i.e. indicators that can be used directly (without a bridge) to

Chart 3

FORECASTING VIA BRIDGE MODEL

Indicator 1

15
10
5
0
-5
-10
-15
-20

Jan Jul Jan Jul Jan Jul

Indicator 2

15
10
5
0
-5
-10
-15
-20

Jan Jul Jan Jul Jan Jul

Variable to be forecasted (quarterly)

10
8
6
4
2
0
-2
-4
-6
-8
-10

Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4

Choosing the indicators *Short-run forecasting the indicators* *Bridge model*
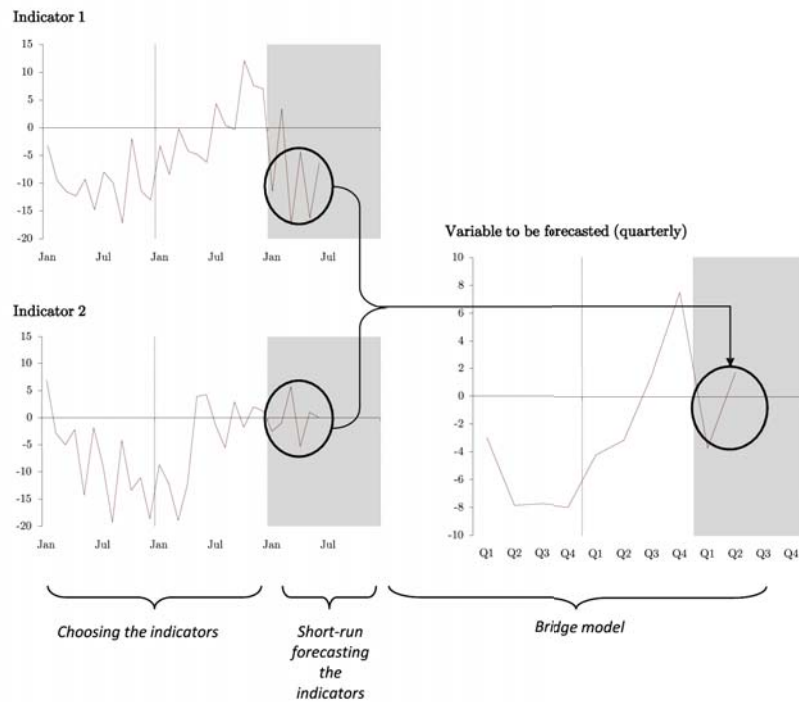
Source: Authors' calculations.

capture the evolution of the variable of interest. The two main examples refer to vehicle sales[4] and nominal external trade figures, which are available a few days and 45 days after the end of the reference month, respectively.

The second types of indicators include indirect indicators, *i.e.* indicators that are related with the variable of interest but cannot be used directly to assess its evolution. Such indicators can be broken down into quantitative (hard data) and qualitative (soft data) indicators.

Within the innumerous quantitative indicators the following should be highlighted. In the case of private consumption, reference should be made to the real retail trade turnover index and its disaggregation, usually published by INE around a month after the reference period, as well as data referring to Automated Teller Machines and Point of Sale (ATM/POS) terminals provided by SIBS and disclosed by Banco de Portugal a few days after the end of the month.[5] Other examples include, for instance, cement sales for the domestic market to track construction GFCF and equipment imports to assess machinery and equipment GFCF.

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4 However, in the case of vehicle sales, the quality effect is also taken into account. The quality effect endeavours to adjust the volume of vehicle sales based on the respective segments. A nil quality effect translates into a uniform distribution of vehicle sales over the different segments whereas a positive (negative) quality effect implies a bias in this distribution towards higher sales of vehicles in the higher (lower) range segments.

5 Regarding the usefulness of ATM/POS data to estimate the behaviour of private consumption see Banco de Portugal (2011a).

In addition to quantitative indicators, the use of qualitative data is also quite important.[6] This results from the fact that consumers and business surveys have several important properties such as: i) availability, both in terms of time span as well as in terms of sectoral coverage; ii) it includes questions about expectations; iii) monthly frequency; iv) timeliness since it is released immediately after the end of the reference period; v) real-time reliability as there are usually no revisions to the series.

Regarding the use of this qualitative information, special reference should be made to the importance of confidence indicators due to their ability to track economic fluctuations, which also have some leading properties vis-à-vis some demand side components. Banco de Portugal (2009) illustrates the usefulness of the consumer confidence indicator to anticipate private consumption developments. Maria and Serra (2008) analyze the relationship between qualitative indicators and business investment while Cardoso and Duarte (2006) use qualitative data to forecast merchandise exports.

Naturally, along with the continuous development of the national statistics framework, there is a permanent search for and re-evaluation of potential indicators for forecasting purposes.

2.2.2. Short-run forecasting the indicators

Before establishing a bridge between the selected indicators and the variable to be forecasted, it is crucial to predict the near term developments of these indicators to enable the real-time forecasting exercise to be performed.

A SARIMA (Seasonal AutoRegressive Integrated Moving Average) model, enabling the capture of seasonal and non-seasonal short-run dynamics is used for most indicators

$$\phi(L)\varphi(L^s)(\Delta^d x_t - \alpha - \beta_1 D_1 - ... - \beta_{11} D_{11}) = \theta(L)\delta(L^s)\varepsilon_t$$

in which α denotes the constant term, d corresponds to the differencing order necessary to make x stationary, D_i is a seasonal dummy ($i = 1, ..., 11$), β_i is the corresponding coefficient, ε_t is a white noise and the polynomials in the lag operator (L) are defined as usual($\phi(L)$ – autoregressive polynomial; $\varphi(L^s)$ – seasonal autoregressive polynomial; $\theta(L)$ – moving average polynomial; $\delta(L^s)$ – seasonal moving average polynomial). The identification of the model is based on the well known Box-Jenkins approach and the corresponding estimation uses non-linear least squares. Although multivariate models may be considered, within the bridge models literature, it is usual for univariate models to be considered for predicting the short-run developments of the indicators in which each variable is forecasted on the exclusive basis of its past regularities (see, for example, Rünstler *et al* (2009)).[7]

In the case of some economic indicators, the short-run evolution is predicted by using specific models developed in several studies. For example, the behaviour of nominal goods exports is based on several qualitative indicators (see Cardoso and Duarte (2006)). It is occasionally necessary to apply a rule-of--thumb, such as the carry-over assumption (*i.e.* that the variable maintains its last observed value). This is done essentially for variables with a high volatility and for which it was not possible to find any model with a satisfactory predictive ability.

The use of the above mentioned models is also complemented by information provided by large firms, namely, related to the auto, aviation and energy sectors. This information is also reflected in the external trade data due to its importance.

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6 As an example of how quantitative and qualitative data complement each other, reference may be made to the monthly coincident indicators for economic activity and private consumption regularly released by Banco de Portugal (see Rua (2004, 2005)).

7 A recent application of this approach to predict passenger vehicle sales is presented by Banco de Portugal (2011b).

Finally, the short-run forecasts can be influenced by judgment, especially, when there are reasons to believe that there might be special factors at play which are not captured by the models. In particular, the judgment can reflect developments which models cannot forecast (resulting from information provided by some economic agents) or simply the expertise of the individuals involved regarding the latest forecast errors.

2.2.3. The bridge between the economic indicators and the variable of interest

When the economic indicator is not a direct one, the relationship between the selected indicators and the variable to be forecasted must be estimated. In particular, it is considered a bridge model

$$y_t \;=\; \alpha + \sum_{j=1}^{J} \theta_j y_{t-j} + \sum_{m=1}^{M} \sum_{k=0}^{K} \beta_{m,k} x_{m,t-k} + \varepsilon_t$$

in which y_t denotes the variable to be forecasted and x_m the m economic indicator. The forecast, therefore, depends on the past history of the dependent variable – autogressive component – and on the current and past values of the selected indicators.[8] In particular, several alternative specifications may be considered, including a single economic indicator or several at the same time. Instead of using only the best forecasting model, Bates and Granger (1969) suggest that a combination of forecasts should be considered. Empirical results in the related literature show that combining the forecasts of different models can be very useful, in particular, in a context of parameter instability or model uncertainty (see, for example, Aiofli *et al.* (2010)).

A possible way of combining the forecasts is described in Diebold (1988). It basically consists of weighting the different forecasts based on the past performance of each model and the correlation structure among the corresponding forecast errors. In particular, the forecast for a given variable is defined as a weighted average of the forecasts coming from N estimated models,

$$y^P = \sum_{n=1}^{N} \omega_n^* y_n^P$$

in which $y_n^{\,P}$ is the predicted value given by model n (n=1,…,N) and the optimal weights are given by

$$W_{(N \times 1)}^* = \Omega^{-1} i \,/\, \left(i' \Omega_i^{-1} i \right)$$

in which Ω is the variance-covariance matrix between the N one step ahead forecast errors and i is a unit vector of dimension N. Granger and Ramanathan (1984) have shown that these weights can be obtained through the regression of the observed values for y in the forecasts provided by the different models, without constant term and assuming that the sum of the coefficients is one.

In practice, the forecast obtained from this aggregation procedure may be compared with the one resulting from a simple average (*i.e.* equal weights for the different forecasts). For example, Smith and Wallis

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8 An alternative forecasting model, which has become increasingly popular in the literature in the last few years, is the factor model. This model assumes that the behaviour of each variable can be decomposed in two parts: the common component, which can be captured by a limited number of factors, and an idiosyncratic component which reflects the specific dynamics of each variable. An attractive feature of the factor models is that it allows to take on board many time series simultaneously. However, one of the practical problems is the fact that considering more series does not result necessarily in better forecasting performance (see, for example, Boivin and Ng (2006)). In this context, several alternatives have been proposed in the literature to address this issue (see, for example, Dias et al. (2010)).

(2009) have shown that considering different weights may not prove to be better, in terms of forecasting performance, than using a simple average due to the estimation error in finite samples.

To provide a clearer illustration of the above discussion, the application thereof is considered to the case of non-durables, non-food private consumption. This component accounts for around 2/3 of Portuguese private consumption.

To forecast this variable, several possible economic indicators are considered, namely: i) the real retail trade turnover index for non-durables, non-food goods; ii) the consumer confidence indicator; iii) ATM/POS data. A model including each variable and a model with all indicators simultaneously are considered. The corresponding estimated models for the last decade are as follows:

i)
$$\hat{y}_t = \underset{(0.227)}{1.117} + \underset{(0.089)}{0.628}\, y_{t-1} - \underset{(0.075)}{0.301}\, y_{t-4} + \underset{(0.042)}{0.245}\, x_{1,t}$$

ii)
$$\hat{y}_t = \underset{(1.089)}{5.711} + \underset{(0.123)}{0.463}\, y_{t-1} - \underset{(0.075)}{0.260}\, y_{t-4} + \underset{(0.016)}{0.085}\, x_{2,t} + \underset{(0.027)}{0.056}\, x_{2,t-2}$$

iii)
$$\hat{y}_t = -\underset{(0.281)}{0.144} + \underset{(0.100)}{0.838}\, y_{t-1} - \underset{(0.097)}{0.198}\, y_{t-4} + \underset{(0.059)}{0.231}\, x_{3,t} - \underset{(0.055)}{0.161}\, x_{3,t-1}$$

iv)
$$\hat{y}_t = \underset{(0.762)}{2.752} + \underset{(0.090)}{0.631}\, y_{t-1} - \underset{(0.080)}{0.208}\, y_{t-4} + \underset{(0.064)}{0.108}\, x_{1,t} + \underset{(0.023)}{0.055}\, x_{2,t} + \underset{(0.049)}{0.074}\left(x_{3,t} - x_{3,t-1}\right)$$

in which y denotes the year-on-year (y-o-y) real growth rate of non-durables, non-food private consumption; x_1 refers to the y-o-y growth rate of the retail trade turnover index for non-durables, non-food goods; x_2 represents the consumer confidence indicator and x_3 denotes the y-o-y ATM/POS data growth rate indicator. The figures set out in brackets are the standard errors of the estimated coefficients and all the models have been checked by a battery of tests including model specification, autocorrelation, heterocedasticity and residuals normality.

The following should be noted regarding the selected specifications. The term corresponding to the y variable lagged one period, suggests a high persistence in terms of behaviour of the dependent variable. This is expected as the variable is considered in y-o-y growth rates. The same applies to the y variable lagged four periods. Its statistical significance reflects the importance of base effects when y-o-y growth rates are considered.

Reference should be made to the following in terms of economic indicators: the retail trade index for non--durables, non-food goods appears contemporaneously as expected; the consumer confidence indicator has leading properties (in particular, in model ii)); as regards ATM/POS data, both the contemporaneous and the one period lags are significant although the fact that they have opposite signs suggests that such a nominal indicator is more useful in terms of acceleration/deceleration, with the hypothesis of being symmetric not being rejected in model iv).

Chart 4 presents the fit of each individual model throughout the sample period as well as the one resulting from optimal weighting. In particular, the optimal weights are given by: i) 1%; ii) 30%, iii) 5%, iv) 64%.

Chart 5 illustrates the above described procedure for the first out-of-sample period, *i.e.*, the first quarter of 2012. It presents two possible ways of obtaining a forecast. The first forecast (P1) results from the direct application of the above procedure in which the forecast for the year-on-year real growth rate for non-durables, non-food private consumption corresponds to the weighted average of the forecasts of the various estimated models, using the weights derived above. The second forecast (P2) corresponds to the prediction of the change in the year-on-year real growth rate, *i.e.* acceleration/deceleration. In

Chart 4

NON-DURABLES NON-FOOD PRIVATE CONSUMPTION | ESTIMATED MODELS AND OPTIMAL WEIGHTED AVERAGE

Legend:
- Residual
- Observed
- Optimal weighted average (based on the four models (gray lines))
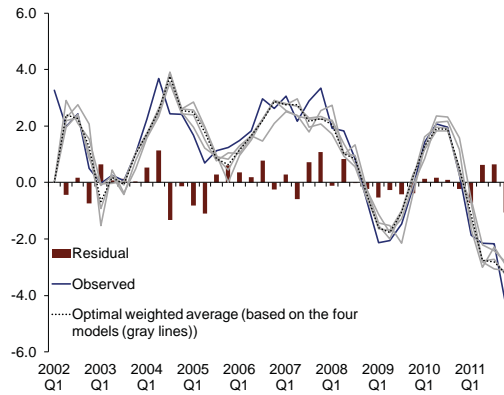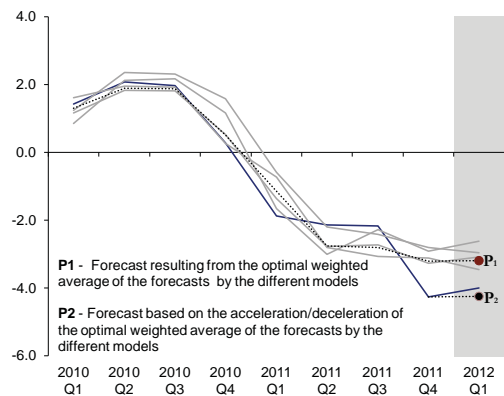
Source: Authors' calculations.

this case, it is implicitly assumed that the residual will have the same value that was observed in the last period (referred to as the constant adjustment). This way of proceeding can be quite relevant when a substantial difference between the last observation and the forecast is noted, as in the case of the last quarter of 2011 (see Chart 4).

In general, through the residual analysis many other possible ways could be envisaged as, for example, using the average of the more recent residuals. Such a choice will eventually be up to the expert and on the interpretation of the nature of the observed residuals in the more recent period. When conducting the forecasting exercise, this is the step that usually involves a greater input from the expert.

3. Short-term forecasting at other central banks

Chart 5

NON-DURABLES NON-FOOD PRIVATE CONSUMPTION | ALTERNATIVE FORECASTS

P1 - Forecast resulting from the optimal weighted average of the forecasts by the different models

P2 - Forecast based on the acceleration/deceleration of the optimal weighted average of the forecasts by the different models

Source: Authors' calculations.

As in the case of Portugal, in most central banks, the type of models used for forecasting is conditional on the forecast horizon. In particular, there is a clear distinction between short-term and medium/long term forecasting (see, for example, Gerdrup and Nicolaisen (2011) for a detailed description of how the forecasting exercise is organized in Norges Bank, Bundesbank (2009) for the German case while Pagan and Robertson (2002) portray the process in several central banks including the U.S. Federal Reserve, Bank of Canada, Reserve Bank of New Zealand, Bank of England and Reserve Bank of Australia). In general, the forecast horizon includes the first two quarters in the former case, as the starting point for the medium/long term forecasting in which a completely different approach is used. Such a distinction reflects, *inter alia*, the fact that when conducting the short-term forecasting exercise, there is a special interest in including high frequency, namely monthly, data whereas in a structural model of simultaneous equations only quarterly or annual data are usually considered. The fact that the release of the information in real-time also occurs with different time lags, constitutes *per se* an additional problem in the short-run evaluation of economic activity. The econometric tools used should therefore differ depending on the forecast horizon in other to address the corresponding specific issues.

Typically, for the reasons referred to above, the short-term forecasting exercise at central banks follows a bottom-up approach.[9] For example, at the Bundesbank a bottom-up approach is used for both the demand and supply sides despite the fact that, in the case of the demand side, the level of disaggregation considered is lower than at Banco de Portugal. Although it is more usual to follow a demand side approach, at some central banks, namely at the Bundesbank and Bank of England, the supply side is also considered. In the case of Germany, this is due to the importance of the industrial sector on the behaviour of economic activity. As a result, the industrial production index is followed with particular attention when assessing the current economic situation. In turn, in the United Kingdom, there are more economic indicators on the supply side and they are also more timely released. This is reflected in the fact that the UK Office for National Statistics compiles its first estimate for GDP based on supply side statistics.

As mentioned above, concerning the econometric models that can be used for short-term forecasting, there are many potential alternatives (see, for instance, Rünstler *et al*. (2009) for a discussion on several econometric models for nowcasting and short-term forecasting and their corresponding application to several European countries). However, despite the innumerous alternatives, the use of bridge models is a standard practice within the Eurosystem. Nevertheless, it is worth mentioning that an increasing number of central banks has been implementing factor models benefiting from the developments in this strand of literature. However, the practical use of such models raises some issues in terms of monitoring and the inclusion of judgment is less straightforward due to the wide range of data involved.

Concerning the information to be assimilated, it is standard practice to use both quantitative and qualitative data. In contrast with, for example, the United States, the information conveyed by consumer and business surveys constitute an important part of the data used for forecasting purposes in European countries (in some cases, this can be as or even more important than quantitative data). Among the advantages discussed previously, reference should once more, be made to the ability of qualitative data to anticipate the evolution of economic activity.

Although reflecting the idiosyncrasies of each country, another common feature is the continuous search for additional indicators for the real-time tracking of the behaviour of the main macroeconomic variables. For example, at the Danmarks National Bank credit card payments are used to anticipate retail sales in Denmark (Carlsen and Storgaard (2010)); Fenz and Schneider (2009) suggest using truck mileage as a leading indicator of Austrian exports; Huurman *et al*. (2009) suggest using weather forecasts to improve the forecasts of electricity prices in the Nordic countries.

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9 In some cases, the bottom-up approach is complemented by direct forecasts for GDP, namely through the use of factor models. For applications of this type of model developed at Banco de Portugal see, for example, Dias *et al*. (2010) and Rua (2011).

4. Conclusions

A timely evaluation of the current economic situation as well as a correct perception of the near term developments is crucial for several economic agents. Without knowing the starting point it is harder to know where we are heading. In such a context, short-term forecasting is particularly relevant.

As in the case of other central banks, this article aims to describe the methodology currently in use for the short-term forecasting of economic activity in Portugal. It should be remembered that the current approach has evolved over time and has been influenced by the developments observed on the national statistical level and stimulated by the more demanding requirements resulting from Portuguese participation in the regular Eurosystem forecasting exercises.

Naturally, the synopsis contained in this article as well as the results herein presented should be considered illustrative. The short-term forecasting approach is always evolving through the search for additional economic indicators and the development of alternative forecasting models.

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