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Survey Data as Coincident or Leading Indicators*

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Abstract

In this paper we propose a monthly measure for the euro area Gross Domestic Product (GDP) based on a small scale factor model for mixed frequency data, featuring two factors: the first is driven by hard data, whereas the second captures the contribution of survey variables as coincident indicators. Within this framework we evaluate both the in-sample contribution of the second survey-based factor, and the short term forecasting performance of the model in a pseudo-real time experiment. We find that the survey-based factor plays a significant role for two components of GDP: Industrial Value Added and Exports. Moreover, the two factor model outperforms in terms of out of sample forecasting accuracy the traditional autoregressive distributed lags (ADL) specifications and the single factor model, with few exceptions for Exports and in growth rates.

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1 Introduction

Survey data represent a very timely piece of economic information which originates from the quantification of qualitative survey questions, asking firms and consumers opinions on the state of the economy. For the Euro area, official surveys are compiled by the European Commission in the form of balances of opinions. Their role for the construction of coincident indicators is rather controversial. In the U.S., despite their availability (the Conference Board produces the Consumer Confidence Index, the University of Michigan produces the authoritative Consumer Sentiment index, the Institute for Supply Management releases monthly business activity indices for the manufacturing and service sectors), they are not listed among the set of series that enter the Conference Board and the Stock and Watson (1989) indices of coincident indicators; moreover, they are not monitored by the NBER experts when dating the US business cycle. On the contrary, the survey series are featured in the Eurocoin indicator for the euro area produced by the CEPR and in Euro-Sting, the short term indicator of the Euro area growth produced recently by the Spanish central bank.

In a recent paper, Frale, Marcellino, Proietti and Mazzi (2008, FMMP henceforth) concluded that the survey variables did not contribute significantly to the factor based indicator of the euro area economic activity, Euromind. However, FMMP adopted a single factor model, following Stock and Watson (1989), did not conduct a real time experiment, and did not consider the accrual of new information in time.

In this paper we report a modification of the FMMP model which deals with the introduction of a second common factor, capturing the contribution of the survey variables as coincident indicators. We also propose a specification of the first factor that embodies a smoothness prior. The multivariate extended model, which allows the use of mixed frequency (monthly/quarterly) data, is cast into the state-space form and inference is carried out using the Kalman filter based methods illustrated in FMMP.

Besides evaluating the in-sample contribution of the additional common factor, we also compare the short term forecasting performance of the model, with respect to the original FMMP formulation and a more standard autoregressive distributed lag (ADL) model. We focus on value added by sector and on the components of GDP by expenditure type; the results for GDP can be obtained by aggregating the forecasts with some weights reflecting their precision (as already done in FMMP). Notice that the forecasts are produced monthly while the target variable is quarterly. Therefore, it is of interest to evaluate both the monthly evolution of the forecast for the same quarter, to assess the usefulness of the timely information, and the performance more than one-quarter ahead, to evaluate for how long the coincident indicators maintain their predictive content. The forecast evaluation is conducted in a pseudo-real time context, and it is based both on standard measures such as the mean squared forecast error (MSE) and mean absolute forecast error (MAE), and on formal statistical tests to assess whether the differences in loss functions across alternative methods are statistically significant.

Finally, using a real-time database, we attempt to isolate the news content of each block of series used in the estimation of GDP, namely survey data and hard data.

Looking ahead to the results, we anticipate that the second factor loads significantly on the survey variables for the Industry sector and for Exports. This might be two sides of the same coin: Exports are mainly in goods and hence mainly produced by the Industry sector. In addition, it is encouraging that the results are significant just for the sector on which are based the majority of short term conjunctural indicators. However, the resulting monthly measure of euro area GDP is very similar to that by FMMP. Instead, the forecasting performance of the survey based factor model improves substantially over both the single factor and ADL models, especially for Industry and in the level specification. Moreover, the analysis of revisions in the data indicates that the contribution of survey data is not negligible, the more so the longer the horizon and the smaller the information set, and the impact is higher in the first month of the quarter, due to lack of hard data information and in line with the findings of Giannone *et al.* (2005).

The paper is structured as follows. In Section 2 we present the dynamic survey-based factor model cast in State Space form, for which in Section 3 we summarize the main estimation results as applied to the disaggregation of components of quarterly Euro Area National Accounts. Section 4 discusses the forecasting performance of the proposed model with respect to FMMP and ADL specifications in a pseudo real time context, while Section 5 studies the information content of real time data. Finally, Section 6 summarizes and concludes.

2 The dynamic survey-based factor model

In this section we provide an overview of the survey based dynamic factor model with mixed frequency data, highlighting the changes with respect to the original specification considered in FMMP.

The dynamic factor model in FMMP was formulated for a set of monthly indicators and a quarterly variable, such as sectorial Value Added, and expressed the series in terms a of a linear combination of a single common factor, generated by a cyclical trend model, with specific loadings and idiosyncratic components for each variables. The evidence arising from the full sample estimation of the model, using a batch of data that includes the latest release of the monthly indicators and the survey variables, was that the estimated common factor was driven mostly by the business survey variables, which dominate in variation the other quantitative variables. Moreover, the factor loading of value added turned out to be insignificant, which implies that the extracted common factor does not contain relevant information for the temporal disaggregation of the quarterly aggregate. When the business survey indicators were removed from the analysis, the estimation results were much more satisfactory, in so far as the common factor became strongly related to the dynamics of the hard indicators (i.e. the monthly quantitative indicators) and value added loaded significantly on the common factor.

It turns out that this evidence was in part the consequence of imposing a single common factor on the series, and of neglecting the timeliness of the economic data: business and consumer survey data are available immediately after the closing of the month to which they refer, whereas the quantitative indicators are available with a longer delay. The recent upsurge in interest in survey data and some evidence of their relevance in macroeconomic forecasting (Giannone *et al*. 2005, Altissimo *et al*. 2007) suggests a more in-depth investigation of the role of survey data for monitoring the evolution of GDP growth in the euro area on a monthly basis.

2.1 Survey data in a factor model

The extensions of the original model specification in FMMP are twofold. As hinted above we bring in an additional common factor, which ex post will turn out to be driven by the survey variables. Secondly, we model the first common factor as an integrated modified high-order autoregressive process, referred to as IZAR(p). The ZAR(p) process was originally proposed by Morton and Tunnicliffe-Wilson (2004) as a model with improved resolution at the low frequencies. It is essentially based on the following modification of a standard AR process,

$$\phi(L)x_t = (1 - \theta L)^p \eta_t,$$

where $\phi(L)$ is a lag polynomial of the form $(1 + \phi_1 L + \phi_2 L^2 + ... + \phi_p L^p)$, θ is a specified parameter in the interval [0.4-0.7] (Morton and Tunnicliffe-Wilson suggest to fix it at $\theta = 0.5$), and $\eta_t \sim \mathrm{WN}(0, \sigma^2)$. The inclusion of the moving average (MA) polynomial (which appears to be rather ad hoc, due to the restriction on the MA parameter) aims at enhancing the fit across the low frequency range. In fact, Morton and Tunnicliffe-Wilson argue that this re-parametrization squeezes the spectrum in the fraction $(1 - \theta)/(1 + \theta)$ of frequencies at the lower end of the range, and therefore can better account for low frequency cycles.

To get more insight on this point, let us rewrite the model as

$$\phi(L)x_t^* = \eta_t, x_t^* = \frac{x_t}{(1-\theta L)^p}.$$

When $p = 1$, x_t^* is (proportional to) a one-sided exponentially weighted moving average (EWMA) of its current and past values, i.e. $x_t^* = \sum_{j=0}^{\infty} \theta^j x_{t-j}$; in general, x_t^* results from the repeated application of the EMWA filter, and thus it is much smoother than the original series. The original motivation for the introduction of the ZAR process was multi-step ahead forecasting, which requires the selection of the information on the long run behaviour from a time series, abstracting from high frequency fluctuations that do not contribute to the multi-step forecasts. Our motivation is similar in spirit, but refers to the fact that the common factor is a carrier of the information that is useful for disaggregating the national accounts quarterly time series. The estimated factor should be devoid of the high frequency variation that is typically aliased, due to temporal aggregation, which on the contrary should be ascribed to the idiosyncratic components.

Let $\mathbf{y}_t$ denote a $N \times 1$ vector of time series, possibly sampled at different frequencies, with t indicating the finest frequency (monthly in our case). We assume $\mathbf{y}_t$ to be integrated of order one, and not cointegrated. The extended survey-based dynamic factor model expresses $\mathbf{y}_t$ as the linear combination of two common cyclical trends, denoted by μ_t and $\widetilde{\mu}_t$ respectively, and idiosyncratic components, $\boldsymbol{\gamma}_t$, specific for each series. Letting $\boldsymbol{\vartheta}$ and $\widetilde{\boldsymbol{\vartheta}}$ denote the two $N \times 1$ vectors of loadings, and assuming that both common and idiosyncratic components are difference stationary and subject to autoregressive dynamics, we can write the specification in levels as:

$$\begin{array}{lcll}
\mathbf{y}_t & = & \boldsymbol{\vartheta}_0\mu_t + \boldsymbol{\vartheta}_1\mu_{t-1} + \widetilde{\boldsymbol{\vartheta}}_0\widetilde{\mu}_t + \widetilde{\boldsymbol{\vartheta}}_1\widetilde{\mu}_{t-1} + \boldsymbol{\gamma}_t + \mathbf{X}_t\boldsymbol{\beta}, & t = 1, ..., n, \\
\phi(L)\Delta\mu_t & = & (1-\theta L)^p \eta_t, & \eta_t \sim \text{NID}(0, \sigma_\eta^2), \\
\widetilde{\phi}(L)\Delta\widetilde{\mu}_t & = & \widetilde{\eta}_t, & \widetilde{\eta}_t \sim \text{NID}(0, \sigma_{\widetilde{\eta}}^2), \\
\mathbf{D}(L)\Delta\boldsymbol{\gamma}_t & = & \boldsymbol{\delta} + \boldsymbol{\xi}_t, & \boldsymbol{\xi}_t \sim \text{NID}(\mathbf{0}, \boldsymbol{\Sigma}_\xi),
\end{array} \tag{1}$$

where $\phi(L)$ and $\widetilde{\phi}(L)$ are autoregressive polynomials of order p and $\widetilde{p}$ with stationary roots:

$$\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p, \widetilde{\phi}(L) = 1 - \widetilde{\phi}_1 L - \cdots - \widetilde{\phi}_{\tilde{p}} L^{\tilde{p}},$$

and $(1-\theta L)^p \eta_t$ is the pre-specified MA(p) term allowing for low-frequency cycles. We assume that we do not need a similar correction for the second factor, since empirically this will be mostly survey based. The matrix polynomial $\mathbf{D}(L)$ is diagonal:

$$\mathbf{D}(L) = \text{diag}\left[d_1(L), d_2(L), \ldots, d_N(L)\right],$$

with $d_i(L) = 1 - d_{i1}L - \cdots - d_{ip_i}L^{p_i}$ and $\mathbf{\Sigma}_\xi = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2)$. The disturbances η_t ,$\widetilde{\eta}_t$ and $\boldsymbol{\xi}_t$ are mutually uncorrelated at all leads and lags. The matrix $\mathbf{X}_t$, is a $N \times k$ matrix containing the values of k exogenous variables that can be used to incorporate calendar effects (trading day regressors, Easter, length of the month) and intervention variables (level shifts, additive outliers, etc.).

FMMP show how the model can be modified to handle cointegration and variables expressed in logs rather than levels. They also provide evidence in favour of the no cointegration hypothesis, and of the levels rather than log specification.

2.2 State space representation of the model

In this subsection we cast model (1) in the state space form (SSF). For the sake of exposition, we present the state space of every component separately, the two coincident indexes and the idiosyncratic components, and finally we combine all blocks to get the complete form.

Let us start from the single index, $\phi(L)\Delta\mu_t = (1 - \theta L)^p \eta_t$, that is an autoregressive process of order (p), AR(p) with the mentioned Morton and Tunnicliffe Wilson (2004) modification, or a ZAR(p). It is possible to write the stationary ZAR(p) model $\Delta\mu_t$ using the following SSF:

$$
\begin{aligned}
\Delta\mu_t &= \mathbf{e}'_{1p+1}\mathbf{g}_t, \\
\mathbf{g}_t &= \mathbf{T}_{\Delta\mu}\mathbf{g}_{t-1} + \mathbf{h}\eta_t,
\end{aligned}
\tag{2}
$$

where

where $\mathbf{h} = \sigma_\eta[1, -p\theta, \binom{p}{2}(-\theta)^2, \binom{p}{3}(-\theta)^3, \ldots, (-\theta)^p]'$ and

$$
\mathbf{T}_{\Delta\mu} = \begin{bmatrix} \phi_1 & \\ \vdots & \mathbf{I}_p \\ \phi_p & \\ \phi_{p+1} & \mathbf{0}' \end{bmatrix}.
$$

Nevertheless, model (1) is expressed in levels and thus we should derive the corresponding SSF for μ_t. Hence, considering that $\mu_t = \mu_{t-1} + \mathbf{e}'_{1p+1}\mathbf{g}_t = \mu_{t-1} + \mathbf{e}'_{1p+1}\mathbf{T}_{\Delta\mu}\mathbf{g}_{t-1} + \mathbf{h}\eta_t$, and defining

$$
\boldsymbol{\alpha}_{\mu,t} = \begin{bmatrix} \mu_t \\ \mathbf{g}_t \end{bmatrix}, \quad \mathbf{T}_\mu = \begin{bmatrix} 1 & \mathbf{e}'_{1p+1}\mathbf{T}_{\Delta\mu} \\ 0 & \mathbf{T}_{\Delta\mu} \end{bmatrix},
$$

the SSF representation of the model for μ_t becomes

$$\mu_t = \mathbf{e}'_{1,p+2}\boldsymbol{\alpha}_{\mu,t}, \quad \boldsymbol{\alpha}_{\mu,t} = \mathbf{T}_\mu \boldsymbol{\alpha}_{\mu,t-1} + \mathbf{H}_\mu \eta_t, \tag{3}$$

where $\mathbf{H}_\mu = [1, \mathbf{h}']'$.

A similar approach can be followed to derive the SSF of the second coincident index, that is a standard AR($\tilde{p}$) process. The index in difference $\Delta\widetilde{\mu}_t$ is expressed by:

$$\begin{aligned} \Delta\widetilde{\mu}_t &= \mathbf{e}'_{1\tilde{p}}\widetilde{\mathbf{g}}_t, \\ \widetilde{\mathbf{g}}_t &= \mathbf{T}_{\Delta\tilde{\mu}}\widetilde{\mathbf{g}}_{t-1} + \mathbf{e}_{1\tilde{p}}\widetilde{\eta}_t, \end{aligned} \tag{4}$$

where $\mathbf{e}_{1\tilde{p}} = [1, 0, \ldots, 0]'$ and

$$\mathbf{T}_{\Delta\tilde{\mu}} = \begin{bmatrix} \tilde{\phi}_1 & \\ \vdots & \mathbf{I}_{\tilde{p}-1} \\ \tilde{\phi}_{\tilde{p}-1} & \\ \tilde{\phi}_{\tilde{p}} & \mathbf{0}' \end{bmatrix}.$$

Hence, as before, we derive the SSF for the level considering that $\widetilde{\mu}_t = \widetilde{\mu}_{t-1} + \mathbf{e}'_{1\tilde{p}}\widetilde{\mathbf{g}}_t = \widetilde{\mu}_{t-1} + \mathbf{e}'_{1\tilde{p}}\mathbf{T}_{\Delta\tilde{\mu}}\widetilde{\mathbf{g}}_{t-1} + \widetilde{\eta}_t$, and defining

$$\boldsymbol{\alpha}_{\tilde{\mu},t} = \begin{bmatrix} \widetilde{\mu}_t \\ \widetilde{\mathbf{g}}_t \end{bmatrix}, \quad \mathbf{T}_{\tilde{\mu}} = \begin{bmatrix} 1 & \mathbf{e}'_{1\tilde{p}}\mathbf{T}_{\Delta\tilde{\mu}} \\ 0 & \mathbf{T}_{\Delta\tilde{\mu}} \end{bmatrix}.$$

The final SSF of the model for $\widetilde{\mu}_t$ becomes

$$\mu_t = \mathbf{e}'_{1,\tilde{p}+1}\boldsymbol{\alpha}_{\tilde{\mu},t}, \quad \boldsymbol{\alpha}_{\tilde{\mu},t} = \mathbf{T}_{\tilde{\mu}} \boldsymbol{\alpha}_{\tilde{\mu},t-1} + \mathbf{H}_{\tilde{\mu}} \eta_t, \tag{5}$$

where $\mathbf{H}_{\tilde{\mu}} = [1, \mathbf{e}'_{1,\tilde{p}}]'$.

A similar representation holds for each individual γ_{it}, with $\widetilde{\phi}_j$ replaced by d_{ij}, so that, if we let p_i denote the order of the i-th lag polynomial $d_i(L)$, we can write:

$$\gamma_{it} = \mathbf{e}'_{1,p_i+1}\boldsymbol{\alpha}_{\mu_i,t}, \quad \boldsymbol{\alpha}_{\mu_i,t} = \mathbf{T}_i \boldsymbol{\alpha}_{\mu_i,t-1} + \mathbf{c}_i + \mathbf{H}_i \xi_{it}, \tag{6}$$

where $\mathbf{H}_i = [1, \mathbf{e}'_{1,p_i}]'$, $\mathbf{c}_i = \delta_i \mathbf{H}_i$ and δ_i is the drift of the $i - th$ idiosyncratic component, and thus of the series, since we have assumed a zero drift for the common factor.

Combining all the blocks in (2)-(6), we obtain the SSF of the complete model by defining the state vector $\boldsymbol{\alpha}_t$, with dimension $\sum_i (p_i + 1) + (p + 2) + (\widetilde{p} + 1)$, as follows:

$$\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}'_{\mu,t}, \boldsymbol{\alpha}'_{\tilde{\mu},t}, \boldsymbol{\alpha}'_{\mu_1,t}, \ldots, \boldsymbol{\alpha}'_{\mu_N,t}]'. \tag{7}$$

Consequently, the measurement and the transition equation of the model in levels are:

$$\mathbf{y}_t = \mathbf{Z}\boldsymbol{\alpha}_t + \mathbf{X}_t\boldsymbol{\beta}, \quad \boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \mathbf{W}\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t, \tag{8}$$

where $\boldsymbol{\epsilon}_t = [\eta_t, \widetilde{\eta}_t, \xi_{1,t}, \dots, \xi_{N,t}]'$ and the system matrices are given by:

$$\begin{aligned} \mathbf{Z} &= \left[\boldsymbol{\theta}_0, \,\vdots\, \boldsymbol{\theta}_1 \;\; \vdots\, \mathbf{0} \,\vdots\, \tilde{\boldsymbol{\theta}}_0, \,\vdots\, \tilde{\boldsymbol{\theta}}_1 \;\; \vdots\, \mathbf{0} \,\vdots\, \text{diag}(\mathbf{e}'_{p_1+1}, \dots, \mathbf{e}'_{p_N+1})\right], \\ \mathbf{T} &= \text{diag}(\mathbf{T}_\mu, \mathbf{T}_{\tilde{\mu}}, \mathbf{T}_1, \dots, \mathbf{T}_N), \\ \mathbf{H} &= \text{diag}(\mathbf{H}_\mu, \mathbf{H}_{\tilde{\mu}}, \mathbf{H}_1, \dots, \mathbf{H}_N). \end{aligned} \tag{9}$$

The vector of initial values is $\boldsymbol{\alpha}_1 = \mathbf{W}_1\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_1$, so that $\boldsymbol{\alpha}_1 \sim \text{N}(\mathbf{0}, \mathbf{W}_1\mathbf{V}\mathbf{W}_1' + \mathbf{H}\text{Var}(\boldsymbol{\epsilon}_1)\mathbf{H}')$, $\text{Var}(\boldsymbol{\epsilon}_1) = \text{diag}(1, \sigma_1^2, \dots, \sigma_N^2)$.

The state space form (8)-(9) is linear and, assuming that the disturbances have a Gaussian distribution, the unknown parameters can be estimated by maximum likelihood, using the prediction error decomposition, performed by the Kalman filter. Given the parameter values, the Kalman filter and smoother will provide the minimum mean square estimates of the states and thus of the missing observations in $\mathbf{y}_{2,t}^c$. Hence, by using $\mathbf{y}_{2,t} = \mathbf{y}_{2,t}^c - \psi_t\mathbf{y}_{2,t-1}^c$, it is possible to derive the estimates of $\mathbf{y}_{2,t}$. In order to provide the estimation standard error, however, the state vector must be augmented of

$$\mathbf{y}_{2,t} = \mathbf{Z}_2\boldsymbol{\alpha}_t + \mathbf{X}_2\boldsymbol{\beta} = \mathbf{Z}_2\mathbf{T}\boldsymbol{\alpha}_{t-1} + [\mathbf{X}_2 + \mathbf{Z}_2\mathbf{W}]\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t.$$

Since estimation of the multivariate dynamic factor model can be numerically complex, computational efficiency is achieved by implementing univariate filtering and smoothing procedures. Anderson and Moore (1979) first considered the univariate treatment of multivariate models, and Koopman and Durbin (2000) showed that it is a very flexible and convenient device for filtering and smoothing, and for handling missing values. The main idea is that the multivariate vectors of indicators, where some elements can be missing, are stacked one on top of the other to yield a univariate time series, whose elements are processed sequentially. The aggregation constraint of monthly values to quarterly GDP is solved following Harvey (1989), that is by augmenting the state vector in the SSF (8)-(9) with an appropriately defined cumulator variable. This cumulator coincides with the observed aggregated series (quarterly GDP) in the last month of the quarter, otherwise it contains the partial cumulative value of the aggregate months making up the quarter up to and including the current one (see FMMP for more details).

3 Estimation results

We now apply the model in the previous Section to obtain timely monthly estimates of euro area sectorial value added, which can be added up to provide a monthly estimate of GDP and its growth rate. This disaggregate approach to monthly estimation of GDP allows us to exploit specific indicators for each sector, and also to monitor the sectorial evolution of the economy on a monthly basis.

As in FMMP, we consider both the output side (six branches of the NACE classification) and the expenditure side (the main GDP components). For each disaggregate GDP component, a set of monthly indicators are carefully selected, including both macroeconomic variables and survey answers.

Special attention is paid to chain-linking and its implications for the construction of a monthly indicator of GDP, via a multistep procedure that exploits the additivity of the volume measures expressed at the prices of the previous year (fully detailed in FMMP). The final estimate of the monthly euro area GDP is then obtained by combining the estimates from the output and expenditure sides, with optimal weights reflecting their relative precision. The resulting pooled estimator is more precise than each of its two components, paralleling the results on the usefulness of pooling in the forecasting literature (see e.g. Stock and Watson (1999)).

The series of quarterly Value Added are available from the beginning of 1995 to the fourth quarter of 2007. Observations are seasonally adjusted and working day adjusted and refer to the Euro Area. Our information set is mainly based on FMMP and includes National Account data, monthly ”hard” indicators, such as industrial production, employment, hours worked etc., and Business and Consumer survey data published by the European Commission. In particular, given the forecasting focus of the paper, we include in the information set both assessment survey variables and expectations. The monthly indicators available for each branch are listed in Table 1, along with their publication delay. No indicator is available for the primary sector (AB). For Industry (CDE) and Construction (F), a core indicator is represented by the index of industrial production. For the remaining branches (services), the monthly variables tend to be less directly related to the economic content of value added.

For the disaggregation of the components of GDP from the expenditure side, the monthly indicators suitable for construction of the coincident index are listed in Table 2. In particular, for *Final consumption expenditures* some indicators of demand are available together with the production of consumer goods. For *Gross capital formation* a core indicator is the production index (both for industry and constructions), in addition to some specific variables for constructions. As far as the *External Balance* is concerned, the monthly volume index of Imports and Exports is provided by Eurostat, although with more than 2 month of delay. In order to catch sentiments and expectations of economic agents we complete this set of variables with the Survey data published by the European Commission on Consumers, Business, Building and Services.

The model specification has followed two criteria: statistical relevance of indicators and residual diagnostics. As for the variable selection, we followed the ”general to specific” approach, taking out of the specification indicators whose loadings where insignificant. In combination with that, we based the lag length selection on the BIC criterion. In addition, every month the possibility of 1 or 2 factor model, with or without ZAR modification, is evaluated. Diagnostic checking and goodness of fit assessment are based on the standardised Kalman filter innovations.

We find the two factor ZAR model encompasses the standard FMMP single index model only in two, but important, cases: Industry and Exports, which represents respectively 23% and 24% of the total GDP by sector and expenditure type. For the others sectors/components of demand, there is not enough improvement in the estimation results when a second survey-based factor is added to FMMP.

We summarize here the estimation results for the cases where the FMMP model results best [1], while full details on the two new survey-based factor indicators, namely for the Industry sector and the Exports demand component, are reported in the next two subsections.

For the Construction sector we complement the indicators selected in FMMP (Industrial production in construction, Building permits, employment and hours worked) with data coming from the survey on buildings. The three most relevant variables turn out to be business climate, building activity development over the past 3 months, and prices expectations over the next 3 months. However, none of them is statistically significant at the conventional 5% level. For Services, the most informative survey indicators appear to be: business situation development over the past 3 months, evolution of the demand over the past 3 months, expectation of the demand over the next 3 months. However, the resulting survey based factor model is outperformed in terms of fit by the FMMP specification, mainly because survey data dominate in variation the other variables, which come up to be insignificant.

With respect to the estimation from the expenditure side, we have a similar situation. In particular, for Investment, when we add to the Industrial production index (industry and construction) the series from the Business survey, only the climate in construction

[1] Full results, including innovations and forecast exercises are available under request.

is significant but at the cost of loosing the significance of the hard data. For Consumption, there is a wide range of indicators available from the Consumer Survey. The best factor specification we estimate includes the Financial situation over the last 12 months, the General economic situation over the last 12 months, the Price trends over the last 12 months, the Major purchases at present Confidence Indicator (-1), Car registration and Retail sales. Again, when survey data are introduced, the significance of hard data vanishes. Instead, for Imports the survey data never enter in the model with statistically significant coefficients.

We should also mention that the BIC criterion is in favour of the model with two factors in almost all cases. Hence, one could imagine that, notwithstanding the loose statistical significance of the survey data (or of the hard data when the survey data are included), the survey based factor model could outperform the standard FMMP model in forecasting. However, a forecast evaluation exercise suggests that this is not the case, as we will see in detail in Section 4.

3.1 Industry

We start with a general model based on the information set described in Table 1 and we proceed by sequentially dropping the indicators that resulted not statistically significant. The final model, also supported by the BIC criterion, relies on five monthly indicators, which are graphed in Figure 1. Two of them are quantitative indicators: the index of industrial production (prod) and hours worked (howk). The remaining three are business survey indicators compiled in the form of balances of opinions by the European Commission: business climate confidence (S.clime), Production expectations for the months ahead (S.prod.exp), Selling price expectations for the months ahead (S.price.exp). [2]

Survey indicators are supposed to be stationary (see also stationarity tests in Proietti and Frale, 2007). Therefore, we include survey variables in our models in cumulated (integrated) form so as to preserve the level specification of the regression and the dynamic factor model. We leave to future research the investigation of alternative specifications and quantifications for survey data.

The estimation results for the two-factors model (FMMP-survey henceforth) are presented in Table 3. For the first differences of the first factor, $\Delta\mu_{1t}$, we propose a ZAR(2) specification, meanwhile for the second index, $\Delta\widetilde{\mu}_{2t}$, we use an AR(2). This is the best model in terms of significance of coefficients and likelihood, in a set of alternative pa-

[2]See Pesaran and Weale (2006) for a discussion on the quantification of surveys and their role in econometric analysis.

rameterizations characterized by different number of common factors, indicators and lag length. The BIC information criterion confirms the superiority of the survey based model.

It is important to notice that, firstly, survey data are strongly significant in this model and, secondly, that there is a clear separation between indicators, with hard data loading on the first coincident index and survey data on the second one. This confirms our a priori that allowing for more than one factor might be needed to capture the particular nature of soft data. We have also considered that variables could enter in the model with lags, but we have found no evidence in favor of this specification.

In the top panel of Figure 2 we present for Industry the two coincident indices, the estimated monthly value added (in level and annual growth rate) along with the 95% approximated confidence bands around them and the indicators innovations, which could be used for residual diagnostics. The bottom panel reproduces the same plots for Exports.

For Industry we observe that the first coincident index is more volatile than the second which appears more smooth, while for Export is the opposite. The visual inspection of the innovations confirms the better quality of the estimation from the supply side with respect to the demand side.

3.2 Exports

As far as Exports in good and services are concerned, we firstly should mention that monthly indexes on Imports and Exports are actually published by Eurostat, but unfortunately with a delay of about 90 days. Their late arrival prevents the direct use of these series as proxy for the National Account features, but does not prevent their usefulness for the disaggregation. Other indicators of interest are the Index of production in intermediate goods (IP.int) and the real exchange rate of the euro, although the second never resulted significant in our preliminary analysis for indicators selection. Among survey data, we include in the information set the assessment of export order-book levels (S.exp.order), the assessment of current production capacity (S.prod.cap), Export expectations for the months ahead (S.exp.expect) and the Competitive position over the past 3 months (S.comp). The last three survey variables are collected quarterly, but it turns out that they still bring useful information for the monthly estimation of the quarterly Exports given their short delay of publication. The indicators used for Exports are shown in the bottom panel of Figure 1. As in the case of Industry, we find the 2 factor survey-based model more informative than the single FMMP index, based on BIC (Table **??**), estimation results and innovations properties.

The parameter estimates are reported in the bottom panel of Table 3, while Figure

?? shows the monthly estimates of Exports and their 95% estimated confidence bands, along with the two common factors, which follow respectively a ZAR(2) and AR(2), in comparison with FMMP. As for the case of Industry, we observe a clear separation of indicators on the two factors: hard data load on the second index and survey data on the first one. It should be noticed that the GDP loading is only significant for the first index, but as we show later on this does not prevent the usefulness of a second factor in terms of forecasting ability.

As discussed previously, summing up the estimated monthly sectoral Value Added (or components of expenditure) we get the indicator for the total monthly GDP at market prices. Indeed, given the chain linked nature of National accounts, the summation step is not straightforward, but still feasible applying the same routine suggested by FMMP.[3]

It turns out that the estimates of monthly euro area GDP from FMMP and FMMP-survey are quite similar in sample, see Figure 3. On the contrary, as we will discuss more in detail in the following Section, the forecast ability of the model improves strongly when the survey data are taken into consideration.

4 Comparative forecasting performance

Besides monthly estimation of quarterly aggregates, the dynamic factor model can be also used for short term forecasting. The survey-based specification, by exploiting timely data and expectation indicators, might in this sense produce better results than the standard FMMP. We check empirically this issue by evaluating in terms of forecast accuracy three competitor models: the Autoregressive Distributed Lag (ADL) in differences[4], the FMMP single index model and the FMMP-survey specification of this paper. We focus on the forecast ability for Industry and Exports, leaving to future research the comparison of total GDP forecasts, which could not be directly addressed due to the chain link.[5]

As common in the literature, we start with a pseudo real time forecasting exercise, while real time data will be examined in the next Section. Considering that the sample starts in 1995 and we are interested in short term forecasts, we run the forecast evaluation

[3]As it is well known, chain-linking results in the loss of cross-sectional additivity. However, for the annual overlap, the disaggregated (monthly and quarterly) volume measures expressed at the prices of the previous year preserve both the temporal and cross-sectional additivity. This facts motivate the choice of a multistep procedure for the estimation of monthly GDP at basic and market prices, which is advocated by the IMF manual (see Bloem *et al.*, 2001) and used in this paper as was in FMMP.

[4]The ADL model is described in details in an Appendix available upon request.

[5]Although the monthly GDP chain linked values do not sum up to the quarterly numbers published by Eurostat, the quarterly additivity is maintained sectors by sectors (or components by components).

over 36 consecutive observations in the sample 2003M10-2006M8. Hence, starting from October 2003, the three models are estimated at the monthly level, and quarterly forecasts of the value added are computed up to 3 step-ahead summing up the monthly values. Then, the forecast origin is moved one month forward, and the process is repeated until the end of sample is reached, for a total of 36 times. It results that the first estimated quarterly values is for 2003Q4, and the last one for 2007Q2. The model is re-estimated each time the forecast origin is updated, and so parameter estimation will contribute as an additional source of forecast variability. For comparison, we run the same exercise keeping the parameters constant at the full sample estimated values and using a recursive sample, finding similar results in terms of ranking of the forecast methods.[6] We use rolling estimation, month by month, to get some robustness to possible parameter changes.

All forecast experiments are made in "pseudo" real-time, using the final vintage of the monthly and quarterly indicators, but recreating the ragged edge due to the different time delay in the release of the indicators. In our model, the resulting unbalanced dataset is efficiently handled by the state space methodology. Moreover, the position of the month inside the quarter matters. In particular, for the third month in the quarter, we should incorporate in the forecast the anticipated release of the quarterly value added. [7]

In Tables 4 and 5 we report a few basic statistics upon which forecasting accuracy will be assessed, for the Industry sector and Exports respectively. Monthly estimates are aggregated at quarterly frequency before computing any measure of errors, being our benchmark the national account value added. We consider forecasts both for the levels and for the quarter on quarter growth rates.

Denoting the l-step ahead forecast by $\widehat{y}_{t+l|t}$ and the true realized value by y_{t+l}, we compute for the three competitor models: the average of the forecast mean error (ME), $(\widehat{y}_{t+l|t} - y_{t+l})$, of the absolute error (MAE), and of the squared error (MSFE). We also consider the symmetric mean absolute percentage error (sMAPE), given by the average of $100|y_{t+l} - \widehat{y}_{t+l|t}| \setminus [0.5(y_{t+l} + \widehat{y}_{t+l|t})]$, which treats symmetrically underforecasts and overforecasts, and the median relative absolute error (mRAE), a robust comparative measure of performance obtained by computing the median of the distribution of the ratios $|y_{t+l} - \widehat{y}^{(M)}_{t+l|t}| \setminus |y_{t+l} - \widehat{y}^{(ADLD)}_{t+l|t}|$, where M is the model under consideration.

[6]Detailed results for this case are available upon request.

[7]Due to the anticipated release of the quarterly GDP, the 1-step ahead forecasts made in the first and second month refer to the past quarter, while the forecast made in the third month is for the current quarter. Although one should expect that the forecast error decreases as new monthly information in the quarter is made available,- e.g. from first to second and third month-, the short window of forecast analysis, the approximation of growth rates and especially the process of revision in the data might yield empirically contradicting results.

For the ADL(1,1)D [8], the FMMP-survey and the FMMP model, these statistics are reported for each month in the quarter, and for each forecast horizon (1, 2, and 3 quarter ahead).

The results are fairly clear: The ADLD model is almost always outperformed by the multivariate models, between which the FMMP-survey model makes globally the lowest forecast error, with a few exceptions. This evidence is stronger as the forecast horizon increases and the information set shrinks (1st month). The gains from the survey-based model emerge both for Exports and Industry,in level as in growth rates, slightly greater in the latter case.

For other components of GDP it turns out that the FMMP-survey is systematically worse than FMMP, even when it was better in terms of BIC, detailed results are available upon request.

Finally, we assess the statistical significance of the differences in forecast accuracy for Industry and Exports by means of the Diebold and Mariano (1995) test. It is worth to clarify that, although the FPMM and FPMM-survey models are nested, rolling estimation validates the applicability of the Diebold-Mariano test (see Giacomini and White 2006). In Table 6 we report, for the levels and growth rates, the p-values for the pairwise test among the three models, with distinction of the month in the quarter and the forecast horizon, which should be compared with the usual threshold of 5%. It turns out that there is strong evidence of significant differences in MSE between multivariate factor models and univariate ADLD model, while the performance of the FMMP and FMMP-survey is not statistically different, with few exception for the Exports growth rate forecast.

To conclude, overall this forecasting evaluation provides support for multivariate models, especially the FMMP-survey that includes timely information from survey data.

5 Revisions and Contribution to the estimation

In this Section we attempt to isolate the news content of each block of series used in the estimation of GDP, namely survey data and hard data. For this task we present some forecast exercises using real time data from the Euro Area Real Time database (distributed by the EABCN), providing vintages of time series of several macroeconomic variables. The revision process is supposed to incorporate the more recent information available and therefore could matter in our context. In particular, in order to address the issue of timeliness and news content of data, we consider how much estimates change when a

[8]Estimation results for the ADL are reported in the Appendix

new block of series is released. We wish to figure out whether survey data matter for the estimation of GDP because of their timeliness and/or because of their content. As for the forecast exercise, we consider 36 rolling forecasts staring from 2003M10, so that the last estimated quarter is 2007Q2. At each period in time the input in the model are the quarterly revised value added along with the revised indicators. The model is run more than once per month, and in particular every time a block of indicators is made available. Since we consider only two blocks of variables, hard and soft data, twice per month a new estimate of the value added is calculated and compared with the previous one.

For hours worked and monthly export index vintages are not included in the EABCN database. Therefore the revision analysis is limited to Industrial production and National Accounts.

Table 7 displays the results for Industry and Export. The top part of each panel shows the impact on the estimates when new data, survey rather than hard data, enters in the information set. The two additional sections of each panel, present the RMSFE using as actual data either the first or the final vintage of data. As expected, the most relevant change in the estimates occurs when hard data are released, and this evidence is amplified for Exports. Nevertheless, the contribution of survey data seems to matter, the more so the longer the horizon and the smaller the information set. As expected, the impact is higher in the first month of the quarter, because of the lack of hard data information. This is in line with the findings of Giannone *et al.* (2005).

Interestingly enough, the survey based indicator for Industry produces better forecasts in terms of RMSFE when data revision is taken into consideration. For Exports, the evidence is mixed, except for forecasts made in the 3rd month of the quarter, when the FMMP-survey model is outperforming FMMP when the horizon increase.

To summarize, we claim that the survey data contribution to estimation and forecasting is not negligible, and this is probably so because of their timeliness.

6 Conclusions and directions for future research

This paper deals with the timely estimation and forecasting of low frequency variables in the presence of higher frequency information, such as quarterly GDP growth for whose components several monthly indicators are available. The aim is to explore whether the inclusion of the high frequency data might improve estimation accuracy and forecast ability.

The methodology we propose for the estimation of Euro Area GDP at the monthly level is based prominently on the disaggregation procedure developed by FMMP (2007). However, we suggest to extend their framework to allow for more than one common factor, survey based, and to correct for low frequency cycles. We also assess the forecasting performance of the model, evaluate the role of data revisions, and examine the news content in each block of survey and hard data.

We find evidence in favour of the inclusion of a second survey based factor in two important components of GDP, namely, the Industry sector and the Exports demand component. The dominance of the two factor model is evident both in sample and out of sample. As far as the news content of data is concerned, information from survey matters, but mostly as long as hard data do not become available.

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Table 1: Monthly indicators available for the disaggregation of sectorial value added

	Label	*Monthly Indicators*	*Delay*
A–B	**Agriculture, hunting and fishing**		
C–D–E	**Industry, included Energy**		
	prod	Monthly production index (CDE)	45
	empl	Number of persons employed	70
	howk	Volume of work done (hours worked)	60
	clim	Euro area Business Climate Indicator	15
	EA99	Industrial Confidence Indicator	15
	EA.1	Production trend observed in recent months	15
	EA.2	Assessment of order-book levels	15
	EA.3	Assessment of export order-book levels	15
	EA.4	Assessment of stocks of finished products	15
	EA.5	Production expectations for the months ahead	15
	EA.6	Selling price expectations for the months ahead	15
	EA.7	Employment expectations for the months ahead	15
F	**Construction**		
	prod_F	Monthly production index (F)	70
	b4610	Building permits	70
	empl	Number of persons employed	70
	howk	Volume of work done (hours worked)	70
	EA99	Construction Confidence Indicator	15
	EA.1	Building activity development over the past 3 months	15
	EA.3	Evolution of your current overall order books	15
	EA.4	Employment expectations over the next 3 months	15
	EA.5	Prices expectations over the next 3 months	15
G–H–I	**Trade, transport and communication services**		
	prod_cons	Monthly production index for consumption goods	45
	tovv	Index of deflated turnover	35
	empl	Number of persons employed	90
	car_reg	Car registrations	15
	EA99	Retail trade Confidence Indicator	15
	EA.1	Business activity over recent months	15
	EA.2	Assessment of stocks	15
	EA.3	Expectation of the demand over the next 3 months	15
	EA.4	Evolution of the employment over the past 3 months	15
	EA.5	Expectations of the employment over the next 3 months	15
J–K	**Financial services and business activities**		
	M3	Monetary aggregate M3 (deflated)	27
	Loans	Loans of MFI (deflated)	27
L–P	**Other services**		
	Debt	Debt securities issued by central government (deflated)	27
	Total Gross Value Added		
	Taxes less subsidies on products		
	prod	Monthly production index (CDE)	45
	tovv	Index of deflated turnover	35

Table 2: Monthly indicators available for the expenditure side

	Label	*Monthly Indicators*	*Delay*
CONS	**Final consumption expenditure**		
	prod_cons	Monthly production index for consumption goods	45
	car_reg	Car registrations	15
	tovv	Index of deflated turnover retail	35
	EA99	Consumer Confidence Indicator	15
	EA.1	Financial situation over last 12 months	15
	EA.2	Financial situation over next 12 months	15
	EA.3	General economic situation over last 12 months	15
	EA.4	General economic situation over next 12 months	15
	EA.5	Price trends over last 12 months	15
	EA.6	Price trends over next 12 months	15
	EA.7	Unemployment expectations over next 12 months	15
	EA.8	Major purchases at present	15
	EA.9	Major purchases over next 12 months	15
	EA.10	Savings at present	15
	EA.11	Savings over next 12 months	15
	EA.12	Statement on financial situation of household	15
INV	**Gross capital formation**		
	prod	Monthly production index (CDE)	45
	prod_F	Monthly production index (F)	70
	prod_cap	Monthly production index for capital goods	45
	b4610	Building permits	70
	EA99	Construction Confidence Indicator (CDE and F)	15
	EA.1_F	Assessment of order in construction	15
	EA.1	Production trend observed in recent months	15
	EA.2	Assessment of order-book levels	15
	EA.3	Assessment of export order-book levels	15
	EA.4	Assessment of stocks of finished products	15
	EA.5	Production expectations for the months ahead	15
	EA.6	Selling price expectations for the months ahead	15
	EA.7	Employment expectations for the months ahead	15
EXP	**Exports of goods and services**		
	Mexp	Monthly Export volume index	42
	prod_int	Monthly production index for intermediate goods	45
	Er	Real Effective Exchange Rate (deflator: producer price indices)	30
	EA.2	Assessment of export order-book levels (CDE)	15
	EA12	Export expectations for the months ahead	15
	EA.Q9	Assessment of current production capacity (quarterly)	30
	EA.Q14-Q16	Competitive position: domestic market, inside EU, outside EU(quarterly)	30
IMP	**Imports of goods and services**		
	Mimp	Monthly Import volume index	42
	prod_int	Monthly production index for intermediate goods	45
	rex	Real Effective Exchange Rate (deflator: producer price indices)	30
	EA.3	Assessment of order-book levels (CDE)	15
	EA.Q9	Assessment of current production capacity (quarterly)	30
	EA.Q14-Q16	Competitive position: domestic market, inside EU, outside EU(quarterly)	30

Table 3: Dynamic factor model with 2 factors (FMMP survey): parameter estimates and asymptotic standard errors, when relevant

INDUSTRY

Parameters	*prod*	*howk*	*S.clime*	*S.prod.exp*	*S.price.exp*	*Value added*
θ_{i0}	0.608	0.156	-0.005	-0.020	-0.0007	0.649
	(0.113)	(0.062)	(0.013)	(0.030)	(0.024)	(0.140)
$\widetilde{\theta_{i0}}$	0.042	0.022	0.164	0.249	0.097	0.041
	(0.020)	(0.011)	(0.023)	(0.048)	(0.048)	(0.019)
δ_i	0.012	-0.147	0.002	0.055	0.019	0.221
	(0.004)	(0.066)	(0.007)	(0.196)	(0.02)	(0.066)
d_{i1}	0.461	-0.620	1.824	0.831	0.788	
d_{i2}	0.481	-0.130	-0.847	-0.327	0.173	
$\sigma^{\mathbf{2}}{}_{\eta}$	0.274	0.274	0.031	0.119	0.230	0.300

$$\left(1 - 0.44L - 0.41L^2\right)\Delta\mu_t = (1 + 0.5L)^2\eta_t, \quad \eta_t \sim N(0,1)$$

$$\left(1 - 1.36L + 0.41L^2\right)\Delta\widetilde{\mu_t} = \widetilde{\eta_t}, \quad \widetilde{\eta_t} \sim N(0,1)$$

EXPORTS

Parameters	*exp*	*IP.int*	*S.exp.order*	*S.prodcap*	*S.exp.expect*	*S.comp*	*NA*
θ_{i0}	1.107	0.621	-0.001	0.321	0.425	0.130	1.543
	(0.280)	(0.202)	(0.017)	(0.321)	(0.518)	(0.278)	(0.710)
$\widetilde{\theta_{i0}}$	-0.002	0.005	0.168	-0.368	0.308	0.138	0.021
	(0.022)	(0.019)	(0.021)	(0.064)	(0.130)	(0.048)	(0.048)
δ_i	0.352	0.349	0.01	1.121	0.637	0.015	0.973
	(0.108)	(0.108)	(0.02)	(0.478)	(0.254)	(0.005)	(0.169)
d_{i1}	0.032	-0.645	1.780	1.352	0.233	1.779	
d_{i2}	-0.178	-0.226	-0.804	-0.619	0.607	-0.78	
$\sigma^{\mathbf{2}}{}_{\eta}$	1.142	0.595	0.001	0.095	0.704	0.133	1.100

$$\left(1 - 0.57L - 0.43L^2\right)\Delta\mu_t = (1 + 0.5L)^2\eta_t, \quad \eta_t \sim N(0,1)$$

$$\left(1 - 1.35L + 0.371L^2\right)\Delta\widetilde{\mu_t} = \widetilde{\eta_t}, \quad \widetilde{\eta_t} \sim N(0,1)$$

Table 4: Industry-Statistics on forecast performance with estimated parameters for 36 rolling estimates (2003M10-2006M8).

LEVELS

		ADL(1,1)D Model			**FMMP**			**FMMP survey**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	-961	-3214	-5466	-67	-736	-1578	24	-21	-237
	2^{nd}	-516	-2540	-4899	93	-453	-1277	19	64	2
	3^{rd}	-1706	-4041	-6277	-356	-1192	-1954	-23	-225	-449
MAE	1^{st} Month	1665	3716	5755	733	1650	2629	697	1595	2579
	2^{nd}	1099	2898	5291	811	1779	2638	773	1627	2456
	3^{rd}	2071	4423	6370	1265	2764	3753	1215	2284	3093
sMAPE	1^{st} Month	0.48	1.06	1.63	0.21	0.47	0.74	0.2	0.46	0.74
	2^{nd}	0.32	0.83	1.51	0.23	0.51	0.75	0.22	0.47	0.7
	3^{rd}	0.59	1.26	1.80	0.36	0.78	1.06	0.35	0.65	0.88
RMSFE	1^{st} Month	1845	4311	6677	965	1980	3103	909	1844	2857
	2^{nd}	1468	3511	5950	924	2047	3060	866	1914	2861
	3^{rd}	2379	4894	7205	1548	3184	4212	1544	2840	3729
mRAE	1^{st} Month				0.44	0.47	0.42	0.36	0.38	0.35
	2^{nd}				0.73	0.59	0.40	0.85	0.47	0.32
	3^{rd}				0.6	0.63	0.52	0.46	0.38	0.31

GROWTH RATES

		ADL(1,1)D Model			**FMMP**			**FMMP survey**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	-0.27	-0.64	-0.64	-0.02	-0.19	-0.23	0.01	-0.01	-0.06
	2^{nd}	-0.15	-0.58	-0.67	0.03	-0.15	-0.23	0.01	0.01	-0.01
	3^{rd}	-0.49	-0.66	-0.63	-0.10	-0.23	-0.21	0	-0.05	-0.06
MAE	1^{st} Month	0.48	0.67	0.72	0.21	0.36	0.46	0.2	0.35	0.42
	2^{nd}	0.32	0.61	0.71	0.23	0.37	0.46	0.22	0.33	0.42
	3^{rd}	0.59	0.71	0.70	0.36	0.46	0.43	0.35	0.4	0.43
sMAPE	1^{st} Month	200	193	240	263	234	137	121	106	99
	2^{nd}	335	417	179	200	129	137	743	90	98
	3^{rd}	594	193	217	107	137	134	90	109	101
RMSFE	1^{st} Month	0.53	0.77	0.82	0.28	0.45	0.54	0.26	0.44	0.52
	2^{nd}	0.42	0.70	0.82	0.27	0.47	0.54	0.25	0.46	0.52
	3^{rd}	0.68	0.82	0.80	0.44	0.53	0.53	0.45	0.49	0.53
mRAE	1^{st} Month				0.44	0.4	0.54	0.36	0.45	0.38
	2^{nd}				0.73	0.44	0.54	0.85	0.21	0.34
	3^{rd}				0.60	0.55	0.51	0.46	0.42	0.53

Note: The smallest values for each measure are underlined, unless for mRAE where the benchmark is 1.

Table 5: Exports-Statistics on forecast performance with estimated parameters for 36 rolling estimates (2003M10-2006M8).

LEVELS

		ADL(1,1)D Model			**FMMP**			**FMMP survey**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	-6868	-18846	-30242	-1650	-6071	-10074	-598	-5784	-10588
	2^{nd}	-4381	-15389	-26944	-1792	-6424	-10444	-1017	-4624	-7584
	3^{rd}	-9355	-20689	-31263	-2936	-6935	-9999	-2731	-6642	-9552
MAE	1^{st} Month	7352	18846	30242	5907	8123	10817	7065	8265	10999
	2^{nd}	7319	15922	26944	5893	9464	12035	6333	8450	10878
	3^{rd}	9419	20689	31263	6803	9958	12471	6235	9054	11945
sMAPE	1^{st} Month	1.06	2.67	4.25	0.84	1.13	1.5	0.99	1.16	1.54
	2^{nd}	1.05	2.27	3.80	0.84	1.31	1.68	0.89	1.17	1.52
	3^{rd}	1.32	2.88	4.32	0.95	1.37	1.70	0.88	1.26	1.64
RMSFE	1^{st} Month	9351	20766	31801	7139	10293	12094	8006	12330	15947
	2^{nd}	8732	18205	28357	7118	11691	13271	7326	11096	12319
	3^{rd}	12042	22283	32584	8333	11688	13659	7558	10512	13667
mRAE	1^{st} Month				0.81	0.39	0.3	1.0	0.3	0.27
	2^{nd}				0.73	0.59	0.5	0.8	0.3	0.44
	3^{rd}				0.59	0.52	0.4	0.6	0.5	0.38

GROWTH RATES

		ADL(1,1)D Model			**FMMP**			**FMMP survey**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	-1.00	-1.70	-1.60	-0.25	-0.63	-0.55	-0.1	-0.74	-0.66
	2^{nd}	-0.66	-1.57	-1.62	-0.27	-0.66	-0.55	-0.17	-1	0
	3^{rd}	-1.33	-1.59	-1.46	-0.41	-0.55	-0.41	-0.38	-1	0
MAE	1^{st} Month	1.08	1.70	1.60	1	0.98	0.9	1.01	1.07	1.11
	2^{nd}	1.07	1.59	1.62	1	1.07	0.9	0.91	1.07	1.00
	3^{rd}	1.34	1.59	1.46	0.97	0.9	0.78	0.89	0.96	0.87
sMAPE	1^{st} Month	183	196	203	65	74	66	80	128	113
	2^{nd}	106	178	205	66	81	66	68	82	74
	3^{rd}	110	179	210	67	66	60	63	71	67
RMSFE	1^{st} Month	1.37	1.97	1.89	1.02	1.12	1.15	1.13	1.38	1.34
	2^{nd}	1.27	1.86	1.92	1.02	1.25	1.15	1.03	1.25	1.17
	3^{rd}	1.69	1.90	1.76	1.17	1.15	1.06	1.07	1.18	1.14
mRAE	1^{st} Month				0.81	0.55	0.51	1.02	0.52	0.57
	2^{nd}				0.73	0.67	0.52	0.82	0.62	0.59
	3^{rd}				0.59	0.54	0.4	0.61	0.61	0.50

Note: The smallest values for each measure are underlined, unless for mRAE where the benchmark is 1.

Table 6: Diebold-Mariano test (p-values) of equal forecast accuracy by horizon of forecast (1,2,3 quarters) and month of the prevision (1st, 2nd, 3td of the quarter).

LEVELS

Industry	*1-step*	*2-step*	*3-step*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.000	0.001	0.000
FMMP-survey *vs* FMMP	0.243	0.344	0.393
	1^{st} *Month*	2^{nd} *Month*	3^{rd} *Month*
FMMP *vs* ADLD	0.011	0.007	0.017
FMMP-survey *vs* ADLD	0.039	0.035	0.050
FMMP-survey *vs* FMMP	0.721	0.698	0.449
Exports	*1-step*	*2-step*	*3-step*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.051	0.000	0.000
FMMP-survey *vs* FMMP	0.138	0.940	0.535
	1^{st} *Month*	2^{nd} *Month*	3^{rd} *Month*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* FMMP	0.316	0.362	0.496

GROWTH RATES

Industry	*1-step*	*2-step*	*3-step*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.002	0.001	0.000
FMMP-survey *vs* FMMP	0.121	0.228	0.212
	1^{st} *Month*	2^{nd} *Month*	3^{rd} *Month*
FMMP *vs* ADLD	0.002	0.010	0.011
FMMP-survey *vs* ADLD	0.034	0.075	0.050
FMMP-survey *vs* FMMP	0.361	0.349	0.270
Exports	*1-step*	*2-step*	*3-step*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.038	0.000	0.000
FMMP-survey *vs* FMMP	0.252	0.352	0.045
	1^{st} *Month*	2^{nd} *Month*	3^{rd} *Month*
FMMP *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* ADLD	0.000	0.000	0.000
FMMP-survey *vs* FMMP	0.073	0.752	0.045

Table 7: Averaged size of the news in the estimation and Forecast errors, real time vintages for 36 rolling forecasts (2003M10-2006M8).

INDUSTRY

	FMMP			FMMP-survey		
Information set news*	1-step	2-step	3-step	1-step	2-step	3-step
SURVEY ARRIVE						
1^{st} Month				0.03	0.15	0.26
2^{nd}				0.01	0.07	0.17
3^{rd}				0.00	0.04	0.11
HARD DATA ARRIVE						
1^{st} Month	0.24	0.30	0.31	0.23	0.31	0.30
2^{nd}	0.11	0.21	0.22	0.10	0.21	0.21
3^{rd}	0.01	0.29	0.27	0.00	0.30	0.26
RMSFE respect to first National Accounts vintage						
1^{st} Month	7651	11657	15755	7668	11645	15599
2^{nd}	7678	11778	15921	7653	11680	15684
3^{rd}	912	8331	12333	858	8286	12047
RMSFE respect to last National Accounts vintage						
1^{st} Month	28138	28744	29396	28084	28246	28429
2^{nd}	28214	28939	29590	28216	28589	28783
3^{rd}	26509	26765	27143	26527	26487	26219

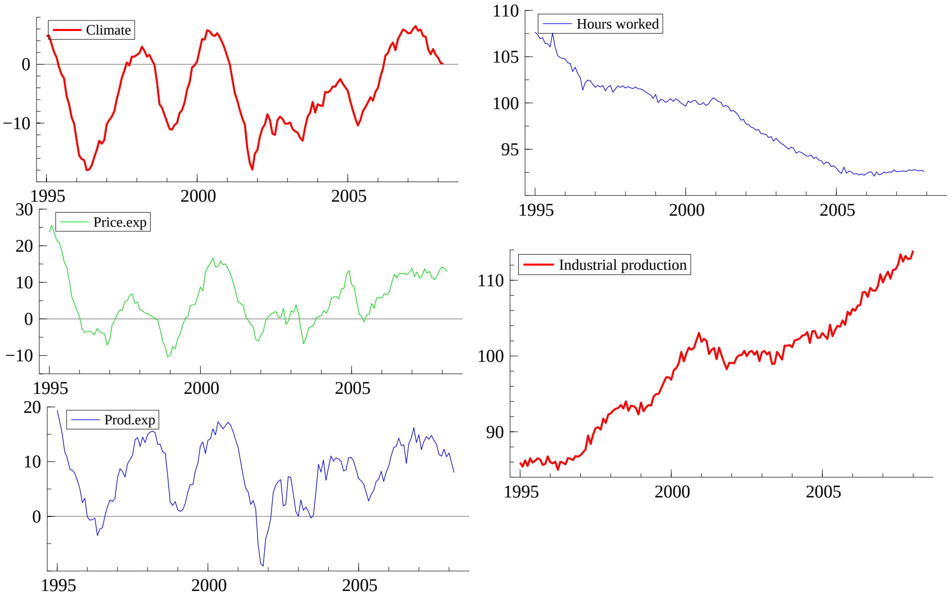
EXPORTS

	FMMP			FMMP-survey		
Information set news*	1-step	2-step	3-step	1-step	2-step	3-step
SURVEY ARRIVE						
1^{st} Month				0.35	0.55	0.74
2^{nd}				0.19	0.40	0.57
3^{rd}				0.28	0.48	0.59
HARD DATA ARRIVE						
1^{st} Month	0.39	0.36	0.36	0.61	0.80	1.03
2^{nd}	0.14	0.20	0.20	0.47	0.69	0.82
3^{rd}	0.13	0.27	0.28	0.50	0.85	0.99
RMSFE respect to first National Accounts vintage						
1^{st} Month	19892	24913	34780	20365	26322	37627
2^{nd}	19825	26890	35498	20722	28806	36798
3^{rd}	10618	22144	27486	12349	23738	28219
RMSFE respect to last National Accounts vintage						
1^{st} Month	49726	52718	58084	51127	54833	63803
2^{nd}	51059	54331	58951	52434	55922	60616
3^{rd}	46904	49807	53138	45168	47035	49420

(*) The news is measured by the Mean Absolute Relative difference between two consecutive estimates first and afterwards the updated information set: $100 * abs[(Y1 - Y0)/Y0]$. The smallest values for each measure are underlined.

Industry

Industry Indicators



Exports

Exports Indicators

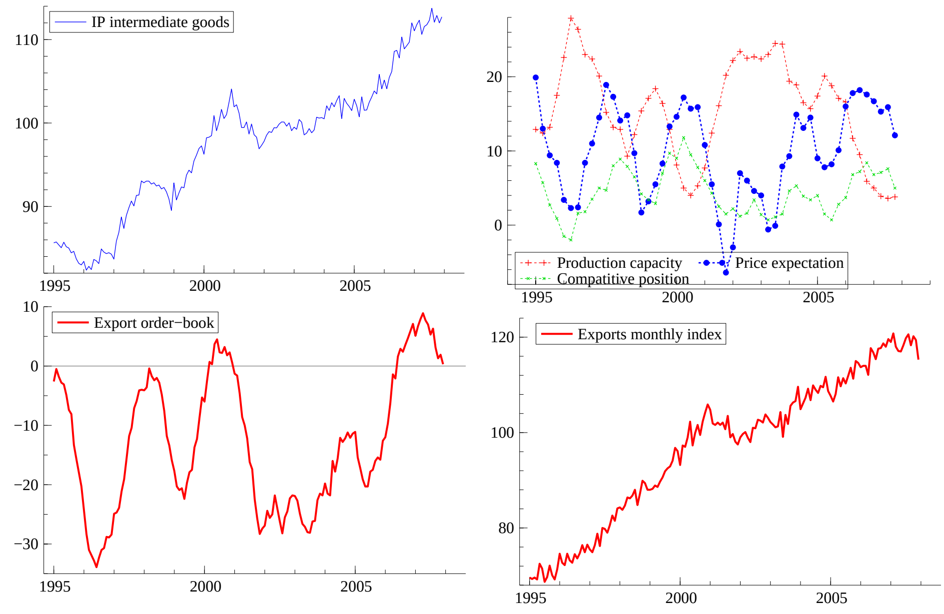


Figure 1: Monthly Indicators and Quarterly Value Added 1995-2008: Eurozone12, 1995-2008.

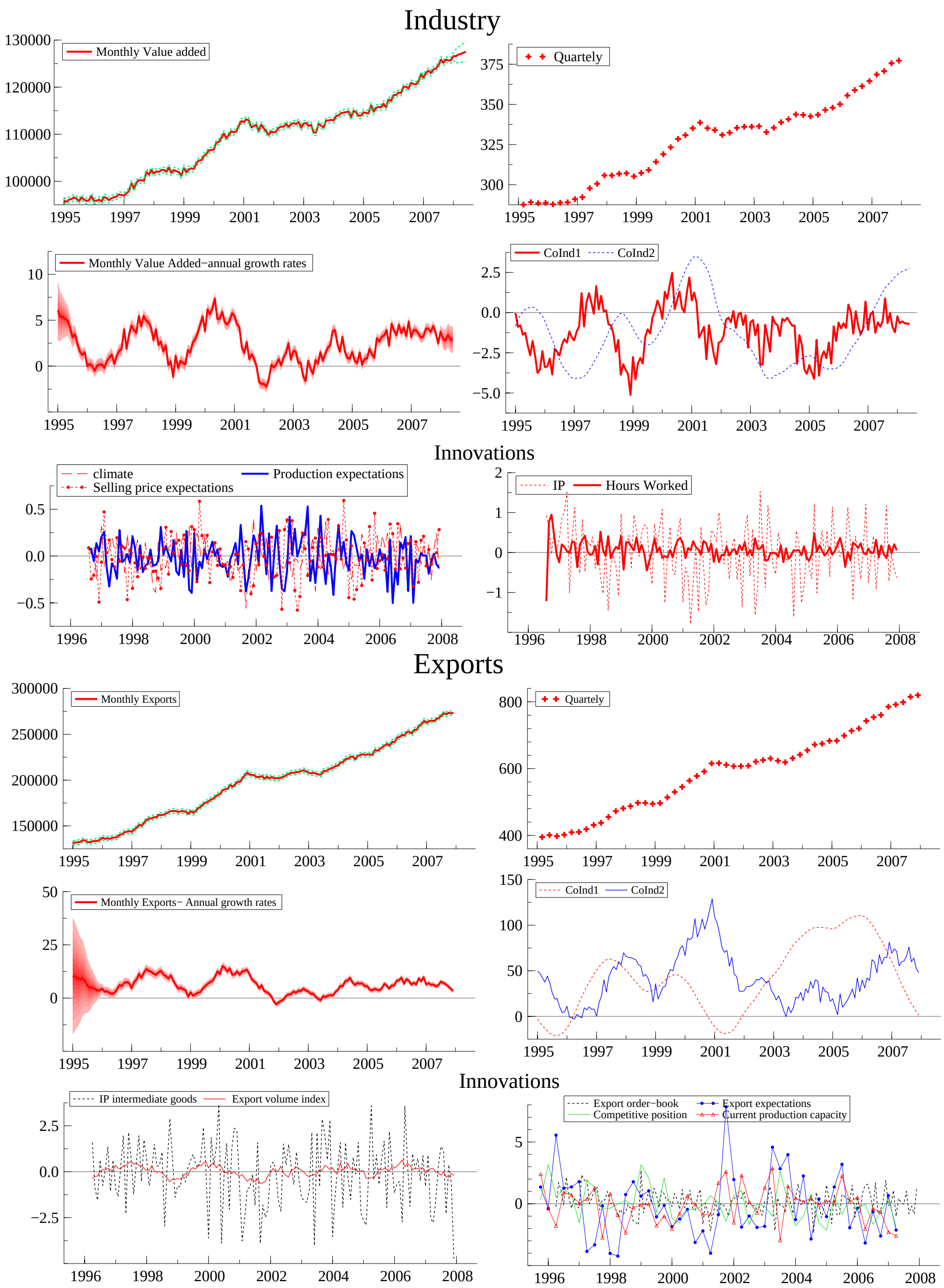


Figure 2: Survey coincident index, monthly disaggregated estimates and Innovations for Industry and Exports: Eurozone12, 1995M1-2008M5.

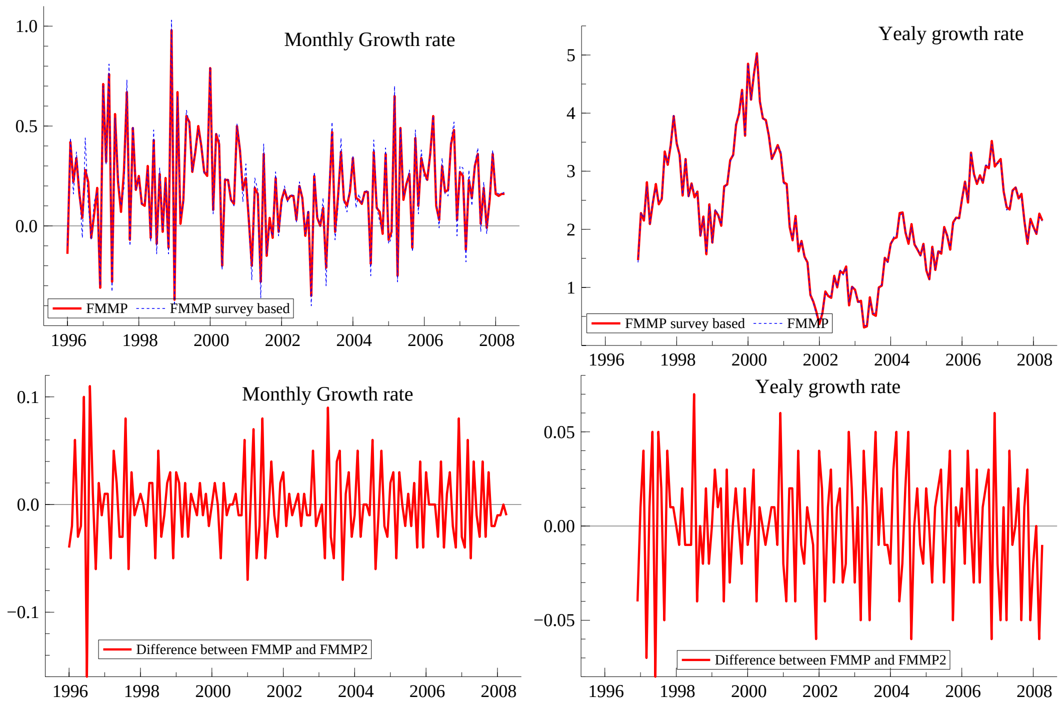


Figure 3: Estimated Monthly GDP: FMMP and FMMP survey-based