MEETING OUR D€STINY. A DISAGGREGATED €URO AREA SHORT TERM INDICATOR MODEL TO FORECAST GDP (Y) GROWTH

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Abstract

In this paper we propose a new real-time forecasting model for euro area GDP growth, D€STINY, which attempts to bridge the existing gap in the literature between large- and small-scale dynamic factor models. By adopting a disaggregated modelling approach, D€STINY uses most of the information available for the euro area and the member countries (around 100 economic indicators), but without incurring in the nite sample problems of the large-scale methods, since all the estimated models are of a small scale.

An empirical pseudo-real time application for the period 2004-2013 shows that D€STINY´s forecasting performance is clearly better than the standard alternative models and than the publicly available forecasts of other institutions. This is especially true for the period since the beginning of the crisis, which suggests that our approach may be more robust to periods of highly volatile data and to the possible presence of structural breaks in the sample.

Keywords: business cycles, output growth, time series, Euro-STING model, large-scale model.

JEL classification: E32, C22, E27.

Resumen

En este trabajo se propone un nuevo modelo de predicción en tiempo real del crecimiento de PIB de la zona euro, llamado D€STINY, con el que se pretende complementar la literatura de modelos de previsión de corto plazo, rellenando el hueco existente entre los modelos dinámicos factoriales de pequeña escala y los de dimensión grande. El modelo D€STINY adopta un enfoque de modelización desagregada, utilizando toda la información disponible para la zona del euro y los países que la forman (alrededor de 100 indicadores económicos), pero sin incurrir en los sesgos econométricos característicos de los modelos de gran dimensión, ya que todos los modelos son estimados con métodos de pequeña escala.

Una aplicación empírica para el período 2004-2013 en pseudo tiempo real muestra que la precisión de la predicción de D€STINY es claramente mejor que la de los modelos estándares alternativos y que la de las previsiones públicas de otras instituciones. Esto se da, sobre todo, para el período desde el comienzo de la crisis, lo que sugiere que el enfoque adoptado en este trabajo seria más robusto en períodos caracterizados por una elevada volatilidad y posibles cambios estructurales.

Palabras claves: ciclos económicos, crecimiento del PIB, series temporales, modelo Euro-STING, modelo de escala grande.

Códigos JEL: E32, C22, E27.

1 Introduction

Forecasting GDP in the short term is a complex task, among other reasons, because the macroeconomic variables required are published with a substantial lag, and as a result the available data are incomplete or insufficient. In this context, real-time forecasting models have demonstrated that they are a useful way of selecting the signals obtained from the relevant monthly indicators and combining them into an overall vision of developments in GDP growth.

In the last few years there has been a great debate in the academic literature on what is the optimal strategy when dealing with a short-term real-time forecasting problem. Some authors have argued in favor of starting from a simple small scale dynamic factor model (SSDFM) that reasonably selects the indicators and which is enlarged if necessary (see Camacho and Pérez-Quirós (2010 and 2011)), while others prefer to deal with a large scale dynamic factor model (LSDFM) whose dimension can be selectively reduced to eliminate the redundant information (see Forni et al. (2005), Giannone et al. (2008) and Angelini et al. (2011)). The advocates of the latter approach have argued that LSDFM have better asymptotic properties and are more efficient since they make use of all the available information at every moment in time. However, this may come at a cost in practice. Álvarez et al. (2012) show that the finite-sample performance in factor estimation and forecasting of LSDFM may be greatly affected when there is a high degree of correlation across the idiosyncratic component of the indicators included in the model, and, specially, for a high persistence in either the common factor or the idiosyncratic errors. In this case, the small dynamic factor models with a few chosen indicators tend to outperform large scale ones. A good example of this is the Euro-STING model (Camacho and Pérez-Quirós (2010)), which is a dynamic factor model that incorporates the information from a few chosen indicators as this information becomes available and has been shown to be a good model to forecast euro area GDP growth. In this line, Banbura and Modugno (2010) also find that a LSDFM applied to a small (14 series) dataset outperforms the forecasts obtained from medium (46 series) and large (101 series) datasets.

In this paper we propose a new forecasting model for euro area GDP growth, *D€STINY* (*D*isaggregated €-area *S*hort *T*erm *IN*dicators model of GDP (Y) growth), which tries to bridge the gap between the large and small scale dynamic factor models by using the best of both methodologies. Our approach uses as much of the information available as possible, but imposing the economic structure implicit in the quarterly National Accounts. The idea is to adopt a disaggregated approach in which a small factor model (with less than 14 indicators) is estimated and used to forecast each of the components of GDP by the production, expenditure and countries National Accounts disaggregations. This procedure allows us to consider the information provided by almost one hundred indicators (76 monthly and 21 quarterly) referred to the euro area or member countries, but without incurring in the finite sample problems of the large scale approach, since all the estimated models are of a small scale. Next, these forecasts are mixed efficiently, taking into account their relative accuracy over time so as to extract a sign of activity growth in the most precise way.

There are two further advantages of our approach. Firstly, it provides very useful information for the conjunctural analysis since it evaluates separately the performance of the main sectors of production, of the expenditure components and of the various countries which make up the euro area. This may be of great importance at times of change of cycle or of high uncertainty such as at present, when indicators, including economic agents' sentiment, which are published earlier and, consequently, are a basic part of forecasts, and those which reflect the actual performance of various sectors or quantitative indicators, on which the National Accounts are based, may provide a different vision of developments in activity at aggregate level. Secondly, this model should be able to cope better with model misspecification and structural breaks in the data, since the independent forecasts obtained through the different aggregations are combined efficiently into a single forecast (Clements and Hendry (2004)). Overall, we feel that our methodology develops a broad enough model for the orderly inclusion of relevant information on the euro area that at the same time, is flexible since it efficiently combines different approximations of GDP growth.

This methodology is not completely novel. Hahn and Skudelny (2008), are amongst the first to propose a model to forecast GDP that uses a disaggregated approach. However, they only look at the production side of GDP and model the value added of each branch of activity through simple linear regressions or bridge equation models. Frale et al. (2011) are more in line with our approach. They develop a model, EUROMIND, which uses both the production and expenditure disaggregations to forecast euro area GDP and model each component using a small scale dynamic factor model like ours. However, there are two main differences with our paper. First, they neither consider the countries side of GDP, nor do they combine the indirect or disaggregated approximations with a direct one, Euro-STING in our case. Second, and more importantly, they estimate the dynamic factor model in levels. In theory, it should be equivalent to modelling it in levels or growth rates, but not in practice. The problem is that surveys, as opposed to quantitative indicators, are constructed so that their level is correlated with the growth rate of GDP and not its level. As a consequence surveys are much more likely to be significant in a model of GDP's growth rate than of its level. That is indeed what they find in their paper. They discard almost all surveys from the models of GDP components, because their factor loadings are always not significant. They try to correct this by introducing a second factor, which would be related with surveys, but find that it only works for the industrial value added and exports. This is not true in our case, where we model each component in growth rates and we always find surveys to be very significant and to explain a great share of the dynamics of the objective variable, specially in the initial forecasts of each quarter of data. In addition, a number of papers have extended the methodology developed in Camacho and Pérez-Quirós (2010); Camacho et al (2013) showed that accounting for nonlinearities improves Euro-STING's forecasting performance, specially during the crisis, while Gadea and Pérez-Quirós (2012) proved that financial variables are not helpful to forecast the economic cycle in real-time.

D€STINY's forecasting performance is tested against two alternative models, a small scale dynamic factor model with 11 indicators, Euro-STING, and a large scale dynamic model with exactly the same indicators included in D€STINY (76), named LSDFM-UEM. These comparisons are undertaken through a "pseudo real-time evaluation" that uses a monthly database compiled in October 2013 and covering the period January 2004 - September 2013. In addition, the robustness of these results to data revisions is tested by doing an additional truly real-time exercise using a daily database which has been compiled since the 1st of March 2011. The results show that D€STINY's forecast is significantly more accurate than both alternatives considered, with around 30% and 50% reduction in the root mean squared error for the whole sample, respectively. In the case of Euro-STING these differences become much smaller in the period prior to the crisis (around 10%), while they only go down to 40% for LSFDM-UEM. Finally, D€STINY's performance is also compared with the forecasts of other institutions publicly available for a similar sample with qualitatively similar results.

The paper proceeds as follows. Section 2 describes the structure of the new model D€STINY. In section 3 details the econometric methodology used to estimate the forecasting models of each component of the disaggregations considered and the procedure to pool the forecasts. Section 4 details the exact model specification finally chosen for each component, while section 5 shows the estimation and forecast results of two different real-time exercises undertaken with the model. Section 6 compares D€STINY's forecast with the one of a large scale dynamic factor model including the same indicators over the same sample, while section 7 compares it with the forecasts of other institutions. Finally, section 7 concludes.

2 Structure of D€STINY

D€STINY adopts an indirect or disaggregated approach, which consists in estimating euro area GDP growth by aggregating the forecasts of its different components. In particular, a separate forecasting model is estimated for each GDP component using the methodology proposed by Camacho and Pérez-Quirós (2010), explained in more detailed in the next section. Then, the forecasts obtained for all the components are aggregated according to the National Accounts rules.

The euro area quarterly National Accounts (QNA), published by Eurostat, provide timely three different disaggregations for euro area GDP (see Table 1 below)[1]: Firstly, a breakdown according to the nature of the economic activity or *production side,* is published for 6 or 10 NACE industries with 1 month delay with respect to the preliminary GDP growth estimate[2]. Secondly, a breakdown by expenditure component or *expenditure side*, is also published with 1 month delay. Finally, a geographical disaggregation of quarterly euro area GDP is published by

[1] We can also find a breakdown of activity according to the *income side* of GDP. However, this is published less timely, so we will not consider it here.

[2] More detailed breakdowns are available but with a greater delay. NACE is the acronym in french for "Statistical classification of economic activities in the European Community".

the National Institutes of (almost) all member states. The data referred to the largest countries is published a few days prior to the euro area figures.[3]

The level of disaggregation used for each breakdown depends mainly on the availability of relevant indicators for each component on a timely basis. However, we have also tried to keep the model as parsimonious as possible. Given this, we have decided to estimate 16 separate models (see table 1 for their weights in GDP) covering 6 industries (agriculture, industry including energy, construction, trade, financial services and other services), plus indirect net taxes[4], 5 expenditure components (total consumption, gross capital formation, exports, imports and the contribution of net exports to GDP growth) and the 4 largest country members (Germany, France, Italy and Spain). A separate model for public and private consumption is under development and will be included in future versions of the model. It was decided not to estimate for the time being a separate model for the change in stocks, given the difficulty to forecast them reliably, nor for the different components of investment, since it is difficult to find timely indicators for some of them.

Table 1. Weight of components in GDP

	Description	Weight in GDP (%) (1)
PRODUCTION APPROACH (2)	Agriculture, hunting and fishing (A)	1.5
	Industry, including energy (BCDE)	17.3
	Construction (F)	5.2
	Trade, transport and communication services (GHI)	16.9
	Financial services and business activities (JKLMN)	28.0
	Other services (OPQRSTU)	20.8
	Taxes	10.3
EXPENDITURE APPROACH	Consumption (private+public)	79.0
	Gross capital formation	18.3
	Exports	45.8
	Imports	43.2
LARGE COUNTRIES APPROACH	Germany	28.1
	France	21.4
	Italy	16.5
	Spain	10.9

(1) The data correspond to 2012
(2) The letters in brackets correspond to NACE 2 classification

[3]Since the introduction by Eurostat of chain-linking methods into the calculation of quarterly National Accounts, variables expressed in real terms no longer satisfy the temporal aggregation constraints. Thus, to aggregate one has to use a weighted sum, where the weight for each component is its nominal weight for the prior year in the aggregate. However, in general, the statistical discrepancy due to this issue is of second order and much smaller than the standar error of any forecasting model. Therefore, in this paper we ignore this issue and calculate the aggregate as the simple sum of its components. See Frale et al (2011) for an example of a model that takes this issue into consideration.

[4]Taxes are necessary to go from value added to GDP.

The next step is to choose the relevant indicators to be included in each of the 15 models. Given the great number of models to be specified and of potential indicators available, we will limit our search. In particular, for the *production* and *expenditure* sides we start by considering only the indicators pre-selected by Frale et al. (2011), plus the purchasing manufacturing indices (PMI), published by Markit. In the case of the models for Germany, France and Italy, we start from the national component of the set of indicators included in Euro-STING for the euro area, plus the opinion surveys compiled by the most important institutions in each country, such as Germany's IFO and France's INSEE. Finally, in the case of the model for Spain, we adopt the structure of Spain-STING model developed by Camacho and Pérez-Quirós (2011). The pre-selection of potential indicators varies considerably in size across models, ranging from the case Agriculture's Value added, for which there are no relevant indicators, to the case of Germany's GDP with more than 15. In total, there are around 200 potential indicators pre-selected. It is worth mentioning that the list of potential indicators may have a different frequency, release date and sample periods, thanks to the techniques developed by Camacho and Pérez-Quirós (2010). Finally, we have decided not to consider financial variables, other than the ones related to the financial services branch of activity, since Gadea and Pérez-Quirós (2012) have shown that these are not helpful to forecast the economic cycle in real time.

The (real-time) Database All the indicators pre-selected make part of a real time database that has been collected every working day since the first of march 2011. This database is composed of 194 indicators, with monthly, quarterly and yearly frequency (necessary to aggregate the quarterly figures to get the euro area figures), referred to the euro area as a whole, as well as to Germany, France, Italy and Spain. It starts in 1995.3, first quarter for which official quarterly National Accounts for the euro area aggregate published by Eurostat are available. However, most indicators do not start until 1999.01 and some of them until the early 2000s.

The series included in the dataset can be divided into qualitative and quantitative indicators. The qualitative ones, or soft, based on surveys, are released in the last few days of the reference month, thus anticipate the performance of activity with a substantial lead. Amongst them, the most important ones are the ones published by the European Commission and the ones published by Markit, or Purchasing Managers Indices. In general, these are constructed so that their level is well correlated with the growth rate of GDP. The quantitative indicators, or hard, are published with a lag of approximately 45 days with respect to the end of the reference month and are the basis of the Quarterly National Accounts. Therefore, their growth rate tends to be well correlated with the growth rate of GDP.

3 Econometric methodology

We start by detailing the methodology used to forecast each component of GDP, then we focus on how the different forecasts are pooled together.

3.1 Individual forecasting models

Each one of the models forming D€STINY follows the lines proposed by Camacho and Pérez-Quirós (2010), which is an extension of the dynamic factor model suggested by Stock and Watson (1991). Dynamic factor models are the appropriate framework to characterize comovements in macroeconomic variables that admit factor decompositions. To consider the notion of comovements among GDP (or any other objective variable) and the economic indicators, the time series are modelled as the sum of two orthogonal components. The first component, called common factor and denoted by f_t, captures the notion that the series dynamics are driven in part by common shocks and can be interpreted as a coincident indicator of the GDP growth rate. The second one, called idiosyncratic component and denoted for each indicator i by u_{it}, captures the idiosyncratic behavior of each variable included in the model.

The indicators available in the database can be split into three categories: hard indicators (monthly or quarterly), soft indicators in general and soft indicators published by the European Commission (EC-type). In the case of hard indicators, like industrial production, their level (or growth rate) is assumed to be related to the level (or growth rate) of GDP. Thus these indicators, z^h_{it} will affect only the contemporaneous value of the monthly factor

$$z^h_{it} = \beta^h_i f_t + u^h_{it} \tag{1}$$

In the case of soft indicators, by construction their level (z^s_{it}) is related to the quarterly growth rates of GDP, which in our model can be written as the sum of current values of the common factor and its first two lags:

$$z^s_{it} = \beta^s_i (f_t + f_{t-1} + f_{t-2}) + \left(u^s_{it} + u^s_{it-1} + u^s_{it-2}\right) \tag{2}$$

Lastly, as stated by the European Commission (2006), the guiding principle for the selection of questions in their survey aims at achieving as high as possible coincident correlation of the confidence indicator with year-on-year growth of the reference series. Therefore, the level of EC-type soft indicators (z^{EC}_{it}) are most correlated with the year on year growth rate of GDP, that is, with the current value and the first 11 lags of the factor:

$$z^{EC}_{it} = \beta^{EC}_i \sum_{j=0}^{11} f_{t-j} + \sum_{j=0}^{11} u^{EC}_{it-j} \tag{3}$$

However, when building the model one also has to take into account the fact that the objective variable (e.g.: GDP) (and possibly some of the hard indicators) are of quarterly frequency, while the rest are monthly. This can be easily accommodated using the techniques developed by Mariano and Murasawa (2003) and Camacho and Pérez-Quirós (2010). They show that the quarterly growth rate of a nonstationary series observed each quarter, g_t, whose logs are integrated of order 1 and may be expressed as the result of the aggregation of a monthly series X_t, can be approximated as a weighted sum of monthly growth rates

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

Therefore, the relationship between a hard indicator of quarterly frequency, y_t^q, and the monthly factor can be approximated as follows

$$y_t^q = \beta_q \left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4} \right) + \left(\frac{1}{3}u_{qt} + \frac{2}{3}u_{qt-1} + u_{qt-2} + \frac{2}{3}u_{qt-3} + \frac{1}{3}u_{qt-4} \right). \tag{5}$$

Let us collect the r^h hard indicators in the vector Z_t^h, the r^s soft indicators in the vector Z_t^s and the r^{EC} EC-type soft indicators in the vector Z_t^{EC}. Let u_t^y, and U_t^h, U_t^s and U_t^{EC} be the scalar and the r^h-dimensional, r^s-dimensional and r^{EC}-dimensional vectors determining the idiosyncratic dynamics of the objective variable (e.g.. GDP) and of the economic indicators, respectively. The measurement equation can be defined as

$$\begin{pmatrix} y_t^q \\ Z_t^h \\ Z_t^s \\ Z_t^{EC} \end{pmatrix} = \begin{pmatrix} \beta_q \begin{pmatrix} \frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} \\ +\frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4} \end{pmatrix} \\ \beta_h f_t \\ \beta^s(f_t + f_{t-1} + f_{t-2}) \\ \beta^{EC} \sum_{j=0}^{11} f_{t-j} \end{pmatrix} + \begin{pmatrix} \frac{1}{3}u_{qt} + \frac{2}{3}u_{qt-1} + u_{qt-2} \\ +\frac{2}{3}u_{qt-3} + \frac{1}{3}u_{qt-4} \\ U_t^h \\ U_t^s \\ U_t^{EC} \end{pmatrix}$$

where $U_t^h = (u_{1t}, ..., u_{r^h t})'$, $U_t^s = \left(u_{r^h+1t}, ..., u_{r^h+r^s t}\right)'$, $U_t^{EC} = \left(u_{r^h+r^s+1t}, ..., u_{rt}\right)'$ and $r = r^h + r^s + r^{EC}$. The factor loadings, $\beta = (\beta_q, \beta_h', \beta_s', \beta_{EC}')$, measure the sensitivity of each series to movements in the latent factor and have dimensions that make them conformable with each equation.

The dynamics of the model are achieved by assuming that

$$\begin{aligned} f_t &= a_1 f_{t-1} + ... + a_{m_f} f_{t-m_f} + \varepsilon_t^f \\ u_{qt} &= a_{q1} u_{qt-1} + ... + a_{qm_q} u_{qt-m_q} + \varepsilon_t^{u_q} \\ u_{jt} &= a_{j1} u_{jt-1} + ... + a_{jm_{u_j}} u_{jt-m_{u_j}} + \varepsilon_t^{u_j} \qquad \text{for } j = 1, ..., r \end{aligned}$$

where $\varepsilon_t^k \sim i.i.d.N\left(0, \sigma_k^2\right)$, for $k = f, u_q, u_1, ..., u_r$, and all the covariances are assumed to be zero. The identifying assumption implies that the variance of the common factor, σ_f^2, is normalized to a value of one.

However, due to the large number of models (16) included in D€STINY we have adopted a parsimonious approach to modelling. In particular, we have decided a common structure that will be applied to all the models, so that the common factor f_t and the objective variable, y_t^q, follow an $AR(6)$, which is approximately equal to a quarterly $AR(2)$, while all the monthly economic indicators follow an $AR(2)$.

More compactly, we use the expression for the measurement and transition equations:

$$\begin{aligned} Y_t &= Hh_t + \epsilon_t \qquad & \epsilon_t &\sim i.i.d.N(0,R) \\ h_t &= Fh_{t-1} + \omega_t \qquad & \varpi_t &\sim i.i.d.N(0,Q) \end{aligned} \tag{6}$$

The fundamental goal is to estimate the vector of unobservables, h_t.

Missing observations We also have to take into account the fact that there are missing observations in our dataset. The missing values are not only due the different lengths of the series considered, but also to the inclusion of series with different frequencies. A quarterly series has to be treated as if it had missing observations during the two months in between observations. Following Mariano and Murosawa (2003) and Camacho and Pérez-Quirós (2010), this can be handled by filling in the gaps with random draws θ_t from a normal distribution with mean equal to 0 and variance equal to 1, which are independent of the model parameters. The substitutions allow the matrices to be conformable but they have no impact on the model estimation since the Kalman filter uses the data-generating process of the normal distribution for them. In that sense, the missing observations simply add a constant to the likelihood function of the Kalman filter process. Let Y_{it} be the ith element of the vector Y_t and R_{ii} be its variance, H_i be the ith row of the matrix H, which has α columns, and $0_{1\alpha}$ be a row vector of α zeroes. Then, the measurement equation can be replaced by the following expressions

$$Y_{it}^* = \begin{cases} Y_{it} \quad \text{if} \quad Y_{it} \quad \text{observable} \\ \theta_t \quad \text{otherwise} \end{cases}$$

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

$$\epsilon_{it}^* = \begin{cases} 0 \quad \text{if} \quad Y_{it} \quad \text{observable} \\ \theta_t \quad \text{otherwise} \end{cases}$$

$$R_{iit}^* = \begin{cases} 0 \quad \text{if} \quad Y_{it} \quad \text{observable} \\ 1 \quad \text{otherwise} \end{cases}$$

This trick leads to a time-varying state space model with no missing observations so that the Kalman filter can be directly applied without any further transformation. Let us remark that when a missing observation is present, the contribution to the likelihood of that observation at this period boils down to a constant so that it does not interfere in the maximization process as it does not add any extra information.

Estimation: Let $h_{t|\tau}$ be the estimate of the unobservable component at time t, h_t with information up to period τ and $P_{t|\tau}$ be its covariance matrix, we can write the *prediction* *equations* as

$$h_{t|t-1} = Fh_{t-1|t-1} \tag{7}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q \tag{8}$$

The prediction errors will be given by

$$\eta_{t|t-1} = Y_t^* - H_t^* h_{t|t-1} \tag{9}$$

with covariance matrix

$$\xi_{t|t-1} = H_t^* P_{t|t-1} H_t^{*\prime} + R_t^* \tag{10}$$

Taking into account that assuming normality implies that

$$Y_t^*|\Omega_t \sim N(H_t^* h_{t|t-1}, H_t^{*\prime} P_{t|t-1} H_t^* + R_t^*)$$

where Ω_t denotes all the information available at period t, we can evaluate the pseudo log-likelihood function via the prediction error decomposition each period as

$$l_t = -\frac{1}{2}\ln(2\pi|\xi_{t|t-1}|) - \frac{1}{2}\eta'_{t|t-1}(\xi_{t|t-1})^{-1}\eta_{t|t-1} \tag{11}$$

The estimation of h_t is revised using the *updating equations*

$$h_{t|t} = h_{t|t-1} + K_t^* \eta_{t|t-1} \tag{12}$$

$$P_{t|t} = P_{t|t-1} - K_t^* H_t^* P_{t|t-1} \tag{13}$$

where K_t^* is usually known as the *Kalman gain* and takes the form

$$K_t^* = P_{t|t-1} H_t^{*\prime} (\xi_{t|t-1})^{-1} \tag{14}$$

This system of equations determines completely the mechanics of the Kalman filter. The filter itself will be obtained recursively with the help of the *prediction equations* and *updating equations* starting from some initial conditions $h_{0|0}$ and $P_{0|0}$, assumed to be a vector of zeroes and the identity matrix. Note that when at any date all the elements of the vector Y_τ are not observed, the updating equation is $h_{\tau|\tau} = h_{\tau|\tau-1}$ and time τ does not change the estimated dynamics of the model. This feature can be used to easily compute forecasts by adding missing data for all the variables in the model at the end of the sample.

Finally, the Kalman filter allows computation of the contribution of each series to the forecast of the objective variable (see Banbura and Rustler (2007) and Camacho and Pérez-Quirós (2010)). Substituting the prediction errors $\eta_{t|t-1}$ and (7) into the updating equation (12), one obtains

$$h_{t|t} = (I - K_t^* H_t^*)\, Fh_{t-1|t-1} + K_t^* Y_t^*$$

Iterating this expression it becomes $h_{t|t} = \sum_{j=1}^{t-1} M_{jt}^* (L) Y_t^*$. Assuming that K_t^* and H_t^* remain unchanged, the matrix of lag polynomial can be approximated by $M_t^* (L) = (I - (I - K_t^* H_t^*) FL)^{-1} K_t^*$. Then, the first component of this polynomial $M_t^* (1)$ represents the cumulative impacts of the individual observations in the inference of the state vector if the information set contained only the variables that we observe in period t. Combining this with equation (5) one can compute the cumulative impact of each indicator on the forecast of GDP growth.

3.2 Pooling of forecasts

Since the seminal work of Bates and Granger (1969), forecast combinations have come to be viewed as a simple and effective way to improve and robustify the forecasting performance over that offered by individual models. Empirical applications have confirmed these results. Stock and Watson (2001, 2004) undertook an extensive study across numerous economic and financial variables using linear and nonlinear forecasting models and found that, on average, pooled forecasts outperform predictions from the single best model. Their analysis was extended to a large European data set by Marcellino (2004) with essentially the same conclusions. As a result, forecast combinations are now in widespread use in central banks, among private sector forecasters and in academic studies.

There are many reasons why pooling forecasts may work in practice, but the two most relevant for our empirical exercise are that it can cope better with model misspecification and structural breaks in the data (see Clements and Hendry (2004)). Given that our sample includes the "Great Recession", instability has been dominant in the later part of the sample. In particular, it is well known that most models failed to capture the depth of the 2008 crisis and the timing of the subsequent recovery, as well as the second dip of the recession in 2012Q4. A forecast combination that puts more weight on those models that had performed better in the immediate quarters could have, at least partially, overcome this problem.

Thus, our best predicting model will be the linear combination of forecasts produced by the three different aggregations of euro area GDP, plus the direct estimation from Euro-STING:

$$\widehat{y}_t^{best} = \sum_i w_i \widehat{y}_t^i \quad \text{where } i = P, E, C, € \tag{15}$$

where two sets of weights w_i are considered. The first one updates the weights dynamically according to a past performance criterion based on the inverse Mean Square Error of each forecast for a certain time window[5]. This is compared with a forecast combination with equal weights.

[5] The criterion that yielded better results was one displaying a moving rolling window of 3 months (1 quarter)

4 Model Specification

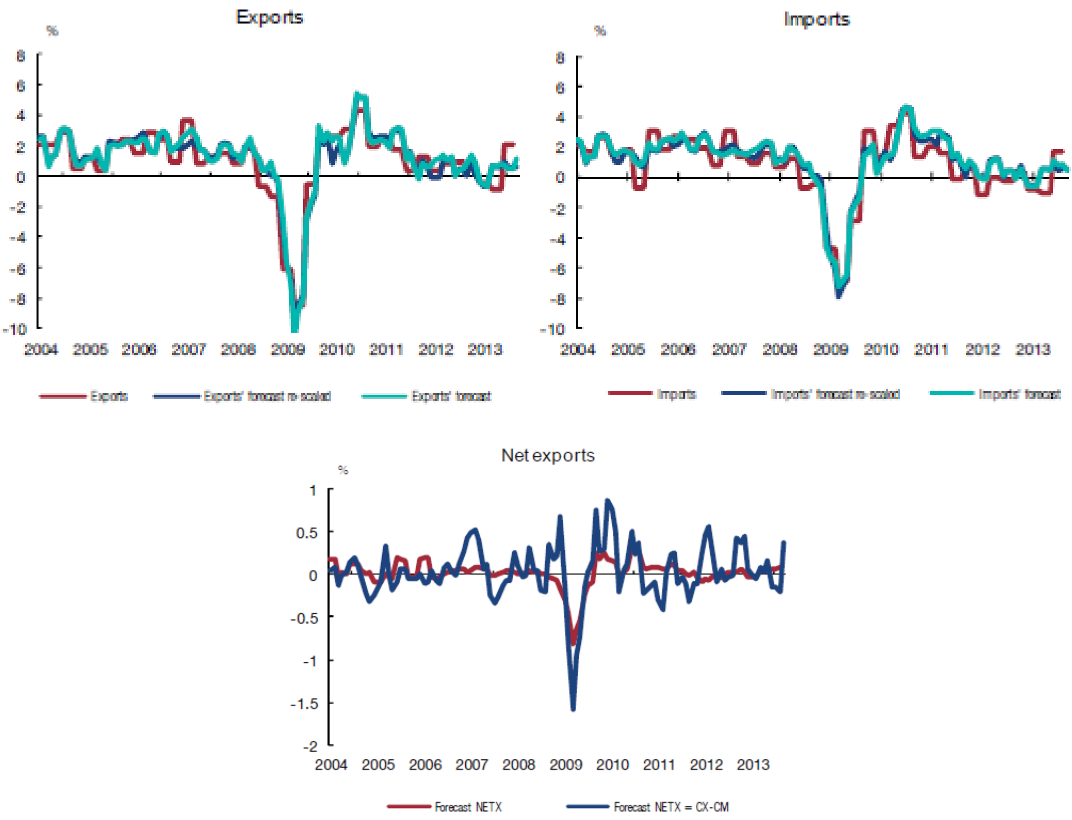
The next step is to choose the exact specification for each of the 15 models from the pre-selection of indicators detailed above. To do this we follow a two step procedure. First, we start from a parsimonious model with only the most relevant indicators among the ones pre-selected above (highest correlation with the objective variable) and only add a new indicator when it increases the percentage of variance explained by the common factor, as in Camacho & Pérez-Quirós (2010). Second, once we have chosen a set of indicators we check that each one of them contributes to the model's forecasting performance. This is done by comparing the forecasts, through Diebold-Mariano tests, of the baseline model with the ones excluding that indicator in a pseudo-real time estimation exercise for the period 2004-2013 (results available from the authors upon request). We also check that each indicator contributes positively to both, the pre-crisis (2004-2007) and crisis subsamples (2008-2013), to make sure the results are not driven only by outliers during the crisis. That is, we confirm that we are not selecting indicators now that would not have been chosen prior to the crisis (see Gadea and Pérez Quirós (2012)).

As mentioned above, depending on the nature of the data, the time series are transformed in different ways. Sectorial value added, expenditure component and country GDPs, as well as country employment are used in quarterly growth rates. Hard indicators are transformed by taking monthly growth rates, while soft indicators are included in levels. In addition, to be included in the dynamic factor model, all of these series have been normalized to have zero mean and unit variance.

The result of this procedure is shown in table 1 in the appendix. From the production side, a remarkable fact is that no indicator is available for the primary sector (AB, agricultural, forestry and fishery production). Thus we estimate a univariate AR1 model for this sector. For industry (CDE), construction (F) and trade (GHI), core quantitative indicators are represented by the industrial production index, the production in construction index and the industrial production of consumer goods and retail sales, respectively. These are complemented with the relevant qualitative indicators elaborated for these branches - confidence, orders and employment - published by the European Commission and Markit. In the case of financial services (JK), we selected as a quantitative indicator of activity the loans of the monetary and financial institutions, provided by the European Central Bank, complemented with two surveys which are correlated with the value added of this sector. Finally, other services (LMNOP), includes a variety of economic activities (public administration and defence, compulsory social security, education, health and social work, other community, social and personal service activities, and private households with employed people) for which it is not easy to find reliable and timely monthly indicators of value added. We selected a single monthly hard indicator, the total amount of debt securities issued by central government, and two surveys which capture expenditure in consumption.

From the expenditure side, for final consumption expenditure retail sales are used as an indicator of demand, while the unemployment rate captures the economic situation of households, together with the production of consumer goods. For gross capital formation a core indicator is the production index for industry and capital goods. To capture sentiments and expectations of economic agents we complete this set of variables with the relevant Business and Consumers Surveys data that are published by the European Commission and Markit for each component. As far as the external balance is concerned, we follow a slightly different approach. The problem is that, as can be seen in figure 1, although the models for exports and imports perform fairly well, given the volatility of these components, the derived contribution of net exports does not. Instead, we estimate directly a model for the contribution of net exports to GDP growth, that we use to obtain GDP growth through the expenditure side. Then, we re-scale the forecasts for exports and imports' growth to make them consistent with the net exports' forecast obtained directly through its specific model. The three models have a similar structure, using as core quantitative indicators the trade (nominal) monthly index provided by Eurostat[6], the industrial production in intermediate goods (total industrial production for imports) and the effective euro exchange rate. These are complemented with the EC survey on foreign orders in the case of exports and imports, while the model for net exports includes the PMI manufacturing global index relative to the euro area one.

Figure 1. Forecasting net exports



[6] In the case of net exports we used monthly exports, since monthly net exports were too volatile.

The models for the four largest countries in the euro area try to mimic the structure of the Euro-STING model (see Camacho and Pérez-Quirós (2010)), but using the national components of each indicator. The exception is the model for Spain that follows the structure of the Spain-STING model (Camacho and Pérez-Quirós (2011)). Thus, all the models include as core quantitative indicators the industrial production (in the case of Germany it is total industrial production), industrial orders (not in the case of France, since this variable is no longer published), retail sales, exports, imports and quarterly employment. Germany's model also includes building permits, to capture better the construction sector. There is more variety in terms of the qualitative indicators considered. All of them include at least one survey for the manufacturing sector and another for the services sector, from the EC and/or Markit's surveys. In addition, Italy considers the ISAE industrial confidence indicator, while France includes the one produced by INSEE.

5 Empirical results

In order to evaluate D€STINY's forecasting performance two complementary real-time forecasting exercises were undertaken. The first one is a "pseudo real-time evaluation" that uses a monthly database compiled in October 2013 and covering the period January 2004 - September 2013, while the second is a truly real-time exercise using a daily database which has been compiled since the 1st of March 2011. In this section, we will use the Euro-STING model as a benchmark, for two reasons. Firstly, because it is a good benchmark since it has been shown to be a good model to forecast euro area GDP (see Camacho & Pérez-Quirós (2010) and Álvarez et al. (2012)). Secondly, because the comparison will be an empirical contrast of how beneficial is the disaggregated approach to forecasting GDP, used in this paper, with respect to the aggregate or direct approach used in Euro-STING.

5.1 Pseudo-real time exercise

The pseudo-real time forecasting experiment runs from the first quarter of 2004 to the second quarter of 2013 (published in mid-august of that year). This is a "pseudo-real time" evaluation because it is done using a monthly database compiled in october 2013, instead of the initial data for each indicator published each month. The difference with a truly real-time evaluation exercise is that we do not take into account the data revisions occurred between the first publication of the data for each indicator and the one available in october 2013. The exercise then consists in reorganizing the information included in the database so that each month of the period considered we reestimate the model and derive a forecast using only the information that was really available at that moment in time. That is, at the beginning of january 2004, first month considered, we would only have had available the National Accounts data for 2003 Q3, the hard indicators would have referred to November 2003 or earlier, while we would already have the surveys for December. Using this information euro area growth is projected for the following six months, i.e. 2003Q4 and 2004Q1 (as well as the growth of each of the

16 components forecasted). This exercise is repeated recursively each month of the sample until september 2013, so that we reestimate the model and derive a forecast 122 times[7]. In the analysis of the results we will distinguish between the period before the crisis, 2004Q1 to 2007Q4, and the crisis and posterior recovery, 2008Q1 to 2013Q2, to make sure the results are not driven only by outliers during the crisis. This is particularly relevant for the choice of the best forecast combination, since we want to confirm that we are not sellecting a forecast combination now that would not have been chosen prior to the crisis (see Gadea and Pérez Quirós (2012)).

Table 2 includes the root mean square error of the one-quarter-ahead forecast derived from each component of the three approximations to GDP considered. Given the large number of models and approaches, we only include results for the one-quarter-ahead forecasts, that is the forecast for the following three months. However, the results for the two-quarter-ahead forecasts are qualitatively similar (available from the authors upon request). First of all, there is a great variation across models in forecast performance. In some cases this is due to the fact that the data display a greater variance, like industry's value added, exports, imports or Germany's GDP. In other cases, the main reason is that it is difficult to find relevant indicators to forecast them, like the value added of agriculture, other services or investment expenditure. Secondly, as one would expect, the models performed better before the crisis, again because of the greater volatility of the data during the crisis. However, there is also some evidence of structural breaks in the relationship between some relevant indicators and the data.[8]. Finally, it is worth mentioning the great performance of the models for industrial value added, exports, imports, and the largest countries, once you control for the variance in the data (see the numbers in brackets right below the full sample).

[7] That is, almost two thousands estimations (122 times 16 models).

[8] However, this issue is beyond the scope of this paper, so we leave it for further research.

Table 2. Root mean square error by GDP component of one-quarter-ahead forecast.

	Production approach						
	Agriculture, hunting and fishing	Industry, including energy	Construction	Trade, transport and communication services	Financial Services	Other services	Taxes
PSEUDO REAL TIME							
Full sample (2004-2013)	5.49	1.56	1.16	0.35	0.13	0.08	0.57
RMSE/variance (1)	*(1.02)*	*(0.35)*	*(0.62)*	*(0.45)*	*(0.40)*	*(1.19)*	*(0.69)*
Pre-crisis (2004-2007)	11.48	0.25	0.90	0.15	0.09	0.04	0.58
Crisis (2008-2013)	1.35	2.46	1.34	0.49	0.16	0.11	0.57
1-3-2011 / 1-10-2013	1.75	1.35	1.06	0.21	0.09	0.11	0.41
REAL TIME (2)	0.51	0.68	0.78	0.12	0.11	0.09	0.30

	Expenditure approach				
	Consumption (private and public)	Gross capital formation	Exports	Imports	Net Exports
PSEUDO REAL TIME					
Full sample (2004-2013)	0.09	3.28	0.81	0.84	0.11
RMSE/variance (1)	*(0.85)*	*(0.46)*	*(0.15)*	*(0.19)*	*(1.02)*
Pre-crisis (2004-2007)	0.04	2.43	0.60	0.59	0.08
Crisis (2008-2013)	0.13	3.87	0.95	1.02	0.13
1-3-2011 / 1-10-2013	0.21	0.65	0.71	0.94	0.10
REAL TIME (2)	0.10	0.61	0.65	0.75	0.04

	Country approach			
	Germany	France	Italy	Spain
PSEUDO REAL TIME				
Full sample (2004-2013)	0.26	0.14	0.25	0.09
RMSE/variance (1)	*(0.27)*	*(0.41)*	*(0.36)*	*(0.18)*
Pre-crisis (2004-2007)	0.15	0.09	0.13	0.13
Crisis (2008-2013)	0.35	0.18	0.34	0.07
1-3-2011 / 1-10-2013	0.17	0.13	0.21	0.06
REAL TIME (2)	0.14	0.14	0.13	0.04

(1) The variance is calculated using the data published for each component over the whole period (2004-2013).

(2) The real time period correspond with estimations from March of 2011 to October of 2013.

The performance of the different approaches to forecast GDP is shown in table 3 and figure 2. The first three columns of the table include the RMSE of the one-quarter-ahead forecast from the three disaggregated or indirect approaches, namely *production, expenditure and countries*, while the fourth reports the one for the *Euro-STING* model. Since the Euro-STING represents the aggregate or direct approach to forecasting GDP, we will take it as a benchmark to study how beneficial is the disaggregated approach of this paper. Considering the full sample, the three disaggregations perform better than Euro-STING, though the countries approach is clearly better, because of its performance in the second part of the sample. However, prior to the crisis the best approximation is the expenditure side. Prior to the crisis Euro-STING's performance is comparable to the country and expenditure approaches, however it is during the crisis and posterior recovery where the gains of disaggregating are clearer[9].

[9] Note that further gains might be obtained in the *country* approach if the remaining 20% countries were to be modelled.

Table 3. Root mean square error of the different GDP approximations and forecast combinations

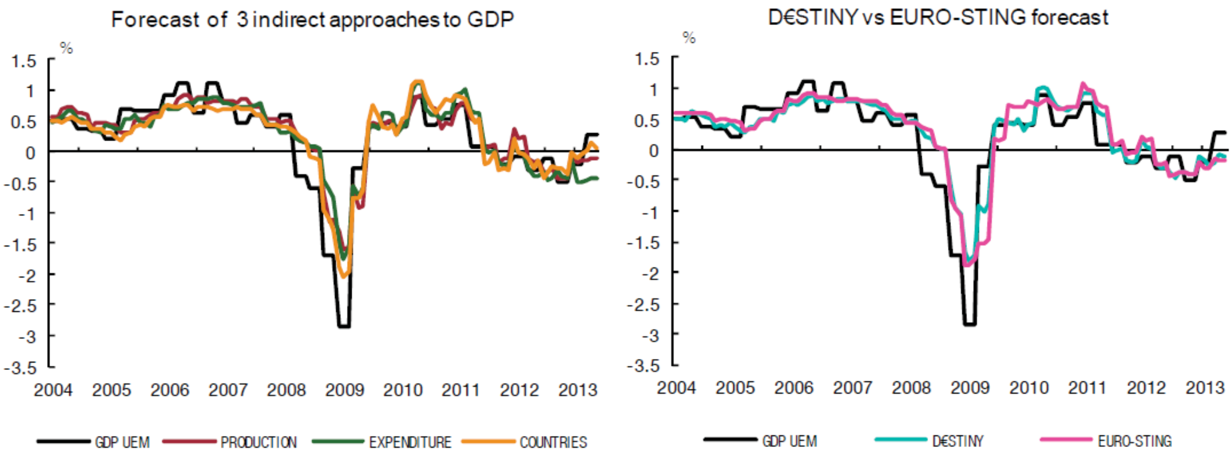
	Different apporaches to forecast GDP				Forecast combinations			
	Indirect			Direct			rel. to Euro-STING (%) (1)	
	Production Approach	Expenditure Approach	Country Approach	Euro-STING	Prod, exp & countries	D€STINY	Prod, exp & countries	D€STINY
PSEUDO REAL TIME								
Full sample (2004-2013)	0.13	0.14	0.09	0.15	0.10	0.11	-34***	-31***
Pre-crisis (2004-2007)	0.04	0.03	0.04	0.04	0.04	0.03	-10	-14
Crisis (2008-2013)	0.19	0.22	0.13	0.24	0.15	0.16	-37	-34
1-3-2011 / 1-10-2013	0.05	0.10	0.05	0.08	0.06	0.06	-31	-30
REAL TIME								
1-3-2011 / 1-10-2013	0.05	0.15	0.04	0.07	0.05	0.05	-31	-25

(1) *** refers to 1% significance level in the Diebold-Mariano test. The sample size is too small to perform the test separately for the subsamples of the real time exercise.

Finally, the LHS of table 3 and figure 3 compare the performance of the different forecast combinations considered. The first step to calculate the forecast combination is to decide which is the best weighting scheme and what is the optimal dynamic window to use for the weights. The literature on choosing forecast weights is very wide and, to some extent, frustrating, since it does not provide a general rule. In some cases, it even shows that simple rules perform better, like the simple average of the forecasts. In this paper we use the (inverse of) RMSEs (over the sum of (inverse) RMSEs across all models) as a measure of the recent forecasting performance of each approach. With respect to the size of the weighting window, we find that in our model the one that displays better forecasting performance uses the information from the prior 3 months with published NA data (see table A.2. in the appendix). It is worth pointing out that we only consider forecast combinations that perform well before and after the crisis, to make sure the results are not driven only by outliers during the latter period, and that we are not selecting a combination now that would not have been chosen prior to the crisis (see Gadea and Pérez Quirós (2013)). This is why we do not prefer the country approach to any forecast combination despite having the lowest RMSE for the whole sample, since it performs worse before the crisis.

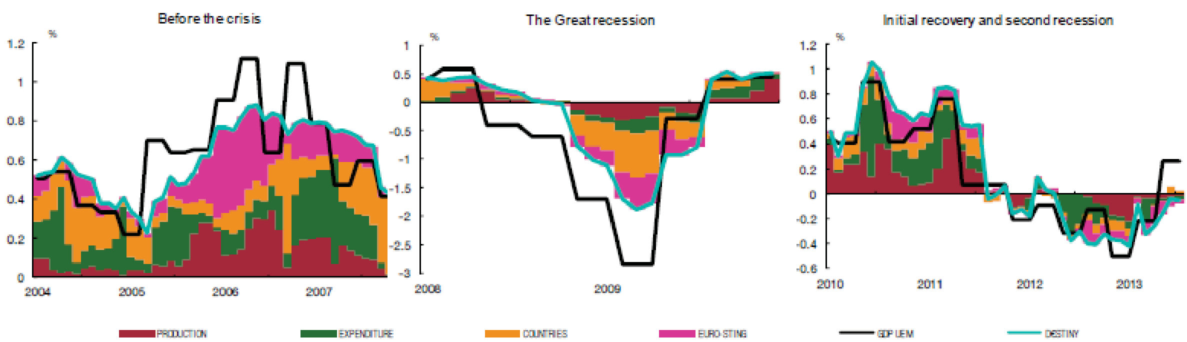
When we compare the forecast combinations with Euro-STING we find that the gains in terms of RMSE are quite important, more than 30% for the whole sample. The benefits of pooling the forecasts become apparent for the crisis period, where the forecast combinations are closer to the best approach in terms of performance, the country side, than to the average. Moreover, it is in this period when Euro-STING performs much worse than any of the indirect approaches. This may be related to the presence of structural breaks in some relevant indicators, which could have affected more intensely the direct approach than the indirect one. In fact, during the more stable part of the sample, the gains from pooling are clearly smaller.

Figure 2. Forecast for Euro area GDP growth by the 3 aggregations and D€STINY.



There is now a growing evidence documenting the fact that the usefulness to predict euro area GDP growth of some historically relevant quantitative indicators might have diminished since the beginning of the crisis. In this sense, Burriel (2012) and others show that the (m-o-m growth rate of) industrial production, industrial new orders and (nominal) exports fell by more and recovered quicker than GDP (q-o-q growth) during this crisis, while the opposite occurred in prior recessions. This should have had a greater impact in models with fewer, but very relevant indicators, than in models with a very large number of indicators. In fact, since the beginning of the crisis the Euro-STING model has on average overpredicted GDP growth, while the average bias in D€STINY's forecast over this period is very close to zero. Moreover, since 2008 Euro-STING's overprediction was greater than D€STINY's every year, except for 2009. This is also true for the bias in the forecast of the three different indirect approximations used in this paper. This result might be taken as evidence suggesting that combining a disaggregated approach to predicting euro area GDP with pooling forecasts might be able to cope better with structural breaks (as shown in prior work by Clements and Hendry (2004)).

Figure 3. Contributions to D€STINY's forecast



Finally, to understand how does the pooling of forecast work in practice, figure 2 compares the one-quarter-ahead forecast of the three aggregations of GDP (LHS), Euro-STING and D€STINY (RHS) with the corresponding published euro area q-o-q growth rate, while figure 3 shows the contributions to D€STINY's forecast from each of its four components. These graphs show the advantage of pooling forecasts with dynamic weights, because at each moment in time the model that has performed better in the previous quarter is attributed a larger weight in the overall forecast. In this way, since Euro-STING performed fairly well from 2004 to 2008, it contributed strongly to D€STINY's forecast during this period (RHS of figure 3). During the Great Recession, the aggregation of forecasts for the four largest countries captured better the timing and depth of the crisis, which is why its contributions to D€STINY's forecast are largest at this moment (see middle panel of figure 3). However, this approach, together with Euro-STING, overpredicted the strength of GDP during the posterior recovery, and thus the production and expenditure aggregations display a greater contribution for this period (LHS of figure 3).

5.2 Real-time exercise

The second forecasting exercise is a truly real-time one since it uses a database that has been compiled daily since the 1 March 2011. The exercise consists in every day new data for one indicator is published, each model that includes this indicator is re-estimated and a new prediction is derived. Then the aggregation corresponding to that model is recalculated and a new forecast for D€STINY is obtained. Therefore, the main difference with the pseudo-real time exercise above is that in this case we take into account all the revisions to both the National Accounts data and the indicators. In fact, given the short sample size, the main purpose of this exercise is to confirm that taking into account all the revisions of the data does not alter the results obtained above from the pseudo-real time exercise.

The result of the real-time forecasting for the period 1st of march 2011 to 1st of october 2013 is shown under the heading "Real time" of tables 2 and 3 above. As expected, the comparison of the real and pseudo real time analysis (last row of the pseudo-real time analysis for each component) over the same sample horizon, gives qualitatively similar results for the three aggregations, Euro-STING and D€STINY forecasts. However, there are more differences in the individual models, specially in the case of the components of value added (agriculture, industry and construction display lower RMSEs in real time) and countries (Germany and Italy also perform better in real time). This might be related to the size of revisions over this sample for these components.

It is worth mentioning here that although the real time forecasting exercise is not very relevant to check the performance of the model due to the small sample size, it is a tool of fundamental importance for policy purposes, since it provides early signals for the evolution of economic activity for GDP growth and 16 of its components for the six-months period prior to the publication of the preliminary release. For this purpose, each model has been developed to forecast a rolling window of six months that moves according to the publication date of the first estimation available (preliminary release in the case of euro area and countries GDP, while first release in the case of production and expenditure sides components). That is, for example, on November 14th 2013 Eurostat published the preliminary release of GDP for the third quarter of 2013. On that day the model started to produce a forecast for the first quarter of 2014, and will continue to do so until early may 2014 when the preliminary release for that quarter will be published. Since GDP is part of the observed variables in the measurement equation, it is fairly simple to obtain these forecasts within the model from the Kalman filter iterations by imposing six months of missing observations after the last figure that is available for that variable. Therefore, everyday a new indicator is published, for example on the 14th of october after the release of the august data for industrial production, D€STINY is re-estimated and the forecasts are circulated to the analysts and policy makers within our institution. Examples of the type of information that is generated on that day are table A3 in the appendix with the forecasts for the 15 components of GDP, for the production, expenditure and country sides aggregations, for the direct estimation from Euro-STING, and for the combined forecast for D€STINY and figure A2 in the appendix with the evolution of the combined forecast of D€STINY over the six-month rolling window.

Moreover, our approach also calculates the contribution of each indicator published to the growth rate of the component of GDP that the model is predicting, to the growth rate of the approach this component belongs to and, finally, to the final forecast of GDP growth. To illustrate it with an example, the 14th of october 2013 Eurostat published the first hard indicator referred to the month of august, the euro area industrial production index, with a 2-month lag, but one month before the first numbers for that quarter are published (see table 4). That day the models for industrial value added, net taxes, gross capital formation, imports and Euro-STING were re-estimated taking into account the new data point and in all cases the forecast for 2013 Q3 improved (by 0.01, 0.22, 0.02, 0.52 and 0.01 percentage points, respectively). The reason was that the published m-o-m growth rate for august (1%, after a fall of 1.5% in July) was higher than what each model had expected (0.95%, 0.50%, 0.42%, 0.51% and 0.52%, respectively). As a consequence, the production aggregation of GDP for Q3 improved by 0.02pp., while the expenditure aggregation worsened by 0.23pp, since greater imports growth reduces GDP growth. However, the result of these offsetting movements was that D€STINY's (combined) forecast for 2013 Q2 remained unchanged. That is, after this analysis we would have said that industrial production in august was better than initially expected, signaling an improvement in industrial value added, net taxes and investment, however this outcome was offset by a rise in imports. Moreover, our disaggregated analysis gave a slightly different picture to the direct one of Euro-STING, which expected a small increase in GDP growth.

Table 4. Industrial Production relative to August 2013

Model of GDP components	Value at t	Forecast for t	Value at t-1	Contribution to GDP (p.p.) Component	Approx.	Euro area
Industry	1.02%	0.95%	-1.54%	0.01	0.00	0.00
Net taxes	1.02%	0.51%	-1.54%	0.22	0.02	0.01
Gross capital formation	1.02%	0.42%	-1.54%	0.02	0.00	0.00
imports	1.02%	0.51%	-1.54%	0.52	-0.23	-0.01
Euro-STING	1.02%	0.52%	-1.54%	0.01	0.01	0.00

An additional interesting feature of the real-time analysis using our approach is that it allows us to do backward inference for the GDP components that are published later. In particular, GDP for the euro area and larger countries is published around 45 days after the end of the quarter (in the case of Spain is closer to 30 days), but the disaggregation of GDP into the production and expenditure components is published one month later (with about 70 days delay). Therefore, during this interim period of approximately 30 days, where the flash estimate of GDP (available for the euro area and individual countries) has already being released, we can take advantage of that to improve our point estimates of the expenditure and production components of GDP. That is, we recalculate the forecast for the six branches of value added and net taxes, and for the four expenditure components, to make it consistent with the flash GDP number.

6 D€STINY versus a Large Scale Model

As was discussed in the introduction, our approach is an attempt to bridge de gap between the large and small scale dynamic factor models. In principle, one can argue that the so called large scale dynamic factor models (LSDFM) are more efficient since they make use of all the available information at every moment in time (see Forni et al. (2005), Giannone et al. (2008) and Angelini et al. (2011) for some recent applications of these techniques to forecast euro area GDP growth). However, as Álvarez et al. (2012) have shown this may come at a cost. The finite-sample performance in factor estimation and forecasting of LSDFM may be greatly affected when there is a high degree of correlation across the idiosyncratic component of the indicators included in the model. In this case, small dynamic factor models (SSDFM) with a few chosen indicators tend to outperform large scale ones. In this line, Banbura and Modugno (2010) find that a LSDFM applied to a small (14 series) dataset outperforms the forecasts obtained from medium (46 series) and large (101 series) datasets.

In this paper, we have tried to get the best of both methodologies by using as much of the information available as possible, but imposing the economic structure implicit in the quarterly National Accounts. As explained in the section describing the structure of the model, this is done by adopting a disaggregated approach in which a small factor model (with less than 14 indicators) is estimated and used to forecast each of the components of GDP by the production, expenditure and countries National Accounts disaggregations. This procedure allows us to consider the information provided by almost one hundred indicators (76 monthly and 21 quarterly) referred to the euro area or member countries, but without incurring in the finite sample problems of the large scale approach, since the estimated models are of a small scale.

In this section we test the benefits of our approach. This is done by comparing the forecasting performance of D€STINY over the pseudo-real time sample used in the section above, with a large scale dynamic factor model that uses the same set of indicators included in D€STINY, but without imposing any economic structure on them. That is, both models use the same set of indicators and sample, but in D€STINY we use a set of small scale models for all the disaggregated components of GDP and aggregate their predictions, while in LSDFM we use all the (monthly) indicators together in a large scale model.[10] This comparison exercise is repeated for four different sets of indicators: the LSFDM-UEM refers to the model using all the indicators (76), the LFSDM-production to the one with the set of indicators included in the models of the production side (25), LFSDM-expenditure to the one using the variables included in the expenditure side (18), and LFSDM-countries, when using the ones for the large countries side (37).[11]

Each LSDFM is estimated using the quasi-maximum likelihood approach suggest by Doz et al. (2007, 2011).[12] However, this procedure requires a balanced dataset, which would imply discarding the most up-to-date information and would reduce greatly the usefulness of the (pseudo) real time exercise. Instead, here at every date that we perform the estimation and forecast of the model we rebalance the dataset using the algorithm proposed by Cuevas & Quilis (2012). This procedure consists in five steps:

1. Compute the common dynamic factors of the largest balanced panel available, discarding some indicators and some of the earliest and most recent data (longitudingal panel in figure A3 in the appendix). In our application the balanced panel discards 7 indicators and covers the period January 1999 until 3 months prior to the estimation date (t=49, ..., T_1 in the graph).[13]

2. The missing values of the indicators not included in that panel (grey areas in the chart for the period t=49, ..., T_1) are forecasted through OLS regressions with the common factors as explanatory variables.

[10] The standard LSDFM methodology does not allow for indicators with different frequency. Although we think this limitation can be overcome, we have not found any empirical application doing it. Therefore, we have decided to use the standard procedure, to make our results comparable with the standard methods used in applied work.

[11] Given their size, the last three models should be classified as medium or small size dynamic factor models.

[12] We use a slightly modified version of the paper codes from Domenico Giannone's web site: http://homepages.ulb.ac.be/~dgiannon/DGRreplication.zip

3. The statistically re-balanced panel is then used to compute a new set of common factors for the period t=49, ..., T_1.

4. These factors are then projected forward until the last month of the sample (normally two months, T_2 in the graph).

5. This data is then used to rebalance again the panel until the most recent date using the same procedure as before (that is fill in the grey are in the graph from T_1 to T_2).

These 5 steps are repeated until the algorithm converges, when the change in the likelihood is below a certain threshold.

Finally, to obtain the forecast for euro area q-o-q GDP growth, we transform the monthly factor into quarterly frequency (using the Mariano & Murosawa (2003) approximation) and estimate a simple transfer function by OLS between the common factor and GDP growth. Then we use this equation to forecast GDP two quarters ahead.

Figure 4. One-quarter-ahead forecast of euro area GDP q-o-q growth

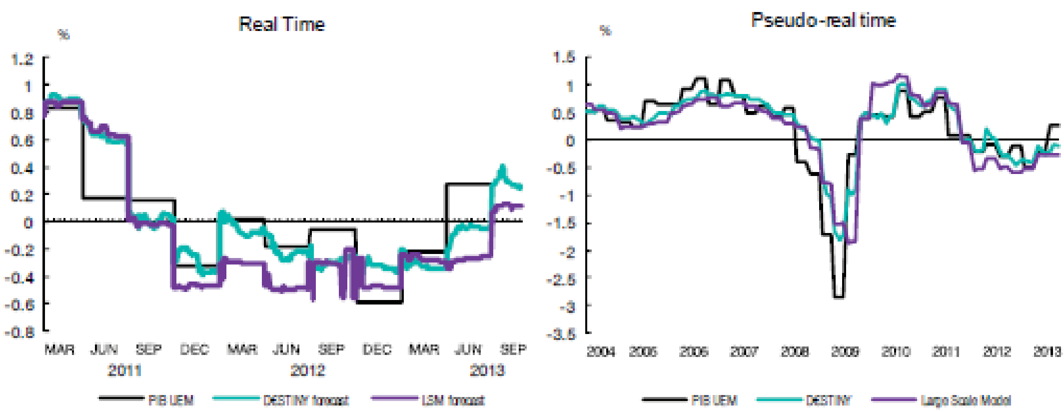


Figure 4 compares the one-quarter-ahead forecasts of D€STINY and LSDFM-UEM (using the sample including all the indicators), while table 5 compares the performance in terms of the RMSEs of the four models considered both, for the pseudo and the truly real-time exercises. We find that D€STINY performs better than LSDFM across all approaches and samples. The graph indicates that the forecast from the large scale model is clearly worse for the whole sample. It underestimated GDP growth during most of the initial expansion, it missed the timing of the crisis, with the trough happening two quarters too late, it overestimated the recovery and underestimated the subsequent recession. This is reflected in the table by a RMSE almost double than D€STINY's, which according to the Diebold-Mariano test is significantly worse at the 1%

[13] It is complicated to start earlier than this date since a large number of indicators start to be published at this moment.

significance level.[14] Moreover, a similar picture is found for both subsamples, for the truly real-time comparison, as well as for the three aggregations approaches.[15] There are only two cases where one cannot reject that the performance is statistically similar across both methodologies: the period 2004-2007 of the pseudo-real time exercise for the country approach and the real-time exercise for the demand approach. Nevertheless, the Diebold-Mariano test shows that the country aggregation has performed better over the whole sample than the LSDFM at the 10% significance level.

Therefore, one can conclude that in the case of our empirical application a disaggregate approach, which imposes a certain economic structure to a large dataset is superior to both, a large scale model, that includes all the information in a disorderly manner, and a small scale model, that uses only a small number of relevant indicators.

Table 5. Comparison of RMSEs for D€STINY and LSDFM

			UEM	Production approach	Demand approach	Country approach
Pseudo-real time	2004-2013	LSDFM	0.23	0.21	0.27	0.16
		D€STINY	0.12	0.13	0.14	0.09
		DM test (1)	3.37***	2.99***	2.66***	1.88*
	2004-2007	LSDFM	0.06	0.06	0.06	0.04
		D€STINY	0.03	0.04	0.03	0.04
	2008-2013	LSDFM	0.35	0.32	0.42	0.26
		D€STINY	0.18	0.19	0.22	0.13
Real Time	Mar. 2011-Oct. 2013	LSDFM	0.09	0.10	0.10	0.07
		D€STINY	0.05	0.04	0.12	0.04

(1) ***, **, * refer to 1%, 5% and 10% significance level, respectively in the Diebold-Mariano test.

[14] The null hypothesis in the Diebold-Mariano test (1995) is that the two forecast methods display similar prediction errors on average, using as loss function the average of the error squared.

$$S = \frac{\bar{d}}{(\widehat{avar}(\bar{d}))^{1/2}} = \frac{E[e_1^2] - E[e_2^2]}{(\widehat{avar}(\bar{d}))^{1/2}} \sim^a N(0,1)$$

[15] Unfortunately, the sample size is too small to perform a Diebold-Mariano test for the subsamples or the real-time exercise.

7 Comparison with forecasts of other institutions.

Finally, we compare the forecasting performance of D€STINY with the forecast of the public and private institutions that publish them for a comparable sample and frequency. First of all, the results of this comparison should be taken with care since all these forecasting exercises are not directly comparable. In particular, some refer to different moments in time (within the month or quarter) and thus include different information sets, some are real-time while others are pseudo real time forecasts, and in some cases even the objective variable is not GDP growth but its trend. Nevertheless, table 6 shows that D€STINY greatly outperforms all the alternatives for the whole sample, followed by Eurocoin, while the remaining models are left far behind. This is mainly due to the fact that since the beginning of the crisis the performance of the alternative forecasts has deteriorated much more than in the case of D€STINY, although our model also beats the rest in the previous period. This is specially true for the European Commission forecast, which performed best in the period up to the crisis, and has become one of the worse since then. The differences in the quality of forecasts across these two subsamples might be taken as a confirmation of the hypothesis that the approach proposed in this paper is more robust to periods characterized by very volatile data, which are more likely to include structural breaks.

Table 6. RMSE of other institutions forecasts' relative to D€STINY

	Pseudo real time			Real time
	2004-2013	2004-2007	2008-2013	1 Mar 2011 - 11 Oct 2013
Model/Institution				
Eurocoin	1.19	1.68	1.14	1.19
Eurobarometer	4.19		2.83	3.09
IFO-INSEE-ISAE	2.18	1.31	2.26	--
OECD	2.60	1.43	2.68	--
European Commission	2.74	0.73	2.96	--
D€STINY	1.00	1.00	1.00	1.00

8 Conclusions

In this article we have proposed a new real-time short term model to forecast euro area (qoq) GDP growth. D€STINY bridges the existing gap in the short-term forecasting literature between small and large scale dynamic factor models by using a disaggregated approach that is able to benefit from the advantages of both methodologies. On the one hand, the disaggregated approach takes into account all the available information, like large scale models, by imposing the economic structure implicit in the quarterly National Accounts to a very large set of indicators. On the other hand, since we estimate a small scale forecasting model, a la Camacho and

Pérez-Quirós (2010), for each component of GDP by three different disaggregations, we do not incur in the small sample biases of large scale models. Moreover, D€STINY's GDP forecast has proved to be more robust to turbulent times and structural breaks in the data, since it is obtained as the optimal combination of the three indirect or aggregated estimations of GDP, plus the direct estimation from Euro-STING.

Through two empirical real-time exercises we have shown that D€STINY's forecasting performance is greater than both, one of the bests small scale forecasting models for the euro area, Euro-STING, and the standard large scale models used in central banks. This is true for the whole sample period 2004-2013, but specially for the period since the beginning of the crisis. Moreover, D€STINY's forecast also performed better during the last ten years than the forecasts of all other public and private institutions publicly available.

Our results have clearly shown that adopting several disaggregated approaches to forecast (euro area) GDP growth and then combining them efficiently into a single forecast is a very powerful forecasting tool. Since in our applications it has been more robust to both, highly volatile data periods and to the presence of structural breaks in the data. However, Further theoretical research is necessary to understand better under which circumstances this approach performs better than the alternative ones, namely the direct one of small scale and large scale dynamic factor models.

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9 Appendix: Additional figures and tables

Figure A.1. Euro-STING and D€STINY in Real Time

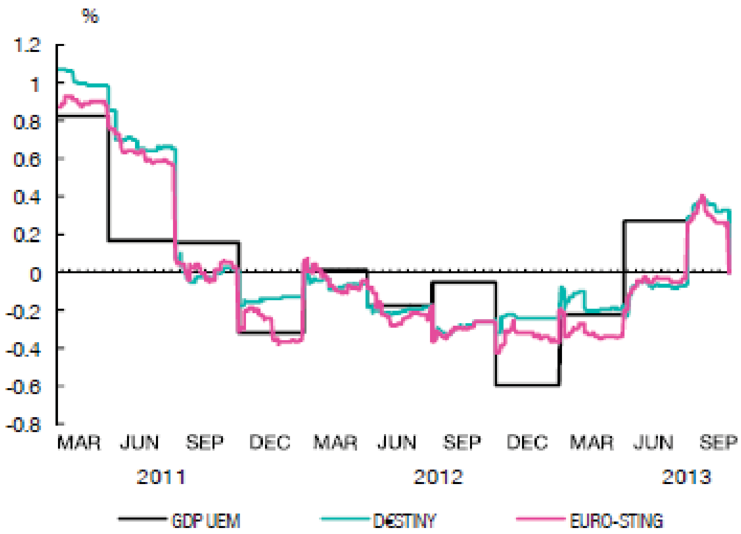

Figure A.2. D€STINY's forecast for 2013Q3

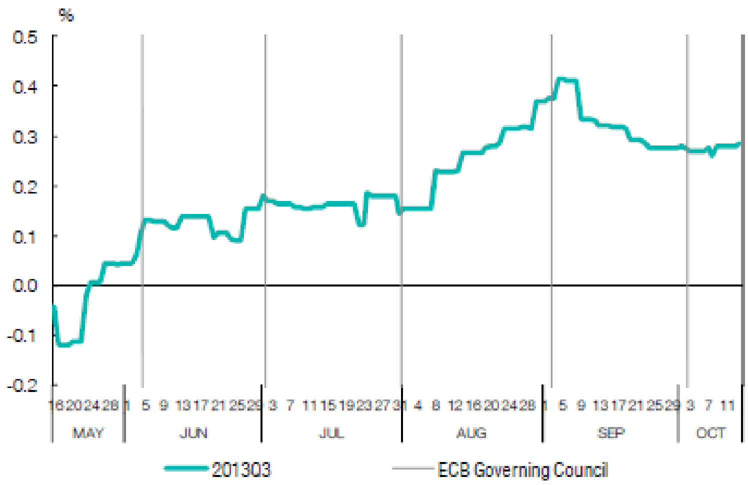

Figure A.3. Rebalancing the panel for the LSDFM

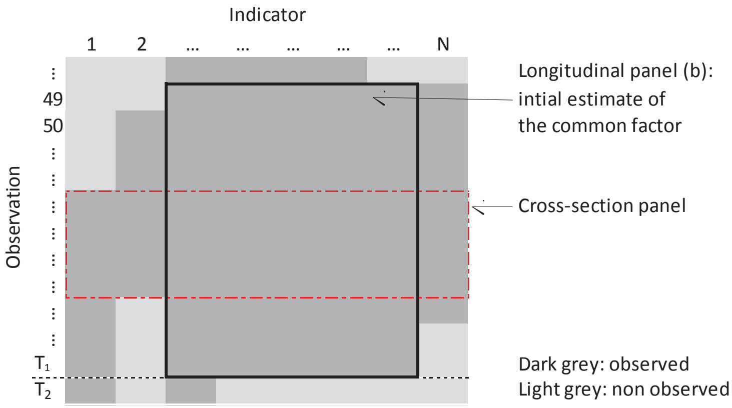

Table A.1. D€STINY's Indicators

Indirect Approximation: Production		Indirect Approximation: Expenditure		Indirect Approximation: Large Countries		Direct Approximation: EURO-STING	
GVA: agriculture, hunting and fishing	q	Final consumption	q	GDP: Germany	q	GDP: euro area	q
GVA: industry (incl. energy)	q	Retail sales	m	Total Industrial production	m	Industrial production	m
Industrial production	m	Unemployment rate	m	New industrial orders	m	New industrial orders	m
EC industrial confidence	m	EC consumer confidence	m	Retail sales	m	Retail sales	m
EC order books assessment	m	EC general economic situation	m	Total employment	q	Total employment	q
EC exports order books assessment	m	EC propensity to buy durable	m	Exports	m	Exports	m
EC employment expectations	m	Composite PMI output	m	Imports	m	EC industrial confidence	m
Manufacturing PMI, output	m	Composite PMI incoming business	m	Building permits	m	IFO indicator	m
Manufacturing PMI, orders	m	Gross capital formation	q	EC industrial confidence	m	NBB indicator	m
GVA: construction	q	Industrial production	m	Services PMI	m	Manufacturing PMI	m
IP: construction	m	IP: capital goods	m	GDP: France	q	Services PMI	m
EC industrial confidence	m	EC industrial confidence	m	Industrial production	m		
Construction PMI, employment	m	EC order book assessment	m	New industrial orders	m		
Construction PMI, new orders	m	Composite PMI output	m	Retail sales	m		
Construction PMI, real estate activity	m	Composite PMI incoming business	m	Total employment	q		
Construction PMI, civil engineering	m	Exports	q	Exports	m		
GVA: wholesale & retail trade, trans. & com	q	Nominal exports	m	Imports	m		
IP: consumer goods	m	IP: intermediate goods	m	EC industrial confidence	m		
Retail sales	m	Real effective exchange rate	m	EC services confidence	m		
EC employment expectations services	m	EC exports order books	m	INSEE industrial confidence	m		
EC price trend	m	Imports	q	Manufacturing PMI	m		
EC wholesale and retail trade activity	m	Nominal Imports	m	Services PMI	m		
EC confidence in consumption	m	Industrial production	m	GDP: Italy	q		
EC industrial confidence	m	Real effective exchange rate	m	Industrial production	m		
EC order books assessment	m	EC exports order books	m	New industrial orders	q		
EC exports order books assessment	m	Net exports	q	Retail sales	m		
Composite PMI output	m	Exports	m	Total employment	m		
Composite PMI incoming business	m	IP: intermediate goods	m	Exports	m		
GVA: financial services	q	Real effective exchange rate	m	Imports	m		
Loans	m	PMI manufacturing Global/Euro	m	EC industrial confidence	m		
EC industrial confidence	m			ISAE industrial confidence	m		
Composite PMI incoming business	m			Manufacturing PMI	m		
GVA: other services	q			Services PMI	m		
Central government debt	m			GDP: Spain	q		
EC confidence in consumption				Industrial production	m		
EC financial situation				VIGES	m		
EC general economic situation				Overnight stays in hotels	m		
GVA: net taxes	q			Cement consumption	m		
Industrial production	m			Social security registrations	m		
Retail sales	m			Exports	m		
EC consumer confidence	m			Imports	m		
	m			EC industrial confidence	m		
				EC retail sales confidence	m		
				Services PMI	m		

NOTE: EC - European Commission; IFO - Information and Forschung (research); INSEE - Institute for Statistics and Economic Studies; ISAE - Istituto di Studi e Analisi Economica; m - monthly frequency; NBB - National Bank of Belgium; PMI - Purchasing Managers' Index; q - quarterly frequency; VIGES - Wholesale corporations' sales; ZEW - Centre for European Economic Research.

Table $A.2$. RMSE of different window weights relative to the 3 month case

	Four approaches (1)					
	w=4	w=5	w=6	w=12	w=18	increasing w
Full sample (2004-2013)	0.49	0.69	0.53	1.06	0.73	1.20
Pre-crisis (2004-2007)	0.34	0.70	**-0.37**	**-4.35**	**-4.33**	4.69
Crisis (2008-2013)	0.51	0.69	0.65	1.79	1.40	0.74

(1) In bold a weighting window with a RMSE lower than the baseline.

Table $A.3$. Forecasts for 14th October 2013

EURO AREA - GDP and its components (growth rate) 14th october 2013

PRODUCTION	2010	2011	2012	12 I	12 II	12 III	12 IV	13 I	13 II	13 III
Agriculture	-3.0	0.4	-1.6	-3.29	-1.75	-1.54	0.13	0.16	-0.53	**0.01**
Industry	9.5	3.0	-0.7	0.39	-0.22	0.03	-1.54	-0.23	0.49	**0.65**
Construction	-5.7	-1.6	-4.2	-1.41	-1.27	-1.02	-1.79	-1.34	-0.59	**-0.04**
Trade, Transport and Comm.	0.7	1.7	-0.9	0.10	-0.46	-0.55	-0.90	-0.39	0.38	**0.24**
Financial Services	1.0	2.4	0.5	-0.11	0.01	0.21	0.10	0.01	0.17	**0.46**
Other services	1.2	1.0	0.5	-0.24	0.03	-0.01	0.38	-0.11	0.19	**0.34**
Taxes less subsides on products	1.4	0.1	-0.5	0.23	-1.11	-0.21	-0.97	-0.28	0.64	**0.24**
Gross Domestic Product (Production)	2.0	1.6	-0.3	-0.10	-0.31	-0.12	-0.50	-0.23	0.26	**0.38**

EXPENDITURE	2010	2011	2012	12 I	12 II	12 III	12 IV	13 I	13 II	13 III
Consumption (private and public)	0.9	0.2	-0.3	-0.34	-0.48	-0.14	-0.27	-0.19	0.19	**0.13**
Gross Capital Formation	2.7	2.9	-4.3	-1.01	-2.36	-1.09	-2.36	-0.51	-0.69	**-0.43**
Exports	11.6	6.5	2.2	0.79	0.93	0.66	-0.49	-0.92	2.06	**1.46**
Imports	10.0	4.5	0.7	0.02	-0.21	0.27	-0.87	-1.01	1.65	**0.92**
Gross Domestic Product (Expenditure)	2.0	1.6	-0.3	-0.10	-0.31	-0.12	-0.50	-0.23	0.26	**0.29**

4 MAIN COUNTRIES	2010	2011	2012	12 I	12 II	12 III	12 IV	13 I	13 II	13 III
Germany	5.1	4.6	0.7	0.66	-0.08	0.20	-0.46	0.00	0.72	**0.43**
France	2.7	3.3	0.4	0.03	-0.34	0.16	-0.16	-0.14	0.52	**0.14**
Italy	2.1	1.8	-2.0	-1.14	-0.64	-0.36	-0.92	-0.60	-0.32	**-0.05**
Spain	-0.1	0.1	-1.4	-0.43	-0.50	-0.38	-0.77	-0.39	-0.10	**0.02**
Gross Domestic Product (Countries)	2.0	1.6	-0.4	-0.10	-0.31	-0.12	-0.50	-0.23	0.26	**0.19**

	2010	2011	2012	12 I	12 II	12 III	12 IV	13 I	13 II	13 III
Euro-STING	2.0	1.6	-0.3	-0.10	-0.31	-0.12	-0.50	-0.23	0.26	**0.34**
D€STINY	2.0	1.6	-0.3	-0.10	-0.31	-0.12	-0.50	-0.23	0.26	**0.29**

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