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Real-time evaluation of GDP in some Eurozone countries

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Abstract

GDP, the key statistics describing the state of the economy, is collected at low frequency, typically on a quarterly basis, and released with a substantial lag. The goal of this paper is to have the most timely and accurate idea about the current real economic activity, measured by the growth rate of GDP, on the basis of all the information that is available. We follow Camacho and Pérez-Quirós (2010) model introducing a simple algorithm which, while forecasting rather well in real time the GDP growth rates, has the advantage of being a transparent and small-scale model, taking into account the data revision procedure used by statistical offices, and addressing all the issues of real-time forecasting (in particular, mixed frequencies and ragged edges). To our knowledge, we are the first to apply the model to the main Eurozone countries: Germany, France, Italy and Spain. Our results show that the model performs well during the sample, both in terms of trend and in terms of magnitude. This paper is part of a project aimed at developing different business cycle indicators to be used in Consob Risk Outlook.

JEL Classifications: E32, C22, E27.

Keywords: Business Cycles, Output Growth, Time Series.

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Contents

1 Introduction

GDP is the key statistics describing the state of the economy, and is collected at low frequency, typically on a quarterly basis, and released with a substantial lag. In January 2014, for example, for the European Union Member States we only had information up to the third quarter of 2013 and we had to wait until mid-February 2014 to obtain a first estimate of the last quarter of 2013.[1]

Nowcasting addresses this issue trying to give timely estimates of GDP to be used for decision-making by the economic agents. Nowcasting is defined as the prediction of the present, the very near future and the very recent past. The term is a contraction for "now" and "forecasting" and has been used for a long time in meteorology and recently also in economics (Banbura et al. 2011).

To estimate current GDP it is crucial to use all the information available today, i.e. to be able to use data which are related to the target variable but are collected at higher frequency, typically monthly, and released in a more timely manner.

Our aim is to have the most timely and accurate idea about the current real economic activity, measured by the growth rate of GDP, on the basis of all the information that is available. The objective is not to explain the economy but to obtain reliable and easily replicable nowcasts or short-term forecasts of GDP.

We follow Camacho and Pérez-Quirós (2010) that introduce a simple algorithm which, while forecasting rather well in real time the euro area GDP, has the advantage of being a transparent and small-scale model, taking into account the data revision procedure used by Eurostat, and addressing all the issues of real-time forecasting (in particular, mixed frequencies and ragged edges).

Our contribution relies on the fact that for the first time, as far as we know, we apply the underlying model to the four main countries of the Euro area in terms of GDP (Germany, France, Italy, and Spain[2]), and obtain a forecast for their short-term GDP growth rates. What is also important is that, while Camacho and Pérez-Quirós (2010) apply the model using data up to 2008, by using information from a time span that goes from 2002 to 2013, we provide a first empirical test of the model when the economy is hit by a recession: this test is extremely important in order to understand how and by how much the model is able to deal with a strong shock to the economy and therefore with a large movement in the time series, and would therefore represent an important robustness check to the estimation algorithm.

1 In the Eurostat framework, Flash estimates correspond to the release issued 45 days after the reference quarter. First estimates correspond to the release issued around 65 days after the reference quarter. Second estimates correspond to the release issued around 100 days after the reference quarter. As of 15 February 2011 (data for the fourth quarter of 2010) Eurostat has renamed the releases: now, Flash estimates correspond to the release issued 45 days after the reference quarter. Second estimates correspond to the release issued around 65 days after the reference quarter. Third estimates correspond to the release issued around 100 days after the reference quarter. Flash estimates do not incorporate revisions to previous periods while Second and Third releases revise all previous quarters. In the current release policy of Eurostat for the calculation of European GDP there are three releases during a quarter Q. The two first releases (T+45, T+65) are database releases that are combined with a news release. The T+100 release is only a database release.

2 Of course, the model can be easily extended to any country of interest.

The paper is organised as follows. Section 2 introduces the problem and discusses the related literature. Section 3 explains the details of the methodology and the data selection. Section 4 evaluates the empirical results. Section 5 concludes and proposes issues for further research.

2 Nowcasting GDP: definition and literature review

As mentioned in the introduction, GDP in the European Union is released by Eurostat only 45 days after the close of the reference quarter. The lag in the publication of GDP data means that GDP in the current quarter must be estimated, nowcasted. In practice, the monitoring of GDP growth must rely on indicators that are released with a higher frequency: monthly data on economic activity such as industrial production, retail sales and unemployment but also various data that reflect market sentiment and expectation about future economic activity, such as business and consumer surveys.

Two main issues arise when it comes to analyse the economy in real time: mixed frequencies and ragged edges. The first issue concerns the fact that data are available at different frequencies. The second issue relates to the staggered release of the monthly data: the monthly panel is unbalanced at the end of the sample due to the fact that monthly indicators are released with different publication lags: this problem is known in the literature as ragged edges issue. Different statistical tools have recently been developed to obtain short-term forecasts of quarterly euroarea GDP from these higher frequency indicators, taking advantage of their earlier publication.

The traditional approach developed by policy institutions to nowcast current-quarter GDP growth goes under the name of bridge equations: these are predictive equations that bridge monthly observations with quarterly ones. More precisely, bridge equations are regressions of quarterly GDP growth on its lags and on a small set of preselected key monthly indicators.[3] Bridge equations present several limitations: they can handle only a limited set of variables and forecast missing observations using standard time series models.

Dynamic factor models are designed to extract the common movement from a large set of time series and to synthesise them into a few artificial latent factors, which represent the main sources of variation in the data set. The idea has been first introduced by Giannone et al. (2008) and applied to US data. In a nutshell, Giannone et al. (2008) propose a framework that formalizes the updating of the nowcast as data are released and evaluates marginal impact of new data releases on precision of nowcast. More precisely, they use a two-steps model. In the first step, the parameters of the model are estimated from an OLS regression on principal components extracted from a balanced panel, which is created truncating the data set at the date of the least timely release. In the second step, the common factors are extracted by ap-

3 See Baffigi et al. (2004) and Diron (2006) for an application of these models to forecast Eurozone GDP

plying the Kalman smoother on the entire data set. The advantage of this approach over that of the simple bridge equations is that, instead of forecasting missing values on the basis of a univariate autoregressive model, the Kalman filter exploits all the multivariate information included in the model. Within this framework, Angelini et al. (2011) compare the accuracy of bridge models (composed by 12 equations) and dynamic factor models (based on 85 variables) for the forecast of Eurozone quarterly GDP growth and find that the dynamic factor model significantly improves upon the pool of bridge equations. They also show that, while the performance of bridge models is fairly constant over the quarter, the forecast error of the factor model decreases with the arrival of new information. The advantage over bridge equations is particularly pronounced in the middle of the quarter, when it exploits a large number of early releases efficiently (soft data early in the quarter and hard indicators at the end of the quarter).

Following the same approach, Banbura et al. (2010) provide an application for the nowcast of Eurozone GDP, enlarging the econometric framework to analyse the link between the news in consecutive data releases and the resulting forecast revisions for the target variable. They argue that the only element that leads to a change of the nowcast is the unexpected (with respect to the model) part of data release, which they label "news": what is relevant is not the release itself but the difference between that release and what had been forecast before it (in the unlikely case that the released numbers are exactly as predicted by the model, the nowcast will not be revised). Data revisions are instead modelled as noise by Evans (2005) who applied a related dynamic factor model to United States. He claims that data releases can be viewed as noisy signal of the real-time estimate of GDP growth, where the noise (that arises from the error in forecasting) is therefore the difference between the first and the subsequent forecasts, and is assumed to be randomly distributed.

Related to these models is the literature on coincident indicators of economic activity where an unobserved state of the economy is estimated from a multivariate model. A seminal paper in the literature of coincident indicators of economic activity is Stock and Watson (1989, 1991). They proposed a single-index linear dynamic factor model to analyse the co-movements among four macroeconomic indicators: industrial production, employment, income and sales. These series have a common element that can be modelled by an underlying unobserved variable representing the overall economic activity (Stock-Watson index). These macroeconomic indicators are therefore assumed to be driven by the common factor and by some idiosyncratic shocks, which are variable-specific.

Mariano and Murosawa (2003) extend the Stock-Watson index by including quarterly Real GDP. Technically, they consider maximum likelihood factor analysis of time series when some series are quarterly and others are monthly. They solve the problem of mixing frequencies by treating quarterly series as monthly series with missing observations, and they obtain a state-space representation of a factor model with missing observations. With this approach, it is possible to include, say, quarterly and monthly variables in the same model. This is very important when one needs to forecast GDP growth because most of the economic time series that can be considered as good predictors of GDP movements are released on a monthly basis.

Altissimo et al. (2001 and 2007) construct a monthly indicator (based on a large dataset, including 145 macroeconomic variables) that tracks Eurozone GDP growth but, unlike the latter, is free from short-run dynamics (Euro-coin indicator). Euro-coin is probably the leading coincident indicator of the euro area business cycle; however, its interpretation is not straightforward: it does not forecast growth rate of GDP as such, but rather a long run component of GDP. Instead of estimating a latent variable (as in Stock and Watson, 1989 and 1991), the model builds an estimate of medium-to-long run component of GDP (which is an observable variable, although with a long delay) after having removed its short run[4] component. In this way, it is able to produce a monthly real-time indicator (named New Euro-coin) that can be used as a forecast of future GDP long run growth. From a technical side, while most of the aforementioned forecasts are made by means of Kalman filter and maximum likelihood estimation, Altissimo et al. (2007) make use of a modified band-pass filter that does not suffer of poor end-of-sample performance. They solve the problem of ragged edges by forward realignment (shifting forward the series whose last observations are missing).

In a recent work, Aprigliano and Bencivelli (2013) build, in line with Altissimo et al. (2007), the Italian counterpart for the Euro-Coin estimator. While they use a different set of variables, the most important difference with the methodology proposed by Altissimo et al. (2001,2007) is that they implement the so called LASSO (Least Absolute Shrinkage and Selection Operator) in order to select the most relevant information about the comovement of the variables.

Finally, Camacho and Pérez-Quirós (2010) build, on the spirit of Stock and Watson (1989,1991), an economic indicator based on a small set of variables and call it Euro-STING (Short-Term Indicators of Growth); they follow Evans (2005) modelling data revisions as noise. They compute a forecast of GDP growth (based on the estimate of a common factor that can be thought of as a coincident indicator of the current business cycle) that has a good forecasting performance especially in the very short run. The advantage of this approach is that it performs quite well compared to other professional forecasters and, at the same time, it is a parsimonious model that produces timely forecasts for GDP with no delay. Also, nothing impedes one to use the structure of the model in order to forecast other variables of interest. Finally, thanks to its estimation procedure (Kalman filter and maximum likelihood), this kind of models need very few adjustments when new information becomes available at the end of the sample.

4 The short run is here defined as a period shorter than 1 year.

3 Methodology

3.1 The model

In order to forecast GDP in the short term, we use a state-space model adapted from Camacho and Pérez-Quirós (2010). The idea of the model is the following: given that most economic time series show similar patterns, we can think of them as the sum of two orthogonal components: a common component (henceforth, we refer to the latter as *common factor,*f_t) and an idiosyncratic component, which is series-specific (i.e., it is different for every series and uncorrelated with the idiosyncratic components of the other series). Being able to obtain an estimate of f_t would allow us to obtain what in the literature is known as coincident indicator, which can be thought of as a proxy of the current business cycle.

The use of factor models is common in the literature on coincident economic indicator.[5] It is important to notice that the factor is not estimated in order to explain which series are more suitable to forecast GDP movements, because our model does not have a purely economic meaning (we do not aim at explaining GDP); the purpose is rather to gather information from the series and build a monthly series that can be thought of as a (latent) indicator of the business cycle. We choose a small set of variables because we think that the framework of small-scale factor models, has the advantage of being easy to update and interpret, without significant losses in terms of forecasting performance.[6] The choice of a parsimonious dataset is coherent with Boivin and Ng (2006), who show that too many data are not always good for factor forecasting because of potentially cross-correlated idiosyncratic errors. Moreover, an application of Boivin and Ng (2006) procedure shows that as few as 11 variables might constitute an optimal dataset for producing factor forecasts of GDP growth rates (see Caggiano et al. 2011).

The biggest advantage of this approach is that we have a timely estimate for GDP growth rate; the forecast is provided on a monthly basis, and as long as new information becomes available (that is, new data for the monthly variables are gathered), the estimate for the common factor can be updated.

There is an important point to be stressed: when new information becomes available, the forecast that embeds this new information can be instantaneously produced, since the model does not require (as we will see) any further adjustment; also, importantly, the forecasts for the previous periods will not change if we add more observations at the end of the dataset. This is a big advantage of the model, especially when timely estimates and forecasts are needed.

In short, this model helps us explaining the observed co-movements among GDP series and other economic indicators. Once we have estimated the common factor f_t, it is straightforward to obtain a forecast for GDP values for which the first

5 A cornerstone of this branch of literature is Stock and Watson (1989).

6 Our model is more parsimonious than other similar works: for instance, Altissimo et al. (2007) employ 145 variables, Angelini et al. (2011) use 85 variables while Giannone et al. (2010) use 64 variables.

available estimates are not yet released. This forecast will therefore be based on all the relevant information taken from the time series through the common factor.

We use 11 variables[7] to estimate the common factor. We can group these variables in four sets: i) Gross Domestic Product, GDP[8] ii) Hard Indicators: Exports, Industrial Production Index (IPI) and Retail Sales, Exports; iii) Employment; iv) Soft Indicators: Economic Sentiment Indicator (ESI), Business Confidence Indicator, Consumer Confidence Indicator, Building Confidence Indicators.[9]

There are several problems to be addressed. The first problem is mixing frequencies: GDP growth rates and Employment are measured quarterly, while all other indicators are available on a monthly basis. In line with the literature[10], we choose to follow Mariano and Murasawa (2003) and express the quarterly series as three times the geometric mean of the monthly series, in a given quarter:

$$g_t = \frac{1}{3}x_t + \frac{2}{3}x_{t-1} + x_{t-2} + \frac{2}{3}x_{t-3} + \frac{1}{3}x_{t-4}$$

where g_t is the quarterly series and x_t are the past month-on-month growth rates.

Another issue to be addressed is the problem of data revisions. As already recalled Eurostat releases three different estimates for the quarter-on-quarter growth rates for GDP. The *flash* estimate (y_t^f), the *first* estimate (y_t^{1st}) and the *second* estimate (y_t^{2nd}).[11.] We follow Evans (2005) and model the three different data revisions as:

$$y_t^f = y_t^{2nd} + e_{1_t} + e_{2_t}$$
$$y_t^{1st} = y_t^{2nd} + e_{2_t}$$

where e_{1_t} and e_{2_t} are independent and zero mean revision shocks, with variances $\sigma_{e\,1}^2$ and $\sigma_{e\,2}^2$ respectively, and for simplicity are assumed to be uncorrelated. With the two assumptions above, we have a monthly measure for quarterly series and a reliable specification for the three different GDP estimates. This assumption is not new in the literature. Aruobaet al. (2008) and Swanson and van Dijk (2006), among others, have found evidence supporting the idea that preliminary data (flash with respect to first, and flash and first estimates with respect to second in our model) cannot be considered rational forecast of revised data; we therefore believe that the assumption that preliminary announcements are noisy signals of revised data works well in our model. Camacho and Pérez-Quirós (2010) further confirm this assumption.

7 Hard indicators are taken in month-on-month growth rates; soft indicators are taken in levels. All variables are seasonally adjusted and transformed so to have zero mean and standard deviation equal to one.

8 As already recalled, we make use of three subsequent revisions for GDP growth rates: flash estimate,first estimate and second estimate, where the flash estimate is the first available.

9 Detailed sources and availability for all the time series are provided in the appendix.

10 The same procedure is used, among the others, by Banbura et al. (2011) and Camacho and Pérez-Quirós (2010).

11 A complete calendar of the release dates for each variable is provided in the appendix.

Finally, we have to take into account the problem of missing observations which arises for two reasons: first, we bridge monthly and quarterly data by treating the latter as monthly series with missing observations; second, usually different series show different lags (*ragged edges problem).* The approach we follow is particularly important because it allows us to avoid the problem of *ragged edges* and mixed frequencies at once, without affecting the results. In literature, other solutions have been proposed: for instance, *ragged edges* problem has been sometimes solved by forward realignment (shifting forward the series whose last observations are missing).[12]

Let us see how the state-space model looks like. First, we assume that we have no missing observation and the panel is balanced. Define Y_t as the vector of observable variables (GDP, hard indicators,employment and soft indicators), h_t the vector including the present and lagged values of the common factor and the idiosyncratic shocks, and the present values of e_{1_t} and e_{2_t}. The *measurement equation* reads:

$$Y_t = Hh_t + w_t$$

where $w_t \sim N(0, R)$.

The *transition equation* links the present and past values of h_t and reads:

$$h_t = Fh_{t-1} + \xi_t$$

where F is the transition matrix and $\xi_t \sim N(0, R)$. The matrix H contains the factor loadings $\beta_1, \beta_2', \beta_3{}', \beta_4$, which measure the impact that the unobservable common factor has on each variable.[13]

Now, we have to handle missing observations. We follow the approach described above, taken from Mariano and Murosawa (2003). Define Y_{it} as the i-th element of the vector Y_t and let R_{ii} be its variance. Let also H_i be the i-th row of the matrix H which has α columns and $0_{1\alpha}$ be a row vector of zeroes. Finally, let ϑ_t be the random variable drawn from a normal distribution $N(0, \sigma_\vartheta^2)$. The measurement equation when the missing values are replaced by ϑ_t then becomes:

$$Y_{it}^* = \begin{cases} Y_{it} & if\ Y_{it}\ is\ observable \\ \vartheta_t & otherwise \end{cases}$$

$$H_{it}^* = \begin{cases} H_{it} & if\ Y_{it}\ is\ observable \\ 0_{1\alpha} & otherwise \end{cases}$$

$$w_{it}^* = \begin{cases} 0 & if\ Y_{it}\ is\ observable \\ \vartheta_t & otherwise \end{cases}$$

$$R_{iit}^* = \begin{cases} 0 & if\ Y_{it}\ is\ observable \\ \sigma_\vartheta^2 & otherwise \end{cases}$$

12 An application of the latter can be found in Altissimo et al. (2007).

13 β_2 and β_3 are the vectors of factor loadings for, respectively, hard indicators and soft indicators. β_1 is the impact of the common factor f_t on the three measures of GDP; finally, β_4 is the impact of f_t on employment.

In this way, the model is fully specified and the matrices are conformable.[14] We are now able to compute and maximize the likelihood function by means of the Kalman filter (see Appendix A for details on Kalman filter estimation).[15] Another important aspect of our approach is that we can easily add missing data at the end of the sample when they become available; the estimated dynamics of the model does not change if we add more observations. We finally estimate the model by means of maximum likelihood (see for instance, Camacho and Pérez-Quirós (2010) and Banbura et al.(2010)). What is interesting now is to notice that the common factor will have a different impact for the four sets of variables, measured respectively by the four factor loadings $(\beta_1, \beta_2', \beta_3', \beta_4)$. These loadings are crucial in order to compute the common factor f_t and, conversely, the forecast for the GDP growth rate.

Notice that the Kalman filter process can be used even if we believed that the coefficients of the model $\beta_1, \beta_2', \beta_3', \beta_4$ changed over time. For simplicity, we assume that these are constant in our sample: in this way, we can evaluate the importance of each series in the entire sample, and not period by period, which for our purposes would be less interesting.

3.2 The data

The descriptive statistics of the data, their availability, their frequency and their source are thoroughly described in the Appendix B. Of course, data selection is a crucial step in developing our indicator, because we need to choose a set of variables which is both parsimonious and descriptive of the state of the economy. Camacho and Pérez-Quirós (2010), after having defined a core set of variables, decide whether to include additional variables in the dataset by testing whether their inclusion increases the percentage of variance of GDP explained by the common factor. We think that this is a reasonable approach and therefore choose (when available) the country-specific counterparts of the set of variables that they choose with this method, together with a more qualitative approach in the choice of the variables that we have already explained above.

We classify the variables used in three groups: GDP revisions, Hard indicators (based on economic activity data), and Soft indicators (based on survey data).

In section B of the Appendix, we plot a comparison between GDP growth revisions for each country, i.e. First, Flash and Second GDP estimates. One can easily notice that while during the years before 2008 these three estimates were often coincident, after the beginning of the crisis the flash (and the first) estimates have often failed to adequately predict the second (and final) estimate for GDP growth rate. For this reason, we find that including the three estimates of GDP will provide

14 This substitution, importantly, has no impact on the model estimation: the Kalman filter used to estimate the coefficients, in fact, uses the data generating process of a Normal distribution, so that we simply add a constant to the likelihood function to be maximized.

15 The Kalman filter makes possible to compute the contribution of each series to GDP forecast.

us with important information on its dynamics, especially in the post-2008 period, when the three values differ the most.[16]

As already recalled, we use both hard and soft indicators. Hard indicators have a direct link with real economic activity but they have the disadvantage of being released with a delay of at least one month; moreover, they do not capture the expectations of the economic agents (i.e., producers and consumers).For this reason we also include soft indicators, because of their ability of capturing the economic sentiment (which is also important in describing the overall state of the economy). Moreover, they have the precious advantage of being available on a timely basis – that is, the soft indicator which refers to a given month is available before the end of that month. A number of authors have emphasized how market confidence can be a good predictor of economic activity. Dées and Soares Brinca (2011), for instance, show that consumer confidence has been in certain circumstances (namely, when household survey indicators feature large changes, which often happens in recessionary periods) a good predictor of consumption for the US and Euro area markets. Banbura and Runstler (2007) also find that survey data contain important information beyond the monthly real activity measures for the GDP forecast.[17]

As hard indicators, we choose three out of four variables of Stock and Watson's (1991) model[18] (Employment, Industrial Production Index and Retail Sales) and add Exports. *Employment* is defined as the total number of employed persons; *Industrial Production Index (IPI)* is Total Industrial Production including Mining, Manufacturing, and Energy but excluding transportation, services, and agriculture. *Retail sales* is defined as Retail sales of medium and large firms; finally *Exports* refer to the transfer of goods and services from residents to non-residents.[19]

As Soft Indicators, we include four of the most important survey data from the European Commission database (Economic Sentiment Indicator, Consumer Confidence Indicator, Business Confidence Indicator, Building Confidence Indicator). From a qualitative point of view, these latter indicators are meant to capture the sentiment about the economy of both the supply (Building Confidence and Business Confidence) and the demand side of the market (Consumer Confidence), as well as a synthesis of the two (Economic Sentiment Indicator). A list of figures plotting the four Soft Indicators for each country is provided in section B of the Appendix.

16 A lot of studies have explored how and by how much recessionary periods can make it more difficult to predict key economic variables. A work by Gonzalez Cabanillas and Terzi (2012) shows how, in the post 2008 period, the accuracy of year-ahead forecast errors of some of the key economic variables (including GDP) has significantly deteriorated. Another example, in the context of the analysis of the impact of fiscal consolidation on GDP, is given by Blanchard and Leigh (2013).

17 As discussed in a recent article, the Bank of England uses two main models to nowcast GDP. One is based on modelling growth in different industries, while the other is based on mapping from survey indicators to GDP at an aggregate level (see Bell et al. (2014)).

18 The choice of including, when possible, the same core variables used in Stock and Watson's model is in line with the recent literature about factor models. We do not include income variables because we do not have this series for the Eurozone countries we are considering.

19 They are valued at FOB (Free On Board) which corresponds to the market price at the border of the exporting country.

Again, we want to stress that we could have easily added more variables to the dataset, and therefore more information, but we must keep in mind that our purpose is to balance a good forecasting performance with parsimony in selecting the variables.

We transform our data in a different way depending on their nature. We take growth rates for Hard Indicators and for GDP revisions, while we use all Soft Indicators in levels. We follow the literature and transform the variables so that they have zero mean and unit variance (as for instance in Altissimo et al. (2007) and Camacho and Pérez-Quirós (2010). This choice is due to the fact that, for instance, month on month growth rates of Exports and Sales are not comparable neither in terms of mean nor in terms of standard deviation.

At the time this paper was written, we have the data for Soft indicators up to January 2014, up to December (in some cases, November) 2013 for Hard indicators, and up to the third quarter of 2013 for GDP revisions. Once more, we stress that our estimation procedure has the big advantage that we can add new data at the end of the dataset as they become available without affecting past estimates, so we can deal quite easily with this implicit problem of real-time forecasting.

Also, with our estimation procedure, it is very easy to compute out-of-sample forecasts: we just have to add missing observations at the end of the sample, and the Kalman iterations will produce estimates for these observations. Recall indeed that our model replaces missing observations with random draws, which as we have said does not change the results (see section 2.1).

4 The empirical results

4.1 Forecasts of GDP growth rates

In this section, we show the results of our forecasting exercise. We implement the model using data from the four most important Eurozone countries: Germany, France, Italy and Spain.

As already recalled the purpose of our exercise is not to explain economic phenomena, but rather to have a timely and reliable forecast for GDP growth rate in a given month, which represents an enormous advantage, since GDP is measured quarterly, and the first available estimates are released only 45 days after the end of the quarter (i.e. the first estimate for the third quarter of 2013 has been released the 15th November 2013).

Also, recall that our interest is in short term forecasting, and for this reason we choose a forecasting window of one month. Technically, longer out-of-sample forecasts can be easily obtained by imposing one (or more) months of missing observations at the end of the sample; the Kalman filter will then compute the common factor f_t up to the last month. However, the farther we want to predict, the less we can trust the predictions, since the model is designed for real-time or short term forecasting.

Figure 1 plots the comparison between actual and forecasted GDP growth rates for Germany. As we can see, the actual values and the monthly estimated values co-move quite well. In particular, the model seems to capture the trend in the movements of GDP growth rates; all actual growth rates lie within the two confidence bands of a unitary standard deviation. According to our estimates, GDP growth in Germany will be positive in January 2014 as well, but the rate will be slightly lower in the latter month (+0.12%) compared to the rates in November 2013 (+0.22%) and September 2013 (+0.36%). The model also seems to behave particularly well during the 2008 crisis.

Figure 1 Germany – Actual and estimated GDP growth rates

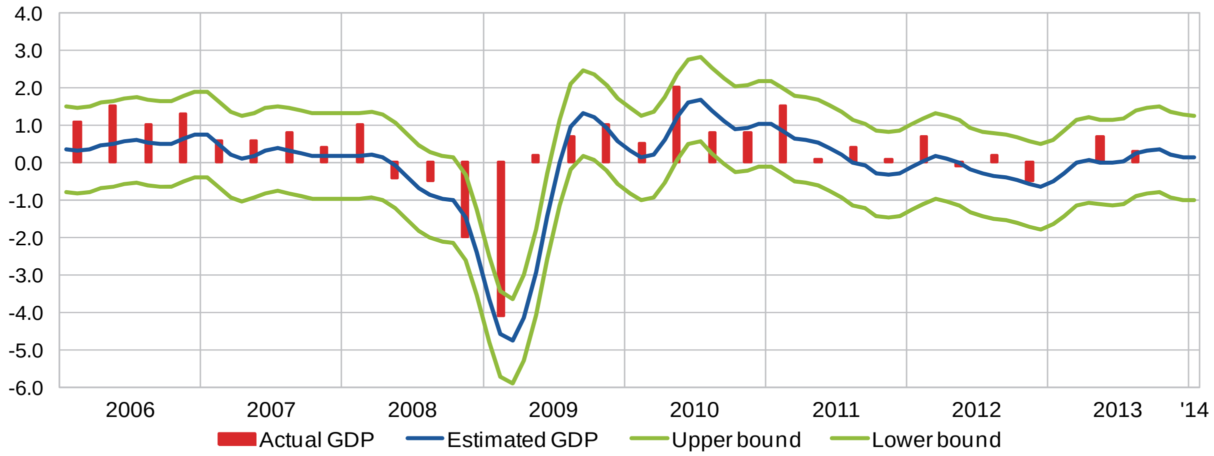


Figure 2 plots the comparison between actual and forecasted GDP growth rates for Italy. Again (except for December 2008) all actual values for GDP growth rates lie within the confidence bands. Importantly, the model behaves particularly well at the end of the sample. We notice, in particular, that the forecasted values for GDP growth rates for the period August 2013-January 2014 are positive. Indeed, the estimate for December 2013 is +0.34%, while for January 2014 is only slightly lower: +0.28%. Again, as for Germany, what is striking is the very good performance during the crisis and in the last months of 2012 and during 2013.

Figure 2 Italy – Actual and estimated GDP growth rates

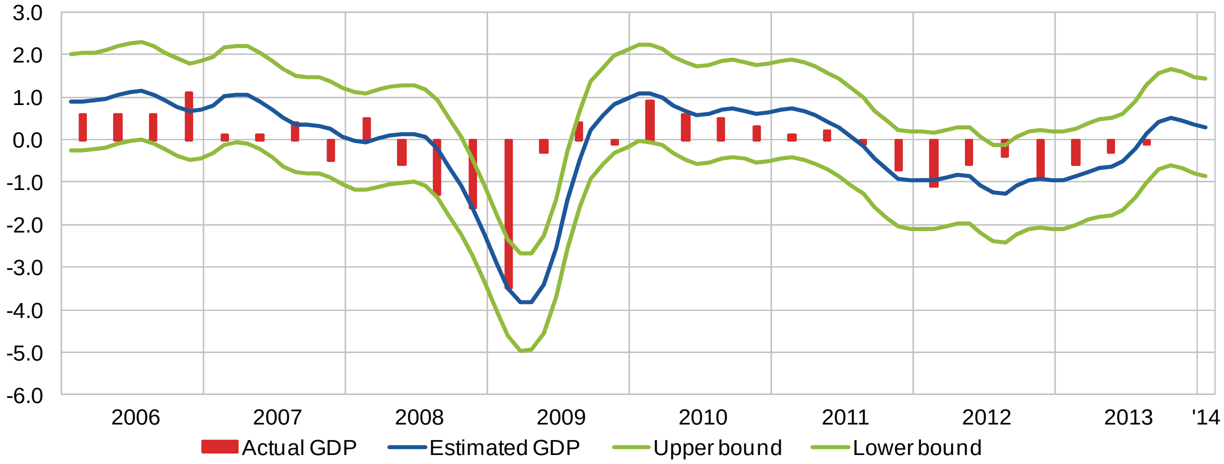


Figure 3 plots the comparison between actual and forecasted GDP growth rates for France. Again (except for the first quarter 2010 and the second quarter 2013) all actual value for GDP growth rates lie within the confidence bands. However, the model for France seems to work poorly in 2013. We notice, in particular, that the second quarter GDP growth rates were negative while the actual GDP has been slightly positive. This worsened performance needs further investigation; however, we can already notice that the standard deviations for estimated French GDP are larger than those of German and Italian estimates. This suggests that the volatility of the sample for French data is higher and this, by consequence, affects the results and the forecasting accuracy.

Figure 3 France – Actual and estimated GDP growth rates

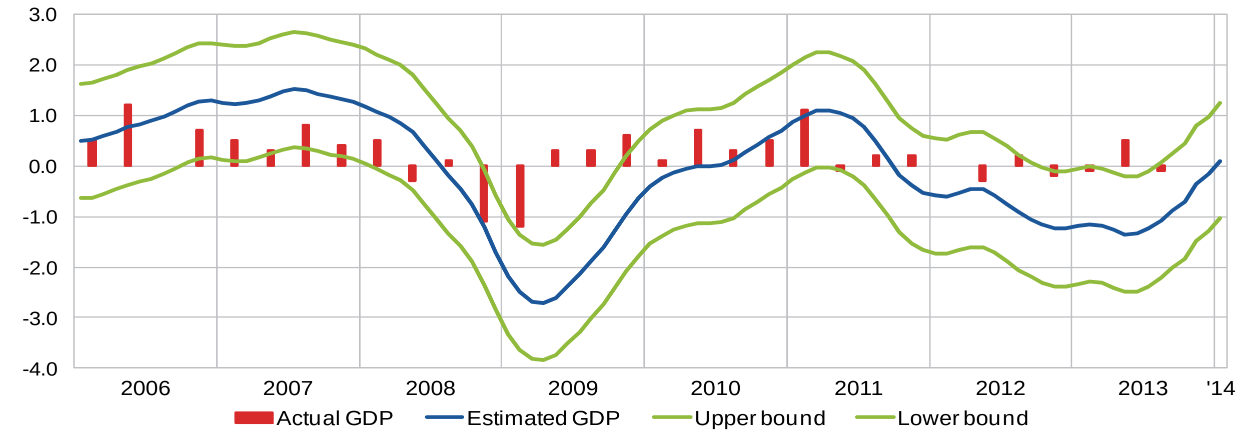
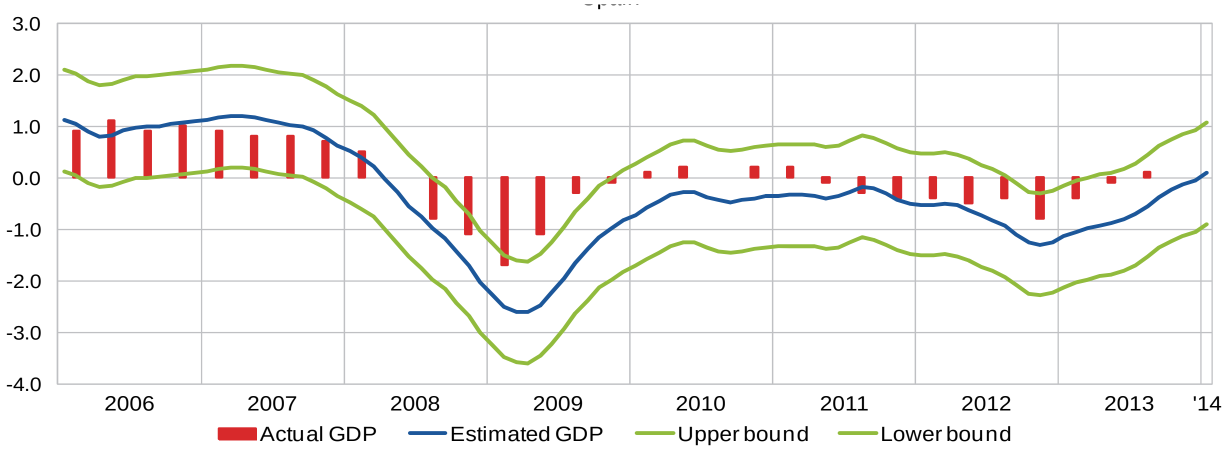


Figure 4 plots the comparison between actual and forecasted GDP growth rates for Spain. The model works well for Spain as shown, again, by the fact that all actual value for GDP growth rates lie within the confidence bands. The model seems to behave particularly well at the end of the sample. The results show that Spanish GDP will keep growing at the end of 2013 and beginning of 2014 at roughly the same pace than during 2013 and the end of 2012. In other words, according to our estimates, Spain seems to be turning the corner from recession to recovery.

Figure 4 Spain – Actual and estimated GDP growth rates



To sum up, the model provides us with monthly growth rates, and the latest available forecast is January 2014. At first glance, the model seems to predict very well (both quantitatively and qualitatively) for Germany and Italy, but seems to follow the overall trend for France and Spain as well.

With a visual inspection, one can easily see that the model performs very well in times of crisis (again, both in terms of trend and in terms of magnitude): recall that the red bars in the figures are the revised estimates for GDP, and therefore they're only released 100 days after the end of the quarter, while we can reasonably predict that value in real time. We can extract from our forecasting exercise that the overall trend for GDP growth rates for the end of 2013 seems to be positive for every country.

Once more, we stress that with this method, we are able to have an estimate for GDP growth rate for January 2014, while - at the moment this paper was written - we had information about GDP growth rates for the third quarter, coming from Eurostat Flash estimate. Therefore, the model anticipate Eurostat preliminary estimates, and at the same time is able to provide us with reliable information about both the trend and the magnitude of present GDP growth rates.

4.2 Common factor estimation

In this section, we plot for each country the estimated common factor which can be intuitively thought of as a synthesis of the business cycle pattern of the country of interest. As we have seen in section 4.1, from the factor we easily build the forecasts for GDP growth rates (recall that the factor is built from monthly series – or quarterly series with missing observations – and therefore is available on a monthly basis). The figures for the common factor series of each country are provided below.

The common factor series is quite similar, in terms of pattern, to the forecast of GDP growth rates. However, it does not provide a point estimate for a given indicator, but rather it can be considered itself an indicator of the current economic activity which presents some clear advantages: it is timely, monthly, and it incorporates the information from both hard and soft indicators. Similar indicators (that is, estimates of the current business cycle), despite the methodological differences, can be found in the literature (see for instance Altissimo et al. (2007)[20]). Our empirical analysis, besides the forecasts of section 4.1, provides a synthesis of the economic activity of the past and of the near future which is constructed with a relatively low number of variables (and therefore of effort required to collect and update them), along the seminal work of Stock and Watson (1991).

20 See section 2 for a detailed description of the advantages and disadvantages with respect to other indicators.

Figure 5 Common factor series – Germany and Italy

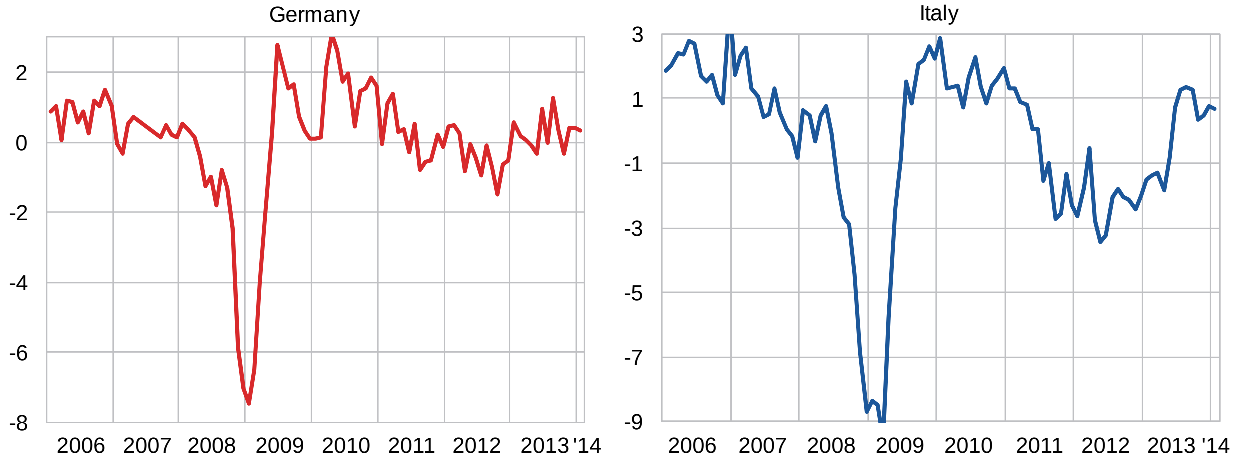
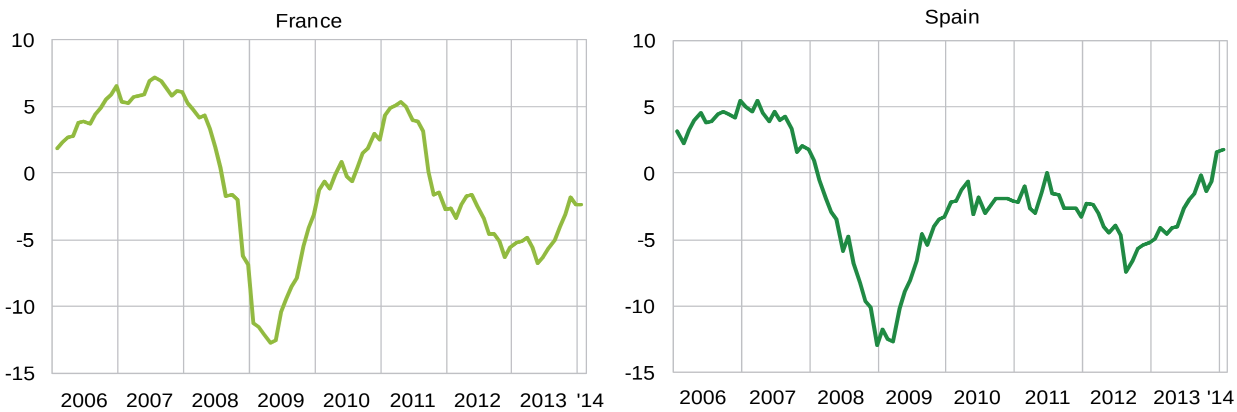


Figure 6 Common factor series – France and Spain



4.3 Factor loadings analysis

In this section, we report the factor loadings resulting from our maximum likelihood estimation. These reflect the degree to which the latent series can explain the variation of a given observed variable or, in other words, what impact the latent factor has in driving a given variable. Positive coefficients mean that these series are pro-cyclical: they are positively correlated with the common factor f_t which, once again, can be thought of as an approximation of the business cycle.

We now report the estimated factor loadings when the dataset ends in January 2014. Firstly, we estimate the common factor and the factor loadings when only soft indicators are available for January 2014 (that is, hard indicators are available up to December 2013). Results are reported below.[21]

Table 1. Factor loadings

	Italy	Germany	France	Spain
Second estimates of GDP	0.15	0.25	0.04	0.07
Export	0.07	0.31	0.03	0.01
Industrial Production Index	0.26	0.43	0.05	0.06
Sales	0.07	0.11	0.01	0.04
Employment	0.02	0.03	0.06	0.06
Building Confidence Indicator	0.03	0.03	0.05	0.07
Economic Sentiment Indicator	0.24	0.13	0.21	0.21
Industrial Confidence Indicator	0.14	0.07	0.21	0.19
Consumer Confidence Indicator	0.22	0.11	0.22	0.18

The above results are interesting for several aspects.

First, the coefficients for Hard Indicators are significantly higher for Italy and Germany than for Spain and France; the opposite is true for the coefficients of Soft Indicators, which are on average more pronounced for Spain and France. In other words, the latent factor is able to explain soft indicators for the French and the Spanish economies. A possible interpretation is that market sentiment and – more generally – expectations about the overall state of the economy are more determinant drivers of the economy in France and Spain, at least with respect to Italian and German economies.

Second, among soft indicators, Economic Sentiment and Consumer Confidence Indicator are the most correlated with the common factor f_t in each country, while the information provided by Building Confidence Indicator is of little relevance for the overall state of the economy (at least with respect to the other indicators). This happens because Economic Sentiment Indicator and Consumer Confidence Indicator are not driven by expectations and opinions about a given sector, but rather about a broader set of determinants of the economy; as a consequence, they embed more information about the overall state of the economy, resulting in a higher correlation with the common factor.

21 Data set for Hard Indicators ends at December 2013; dataset for Soft indicators ends at January 2014. Dataset for Second ends at the third quarter of 2013.

Probably the most striking result is that the forecasts for countries whose latent factor is more correlated to Hard Indicators and Second estimates for GDP (i.e., Germany and Italy) are significantly more accurate than those for the remaining countries. This suggests that, despite their timeliness advantage, soft indicators cannot substitute hard indicators in forecasting GDP movements. In other words, Soft Indicators add precision and timeliness to the forecasts when Hard Indicators are available and they are extremely useful when data on hard indicators have not been released yet. However, they are not sufficient to adequately forecast GDP when they are the more correlated to the latent factor than Hard Indicators. This is a plausible explanation for the poor forecasting performance of the model for French GDP growth rates.

Let us compare the results we obtain for the four biggest countries in the Euro Area with those obtained by Camacho and Pérez-Quirós (2010) for the Eurozone. On one hand, the coefficients on hard indicators are very similar to theirs (for instance, their coefficient of Second is equal to 0.15, and the coefficient of Sales is 0.07). This is an interesting results since it confirms that the country-specific counterparts for Second GDP (as well as most of the Hard indicators) and common factor f_t have the same relationship as those at the Euro area level, that is they have a significant correlation with the latent factor; this in turn means that they will be important when predicting the series for GDP which, as we know, are constructed using the estimate of the common factor.

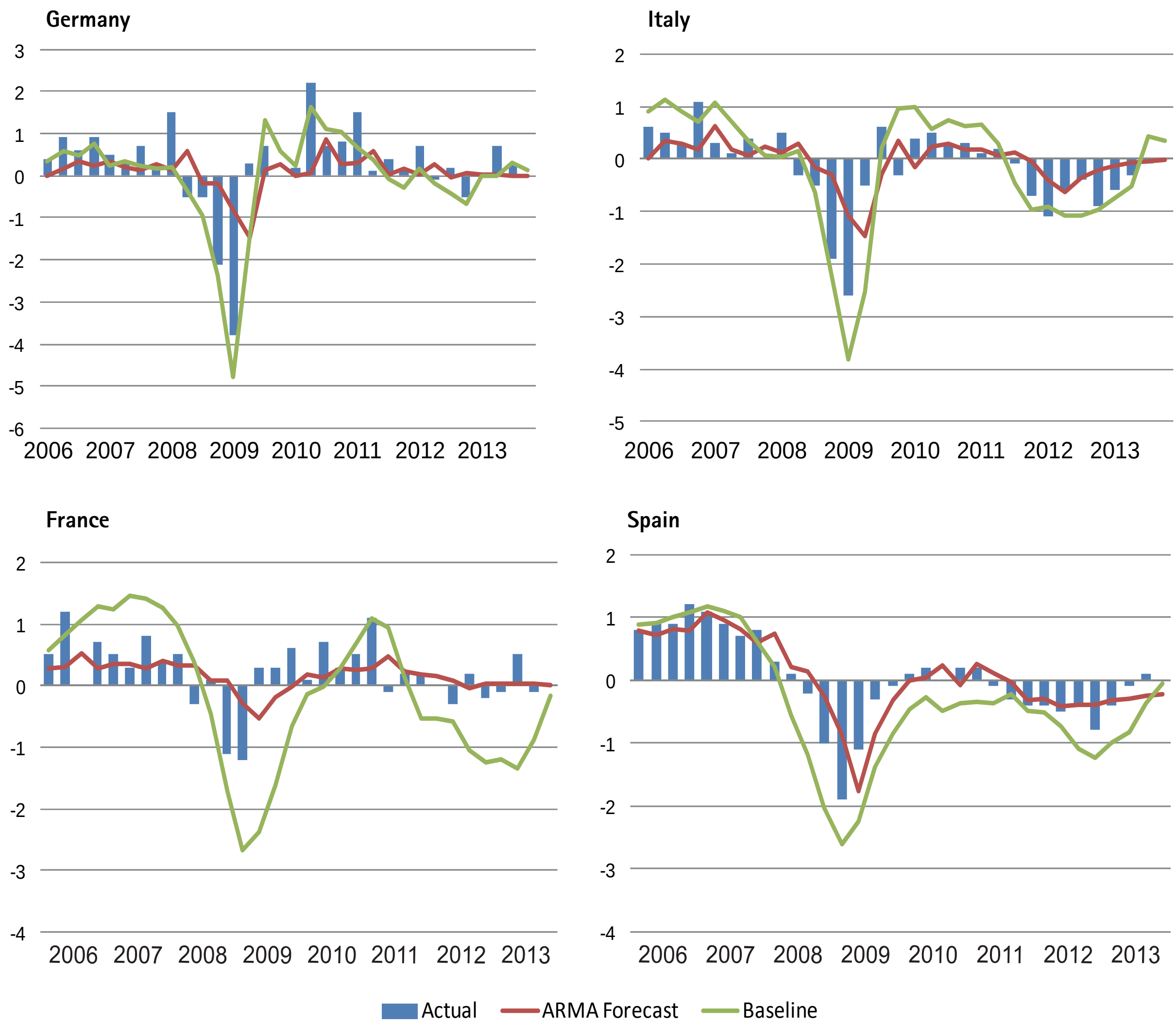
On the other hand, the most striking difference is that, in our estimation sample, soft indicators are much more correlated with the common factor at country-specific level than at Euro area level (i.e, the coefficients are relatively high with respect to those estimated by the two authors). The different importance of the latent factor in explaining Soft and Hard indicators between country-specific and Euro area data is an interesting result. Indeed, a natural interpretation of the small factor loadings for Soft indicators found by Camacho and Pérez-Quirós (2010) is that their explanation power in factor models is not limited *per se*, but becomes small only when Hard indicators are available and are included in the sample.

Our results seem to be in contrast with these findings. However, several interpretations are possible. One could be that survey data are taken into account by economic agents (whose decisions affect the behaviour of the economy) more at country level than at aggregate level: this would explain their importance in our data. Another possible interpretation is that, as we have already recalled, our sample (unlike that of Camacho and Pérez-Quirós, 2010) covers the crisis period. In times of recession or of stagnant economy, opinions ad expectations are more important than in normal times: as a consequence, the factor loadings on these variables are higher. Of course these findings are open to other interpretations.

4.4 Comparison with other forecasting models

We now estimate a standard autoregressive model[22] on the revised series for GDP growth, and we compare it with the actual value of the revised forecasts[23], and with the forecasts of our baseline model. In addition, we also plot a short-term (one period) out-of-sample prediction of the autoregressive model at the end of the sample. Since the latest available estimate for GDP growth rate is the third quarter of 2013, we forecast GDP growth rate for the fourth quarter.

Figure 7 Comparison between Actual, ARMA forecasts and Baseline (our) model forecasts for GDP growth rates



22 In other words, we estimate an ARMA (p,q) for each country, where the lengths of the autoregressive and moving average components – p and q, respectively - depend on each sample.

23 For another application in which standard autoregressive processes are compared to more sophisticated models, see Metheson (2011).

One can easily notice that, both quantitatively and qualitatively, a standard ARMA process is not able to provide a forecast as good as ours (especially in terms of variance), and this holds true for each country. Recall also that a standard ARMA - unlike our model - is obviously not suitable for the forecast of GDP at a monthly frequency since the ARMA forecasts are computed after having estimated the actual series for GDP growth rates, which are available at quarterly frequency.

As we can see, for most of the periods considered, the difference between our estimates and the actual value is significantly smaller than the difference between the latter and estimates from the ARMA model. Another difference is that our model, as we have said, predicts positive growth rates for Italy at the end of 2013, while the forecast provided by the ARMA model is virtually zero.

Besides the poor forecasting performance (at least with respect to our model), a standard autoregressive model has several disadvantages in the purpose of interest. Firstly, as we have said, it is available on a quarterly frequency, while we can have estimate also at a monthly frequency; secondly, the more the periods of the out-of-sample forecast, the poorer its performance will be, while it is not necessarily the case for our model.

These disadvantages depend both on the structure of the two models, and on the fact that our model is based on a much broader set of information linked to the economy.

In short, the comparison between our model and a standard ARMA model strengthens our results, and justifies the use of this model for the purpose of interest.

Out-of-sample forecasts

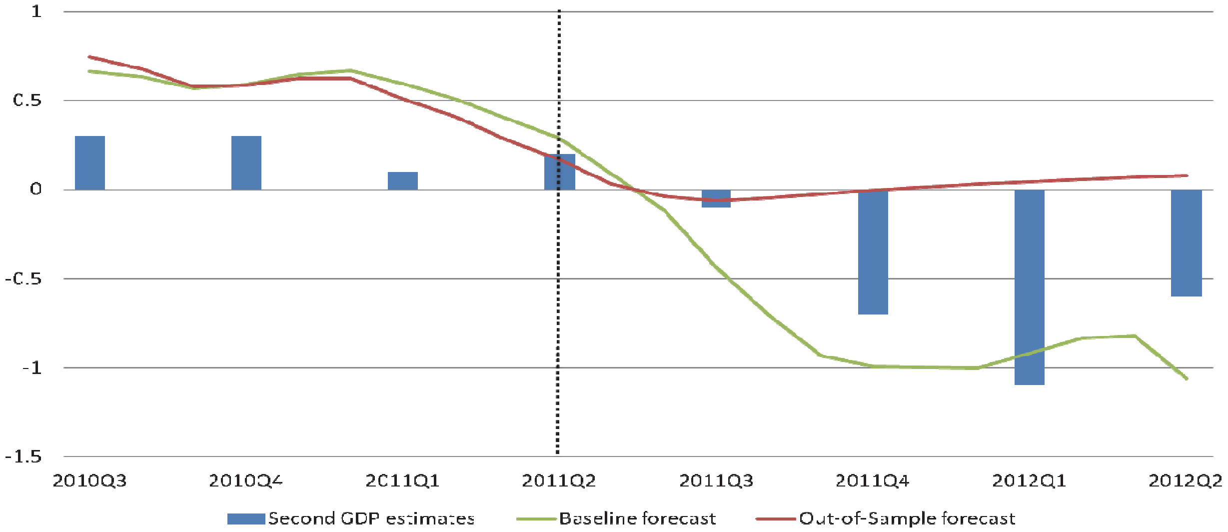
As we have explained in the motivation of the paper, the purpose is to forecast GDP growth rates in real time, and in the very short run. Once more, we want to stress that the model is not suitable to provide us with long-term forecasts (say, two or more quarters). In order to show that, we conduct an out-of-sample exercise and show that, the longer is the forecasting horizon, the worse is the forecast, since trivially the latter does not take into account the latest available information, but just the data up to a given month.

We now compare the forecasts from the model using all available information, the out-of-sample forecasts and the actual GDP growth rates for the period between the second quarter of 2010 and the second quarter of 2012.[24] The results of the comparison are depicted in Figure 8.[25]

24 We choose this sub-sample because data for GDP growth rates that refer to the period before 2013 are already revised, while data regarding 2013 are still to be revised.

25 We make this exercise only for the Italian sample; the results clearly do not vary when considering the other samples.

Figure 8 Comparison between out-of-sample /forecasts, forecasts from the baseline model, and the actual estimates for GDP growth rates



Note: the out-of-sample forecasts (four quarters ahead) are produced using information up to the second quarter of 2011 (black dotted vertical line). The forecasts from the baseline model are those depicted in Figure 2, and are produced using information up to the second quarter of 2012.

Two remarks are worth making: first, before the second quarter of 2011, the forecasts obtained using information up to the second quarter of 2012 and up to June 2011 are different: this happens because in the first case we use more information than in the latter case (that is, the data for the last two quarters of 2011 and the first two quarters of 2012); in other words, when new information become available, we can not only produce new forecasts for future periods, but also revise forecasts for the past periods (similarly to what happens for the different releases of GDP growth rates estimates by the European Commission).

Second, and perhaps more importantly, while for the first three steps ahead (i.e. three months or 1 quarter)[26] the model still delivers quite good estimates (it follows the downward trend of the GDP growth rates in August and September 2011), from the second quarter on the out-of-sample estimates deliver forecasts which are clearly not reliable; trivially, this is due to the fact that we ask the model to forecast for several periods ahead without using the latest information on the variables.

These findings underline, once more, that the model is suitable in order to forecast GDP either in real time, or in the very short run. Out-of-sample forecasts, in other words, should be produced from this model very carefully and only for the very short run. This is an important prescription that differentiates the model from most of the existing nowcasting literature.

26 Three steps ahead correspond to the first quarter of out-of-sample forecast, since one step corresponds to one month.

5 Conclusions

We apply the Euro-Sting model developed by Camacho and Pérez-Quirós (2010) to the main Eurozone countries - Germany, Italy, France and Spain - adapting the empirical analysis to the specific characteristics of the selected countries. This model has the advantage of being a transparent and small-scale model, taking into account the data revision procedure used by Eurostat, and addressing all the issues of real-time forecasting (in particular, mixed frequencies and ragged edges).

Results indicate that the model works quite well for the four countries, and can be quite easily extended to other countries or adapted to another set of variables. Moreover, it has the further advantage that it can be easily updated when new information becomes available.

What emerges from our results as an overall trend for all the countries is that at the end of 2013 and the beginning of 2014, GDP growth rates seem to turn positive for all countries (the size of the growth rate depends on the country considered).

Once more, we want to notice that the main contribution of the paper is not to show a new methodology to be used in order to forecast GDP, but rather to run the underlying model on a combination of variables and countries that, to our knowledge, has not been used in the literature so far. Also, we run the model before and during a crisis period: this is an important test of the ability of the model to forecast during and after recessions, which is another important aspect of our forecasting exercise.

Notwithstanding its good performance in nowcasting GDP growth, the model could be further expanded. In particular, we believe that taking into account the non-linearities that may arise in the data when the business cycle changes regime (as, for instance during the crisis) would be the most natural extension to the model. A possible candidate methodology for the latter purpose is, therefore, to add to our model the non-linear Markov switching methodology[27]; this methodology is able to characterize the behaviour of the time series in different business cycle regimes; with this extension, the model might be able to capture more complex dynamic patterns.

A first work that deals contemporaneously with non-linearities and mixed frequencies and ragged edges is Camacho et al. (2012). Their work overcomes the traditional drawbacks of the baseline Markov-Switching Dynamic Factor Model (MS-DFM) and takes into account both ragged edges and mixed frequencies. Applying the latter model to the above mentioned countries would provide us with a significant empirical contribution in the real time-forecasting literature. We left this for future research.

27 This approach was first introduced by Hamilton (1989).

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Appendix

A – The Kalman filter

Given the matrices (and vectors) $Y_{it}^*, H_{it}^*, w_{it}^*, R_{iit}^*$ described in section 3, we now show the procedure to obtain the estimates (and by consequence, the forecasts) of the model dynamics. Let $h_{t|\tau}$ be the estimate of h_t based on information up to period τ and let $P_{t|\tau}$ be its covariance matrix. The *prediction equations* are:

$$h_{t|t-1} = Fh_{t-1|t-1}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q$$

These equations use the estimate from the previous time step (t-1) to predict the current time step (t). It is important to notice that these equation do *not* use information from the current time step (which is in fact used in the updating equations, whose purpose is to refine estimates). The prediction error $\eta_{t|t-1}$ is given by the difference between the observation and the estimated values, that is:

$$\eta_{t|t-1} = Y_t^* - H_t^* h_{t|t-1}$$

whose covariance matrix is given by $\zeta_{t|t-1} = H_t^* P_{t|t-1} H_t^{*\prime} + R_t^*$. We can now compute the log likelihood function, which reads:

$$logL_t = -\frac{1}{2}\ln\left(2\pi\left|\zeta_{t|t-1}\right|\right) - \frac{1}{2}\eta_{t|t-1}'\left(\zeta_{t|t-1}\right)^{-1}\eta_{t|t-1}$$

With the updating equations the above *a priori* prediction is refined using the current measured values, which are now observed. Two observations are now worth to be mentioned: firstly, the Kalman filter does not uses all past information, but only makes use of the information on the past step to predict the current step, and information of the current step to refine estimates. Therefore, we can easily add new observations at the end of the dataset as they become available without changing the other estimates; secondly, usually the prediction phase and the updating phase are alternate, but this is not necessary: if for instance (as in our case) there are missing observations within the dataset, multiple predictions steps can be performed. The updating equations are:

$$h_{t|t} = h_{t|t-1} + K_t^* \eta_{t|t-1}$$

$$P_{t|t} = P_{t|t-1} - K_t^* H_t^* P_{t|t-1}$$

where the Kalman gain is defined as

$$K_t^* = P_{t|t-1} H_t^{*\prime} \left(\zeta_{t|t-1}\right)^{-1}$$

And can be intuitively thought of as the weight that the filter places on measurements (with a gain of one, the filter ignore the estimate, while with a gain of zero the filter only uses the estimates and measurements are ignored).

Of course, in order to start the process, we need initial values for h and P. Following the convention, we use respectively a vector of zeroes and the identity matrix.

B – Dataset description

Table B1. Hard Indicators – Germany

Variable	Source	Short Explanation	Time span	Publication lag (days)	Descriptive statistics
Flash GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the earliest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q3	45	mean: 0.21 std. dev: 0.90 min: -3.8 max: 2.2
First GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the first GDP estimate (available 65 days after the end of the quarter)	2002q2-2013q3	65	mean: 0.22 std. dev: 0.87 min: -3.8 max: 2.2
Second GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the latest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q2	100	mean: 0.23 std. dev: 0.89 min: -3.8 max: 2.2
Employment	Bundesagentur fur Arbeit (Germany)	quarter on quarter growth rate of employed persons (SA)	2002q2-2013q3	74	mean: 0.13 std. dev: 0.25 min: -0.39 max: 0.64
Industrial Production Index (IPI)	Eurostat	month on month growth rate of Industrial production Index (excluding construction, SA)	2002m6- 2013m10	43	mean: 0.14 std. dev: 1.59 min: -6.92 max: 4.37
Exports	Deutsche Bundesbank	month on month growth rates of volume of exports (SA)	2002m6- 2013m10	48	mean: 0.47 std. dev: 2.74 min: -9.83 max: 8.69
Sales	Deutsche Bundesbank	month on month growth rate of retail sales (SA, excluding cars)	2002m6-2013m10	45	mean: 0.06 std .dev: 1.23 min: -6.84 max: 3.49
Final GDP estimate	Eurostat News Release Euroindicators	last revision of earlier GDP estimates	2002q2-2013q2	100	mean: 0.30 std. dev: 0.85 min: -4.1 max: 2

Table B2. Soft Indicators – Germany

Variable	Source	Short explanation	Time span	Descriptive statistics
Economic Sentiment Indicator (ESI)	Eurostat	Survey (SA, total sector)	2002m6-2013m11	mean: 98.48 std. dev: 9.58 min: 73 max: 117.2
Business confidence indicator	Eurostat	Survey(SA, industry)	2002m6-2013m11	mean: -6.45 std. dev: 12.91 min: -43 max: 16
Consumer confidence indicator	Eurostat	Survey (SA, consumers)	2002m6-2013m11	mean: -8.44 std. dev: 10.03 min: -33 max: 11
Building confidence indicator	Eurostat	Survey (SA, building sector)	2002m6-2013m11	mean: -26.81 std. dev: 15.62 min: -55.4 max: -3

Table B3. Hard Indicators – Italy

Variable	Source	Short explanation	Time span	Publication lag (days)	Descriptive statistics
Flash GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the earliest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q3	45	mean: -0.01 std. dev.: 0.67 min: -2.4 max: 1.1
First GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the first GDP estimate (available65 days after the end of the quarter)	2002q2-2013q3	65	mean: -0.04 std. dev.: 0.64 min: -2.4 max: 1.1
Second GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the latest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q2	100	mean: -0.05 std.dev.: 0.68 min: -2.6 max: 1.1
Employment	Istat	quarter on quarter growth rate of employed persons (SA)	2004q2-2013q3	74	mean: 0.01 std. dev.: 0.35 min: -0.71 max: 0.70
Industrial Production Index (IPI)	Istat	Month on month growth rate of Industrial production Index (excluding construction, SA)	2002m6 -2013m10	43	mean: -0.16 std. dev.: 1.49 min: -4.28 max: 3.41
Exports	Istat	Mon on month growth rates of volume of exports(SA)	2002m6 -2013m9	48	mean: 0.32 std. dev.: 3.06 min: -10.29 max: 10.44
Sales	Istat	Month on month growth rate of retail sales (SA, excluding cars)	2002m6-2013m9	45	mean: -0.01 std. dev.: 0.63 min: -3.15 max: 2.80
Final GDP Estimate	Eurostat News Release Euroindicators	Last revision of earlier GDP estimates	2002q2-2013q2	100	mean: -0.04 std. dev.: 0.79 min: -3.5 max: 1.1

Table B4. Soft Indicators – Italy

Variable	Source	Short explanation	Time span	Descriptive statistics
Economic Sentiment Indicator (ESI)	Eurostat	Survey (SA, total sector)	2002m6-2013m11	mean: 97.26 std. dev.: 8.48 min: 74.5 max: 111.3
Business confidence indicator	Eurostat	Survey(SA, industry)	2002m6-2013m11	mean: -6.5 std. dev.: 9.02 min: -35 max: 9
Consumer confidence indicator	Eurostat	Survey (SA, consumers)	2002m6-2013m11	mean: -21.48 std. dev.: 7.38 min: -42 max: -8
Building confidence indicator	Eurostat	Survey (SA, building sector)	2002m6-2013m11	mean: -22.05942 std. dev.: 12.05798 min: -43 max: 0

Table B5. Hard Indicators – France

Variable	Source	Short Explanation	Time span	Publication Lag (days)	Descriptive statistics
Flash GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the earliest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q3	45	mean: 0.26 std. dev.: 0.47 min: -1.2 max: 1.2
First GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the first GDP estimate (available65 days after the end of the quarter)	2002q2-2013q3	65	mean: 0.26 std dev.: 0.45 min: -1.2 max: 1.1
Second GDP Estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the latest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q2	100	mean: 0.27 std. dev.: 0.47 min: -1.2 max: 1.2
Employment	Insee	quarter on quarter growth rate of employed persons (SA)	2002q2-2013q2	74	mean: 0.07 std. dev.: 0.20 min: -0.56 max: 0.42
Industrial Production Index (IPI)	Eurostat	month on month growth rate of Industrial production Index (excluding construction, SA)	2002m6-2013m10	43	mean: -0.10 std. dev.: 1.43 min: -4.87 max: 4.37
Exports	Direction Generale des Douanes et Droits Indirects (DGDDI)	month on month growth rates of volume of exports (SA)	2002m6-2013m10	48	mean: 0.25 std. dev.: 3.33 min: -13.51 max: 13.64
Sales	Insee	month on month growth rate of retail sales (SA, excluding cars)	2002m6-2013m9	45	mean: 0.14 std. dev.: 1.04 min: -2.71 max: 3.15
Final GDP Estimate	Eurostat News Release Euroindicators	last revision of earlier GDP estimates	2002q2-2013q2	100	mean: 0.24 std. dev.: 0.56 min: -1.7 max: 1.1

Table B6. Soft Indicators – France

Variable	Source	Short explanation	Time span	Descriptive statistics
Economic Sentiment Indicator (ESI)	Eurostat	survey (sa, total economy)	2002m6-2013m11	mean: 99.98 std. dev.: 9.19 min: 74.5 max: 114.2
Business confidence indicator	Eurostat	survey(sa, industry)	2002m6-2013m11	mean: -19.38 std. dev.: 7.72 min: -37 max: 2
Consumer confidence indicator	Eurostat	survey (sa, consumers)	2002m6-2013m11	mean: -8.48 std. dev.: 9.59 min: -39 max: 7
Building confidence indicator	Eurostat	survey (sa, building sector)	2002m6-2013m11	mean: -5.64 std. dev.: 20.47 min: -40 max: 29.1

Table B7. Hard Indicators – Spain

Variable	Source	Short explanation	Time span	Publication lag (days)	Descriptive statistics
Flash GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the earliest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q3	45	mean: 0.18 std. dev.: 0.61 min: -1.8 max: 1.1
First GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the first GDP estimate (available65 days after the end of the quarter)	2002q2-2013q3	65	mean: 0.25 std. dev.: 0.65 min: -1.9 max: 1.2
Second GDP estimate	Eurostat News Release Euroindicators	quarter on quarter growth rate of the latest GDP estimate (available 45 days after the end of the quarter)	2002q2-2013q2	100	mean: 0.23 std. dev.: 0.67 min: -1.9 max: 1.2
Employment	Ministry of economic and finance, Spain	quarter on quarter growth rate of employed persons (SA)	2002q2-2013q2	4	mean: 0.05 std. dev.: 1.10 min: -3.22 max: 1.64
Industrial Production Index (IPI)	Eurostat	month on month growth rate of Industrial production Index (excluding construction, SA)	2002m6-2013m9	43	mean: -0.15 std. dev.: 1.70 min: -5.56 max: 5.57
Exports	Bank of Spain	month on month growth rates of volume of exports(SA)	2002m6-2013m9	48	mean: 0.55 std. dev.: 6.24 min: -13.14 max: 25.73
Sales	Ine	month on month growth rate of retail sales (SA, excluding cars)	2002m6-2013m10	45	mean: -.124 std. dev.: 1.40 min: -7.92 max: 4.10
Final GDP Estimate	Eurostat News Release Euroindicators	last revision of earlier GDP estimates	2002q2-2013q2	100	mean: 0.26 std. dev.: 0.72 min: -1.7 max: 1.3

Table B8. Soft Indicators – Spain

Variable	Source	Short Explanation	Time span	Descriptive statistics
Economic Sentiment Indicator (ESI)	Eurostat	survey (sa, total economy)	2002m6-2013m11	mean: 97.06 std. dev.: 8.74 min: 73.6 max: 108.2
Business confidence indicator	Eurostat	survey (sa, industry)	2002m6-2013m11	mean: -10.49 std. dev.: 9.87 min: -40 max: 5
Consumer confidence indicator	Eurostat	survey (sa, consumers)	2002m6-2013m11	mean: -19.41 std. dev.: 9.88 min: -48 max: 7
Building confidence indicator	Eurostat	survey (sa, building sector)	2002m6-2013m11	mean: -15.40 std. dev.: 30.16 min: -69.3 max: 39

Figure B1. Flash estimates, first and second revision for GDP growth rates

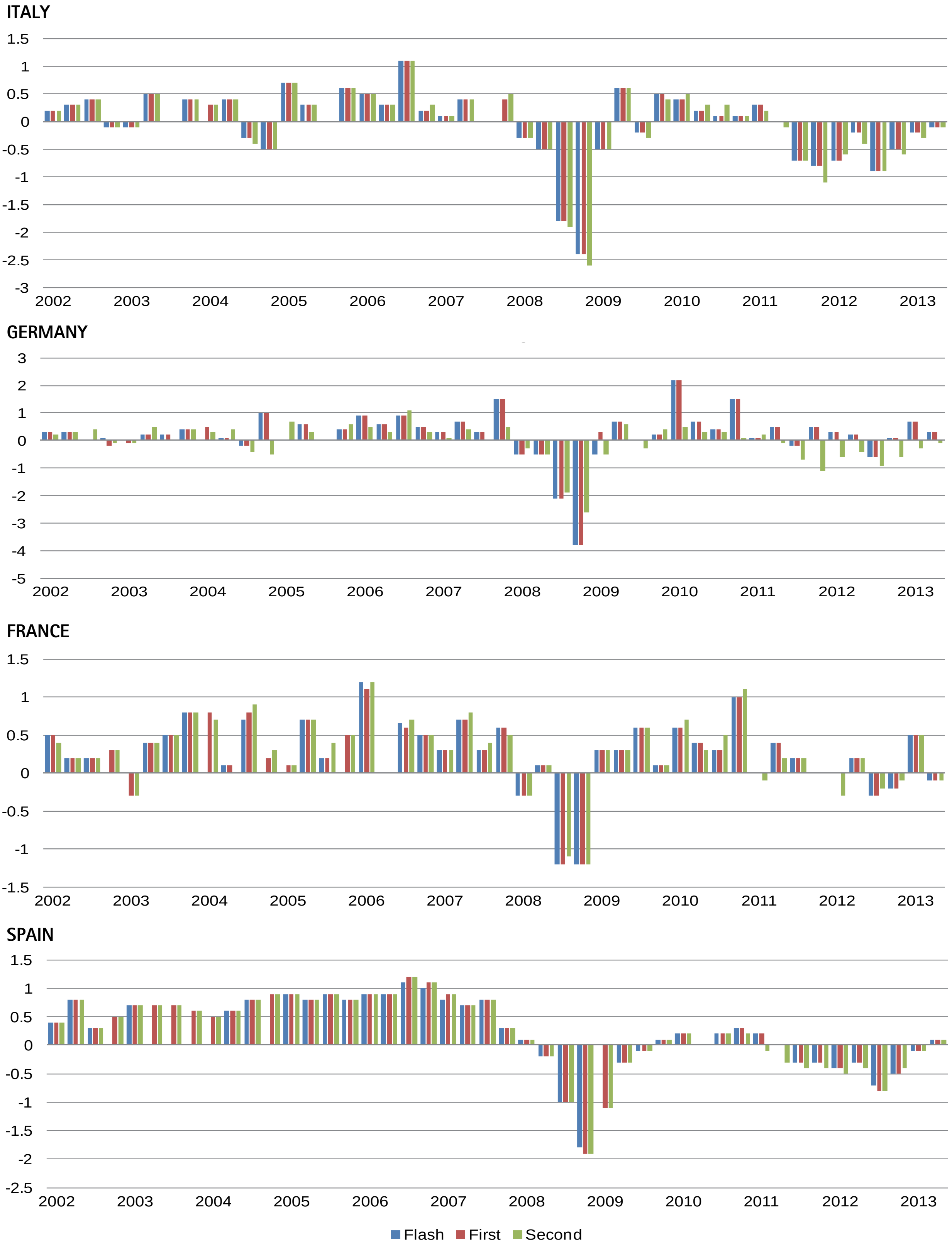
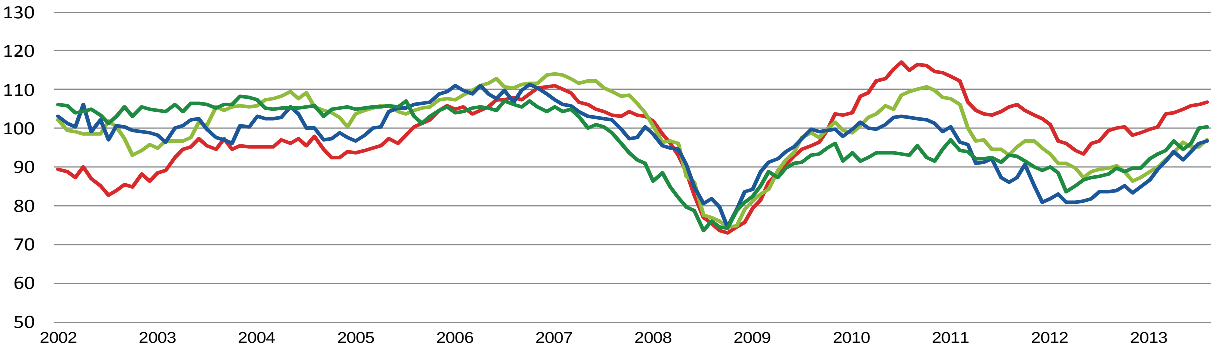
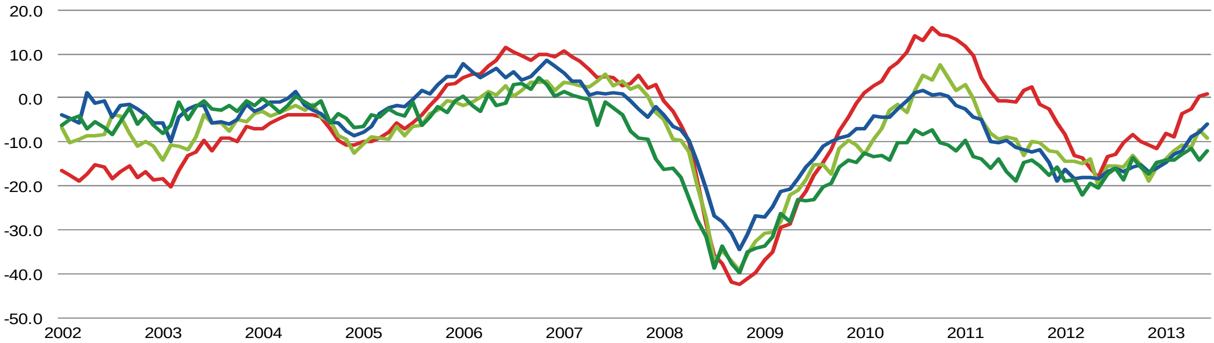


Figure B2. Time series for the four soft indicators

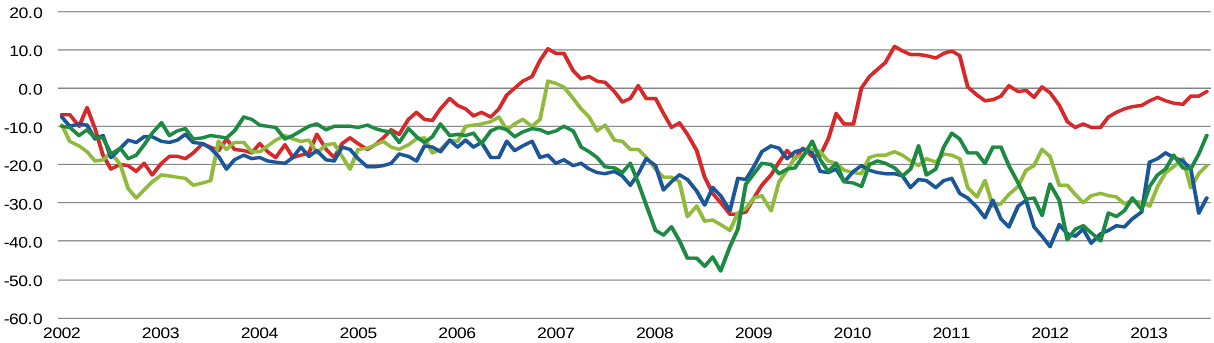
Economic Sentiment Indicator (ESI)



Business Confidence Indicator



Consumer Confidence Indicator



Building Confidence Indicator