Component versus Traditional Models to Forecast Quarterly National Account Aggregates: a Monte Carlo Experiment*

Gustavo A. Marrero†

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†Affiliation: Universidad Complutense de Madrid, Departamento de Economía Cuantitativa, Campus de Somosagua, Madrid, Spain. gustavom@ccee.ucm.es

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ABSTRACT:

Econometric models applied to observed data, specified and estimated using traditional Box-Jenkins techniques, have been widely used to forecast Quarterly National Account (QNA) aggregates. We assess the extent to which an alternative forecasting procedure, based on component models, improves the forecasting accuracy of traditional methods. Component models distinguish between the stochastic processes underlying the low- and the high-frequency component of time series, while traditional methods do not. Relationships between QNA aggregates and their coincident indicators are often significantly different for diverse frequencies, as suggested by even an informal examination of empirical evidence. Under these circumstances, a Monte Carlo out-of-sample experiment reveals that component models improve the forecasting accuracy of traditional methods to predict QNA aggregates when their coincident indicators play an important role in such predictions. Otherwise, specially when dealing with pure univariate specifications, traditional procedures likely beat component methods. We illustrate these findings with several applications for the Spanish economy.

Keywords: Forecasting, QNA aggregates, Coincident indicators, Component models, Monte Carlo experiment.

JEL Classification: C15, C22, C53, E32, E37.

1 Introduction

The decision making process of economic agents is contingent on the expected evolution of the economy in the future. Depending on their expectations, firms and households either adjust or keep invariant their investment and consumption plans, while the Government and the Central Bank do the same with their fiscal and monetary policy schemes. Forecasting institutions share as their main target the elaboration of mid- and long-term predictions for real GDP, together with other relevant variables, such as private consumption, industrial Gross Value Added (GVA), the inflation rate or the unemployment rate.[1] By and large, developing flexible and time-adapted forecasting techniques has become a prime concern among economic analysts.

Econometric methods applied to original data, specified and estimated using traditional Box-Jenkins techniques, called *traditional methods* hereinafter, have been widely used to forecast the evolution of Quarterly National Account (QNA) aggregates. Quite often, they are based on univariate models. However, coincident indicators, such as retail and car sales for private consumption, the industrial production index (IPI) for the industrial GVA or the capital goods component of IPI for business investment, among others, are believed to improve the forecast accuracy of univariate processes.[2] We consider in the paper three alternative specifications: i) a *univariate specification*, in which the evolution of the QNA aggregate is just explained by its own past (or inertia); ii) an *indicator specification*, in which the QNA aggregate is just explained by the current and past evolution of their coincident indicators; iii) a *combined specification*, in which the own past of the QNA aggregate and their indicators are combined into a standard dynamic model to explain the evolution of the aggregate.[3]

Our aim is not to compare the forecasting accuracy of these alternative specifications.

Instead, our purpose is to collate, for *each* specification, the forecasting performance of traditional methods with a procedure based on *component models* [García-Ferrer et al. (1996) and García-Ferrer and Poncela (2002)]. Their main disparity is that component models distinguish between the stochastic processes underlying the high-frequency and the low-frequency component within a given time series, while traditional methods do not. We conduct a Monte Carlo experiment to compare the forecasting ability of both methods *outside the sample.*

Using representative QNA aggregates and coincident indicators for the Spanish economy, we calibrate alternative data generating processes for the Monte Carlo experiment. We restrict in this way the parametric space of the data generating processes reasonably. Nevertheless, our main conclusions do not differ significantly if we perturb the parameterization around the benchmark. Too often, the comparison of forecast accuracy is based on one step ahead predictions, but that is not the major concern when dealing with macroeconomic aggregates, so we consider predictions at longer horizons (up to 8 periods).[4] We use the root mean squared error and the Diebold-Mariano (1995) test as forecasting criteria.

Based on the results of the Monte Carlo experiment, we find that traditional methods are more accurate than component procedures to predict the aggregate under a univariate specification, and this result is quite robust to the data generating process considered. Instead, component procedures are preferable than traditional methods to predict QNA aggregates under an indicator specification. However, this conclusion is not robust to the data generating process, and data must show significant differences in the relationship between similar components of the aggregate and the associated coincident indicator to get this result. Notwithstanding, this characteristic is often detected within real time series, as suggested by even an informal examination of several examples for the Spanish economy. Moreover, a forecasting exercise using real data supports this finding.

Thus, the comparison between component and traditional methods to predict QNA aggregates leads to rather different conclusions depending on whether using an indicator or a univariate specification. Finally, using a standard dynamic model to combine both specifications, we find that results are fairly close to those obtained under a pure univariate specification. This finding suggests that the inertia of the QNA aggregate is leaving little capacity to their indicators to affect its predictions, which emphasizes the interest of designing alternative ways to combine the inertia of the aggregate with their coincident indicators into a forecasting model. Although this study is out the scope of the paper, our findings put forward combining predictions obtained from a univariate-traditional model and from an indicator-component model.

In the last decade, and in parallel to the development of the growth cycle literature, the interest of dealing with component models has greatly increased. The National Bureau of Economic Research (NBER) recommends using the growth cycle to describe the evolution of the economy, roughly defined as sequences of slowdowns and accelerations of substantial size in the level of economic activity.[5] The NBER considers two alternative ways to measure the growth cycle:[6] i) as fluctuations around the long-run growth trend, what is commonly called the *trend-adjusted business cycle*; ii) as periods of increases and decreases in the underlying rate of economic growth, i.e., the growth rate of a smoothed trend. We consider the latter definition in the paper.

The estimation of an unobserved trend (the low-frequency component) is required to measure the growth cycle, and we follow García-Ferrer et al. (1996, 2001) to estimate it.[7] They propose changes in the low-frequency or trend component obtained from an integrated random walk (IRW) model, initially proposed by Young (1984, 1996), as a very convenient way to measure the growth cycle of a time series. These changes are labelled as the trend-derivative. The deviation of the original series from this trend is a suitable way to estimate the high-frequency component, usually labelled as the noise component.

Figure 1 shows several transformations of the US seasonally adjusted real GNP from the first quarter of 1980 to the fourth of 2001: the quarterly growth rate, the trend derivative and the noise component.[8] Shadowed areas show peaks and troughs according to its historical record. The coincidence of local maximum and minimum of the trend derivative with these peaks and troughs is striking. On the other hand, it is easy to realize that the quarterly growth rate is mixing up the trend derivative and the noise component, and the latter is disturbing the smooth pattern of the underlying economic growth, which might constitute an inconvenient when dealing with the first difference of the variable into the forecasting model (i.e., when using traditional methods). Precisely, component methods attempt to scape from this weakness.

[INSERT FIGURE 1 ABOUT HERE]

The paper is organized as follows. Section 2 shows the main elements of component models. In Section 3, we study the relationship between several QNA aggregates and coincident indicators for the Spanish economy, distinguishing between their components at different frequencies. Section 4 presents the way we carry out the Monte Carlo experiment. Section 5 summarizes main results from the forecasting experiment. Section 6 complements the previous section with several applications to the Spanish economy. Finally, Section 7 ends with main conclusions and extensions.

2 Component models

Following Young (1984), any seasonally adjusted times series y could be seen as the sum of an unobserved low-frequency or trend-cycle component, τ_t, and an unobserved high-frequency or noise component, η_t,

$$y_t = \tau_t + \eta_t. \tag{1}$$

This model is appropriate for dealing with seasonally adjusted time series that exhibit pronounced trends, as it is the case for most QNA aggregates.

Zarnowitz and Ozyildirim (2002) and García-Ferrer et al. (1994, 2001) point out the importance of finding a convenient way to estimate the growth rate of the trend (the trend derivative). When set in state-space representation, the trend and noise component can be estimated by passing the fixed interval smoother through the following local linear trend (LLT) model:[9]

$$\begin{aligned} y_t &= \tau_t + \eta_t, & (2)\\ \tau_t &= \tau_{t-1} + d_{t-1} + \varepsilon_t, & (3)\\ d_t &= d_{t-1} + v_t, & (4) \end{aligned}$$

where d_t is the trend derivative and v_t and ε_t are serially and mutually uncorrelated white noise errors with variance σ_v^2 and σ_ε^2, respectively. To allow for persistent fluctuations in the trend derivative, Young (1994) and García Ferrer et al. (1994) propose to restrict σ_ε^2 to zero, thus (2)-(4) is based on an integrated random walk (IRW) process for the trend, uniquely defined by the noise variance ratio, $nvr = \sigma_v^2/\sigma_\eta^2$. The smaller the nvr, the smoother the trend derivative and the higher the fluctuations of the noise.

Depending on the *nvr*, there are infinite ways to split the time series into its high- and low-frequency component. Based on spectral density information, Young (1994) and Bujosa et al. (2001) propose similar methods to estimate the *nvr*. However, dealing with seasonally adjusted times series, both methods tend to make the trend derivative too wrinkled, which is an undesirable property [García-Ferrer et al. (1994)]. As an alternative, the *nvr* can be imposed ex-ante following an arbitrary, but reasonable, criterion.[10] For instance, a reasonable *nvr* would generate a trend derivative matching those cycles in the historical growth cycle record. Following this criterion, García Ferrer and Queralt (1998) concludes that a *nvr* around 0.1 would be an appropriate choice for quarterly time series.

A component model specifies two independent stochastic, dynamic models, one for the low-frequency component and another for the high-frequency. They are estimated following a sequence of steps: i) split the time series into its low- and high-frequency component (the trend-cycle and noise); ii) specify and estimate a stochastic model for each component, independently one to the other, using traditional time series techniques; iii) predict each component and compound the forecast for the original time series.

3 The relationship between QNA aggregates and coincident indicators: evidence for the Spanish economy

Monthly indicators are commonly used to improve the forecasting accuracy of quarterly macroeconomic aggregates. We consider seasonally adjusted Spanish data over 1985:01-2003:02 for the following aggregates: Gross Value Added in industry (IND), private consumption (C), business investment (IK) and quarterly real exports (EX). For each aggregate, we consider one coincident indicator: the industrial production index (IPI), the real income index (RII), the available capital goods (AKG) and f.o.b. exports (X), respectively.

We do not aim in this section to propose a formal test to characterize whether the relationship between two variables - the aggregate and the indicator - differs significantly when looking at different frequencies. For our purpose, a simple graphical examination is enough. Figure 2.a, 2.b and 2.c depict scatter plots and the associated regression line for the quarterly growth rate (i.e., the first difference of the variables in logs) of each aggregate and its coincident indicator, their trend derivatives and their noise components, respectively.[11]

[INSERT FIGURE 2.a TO 2.c ABOUT HERE]

Dealing with first differences, QNA aggregates and indicators show a positive and meaningful relationship. However, the intensity of this relationship may differ significantly when looking at different frequencies. For instance, this difference is extreme for the C-RII case: the relationship between their trend derivatives (the low-frequency components) is highly significant and positive, while it is negligible between their high-frequency components.

On the other hand, for the IK-AKG and the EXP-X case, the relationship is meaningful and positive when looking at their both components, but it is more intense between their low-frequency components than between their noises. Finally, for the IND-IPI case, slopes are highly positive for both frequency components, but their differences are less significant than in the three previous examples.

In principle, this empirical evidence might suggest the use of component models instead of traditional models to characterize the relationship between variables. However, this observation does not show, by itself, this convenience for forecasting purposes. To measure the possible forecasting gain from such specification, we conduct a Monte Carlo experiment and compare the forecasting ability of traditional and component procedures *outside the sample.*

4 The forecasting experiment

4.1 The data generating processes

We consider alternative models to generate data that relates an endogenous variable y - the QNA aggregate - with an exogenous variable x - the quarterly coincident indicator. The causality goes from x to y, both variables are assumed to be $I(1)$ and error terms are mutually uncorrelated and normally distributed. $\triangle$ defines the first difference operator, i.e., $\triangle x_t = x_t - x_{t-1}$.

Data for x are generated from a pure autorregresive model,

$$\triangle x_t = a + \sum_{i=1}^{p_x} b_i \triangle x_{t-i} + v_t. \tag{5}$$

First, we consider *data generating processes* (*dgp*) that relates $\triangle y_t$ with its own past and current and past changes on $\triangle x$, called *traditional-dgp* hereinafter,

$$\begin{aligned} \triangle y_t &= \alpha_1 + \sum_{i=1}^{p} \theta_{1,i} \triangle y_{t-i} + \sum_{i=0}^{q} \pi_{1,i} \triangle x_{t-i} + \varepsilon_{1,t}, \\ \begin{pmatrix} \varepsilon_{1,t} \\ v_t \end{pmatrix} &\sim N \begin{pmatrix} \sigma^2_{\varepsilon 1} & 0 \\ 0 & \sigma^2_v \end{pmatrix}. \end{aligned} \tag{6}$$

In the Monte Carlo experiment, we want data be also generated from models that distinguish between the stochastic nature of the low- and high-frequency components of the time series, and we call them *component-dgp* hereinafter,

$$
\begin{aligned}
d_t^y &= \alpha_2 + \sum_{i=1}^{p} \theta_{2,i} d_{t-i}^y + \sum_{i=0}^{q} \pi_{2,i} d_{t-i}^x + \varepsilon_{2,t}, \\
\eta_t^y &= \sum_{i=1}^{p} \theta_{3,i} \eta_{t-i}^y + \sum_{i=0}^{q} \pi_{3,i} \eta_{t-i}^x + \varepsilon_{3,t}, \\
\tau_t^y &= \tau_{t-1}^y + d_t^y \text{ and } y_t = \tau_t^y + \eta_t^y,\ \tau_0^y \text{ given,}
\end{aligned} \tag{7}
$$

$$
\begin{pmatrix} \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ v_t \end{pmatrix} \sim N \begin{pmatrix} \sigma_{\varepsilon 2}^2 & 0 & 0 \\ 0 & \sigma_{\varepsilon 3}^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{pmatrix},
$$

where d denotes the trend derivative, τ the trend and η the noise. According to the previous section, the relationship process between QNA aggregates and their coincident indicators might well be captured by a component-dgp.

For the traditional-dgp and the component-dgp, we consider 3 alternative specifications: i) a *univariate* specification, when only the past of y affects its current evolution [i.e., $\pi_{j,i} = 0$, $j = 1, 2, 3$, for all i in (6)-(7)]; ii) an *indicator* specification, when only the indicator x affects the evolution of y [i.e., $\theta_{j,i} = 0$, $j = 1, 2, 3$, for all i in (6)-(7)]; iii) a *combined* specification, when both, the past of y and the indicator, affect the evolution of y [$\pi_{j,i}$ and $\theta_{j,i}$ is left free in (6)-(7)]. Hence, we simulate data from six alternative processes.

4.2 Parameterizing the dgp from actual Spanish data

Using data described in Section 3, we estimate traditional and component models under the univariate, indicator and combined specification. Table 1 summarizes the estimation results. We take these estimations to calibrate the alternative data generating processes considered in the Monte Carlo experiment, restricting reasonably the parametric space for these processes.

For component models, we estimate different equations for the trend derivative and the noise. We assume pure autorregresive models of order 3 in all cases.[12] We take the average for each parameter across indicators to parameterize the alternative dgp. Estimations from the univariate specification are used to parameterize the process (5) for x.

Regarding the variance matrix, we take as reference the sample variance of the quarterly real GDP growth rate for Spain during 1985:01-2003:02, which is 0.6%, and $\sigma_{\varepsilon 1}^2$ and σ_v^2 are chosen to match that value when plugged in (6) and (5), respectively; $\sigma_{\varepsilon 2}^2$ and $\sigma_{\varepsilon 3}^2$ are taken to match the estimated variances of d_t^y and η_t^y in (7), respectively.

[INSERT TABLE 1 ABOUT HERE]

For the first difference of the time series as well as for the noise component, the QNA aggregate is much better explained by the indicator than by its own inertia, which gives an idea of the importance that indicators may have on QNA aggregate predictions: the R-squared coefficient under the indicator specification more than doubles that under the univariate specification. Regarding estimations for the trend derivative, their R-squared are similar under both specifications. Notice also that estimations associated to indicators and the R-squared coefficient are similar for the combined and the indicator specifications.

4.3 The Monte Carlo experiment

We simulate 1000 time series of size T=200 for x and y from the six alternative dgp described above.[13] We remove the last 8 data points (2 years for quarterly data) from each simulation. Next, for each dgp and simulation, we alternatively estimate component and traditional models to forecast y for these 8 periods. All forecasting models are assumed to be pure autorregresives, as in the dgp. Using traditional methods, we estimate a univariate, an indicator and a combined version of (6). Simultaneously, we estimate and predict y using a component model (7) under the univariate, indicator and combined specification. Hence, for each simulation and dgp, we generate six alternative prediction paths for y.

The goal of the paper is to compare the performance of traditional and component methods to predict y, given x and a particular specification (univariate, indicator or combined). For that reason, we want forecasts for x (under the indicator and combined specification) be made without error, and we use their 8 removed observations as their predictions.

We consider standard forecasting criteria: i) the root mean squared error ($RMSE$) to measure the average size of forecasting errors and ii) the non-parametric Diebold-Mariano (1995) test that makes pairwise comparisons between forecast errors of alternative models. We compare predictions for the short-run (one and two periods ahead forecasts), the mid-run (three and four periods ahead) and the long-run (five up to eight periods ahead).

5 Results of the forecasting experiment

We compare the forecasting performance of traditional and component models according to the RMSE size and the Diebold-Mariano test.[14] Results are based on the Monte Carlo experiment described above. We consider a random walk (RW) model with a constant term as a baseline reference (a naïve model). Given a particular specification for the forecasting model, we focus on pairwise comparisons between traditional and component methods. Tables 2.a, 2.b and 2.c summarize the main results under a univariate, an indicator and a combined specification, respectively.

Rows are divided into six groups, each group is associated to a particular dgp. Recall that a component-dgp incorporates significant differences in the dgp structure underlying the high- and the low-frequency component of the time series, while a traditional-dgp does not. For the first three groups in the tables, data are simulated from traditional models - from (6) - under a univariate, an indicator and a combined specification, respectively. For the last three groups, data are simulated from component models with a $nvr = 0.1$ - i.e., from (7) - under a univariate, an indicator and a combined specification, respectively.

Columns allude to a particular component forecasting model, with noises and trend derivatives being estimated using a particular nvr level [0.001, 0.01, 0.1, 0.5, 1, 2, 5, 10, 20, 50, 100 and 1000]. The last column refers to the baseline RW model. For a particular dgp, each cell shows the RMSE associated to the corresponding forecasting model as a percentage to the RMSE generated by a traditional method under a common specification. A positive value, said z, means that the RMSE of the traditional model is $z\%$ lower than that of the alternative forecasting method, hence the traditional procedure is doing better according to this criterion. The opposite occurs when z is negative. The Diebold-Mariano test is a way to measure the significance of these differences: a shadowed cell means that the associated forecasting errors are statistically equal at a 10% significance level; otherwise, differences are meaningful and have the associated sign. To simplify the table, we average results for 1 and 2 periods ahead forecasts (the short-run), 3 and 4 periods ahead predictions (the mid-run) and 5 to 8 periods ahead forecasts (the long-run).

[INSERT TABLE 2.a - 2.c ABOUT HERE]

Clearly, the forecasting performance of a component model depends on the nvr used to estimate the high- and the low-frequency components of the time series. Notice that the higher the nvr, the closer is the estimated trend to the original time series and the noise to a flat zero line. Therefore, for a particular specification and dgp, predictions made by traditional and component models turn out to be statistically equal for high enough nvr values. In general, we find that component models with a nvr above 20-50 generate forecast errors that are statistically equal to those obtained using traditional methods. Thus, a first - and obvious - conclusion is that a component model can always replicate results from a traditional model by setting a sufficiently large *nvr* level to estimate their components. The important issue is then to analyze whether component models are able to improve the forecasting performance of traditional methods, and whether this improvement may depend on the dgp or on the model specification. We will come back to that point later. Previously, we comment a minor, but interesting, finding.

Predictions strongly benefit from including inertia and/or indicators into the model.[15] This finding comes out from comparing the forecasting errors obtained from traditional and component models with those coming from using the naïve RW model. This result is robust to the dgp considered, differences being more significant when data are generated from a component-dgp, when an input is included into the dgp and to predict the long-run, all these results were in principle expected. On average, the RMSE gain from using traditional and component models with a *nvr* higher than 0.01, relative to use a RW specification, goes between 30% and 60% in the short-run and between 80% and 200% in the long-run.

Concerning the main aim of the paper, we find that component methods likely beat traditional procedures when the forecasting model only includes an indicator into its specification (the indicator specification) and data are generated from a component-dgp (see Table 2.b for groups (4), (5) and (6)). This result holds for a large range of nvr levels, between 0.01 and 10. For instance, the RMSE gain of using a component model with a nvr of 0.1, relative of considering a traditional model, is 10% in the short-run and 12% in the long-run when data are generated from an *indicator* component-dgp and we *well* specify the forecasting model with an *indicator* specification. However, the RMSE gains are also meaningful when we *badly* specify the model with an indicator specification: it is of 30% in the short-run and 50% in the long-run when data are generated from a combined component-dgp and of 7% in the short-run and 4% in the long-run when data are generated from a univariate component-dgp. On the other hand, component models never beat traditional methods under an indicator specification when data are generated from a traditional-dgp.

The comparison leads to rather different conclusions if we consider a univariate specification (see Table 2.a). Now component models never improve the RMSE obtained from using traditional methods, and this result is independent to the dgp considered (component or traditional). A priory, the generalization of this results is surprising, since we would expect a univariate component model doing better at least when data were generated from a univariate component-dgp.[16] This result reinforces the thesis supported by many authors pointing out the difficulty to defeat Box-Jenkings techniques to forecast aggregate time series under a univariate specification. For instance, the RMSE loss of using a component model with a nvr of 0.1, relative of considering a traditional model, is about 12% in the short-run and 18% in the long-run when data are generated from a *univariate* traditional-dgp and we *well* specify the model with a *univariate* specification. However, the RMSE loss is also significant when we *badly* specify the forecasting model using a univariate specification or data are generated from a combined-dgp. For example, the RMSE loss is about 12% in the short-run and 16% in the long-run when data are generated from an indicator traditional-dgp or about 13% in the short-run and 22% in the long-run when data are generated from a univariate component-dgp.

The comparison between component and traditional methods led up to rather different conclusions depending on whether using an indicator or a univariate specification. Hence, we expect results under a combined specification being in between those obtained under these two extreme models. However, they are closer to those obtained under a univariate specification (compare Table 2.c and Table 2.a). We find that component methods can only beat traditional procedures when data are generated from a *combined* component-dgp and we *well* specify the model with a *combined* specification. Moreover, RMSE gains are notable just to predict the mid- and the long-run and when using nvr levels to estimate components between 2 and 20, values that are well above the benchmark level of 0.1. Otherwise, traditional procedures do better than component methods under a combined specification.

There is a vast literature regarding the interest of combining predictions from different models. The dynamic model considered in the paper is a standard way to combine the univariate and the indicator specification. However, this strategy may leave little capacity to indicators to affect QNA aggregate predictions, since QNA aggregates show, in general, an important inertia component and parameters associated to the indicators and the univariate part are jointly estimated. This fact might be the explanation of the previous result. Considering alternative ways to combine an indicator and a univariate specification is a promising extension of the paper. In this line, our results suggest to combine predictions from a univariate-traditional model with those obtained from an indicator-component model.

6 Applications to Spanish QNA aggregates

We complement previous results with four applications for the Spanish economy. Time series were described in Section 3: i) the Gross Value Added in industry (IND) and the industrial production index (IPI), ii) the private consumption (C) and the real income index (RII), iii) the business investment (IK) and the available capital goods (AKG) and iv) the quarterly real exports (EX) and f.o.b. exports (X). Handling real data, we perform in-sample simulations to conduct the forecasting experiment. For each variable, we ignore the last 40% of the sample and carry out the out-of-sample forecasting exercise, in a similar way as we did with simulated data. We then move one period ahead, adding a new observation, and repeat the exercise until less than eight data are left. We consider alternative *nvr* levels to estimate the trend derivative and the noise for component models: 0.01, 0.1, 0.5, 1, 5, 10, 50, 100 and 1000. Tables 3.a-3.c display similar information to that provided in Tables 2.a-2.c.[17] Results are consistent with conclusions reached in the previous simulation experiment.

[INSERT TABLE 4.a-4.c AROUND HERE]

First, traditional and component models with a nvr above 0.1 show important RMSE gains with respect to using a RW model. These differences are higher than 200% in the long-run under an indicator or a combined specification, while the RMSE improvement is about 30% in the short-run and about 50% in the long-run under a pure univariate specification.

Second, under a univariate specification (see Table 3.a), traditional models generally beat component models for any forecasting horizon. This result is quite robust to the four examples considered, with the weak exception of the IK-AKG case in the short-run, in which a component model with a *nvr* of 0.5 gets a RMSE that is 2% lower than that obtained using a traditional model. On the other hand, component models with a *nvr* between 0.1-10 show, in general, important RMSE gains with respect to using traditional models under an indicator specification (see Table 3.b). The exception is the IND-IPI case, but this result is also consistent with our previous findings, since recall from Section 3 that the relationships between IND and IPI were positive, but similar, between their respective low- and high-frequency components. For the other three cases, the relationship of the indicator and the

QNA aggregate between their similar components were highly different. For these three cases, the *nvr* that minimizes the RMSE average for the eight horizons is between 0.5-1, and the RMSE improvement is between 4% and 8% in the short-run and between 6% and 30% in the long-run.

Finally, under a combined specification (see Table 3.c), we find different results depending on the example considered. However, we can conclude that the only case in which component models clearly beat traditional procedures is in the C-RII case. For the C-RII case, RMSE gains are specially significant in the mid- and long-run and when the used nvr to estimate components is between 0.5 and 10. Both results are consistent with findings in the previous section. Recall that the C-RII case showed the highest difference in the relationship between similar components for the aggregate and the indicator (almost null for the noises and highly positive for the trend derivatives), and this fact is surely playing an important role to get this result.

7 Conclusions

Econometric models applied to observed data, specified and estimated using traditional Box-Jenkins techniques, have been widely used to forecast Quarterly National Account aggregates. We have assessed the ability to which a forecasting procedure based on component models is able to improve the forecasting accuracy of traditional methods. The main difference between traditional and component procedures is that the latter distinguish between the stochastic processes underlying the low-frequency (the trend) and the high-frequency (the noise) components of time series, while traditional methods do not. We have followed Young (1984) and García-Ferrer et al. (1997) to estimate the trend and the noise, a procedure that is mainly parameterized by the noise variance ratio (nvr). A Monte Carlo experiment has been conducted to characterize the out-of-sample forecasting accuracy of component models with respect to traditional procedures. Main findings of the paper were illustrated with several applications for the Spanish economy.

As suggested by even an informal examination of Spanish real data, the relationship between QNA aggregates and their coincident indicators are often significantly different for diverse frequencies (the high and the low). Under these circumstances, the Monte Carlo experiment reveals that component models improve the forecasting accuracy of traditional methods to predict QNA aggregates when their coincident indicators are playing an important role in such predictions. Using a univariate specification, however, traditional procedures likely beat component methods. This result is quite robust to the data generating process considered, which reinforces the thesis that many authors support about the dominance of Box-Jenkings techniques to specify and forecast time series using univariate specifications. Finally, using a standard dynamic model to combine the univariate and the indicator specification, we find that, in general, little capacity is left to the indicators to affect QNA aggregate predictions. In this line, further efforts must be addressed to design alternative combined specifications, that could give more importance to indicators and being time adapted to the economic cycle. Our findings suggest that a convenient strategy is to combine predictions made with a traditional-univariate model and with an indicator-component model.

The application of component models to characterize the relationship between actual time series is clearly another promising extension of the paper. For instance, a relevant application regards the analysis between money and real GDP. Working with original data, most empirical studies fail to find significant evidence in support of any relationship between these two variables. However, this is a clear example in which the relationships between the high- and the low-frequency components of both variables might be substantially different. Dealing with component models to characterize those relationship could throw light on the importance of money as a relevant element in the monetary transmission process, as argued by Meltzer (1995, 1999).

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8 Appendix of figures

Figure 1: Real US GDP quarterly growth rate, the trend-derivative and the trend-adjusted business cycle

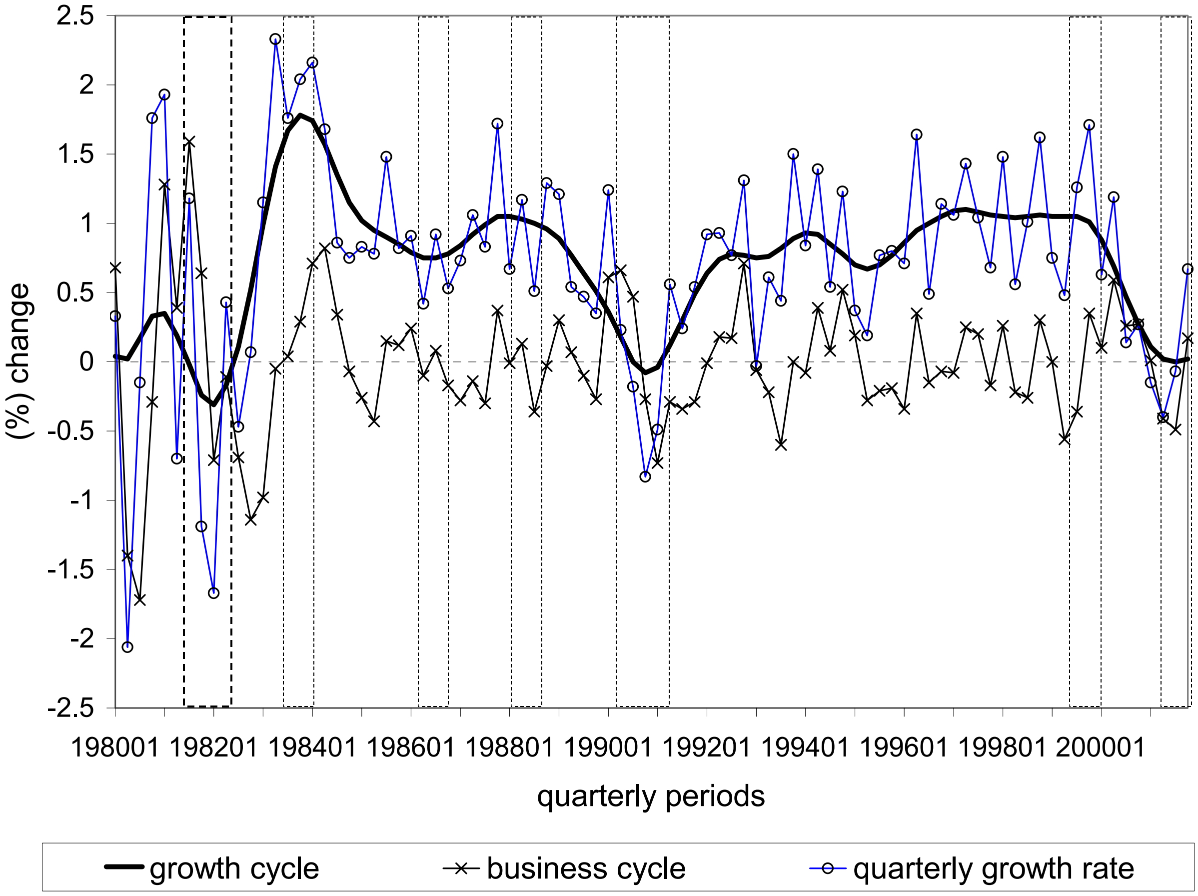


Figure 2.a: Spanish QNA aggregates and coincident indicators (quarterly growth rates)

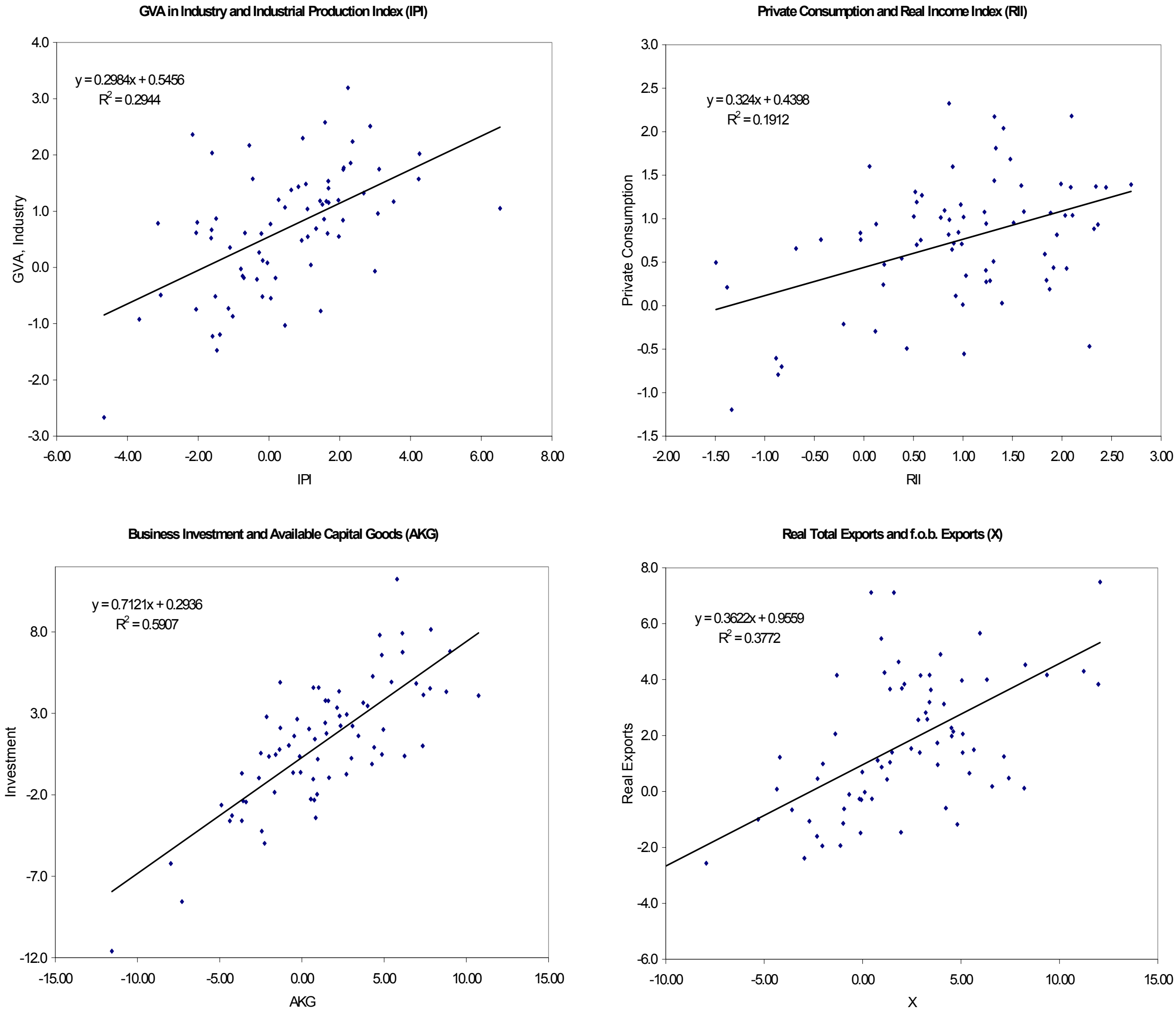


Figure 2.b: Spanish QNA aggregates and coincident indicators (trend derivatives)

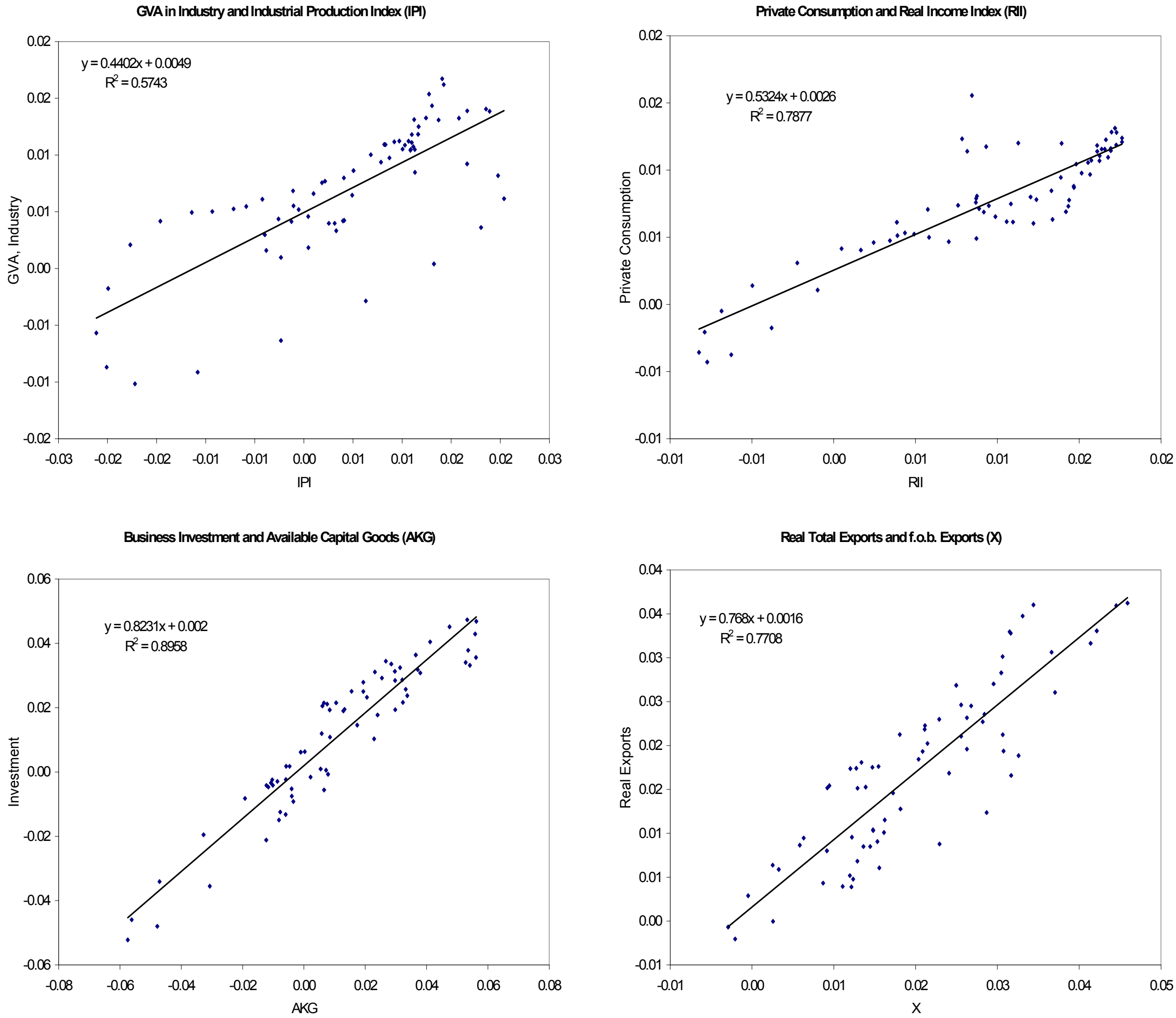
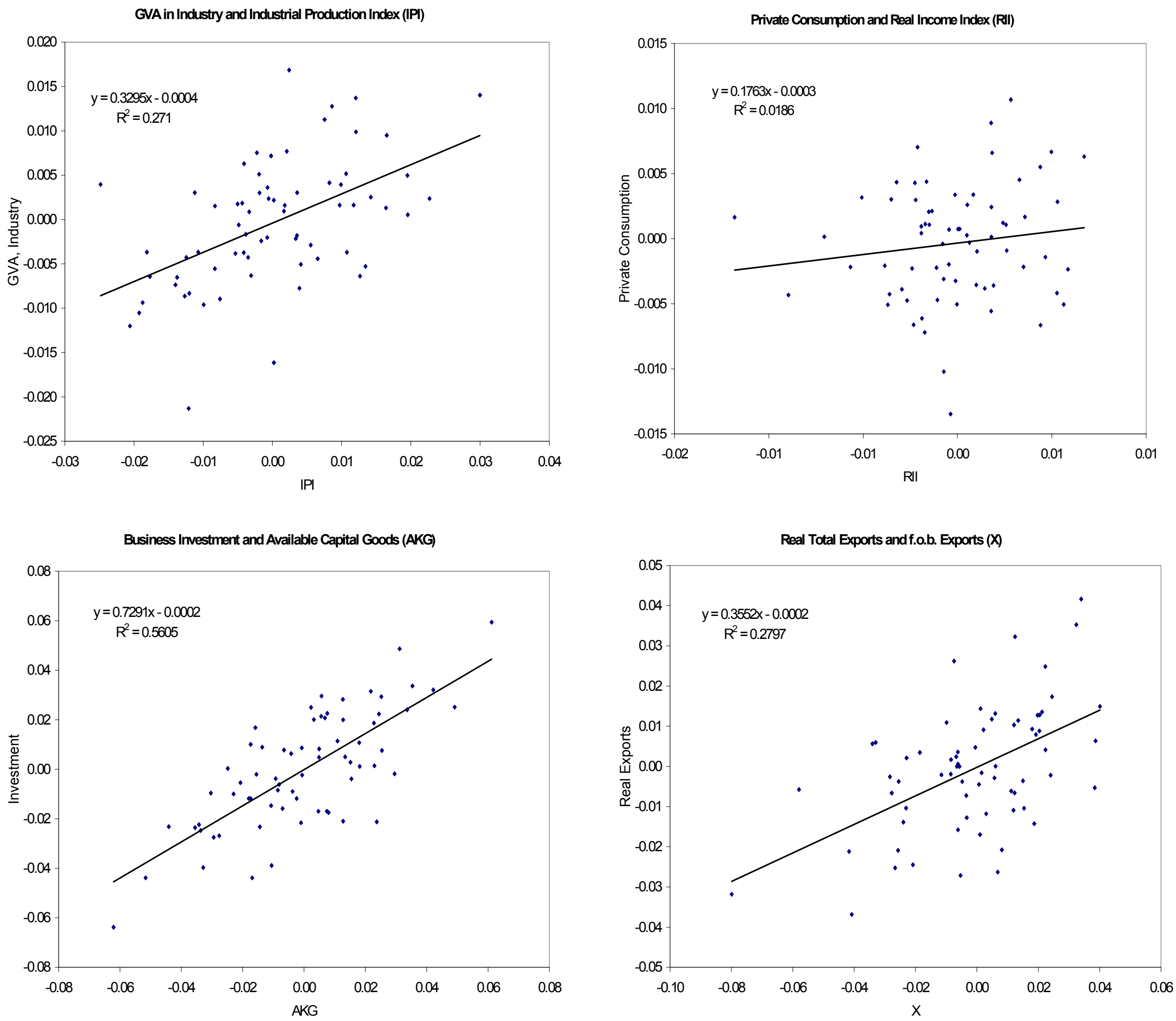


Figure 2.c: Spanish QNA aggregates and coincident indicators (noise components)



9 Appendix of tables

Table 1: Estimation of models for QNA Aggregates and Coincident Indicators. Spain 1985:01-2003:02
(Original variables are seasonally adjusted, real and taken logs)

	First differences (original data)					*Trend-derivative (low-frequency components)*					*Noise (high-frequency components)*				
	IND-IPI	*C-RII*	*IK-AKG*	*EX-X*	*mean*	*IND-IPI*	*C-RII*	*IK-AKG*	*EX-X*	*mean*	*IND-IPI*	*C-RII*	*IK-AKG*	*EX-X*	*mean*
Univariate															
α	0.35	0.36	0.32	1.64	0.66	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
$\theta_{j,1}$	0.27	0.22	0.14	0.07	0.18	2.47	2.46	2.47	2.33	2.43	0.35	0.21	0.24	0.12	0.23
$\theta_{j,2}$	0.08	0.10	0.09	-0.20	0.02	-2.21	-2.15	-2.20	-1.98	-2.14	-0.17	-0.23	-0.16	-0.38	-0.23
$\theta_{j,3}$	0.06	0.18	0.17	0.28	0.17	0.72	0.68	0.70	0.62	0.68	-0.21	-0.18	-0.13	0.12	-0.10
R^2	0.11	0.13	0.09	0.11	0.11	0.99	0.99	0.99	0.99	0.99	0.21	0.14	0.10	0.15	0.15
Relationship															
α	0.43	0.24	0.19	0.71	0.39	0.00	0.00	0.00	0.00	0.00	--	--	--	--	--
$\pi_{j,1}$	0.20	0.31	0.68	0.36	0.38	0.22	0.26	0.97	1.19	0.66	0.27	0.26	0.68	0.36	0.39
$\pi_{j,2}$	0.16	0.13	0.21	0.15	0.16	-0.35	0.84	-0.62	-1.26	-0.35	0.17	-0.03	0.19	0.09	0.11
$\pi_{j,3}$	0.10	0.06	-0.02	0.03	0.04	0.62	-0.58	0.60	1.02	0.41	0.06	-0.07	-0.04	0.00	-0.01
R^2	0.36	0.32	0.60	0.25	0.38	0.75	0.91	0.93	0.84	0.86	0.37	0.05	0.59	0.26	0.32
Combined											--	--	--	--	--
α	0.40	0.34	0.26	0.68	0.42	0.00	0.00	0.00	0.00	0.00					
$\theta_{j,1}$	-0.03	-0.14	-0.29	-0.22	-0.17	2.15	2.13	1.97	1.81	2.01	0.03	0.15	-0.08	-0.12	-0.01
$\theta_{j,2}$	0.01	-0.19	-0.11	-0.31	-0.15	-1.73	-1.78	-1.35	-1.28	-1.54	-0.20	-0.23	-0.19	-0.44	-0.27
$\theta_{j,3}$	0.06	-0.13	0.08	0.19	0.05	0.52	0.54	0.30	0.39	0.44	-0.20	-0.21	-0.02	0.05	-0.09
$\pi_{j,1}$	0.20	0.36	0.67	0.38	0.40	0.23	0.23	0.61	0.41	0.37	0.22	0.24	0.67	0.36	0.37
$\pi_{j,2}$	0.17	0.23	0.40	0.30	0.27	-0.36	-0.23	-0.99	-0.48	-0.52	0.16	0.03	0.24	0.19	0.16
$\pi_{j,3}$	0.10	0.15	0.11	0.15	0.13	0.17	0.06	0.46	0.17	0.22	0.14	0.04	0.12	0.17	0.12
R^2	0.36	0.36	0.63	0.40	0.44	1.00	1.00	1.00	0.99	1.00	0.46	0.17	0.61	0.41	0.41

Quarterly National Accounts. C: private consumption; IK: business Investment; IND: GVA in industry; EXP: real exports of goods and services
Indicators. IPI: industrial production index; RII: real income index; AKG: available capital goods; X: f.o.b. exports.

Table 2.a. RMSE comparisson for alternative forecasting models using a *UNIVARIATE specification*
RMSE values are expressed as a percentage of the one obtained using a traditional *univariate* forecasting model
Monte Carlo experiment (1000 simulations)

		Alternative forecasting models												
		nvr used to estimate the trend derivative and the noise in the univariate component model												***RW***
Alternative dgp	***forecast horizon***	***0.001***	***0.01***	***0.1***	***0.5***	***1***	***2***	***5***	***10***	***20***	***50***	***100***	***1000***	
Traditional dgp														
(1) univariate	*short-run*	14.55	13.43	11.79	4.43	3.52	3.88	3.74	2.44	1.11	0.23	0.04	-0.01	33.76
	mid-run	28.94	24.74	18.34	7.68	6.00	4.94	3.12	1.73	0.82	0.26	0.11	0.01	65.59
	long-run	32.51	26.64	17.67	4.48	2.95	2.23	1.35	0.67	0.24	0.03	0.00	0.00	87.94
(2) indicator	*short-run*	8.94	9.39	11.94	7.20	6.39	6.14	4.90	3.03	1.38	0.32	0.07	0.00	45.66
	mid-run	18.03	18.67	19.97	11.95	9.37	6.89	3.79	2.01	0.94	0.31	0.13	0.01	93.84
	long-run	19.74	20.30	16.42	6.07	4.37	3.17	1.87	0.98	0.38	0.05	-0.01	0.00	113.40
(3) combined	*short-run*	8.84	9.32	11.62	7.61	7.24	7.12	5.49	3.28	1.46	0.33	0.08	0.00	51.34
	mid-run	17.41	18.29	19.49	12.35	10.00	7.37	3.94	2.05	0.95	0.31	0.13	0.01	103.41
	long-run	22.15	23.13	17.67	6.64	4.72	2.99	1.26	0.48	0.11	-0.02	-0.03	0.00	143.21
Component dgp														
(4) univariate	*short-run*	5.49	4.57	13.43	22.09	21.99	18.47	10.97	5.94	2.75	0.92	0.48	0.27	111.17
	mid-run	7.33	8.78	20.80	20.59	14.72	8.38	3.32	1.72	0.99	0.57	0.44	0.33	223.74
	long-run	12.66	16.43	21.89	15.34	9.13	4.59	2.03	1.33	0.99	0.80	0.74	0.70	334.88
(5) indicator	*short-run*	10.42	10.21	4.21	7.91	10.64	11.24	7.83	4.20	1.63	0.24	-0.01	-0.03	83.29
	mid-run	18.40	16.27	9.04	11.03	10.72	8.36	4.30	2.07	0.81	0.13	-0.04	-0.14	147.83
	long-run	22.24	19.66	7.44	5.72	4.94	3.40	1.16	0.14	-0.25	-0.32	-0.29	-0.22	211.01
(6) combined	*short-run*	51.67	84.29	118.16	108.00	76.35	41.16	11.02	2.87	0.55	-0.03	-0.05	0.05	26.54
	mid-run	70.73	98.95	116.87	83.12	52.57	23.85	4.39	0.61	-0.13	-0.16	-0.07	0.09	29.84
	long-run	73.31	91.09	88.98	58.34	32.82	11.19	0.99	0.06	0.07	0.13	0.15	0.18	23.47

Note: The short-run row displays average results for 1 and 2 periods ahead, the mid-run is the average of results for 3 and 4 periods ahead and the long-run for 5 to 8 periods ahead.
According to the Diebold-Mariano test, shadowed cells point out that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model with the same specification.
For the considered specification, bold letters mean that the RMSE of the component forecasting model is statistically lower than the RMSE of the associated traditional model.

Table 2.b. RMSE comparisson for alternative forecasting models using a *INDICATOR specification*
RMSE values are expressed as a percentage of the one obtained using a traditional *indicator* forecasting model
Monte Carlo experiment (1000 simulations)

		Alternative forecasting models												
		nvr used to estimate trend derivative and noise for the univariate component model												***RW***
Alternative dgp	***forecast horizon***	***0.001***	***0.01***	***0.1***	***0.5***	***1***	***2***	***5***	***10***	***20***	***50***	***100***	***1000***	
Traditional dgp														
(1) univariate	*short-run*	85.46	42.86	14.74	6.10	3.85	2.29	1.02	0.50	0.23	0.08	0.03	0.00	27.61
	mid-run	41.38	22.29	8.27	3.81	2.53	1.58	0.76	0.40	0.20	0.08	0.04	0.00	58.68
	long-run	23.40	12.74	5.12	2.67	1.82	1.17	0.61	0.34	0.18	0.08	0.04	0.00	81.94
(2) indicator	*short-run*	58.25	28.59	11.66	5.06	3.04	1.59	0.49	0.11	-0.04	-0.06	-0.04	-0.01	59.01
	mid-run	27.49	11.89	5.44	2.66	1.69	0.93	0.33	0.10	0.00	-0.02	-0.02	0.00	128.68
	long-run	27.24	13.20	5.68	2.79	1.77	1.00	0.40	0.16	0.04	0.00	-0.01	0.00	159.41
(3) combined	*short-run*	52.20	24.30	9.04	3.27	1.59	0.50	-0.18	-0.32	-0.29	-0.17	-0.10	-0.01	72.20
	mid-run	26.24	9.86	4.06	1.44	0.62	0.06	-0.25	-0.29	-0.23	-0.13	-0.08	-0.01	161.28
	long-run	18.06	7.48	3.17	1.47	0.83	0.37	0.06	-0.03	-0.06	-0.05	-0.03	0.00	234.69
Component dgp														
(4) univariate	*short-run*	-0.54	**-7.24**	**-6.62**	**-4.00**	**-2.89**	**-1.92**	-1.00	-0.59	-0.32	-0.11	0.00	0.11	85.51
	mid-run	**-2.75**	**-8.62**	**-8.19**	**-5.54**	**-4.36**	**-3.27**	**-2.01**	-1.23	-0.65	-0.16	0.04	0.26	195.32
	long-run	2.29	**-3.02**	**-3.82**	**-2.94**	**-2.47**	**-1.92**	-1.13	-0.59	-0.16	0.24	0.42	0.61	315.66
(5) indicator	*short-run*	20.27	-0.94	**-9.96**	**-10.09**	**-8.86**	**-7.26**	**-5.00**	**-3.44**	**-2.16**	-1.01	-0.50	0.05	123.72
	mid-run	18.03	**-1.81**	**-9.71**	**-10.37**	**-9.38**	**-7.91**	**-5.55**	**-3.77**	**-2.29**	-0.96	-0.39	0.22	313.60
	long-run	17.04	**-4.64**	**-12.20**	**-12.33**	**-10.98**	**-9.04**	**-6.09**	**-4.00**	**-2.30**	-0.77	-0.09	0.63	615.36
(6) combined	*short-run*	110.17	15.02	**-29.69**	**-17.96**	**-12.31**	**-8.06**	**-4.36**	**-2.62**	**-1.51**	-0.69	-0.38	-0.07	-61.11
	mid-run	-0.10	**-41.30**	**-42.56**	**-22.90**	**-16.01**	**-10.70**	**-5.86**	**-3.50**	**-1.99**	-0.88	-0.45	-0.04	-37.36
	long-run	**-34.04**	**-57.08**	**-45.17**	**-25.12**	**-17.79**	**-12.03**	**-6.70**	**-4.06**	**-2.34**	-1.05	-0.56	-0.07	-6.95

Note: The short-run row displays average results for 1 and 2 periods ahead, the mid-run is the average of results for 3 and 4 periods ahead and the long-run for 5 to 8 periods ahead.
According to the Diebold-Mariano test, shadowed cells point out that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model with the same specification.
For the considered specification, bold letters mean that the RMSE of the component forecasting model is statistically lower than the RMSE of the associated traditional model.

Table 2.c. RMSE comparisson for alternative forecasting models using a *COMBINED specification*
RMSE values are expressed as a percentage of the one obtained using a traditional *combined* forecasting model
Monte Carlo experiment (1000 simulations)

Alternative dgp	forecast horizon	*Alternative forecasting models* — nvr used to estimate the trend derivative and the noise for the combined component model: 0.001	0.01	0.1	0.5	1	2	5	10	20	50	100	1000	RW
Traditional dgp														
(1) univariate	*short-run*	15.49	15.22	11.30	3.90	2.93	3.34	3.34	2.15	0.93	0.14	-0.01	-0.01	32.92
	mid-run	30.52	28.30	18.42	7.75	6.22	5.25	3.42	1.93	0.92	0.30	0.13	0.01	65.51
	long-run	33.77	29.55	17.53	4.86	3.40	2.60	1.54	0.75	0.26	0.03	-0.01	0.00	88.37
(2) indicator	*short-run*	18.68	21.45	21.00	13.12	10.48	8.51	5.66	3.20	1.36	0.28	0.05	-0.01	57.88
	mid-run	35.04	37.59	32.30	18.20	13.37	9.23	4.78	2.51	1.20	0.42	0.19	0.02	128.21
	long-run	36.48	37.58	26.11	10.06	6.80	4.56	2.40	1.19	0.44	0.06	0.00	0.00	158.90
(3) combined	*short-run*	24.76	27.77	26.45	17.15	13.80	10.88	6.67	3.58	1.49	0.31	0.07	0.00	72.30
	mid-run	44.73	47.22	39.81	22.35	16.07	10.56	5.03	2.55	1.22	0.44	0.20	0.02	163.51
	long-run	52.25	53.90	34.89	12.48	7.83	4.48	1.73	0.67	0.19	0.01	-0.01	0.00	234.89
Component dgp														
(4) univariate	*short-run*	5.44	4.42	12.60	20.94	20.95	17.67	10.52	5.67	2.60	0.89	0.51	0.36	109.01
	mid-run	7.31	8.76	20.57	21.18	15.73	9.42	3.95	2.08	1.21	0.72	0.57	0.45	222.36
	long-run	12.58	16.94	22.59	16.65	10.26	5.32	2.26	1.35	0.94	0.74	0.69	0.66	334.07
(5) indicator	*short-run*	83.67	60.22	39.75	27.99	23.12	17.40	9.23	4.24	1.25	-0.13	-0.26	-0.05	171.33
	mid-run	97.03	73.82	36.36	11.66	5.45	2.21	0.82	0.43	0.17	0.08	0.12	0.24	375.92
	long-run	141.07	93.78	19.53	2.67	1.24	-0.03	-1.59	**-1.94**	-1.55	-0.68	-0.17	0.44	692.12
(6) combined	*short-run*	144.75	129.92	142.69	122.55	84.18	43.99	10.44	1.62	-0.52	-0.66	-0.44	-0.07	53.38
	mid-run	195.47	179.89	169.75	99.02	55.96	21.85	0.69	**-2.42**	**-2.14**	-1.18	-0.66	-0.06	93.03
	long-run	217.44	208.43	141.71	50.57	19.78	-0.46	**-7.82**	**-6.00**	**-3.65**	**-1.65**	-0.82	0.05	128.83

Note: The short-run row displays average results for 1 and 2 periods ahead, the mid-run is the average of results for 3 and 4 periods ahead and the long-run for 5 to 8 periods ahead.
According to the Diebold-Mariano test, shadowed cells point out that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model with the same specification.
For the considered specification, bold letters mean that the RMSE of the component forecasting model is statistically lower than the RMSE of the associated traditional model.

Table 3.a. RMSE for alternative forecasting models. *UNIVARIATE specification*
The RMSE is expressed as a percentage of the RMSE obtained using a univariate traditional model
Applications for the Spanish Economy

		Alternative forecasting models									
		Component models (alternative nvr levels)									***RW***
Cases	***forecast horizon***	***0.01***	***0.1***	***0.5***	***1***	***5***	***10***	***50***	***100***	***1000***	
IND-IPI	*short-run*	23.40	14.69	11.25	9.78	7.62	4.77	0.41	0.06	-0.01	35.03
	mid-run	31.55	27.92	22.68	18.48	9.27	5.05	0.56	0.19	0.01	48.55
	long-run	48.91	69.27	63.57	47.73	11.36	4.80	0.58	0.24	0.02	73.25
C-RII	*short-run*	27.69	7.89	3.98	6.38	11.87	9.26	2.45	1.21	0.12	37.41
	mid-run	40.00	21.49	20.08	21.25	20.40	14.87	4.13	2.12	0.21	58.59
	long-run	47.57	83.17	79.90	70.94	46.42	31.55	8.41	4.31	0.44	81.03
IK-AKG	*short-run*	10.81	2.81	**-1.64**	0.38	9.83	7.91	1.27	0.48	0.03	34.23
	mid-run	18.27	10.40	4.00	3.71	8.23	5.45	0.50	0.12	0.00	37.82
	long-run	2.33	12.87	8.84	5.20	-0.06	-1.88	-1.28	-0.74	-0.08	29.47
EX-X	*short-run*	33.89	26.43	10.29	6.20	7.36	5.10	1.07	0.50	0.05	28.42
	mid-run	37.71	37.72	21.11	17.13	14.10	8.62	1.70	0.82	0.08	42.99
	long-run	50.26	69.07	47.71	42.88	31.70	18.36	3.68	1.82	0.18	80.52

Keys: C: private consumption;IK: business Investment;IND: GVA in industry;EXP: real export of goods and services;
IPI: industrial production index;RII: real income index;AKG: available capital goods;X: f.o.b. exports.
Note: Short-run show the RMSE average for 1 and 2 periods ahead, the mid-run for 3 and 4 perdiosa ahead and the long-run for 5 to 8 periods
According to the Diebold-Mariano test, shadowed cells shows that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model under the same specification.
Bold letters mean that the RMSE of the component model is statistically lower than the RMSE of the associated traditional model.

Table 3.b. RMSE for alternative forecasting models. *INDICATOR specification*
The RMSE is expressed as a percentage of the RMSE obtained using an indicator traditional model
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		Alternative forecasting models									
		Component models (alternative nvr levels)									***RW***
Cases	***forecast horizon***	***0.01***	***0.1***	***0.5***	***1***	***5***	***10***	***50***	***100***	***1000***	
IND-IPI	*short-run*	34.73	26.05	7.98	3.79	-0.26	-0.54	-0.26	-0.26	0.03	64.84
	mid-run	16.01	8.44	3.70	2.59	0.86	0.32	-0.01	-0.01	-0.01	99.56
	long-run	0.15	**-6.62**	3.64	4.85	3.14	1.92	0.27	0.15	-0.03	186.28
C-RII	*short-run*	30.95	1.26	**-4.37**	**-6.24**	**-7.69**	**-6.08**	**-2.15**	-1.19	-0.13	52.87
	mid-run	1.36	**-8.45**	**-12.89**	**-14.47**	**-11.22**	**-8.06**	**-2.56**	-1.40	-0.15	79.43
	long-run	**-42.02**	**-26.80**	**-29.31**	**-32.41**	**-19.81**	**-12.87**	**-3.57**	**-1.90**	-0.20	123.74
IK-AKG	*short-run*	57.91	3.70	**-6.88**	**-6.92**	**-5.00**	**-3.94**	**-1.53**	-0.87	-0.10	109.18
	mid-run	46.92	**-2.28**	**-8.85**	**-8.31**	**-5.64**	**-4.23**	**-1.52**	-0.85	-0.10	170.06
	long-run	40.80	**-2.12**	**-5.57**	**-5.64**	**-4.71**	**-3.58**	-1.24	-0.69	-0.08	368.68
EX-X	*short-run*	53.37	17.95	**-3.60**	**-7.26**	**-6.25**	**-4.56**	-1.61	-0.91	-0.10	102.78
	mid-run	35.28	4.90	**-10.18**	**-12.19**	**-8.58**	**-6.04**	**-1.96**	-1.08	-0.12	177.24
	long-run	8.60	**-14.85**	**-19.40**	**-19.17**	**-12.81**	**-9.11**	**-2.91**	-1.59	-0.17	386.77

Keys: C: private consumption;IK: business Investment;IND: GVA in industry;EXP: real export of goods and services;
IPI: industrial production index;RII: real income index;AKG: available capital goods;X: f.o.b. exports.
Note: Short-run show the RMSE average for 1 and 2 periods ahead, the mid-run for 3 and 4 perdiosa ahead and the long-run for 5 to 8 periods
According to the Diebold-Mariano test, shadowed cells shows that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model under the same specification.
Bold letters mean that the RMSE of the component model is statistically lower than the RMSE of the associated traditional model.

Table 3.c. RMSE for alternative forecasting models. *COMBINED specification*
The RMSE is expressed as a percentage of the RMSE obtained using a combined traditional model
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		Alternative forecasting models									
		Component models (alternative nvr levels)									***RW***
Cases	***forecast horizon***	***0.01***	***0.1***	***0.5***	***1***	***5***	***10***	***50***	***100***	***1000***	
IND-IPI	*short-run*	32.65	33.78	14.08	8.24	4.60	2.86	0.07	-0.09	-0.02	55.13
	mid-run	36.52	26.04	1.78	-0.48	6.16	4.83	0.92	0.39	0.03	83.33
	long-run	37.21	18.52	**-21.47**	**-9.42**	8.34	6.15	1.26	0.60	0.06	161.95
C-RII	*short-run*	61.84	17.77	0.57	-1.49	-0.17	-0.45	-0.46	-0.28	-0.03	56.50
	mid-run	66.45	19.74	-0.44	**-2.36**	**-3.17**	**-2.59**	-0.66	-0.33	-0.03	102.43
	long-run	21.72	3.74	**-14.26**	**-17.78**	**-15.88**	**-10.75**	**-2.03**	-0.91	-0.08	207.34
IK-AKG	*short-run*	129.16	65.86	20.95	12.14	4.20	2.26	0.12	-0.02	-0.01	112.88
	mid-run	110.10	61.50	14.64	7.02	2.15	1.10	0.02	-0.03	-0.01	169.63
	long-run	145.04	121.08	20.90	7.38	0.96	0.39	0.07	0.04	0.00	354.96
EX-X	*short-run*	123.04	89.45	31.56	16.30	0.78	**-1.79**	**-1.62**	-0.99	-0.12	104.89
	mid-run	136.95	91.25	26.21	12.66	-0.34	**-2.28**	-1.48	-0.87	-0.10	189.55
	long-run	165.09	70.06	4.97	-1.25	**-4.69**	**-3.73**	-1.08	-0.57	-0.06	412.48

Keys: C: private consumption;IK: business Investment;IND: GVA in industry;EXP: real export of goods and services;
IPI: industrial production index;RII: real income index;AKG: available capital goods;X: f.o.b. exports.
Note: Short-run show the RMSE average for 1 and 2 periods ahead, the mid-run for 3 and 4 perdiosa ahead and the long-run for 5 to 8 periods
According to the Diebold-Mariano test, shadowed cells shows that forecast errors of the associated forecasting model are statistically equal at a 10% level of significance to those errors obtained using a traditional forecasting model under the same specification.
Bold letters mean that the RMSE of the component model is statistically lower than the RMSE of the associated traditional model.

Notes

[1]See Loungani (2001), which evaluates the performance of Consensus Forecasts of real GDP growth for a large number of industrialized and developing countries for the time period 1989 to 1998.

[2]See Baffigia et al. (2004) for a recent paper to forecast the real GDP in the Euro area.

[3]The seminar paper by Bates and Granger (1969) points out the interest of combining individual forecasts. More recent papers regarding this issue is Hibon and Evgeniou (2004).

[4]However, one-period ahead predictions are not without interest. For instance, they are important to validate published data, and the one-period ahead forecast error record can be used to detect turning points and modify longer term predictions [García-Ferrer et al. (1994)].

[5]See Klein and Moore (1985), Moore and Zarnowitz (1986) and Zarnowitz and Ozyildirim (2002), among many others.

[6]Friedman and Schwartz (1963) and Mintz (1969, 1972).

[7]Alternative detrending techniques are proposed in Hodrick and Prescott (1997), Baxter and King (1999) (the Band-Pass filter), Boschan and Ebanks(1978) (the phase average trend), Beveridge and Nelson(1981) (the stochastic Beveridge-Nelson trend), Rotemberg (1999) (an heuristic trend method), among many others.

[8]The noise and the trend derivative have been estimated under a specific parameterization that will be described below.

[9]See, among others, Young (1984, 1994), García-Ferrer et al. (1994) and Harvey (1989, 2000). Alternative methods to extract unobserved trends are in Rottemberg (1999) and Watson (1986).

[10]Harvey (1989) proposes to set $\sigma_\varepsilon^2 = 0$ and impose a very small level of σ_v^2 in (1)-(4), and

estimate σ_η^2 in a second step.

[11]Previously, monthly indicators were quarterly aggregated. To estimate components, we set a $nvr = 0.1$ in (2)-(4) in all cases.

[12]Quarterly seasonally adjusted time series do not usually display a higher autorregresive structure. At any case, we check that residuals are not statistically different from a white noise process.

[13]Increasing the number of simulations does not significantly change the results. In general, using an IRW model to estimate frequency components, there exist anomalies in the estimation of the trend derivative and the noise at the beginning of the sample. Hence, we truncate simulated data coming from a component dgp at the beginning of the sample.

[14]For each specification, we have perturbed the parameterization around the benchmark, and results do not differ significantly.

[15]Notice that this result is in general not true for financial assets time series.

[16]We have taken alternative QNA aggregates for the Spanish and the US economy, and this result is quite robust to the aggregate considered.

[17]Rows refer to each example instead to each dgp, while columns allude to each forecasting model. Each cell shows, for a particular case and model specification (univariate, indicator and combined), the RMSE of a component model or RW model (the last column) as a percentage to the RMSE of a traditional model. According to the Diebold-Mariano test, a shadowed cell means that both models generate forecasting errors, for a given horizon, that are statistically equal at a 10% level of significance. Results are averaged for 1 and 2 periods ahead (the short-run), for 3 and 4 periods ahead (the mid-run) and from 5 to 8 periods ahead (the long-run).