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A Monthly Indicator of the Euro Area GDP[1]

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Abstract

A continuous monitoring of the evolution of the economy is fundamental for the decisions of public and private decision makers. This paper proposes a new monthly indicator of the euro area real Gross Domestic Product (GDP), with several original features. First, it considers both the output side (six branches of the NACE classification) and the expenditure side (the main GDP components) and combines the two estimates with optimal weights reflecting their relative precision. Second, the indicator is based on information at both the monthly and quarterly level, modelled with a dynamic factor specification cast in state-space form. Third, since estimation of the multivariate dynamic factor model can be numerically complex, computational efficiency is achieved by implementing univariate filtering and smoothing procedures. Finally, special attention is paid to chain-linking and its implications, via a multistep procedure that exploits the additivity of the volume measures expressed at the prices of the previous year.

Keywords: Temporal Disaggregation. Multivariate State Space Models. Dynamic factor Models. Kalman filter and smoother. Chain-linking.

J.E.L. Classification: E32, E37, C53

1 Introduction

The availability of a representative, reliable and timely set of high frequency macroeconomic indicators is quintessential for the assessment of the state of the euro area economy and the conduct of monetary policy.

With the purpose of satisfying the information requirements of policy makers, economic analysts, researchers and business cycle experts, Eurostat has organised a very comprehensive and representative number of monthly and quarterly time series in the Euro-IND database, accessible through the Euro-Indicators website. The latter contains time series observations on **8** macroeconomic variables for the Euro-zone, the European Union, as well as for Member States and EFTA countries, concerning the following domains: balance of payments; business and consumer surveys; external trade; industry, commerce and services; labour market; monetary and financial indicators; national accounts; consumer prices. Among this set, 19 indicators have been selected by the ECB and the Commission's Economic and Financial Affairs Directorate-General with the qualification of Principal European Economic Indicators (PEEI**s**).

In **the** recent years there have been substantial advances in the methodology and the quality of infra-annual statistical information for the euro area, well accounted in the report "Towards improved methodologies for euro area statistics and indicators by the Commission of the European Communities (2002). In particular, the statistical methodology has made it possible to increase the length, coverage, and timeliness of short-term statistics for the euro area. Nevertheless, some of the PEEI**s** are available at the quarterly frequency, whereas it would be desirable to have monthly estimates of the corresponding aggregates. The leading example is Gross Domestic Product (GDP), which is usually considered as a comprehensive measure of the level of economic activity of an economy.

The relevance of GDP and the need to make it available at higher (monthly) frequency provides the motivation for this paper. Using recent advances in statistical methodology and the availability of timely and reliable statistical information on related indicators at the monthly frequency, we can produce indirect estimates of monthly GDP that are informative for short run analysis.

A variety of temporal disaggregation methods, both univariate and multivariate, is available for this task. We adopt an indirect approach which revolves around the disaggregation, via a small scale dynamic factor models, of the main quarterly components of GDP according to its decomposition by the output and the expenditure approaches. As the monthly indicators represent measures of sectoral output (industrial production, retail turnover, number of passengers, etc.) or of sectoral input (employment, hours worked), we consider the breakdown of GDP into the value added of six branches of the NACE-Clio rev. 1 classification and, for each branch, we proceed to the estimation of the monthly value added. The observed quarterly value added series will be distributed over the three months composing the quarters so as to preserve the quarterly aggregation constraint, that is, ensuring that the sum of the three distributed values is consistent

with the quarterly figure. The same approach is followed to estimate gross domestic product at market prices from the expenditure side, by using monthly indicators of the final demand. Finally the estimates of total GDP are reconciliated by combining the supply side and expenditure side estimates using optimal weights, which reflect the relative precision.

Of course, several alternative monthly indicators of the economic conditions in the euro area are available. A first type of indicators relies on the non model based methodology adopted by the Conference Board for the US. In this context, a composite coincident index (CCI) is constructed as a simple weighted average of selected standardized single indicators. Examples are provided in Carriero and Marcellino (2007a).

A second type of indicators are model based. Within this approach, two main methodologies have emerged: dynamic factor models and Markov switching models. In both cases there is a single unobservable force underlying the current status of the economy, but in the former approach this is a continuous variable, while in the latter it is a discrete variable that evolves according to a Markov chain. While Markov switching models do not perform particularly well in this context for European countries, likely because of the availability of rather short and noisy time series (see e.g. Carriero and Marcellino (2007b)), factor models have been more successfully used. Examples include Carriero and Marcellino (2007b) for the UK, Charpin (2005) and Altissimo et al. (2001, 2007) for the euro area. The latter reference underlies the Eurocoin indicator, published by the CEPR, and is based on the use of a very large information set.

A third type of indicators are based on survey data. The European Commission (more specifically, DG-Economic and Financial Affairs (DG -ECFIN)) computes a variety of survey based CCIs, using mostly a non-model based procedure. Gayer and Genet (2006) and Carriero and Marcellino (2007c) propose to summarize the data in the business and consumer surveys into a CCI with a large scale dynamic factor model, comparing the static principal component approach of Stock and Watson (2002a,b) and the dynamic principal component approach of Forni et al. (2000, 2003).

A fourth type of monthly indicator of economic activity is more closely related to the method we propose in this paper, since the goal is to provide a montly estimate of GDP. A leading example is Mitchell et al. (2005) for the UK.

With respect to the existing literature on monthly indicators of economic activity in the euro area, the main original features of this paper are the following. First, it considers both the output side (six branches of the NACE classification) and the expenditure side (the main GDP components). Second, for each disaggregate GDP component, a set of monthly indicators are carefully selected, including both macroeconomic variables and survey answers. Third, our indicator is based on information at both the monthly and quarterly level, rather than monthly only, modelled with a dynamic factor specification cast in state-space form. Fourth, we provide an explicit measure of uncertainty around the indicator, which is particularly relevant in a decision making context. Fifth, since estimation of the multivariate dynamic factor model can be numerically com-

plex, computational efficiency is achieved by implementing univariate filtering and smoothing procedures. Sixth, 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 previous year prices. Finally, the estimate of the monthly euro area GDP is 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 paper is structured as follows. Section 2 discusses the information available. Section 3 presents the multivariate disaggregation methods, focusing in particular on the dynamic factor model for the estimation of an index of coincident indicators proposed by Stock and Watson (1991) as a special case of the dynamic factor model introduced by Geweke (1977) and Sargent and Sims (1977). Section 4 discusses the aggregation of the monthly estimates of sectoral value added into GDP at basic and market prices, and how chain-linked volume measures using 1995 as the reference year are obtained. Section 5 reports the main empirical results obtained from the output side, from the demand side, and from an optimal combination of these two approaches to the disaggregation of quarterly value added. At the end of this section, some diagnostics and issues related to the revisions of the indicators and hence of the estimates are presented. Section 6 summarizes the main findings of the paper.

2 The information set

The construction of a monthly indicator of the euro area GDP is carried out indirectly through the temporal disaggregation of the value added of the six branches of the NACE Rev. 1 - Level A6 classification and at the same time through the temporal disaggregation of the main components of the demand from the expenditure side. As mentioned before the two monthly estimates, from the supply and demand approach, are at the end combined with appropriate weights reflecting their precision.

The main part of the analysis is based on quarterly observations on each branch of activity and expenditure components from the national accounts compiled by Eurostat for the sample 1995Q1-2006Q4.[1] Observations for 2007 are used for a real time evaluation of the methodology. All the series are in seasonally adjusted form and refer to the euro area12.

In 2005 and 2006, most euro area member states have introduced chain-linking into their quarterly and annual national accounts to measure the development of economic aggregates in volume terms. This innovation bears important consequences for the estimation of a monthly indicator of the Euro area gross domestic product since, as a result of chaining, additivity is lost. The issue of

[1]Unfortunately a major structural break in the variable concerning the statistical allocation of Financial Intermediation Services Indirectly Measured (FISIM) makes the series relatively short.

aggregation of chain-linked volume measures is the topic of section 4.

The monthly indicators available for each branch are listed in table 1 along with the delay of publication. A remarkable fact is that no indicator is available for the primary sector (AB, agricultural, forestery and fishery production). For Industry (CDE) and Construction (F), a core indicator is represented by the industrial production index and the production in construction index respectively. For the remaining branches (services), the monthly variables tend to be less directly related to the economic content of value added.

From the expenditure side the monthly indicators suitable for the disaggregation of GDP are listed in table 2. In particular, for Final consumption expenditure 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 1 month of delay. In order to catch sentiments and expectations of economic agents we complete this set of variables with the Business and Consumers Surveys data published by the European Commission.

3 Methodology

The construction of an indicator of monthly GDP, that is consistent with Eurostat's quarterly estimates is an exercise in temporal disaggregation. The aggregate series, concerning the quarterly totals of value added and other economic flows, such as taxes less subsidies, have to be distributed across the months, using related time series that are available monthly and timely. In this section we provide an overview of the statistical methods that we adopt in our empirical analysis, and illustrate how univariate filtering and smoothing procedures can be used to analyze multivariate models in order to increase the computational efficiency of the disaggregation procedure.

For the primary sector and taxes less subsidies, due to the lack of reliable related monthly time series, we use univariate disaggregation methods. The procedure for handling temporal aggregation/disaggregation of univariate models in a state space framework is based on Harvey (1989) and Proietti (2006a).

There are two main related sources of criticism that arise with respect to the univariate disaggregation methods. The first deals with the exogeneity assumption, according to which the indicator is considered as an explanatory variable in a regression model. In general there is no causal relationship between, say, the monthly (deflated) turnover of the retail sector and its value added. Rather, the two phenomena share a common environment and they are related measures of the level of economic activity of the branch. The second is that the regression based methods assume that the indicators are measured without errors. The consequence is that the information on the indicators is transmitted to the disaggregated series by a single regression coefficient and thus any outlying and purely idiosyncratic feature, such as trading day variation, is automatically

attributed to the estimated series. This problem can be also better tackled in a multivariate set-up. Therefore, for the disaggregation of the other production sectors and of the demand components, our methodology is based on a multivariate method.

Multivariate disaggregation methods move away from the criticisms that affects the regression based methods. There are however several degrees of freedom as far as the specification of the model is concerned, and there are relatively few examples in the literature of applications of these models for temporal disaggregation. Harvey and Chung (2000) use a bivariate unobserved components model. Moauro and Savio (2005) have proposed multivariate disaggregation methods based on the class of Sutse models.

Stock and Watson (1991, SW henceforth) developed an explicit probability model for the composite index of coincident economic indicators. They proposed a dynamic factor model featuring a common difference-stationary factor that defines the composite index. The reference cycle is assumed to be the value of a single unobservable variable, "the state of the economy", that by assumption represents the only source of the co-movements of four time series: industrial production, sales, employment, and real incomes.

On the other hand, GDP is perhaps the most important coincident indicator, although it is available only quarterly and it is subject to greater revisions than the four coincident series in the original SW model. These considerations motivated Mariano and Murasawa (2003) to extend the SW model with the inclusion of quarterly real GDP growth, proposing a linear state space model at the monthly observation frequency that entertains the presence of an aggregated flow. Although their model is formulated explicitly in terms of the logarithmic changes in the variables, the nonlinear nature of the temporal aggregation constraint is not taken into account. The problem has been solved in Proietti and Moauro (2006), who estimated monthly GDP for the U.S. and the Euro area using a direct approach, by formulating a dynamic factor model proposed by Stock and Watson (1989) in the logarithms of the original variables. This poses a problem of temporal aggregation with a nonlinear observational constraint when quarterly time series are included which can be handled by exact nonlinear filtering and smoothing equations for estimation and temporal disaggregation (see also Proietti, 2006b).

In this paper we apply a modified version of SW dynamic factor model, as extended by Mariano and Murasawa (2003) to handle mixed frequency data, in order to obtain estimates of the monthly GDP components from the output and expenditure sides, to be later aggregated into an indicator of monthly GDP. Since this requires to apply several times the SW model, we also want to improve the computational efficiency of the procedure, by casting the multivariate SW model into an extended univariate framework.

3.1 The Stock and Watson dynamic factor model

Let $\mathbf{y}_t$ denote an $N \times 1$ vector of time series, that we assume to be integrated of order one, or $I(1)$, so that $\Delta y_{it}, i = 1, \ldots, N$, has a stationary and invertible representation. The model is of

course generalisable to higher orders of integration, but our applications concerns only the $I(1)$ case. The dynamic factor model decomposes $\mathbf{y}_t$ into a common nonstationary component and an idiosyncratic one, which is specific to each series.

Although SW formulate their model in terms of $\Delta\mathbf{y}_t$ we prefer to set up the model in the level of the variables. The advantages of this formulation are twofold: in the first place the mean square error of the estimated coincident index are immediately available both in real time (filtering) and after processing the full available sample (smoothing). Moreover, the treatment of the aggregation constraint in the levels is more transparent and efficient from the computational standpoint, in that it leads to a reduced state vector dimension.

The level specification of the SW model expresses $\mathbf{y}_t$ as the linear combination of a common cyclical trend, that will be denoted by μ_t, and an idiosyncratic component, $\boldsymbol{\mu}_t^*$. Letting $\boldsymbol{\vartheta_0}$ and $\boldsymbol{\vartheta_1}$ denote $N \times 1$ vectors of loadings, and assuming that both components are difference stationary and subject to autoregressive dynamics, we can write:

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

where $\phi(L)$ is an autoregressive polynomial of order p with stationary roots:

$$\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$$

and 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 $\boldsymbol{\Sigma}_{\eta^*} = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2)$. $\mathbf{X}_t$ contained deterministic components. The disturbances η_t and $\boldsymbol{\eta}_t^*$ are mutually uncorrelated at all leads and lags.

The lag polynomial $\boldsymbol{\vartheta}_0 + \boldsymbol{\vartheta}_1 L$ can also be rewritten as $\boldsymbol{\theta}_0 + \boldsymbol{\theta}_1\Delta$, where $\boldsymbol{\theta}_0 = \boldsymbol{\vartheta}_0 + \boldsymbol{\vartheta}_1$ and $\boldsymbol{\theta}_1 = -\boldsymbol{\vartheta}_1$. The measurement equation can thus be reparameterised as

$$\mathbf{y}_t = \boldsymbol{\theta}_0\mu_t + \boldsymbol{\theta}_1\Delta\mu_t + \boldsymbol{\mu}_t^* + \mathbf{X}_t\boldsymbol{\beta}. \tag{2}$$

The model postulates that each series, in differences, Δy_{it}, is composed of a mean term δ_i, an individual AR(p^*) process, $d_i(L)^{-1}\eta_{it}^*$, and a common AR(p) process, $\phi(L)^{-1}\eta_t$. Both μ_t and $\boldsymbol{\mu}_t^*$ are difference stationary processes and the common dynamics are the results of the accumulation of the same underlying shocks η_t; moreover, the process generating the index of coincident indicators is usually more persistent than a random walk and in the accumulation of the shocks produces cyclical swings.

Notice that (1) assumes a zero drift for the single index and a unit variance for its disturbances is also assumed. These identification restrictions can be removed at a later stage to enhance the

interpretability of the estimated common index.[2]

The next two subsections are more technical and can be skipped by the reader not interested in the estimation details. They concern the state space representation of the SW model, with the treatment of temporal aggregation, and the efficient implementation of the Kalman filtering and smoothing equations using the univariate state space representation of multivariate models proposed by Koopman and Durbin (2000).

3.2 State space representation

In this subsection we cast model (1) in the state space form (SSF). We start from the single index, $\phi(L)\Delta\mu_t = \eta_t$, considering the SSF of the stationary AR(p) model for the $\Delta\mu_t$, for which:

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

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

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

Hence, $\mu_t = \mu_{t-1} + \mathbf{e}'_{1p}\mathbf{g}_t = \mu_{t-1} + \mathbf{e}'_{1p}\mathbf{T}_{\Delta\mu}\mathbf{g}_{t-1} + \eta_t$, and defining

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

the Markovian representation of the model for μ_t becomes

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

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

A similar representation holds for each individual μ^*_{it}, with ϕ_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:

$$\mu^*_{it} = \mathbf{e}'_{1,p_i+1}\boldsymbol{\alpha}_{\mu_i,t}, \quad \boldsymbol{\alpha}_{\mu_i,t} = \mathbf{T}_i\boldsymbol{\alpha}_{\mu_i,t-1} + \mathbf{c}_i + \mathbf{H}_i\eta^*_{it},$$

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.

[2] We may alternatively restrict to unity one of the loadings in $\boldsymbol{\theta}_0$ and include a nonzero drift in the common index equation, provided we impose one linear constraint on $\boldsymbol{\beta}$.

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

$$\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}'_{\mu,t}, \boldsymbol{\alpha}'_{\mu_1,t}, \ldots, \boldsymbol{\alpha}'_{\mu_N,t}]'. \tag{3}$$

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

$$\mathbf{y}_t = \mathbf{Z}\boldsymbol{\alpha}_t + \mathbf{X}_t\boldsymbol{\beta}, \quad \boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \mathbf{W}\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t, \tag{4}$$

where $\boldsymbol{\epsilon}_t = [\eta_t, \eta^*_{1,t}, \ldots, \eta^*_{N,t}]'$ and the system matrices are given below:

$$\begin{aligned} &\mathbf{Z} = \left[\boldsymbol{\theta}_0, \vdots\, \boldsymbol{\theta}_1 \;\; \vdots\, \mathbf{0} \,\vdots\, \text{diag}(\mathbf{e}'_{p_1}, \ldots, \mathbf{e}'_{p_N})\right], \qquad \mathbf{T} = \text{diag}(\mathbf{T}_\mu, \mathbf{T}_1, \ldots, \mathbf{T}_N), \\ &\mathbf{H} = \text{diag}(\mathbf{H}_\mu, \mathbf{H}_1, \ldots, \mathbf{H}_N). \end{aligned} \tag{5}$$

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

The first $2N$ elements of the vector $\boldsymbol{\beta}$ are the pairs $\{(\mu_{01}, \delta_i, i = 1, \ldots, N\}$, the starting values at time $t = 0$ of the idiosyncratic components and the constant drifts δ_i.

The regression matrix $\mathbf{X}_t = [\mathbf{0}, \quad \mathbf{X}^*_t]$ where $\mathbf{X}^*_t$ is a $N \times k$ matrix containing the values of exogenous variables that are used to incorporate calendar effects (trading day regressors, Easter, length of the month) and intervention variables (level shifts, additive outliers, etc.), and the zero block has dimension $N \times 2N$ and corresponds to the elements of $\boldsymbol{\beta}$ that are used for the initialisation and other fixed effects.

The $2N + k$ elements of $\boldsymbol{\beta}$ are taken as diffuse.

For $t = 2, \ldots, n$ the matrix $\mathbf{W}$ is time invariant and selects the drift δ_i for the appropriate state element:

$$\mathbf{W} = \begin{bmatrix} \mathbf{0} \\ \text{diag}(\mathbf{C}_1, \ldots, \mathbf{C}_N) \end{bmatrix}, \mathbf{C}_i = [\mathbf{0}_{p_i+1,1} \vdots \mathbf{c}_i],$$

whereas $\mathbf{W}_1$

$$\mathbf{W}_1 = \begin{bmatrix} \mathbf{0} \\ \text{diag}(\mathbf{C}^*_1, \ldots, \mathbf{C}^*_N) \end{bmatrix}, \mathbf{C}^*_i = \begin{bmatrix} \mathbf{e}_{1,p_i+1} \vdots \mathbf{c}_i \end{bmatrix}.$$

3.3 Temporal aggregation and the Univariate treatment of multivariate models

Suppose that the set of coincident indicators, $\mathbf{y}_t$, can be partitioned into two groups, $\mathbf{y}_t = [\mathbf{y}'_{1,t}, \mathbf{y}'_{2,t}]'$, where the second block gathers the flows that are subject to temporal aggregation, so that

$$\mathbf{y}^*_{2\tau} = \sum_{i=0}^{\delta-1} \mathbf{y}_{2,\tau\delta-i}, \quad \tau = 1, 2, \ldots, [T/\delta], \tag{6}$$

where δ denote the aggregation interval: for instance, if the model is specified at the monthly frequency and $\mathbf{y}^\dagger_{2,t}$ is quarterly, then $\delta = 3$.

The strategy proposed by Harvey (1989) consists of operating a suitable augmentation of the state vector (3) using an appropriately defined cumulator variable. In our case, the SSF (4)-(10) need to be augmented by the $N_2 \times 1$ vector $\mathbf{y}_{2,t}^c$, generated as follows

$$\begin{aligned} \mathbf{y}_{2,t}^c &= \psi_t \mathbf{y}_{2,t-1}^c + \mathbf{y}_{2,t} \\ &= \psi_t \mathbf{y}_{2,t-1}^c + \mathbf{Z}_2\mathbf{T}\boldsymbol{\alpha}_{t-1} + [\mathbf{X}_{2,t} + \mathbf{Z}_2\mathbf{W}_t]\boldsymbol{\beta} + \mathbf{Z}_2\mathbf{H}\boldsymbol{\epsilon}_t \end{aligned} \tag{7}$$

where ψ_t is the cumulator variable, defined as follows:

$$\psi_t = \begin{cases} 0 & t = \delta(\tau - 1) + 1, \quad \tau = 1, \ldots, [n/\delta] \\ 1 & \text{otherwise} , \end{cases}$$

and $\mathbf{Z}_2$ is the $N_2 \times m$ block of the measurement matrix $\mathbf{Z}$ corresponding to the second set of variables, $\mathbf{Z} = [\mathbf{Z}_1', \ \mathbf{Z}_2']'$ and $\mathbf{y}_{2,t} = \mathbf{Z}_2\boldsymbol{\alpha}_t + \mathbf{X}_2\boldsymbol{\beta}$, where we have partitioned $\mathbf{X}_t = [\mathbf{X}_1' \quad \mathbf{X}_2']'$. Notice that at times $t = \delta\tau$ the cumulator coincides with the (observed) aggregated series, otherwise it contains the partial cumulative value of the aggregate in the seasons (e.g. months) making up the larger interval (e.g. quarter) up to and including the current one.

The augmented SSF is defined in terms of the new state and observation vectors:

$$\boldsymbol{\alpha}_t^* = \begin{bmatrix} \boldsymbol{\alpha}_t \\ \mathbf{y}_{2,t}^c \end{bmatrix}, \quad \mathbf{y}_t^\dagger = \begin{bmatrix} \mathbf{y}_{1,t} \\ \mathbf{y}_{2,t}^c \end{bmatrix} \tag{8}$$

where the former has dimension $m^* = m + N_2$, and the unavailable second block of observations, $\mathbf{y}_{2,t}$, is replaced by $\mathbf{y}_{2,t}^c$, which is observed at times $t = \delta\tau, \tau = 1, 2, \ldots, [n/\delta]$, and is missing at intermediate times. The measurement and transition equation are therefore:

$$\mathbf{y}_t^\dagger = \mathbf{Z}^*\boldsymbol{\alpha}_t^* + \mathbf{X}_t\boldsymbol{\beta}, \quad \boldsymbol{\alpha}_t^* = \mathbf{T}^*\boldsymbol{\alpha}_{t-1}^* + \mathbf{W}^*\boldsymbol{\beta} + \mathbf{H}^*\boldsymbol{\epsilon}_t, \tag{9}$$

with starting values $\boldsymbol{\alpha}_1^* = \mathbf{W}_1^*\boldsymbol{\beta} + \mathbf{H}^*\boldsymbol{\epsilon}_1$, and system matrices:

$$\mathbf{Z}^* = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N_2} \end{bmatrix}, \quad \mathbf{T}^* = \begin{bmatrix} \mathbf{T} & \mathbf{0} \\ \mathbf{Z}_2\mathbf{T} & \psi_t\mathbf{I} \end{bmatrix}, \quad \mathbf{W}^* = \begin{bmatrix} \mathbf{W} \\ \mathbf{Z}_2\mathbf{W} + \mathbf{X}_2 \end{bmatrix}, \quad \mathbf{H}^* = \begin{bmatrix} \mathbf{I} \\ \mathbf{Z}_2 \end{bmatrix} \mathbf{H}. \tag{10}$$

The state space model (9)-(10) 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 $\boldsymbol{\alpha}_t^*$ (see Harvey, 1989, and Shumway and Stoffer, 2000) and thus of the missing observations on $\mathbf{y}_{2,t}^c$ can be estimated, which need to be "decumulated", using $\mathbf{y}_{2,t} = \mathbf{y}_{2,t}^c - \psi_t\mathbf{y}_{2,t-1}^c$, so as to be converted into estimates of $\mathbf{y}_{2,t}$. In order to provide the estimation standard error, however, the state vector must be augmented of $\mathbf{y}_{2,t} = \mathbf{Z}_2\boldsymbol{\alpha}_t + \mathbf{X}_2\boldsymbol{\beta} = \mathbf{Z}_2\mathbf{T}\boldsymbol{\alpha}_{t-1} + [\mathbf{X}_2 + \mathbf{Z}_2\mathbf{W}]\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t$.

The estimation of multivariate dynamic factor model of this sort can be numerically complex. We solve this issue by using a univariate statistical treatment. This was first considered by Anderson and Moore (1979) and provides a very flexible and convenient device for filtering and

smoothing and for handling missing values. Our treatment is prevalently based on Koopman and Durbin (2000). However, for the treatment of regression effects and initial conditions we adopt the augmentation approach by de Jong (1991).

The multivariate vectors $\mathbf{y}_t^\dagger$, $t = 1, \ldots, n$, where some elements can be missing, are stacked one on top of the other to yield a univariate time series $\{y_{t,i}^\dagger, i = 1, \ldots, N, t = 1, \ldots, n\}$, whose elements are processed sequentially.

The state space model for the univariate time series $\{y_{t,i}^\dagger\}$ is constructed as follows. The measurement equation for the i-th element of the vector $\mathbf{y}_t^\dagger$ is:

$$y_{t,i}^\dagger = \mathbf{z}_i^{*'} \boldsymbol{\alpha}_{t,i}^* + \mathbf{x}_{t,i}' \boldsymbol{\beta}, \quad t = 1, \ldots, n, \;\; i = 1, \ldots, N, \tag{11}$$

where $\mathbf{z}_i^{*'}$ and $\mathbf{x}_{t,i}'$ denote the i-th rows of $\mathbf{Z}^*$ and $\mathbf{X}_t$, respectively. When the time index is kept fixed the transition equation is the identity: $\boldsymbol{\alpha}_{t,i}^* = \boldsymbol{\alpha}_{t,i-1}^*, i = 2, \ldots, N$, whereas, for $i = 1$, $\boldsymbol{\alpha}_{t,1}^* = \mathbf{T}_t^* \boldsymbol{\alpha}_{t-1,N}^* + \mathbf{W}^* \boldsymbol{\beta} + \mathbf{H}^* \boldsymbol{\epsilon}_{t,1}$. The state space form is completed by the initial state vector which is $\boldsymbol{\alpha}_{1,1}^* = \mathbf{W}_1^* \boldsymbol{\beta} + \mathbf{H}^* \boldsymbol{\epsilon}_{1,1}$, where $\text{Var}(\boldsymbol{\epsilon}_{1,1}) = \text{Var}(\boldsymbol{\epsilon}_{t,1}) = \text{diag}(1, \sigma_1^2, \ldots, \sigma_N^2) = \boldsymbol{\Sigma}_\epsilon$.

Details on the augmented Kalman filter for this representation, taking into account the presence of missing values, and the computer programs are available upon request. Basically, maximum likelihood estimation is carried out by a quasi-Newton algorithm, such as the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. The smoothed estimates, and thus the disaggregate values of the GDP components are obtained from the augmented smoothing algorithm proposed by de Jong (1988), appropriately adapted to handle missing values.

3.4 The advantages of the dynamic factor approach

The dynamic factor model framework has several appealing features. First and foremost, it rationalises the practice of statistical offices which amounts to summarising the available indicators into a unique index (a weighted average, if a priori weights are available, or a statistical summary achieved through the use of static principal components analysis, or a simple combination with weights that are inversely proportional to the volatility of each indicator). The common indicator would then be smoothed and corrected for outliers and structural breaks. In our approach all these operations are carried out simultaneously in a model based framework, and the common factor extracts the dynamics that are common to the indicators and that are relevant for the disaggregation of the quarterly flows.

Finally, it has the flexibility of handling seasonal effects, calendar components and other effects affecting the level of the series (additive outliers, level shifts, etc.) simultaneously; in the regression approach typically adopted by statistical institutes these operations are carried out as preliminary corrections, which makes the disaggregation exercise more elaborate and less internally consistent.

It should be noticed that the dynamic factor model formulated in the previous section is such that each of the component series is integrated of order 1, or $I(1)$, and there is no cointegration

among the series, unless more than one of the idiosyncratic variances were equal to zero. Under such circumstances, there exists a dynamic linear combination that is stationary. On the contrary, static cointegration is ruled out by the formulation of the model. Another way in which dynamic cointegration may arise is when the representation adopted for the idiosyncratic component is a stationary ARMA process. The original formulation of the model of coincident indicators by Stock and Watson specified an $I(1)$ idiosyncratic component; the presence of cointegration was explicitly ruled out by pretesting. In our case, there are no theoretical and empirical arguments for assuming that, say, retail turnover, new car registrations and value added of the branch *Trade, transport and communication services* are cointegrated. Moreover, the fact that we estimate the model in levels makes the issue of cointegration less relevant. Additional evidence in favour of our no cointegration assumption is reported in the Appendix.

Finally, it should be stressed, perhaps, that the dynamic factor model with idiosyncratic ARIMA(1,1,0) dynamics is an unobserved components version of the Litterman (1983) model, where the common index μ_t summarises the information that is common to a set of indicators. The ARIMA(1,1,0) specification is too rich for the quarterly temporally aggregated GDP series; essentially, this is so because the AR parameter is difficult to identify (see Proietti (2006a) on this point). Therefore, we will constrain the AR parameter to be equal to 0, so that effectively we use a random walk specification for the idiosyncratic component of the temporally aggregated series. It must nevertheless be kept in mind that the monthly indicators are endogenous, which is another desirable feature of our approach.

4 Chain-linking and temporal disaggregation

The disaggregation methods exposed in the previous section are applied to the quarterly chained volume measures of sectoral output and expenditure components produced by Eurostat. Currently the available series feature the year 1995 as the common reference year. Since we disaggregate the individual components of GDP, we need to form a monthly GDP estimate that is consistent with the Eurostat quarterly official figure. Due to chain linking, we cannot simply, say, sum up the value added of the sectors to obtain GDP at basic prices, as the resulting figure would fail to satisfy the temporal aggregation constraints.

The euro area member states chain-link the quarterly data on an annual basis, i.e. the quarterly volume measures are expressed at the average prices of the previous years. Two alternative techniques are applied for annual chain-linking of quarterly data by the member **states**: one quarter overlaps (Austria) and annual overlaps (other countries). These are described in Bloem, et al. (2001, chapter IX); the annual overlap technique, which implies compiling estimates for each quarter at the weighted annual average prices of the previous year, has the advantage of producing quarterly volume estimates that add up exactly to the corresponding annual aggregate. The annual overlap technique is also the method used by Eurostat in the imputation of the chain-linked volume

measures of those countries for which no quarterly data at previous year's prices are available.

As it is well known, chain-linking results in the loss of cross-sectional additivity (if the one quarter overlap is used also temporal additivity is lost and benchmarking techniques have to be employed in order to restore it). 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.

These facts motivate the choice of a multistep procedure for the estimation of monthly GDP at basic and market prices, which is advocated, e.g., also by the IMF (see Bloem et al., 2001). It is described in the sequel.

Let us index the month of the year by $j, j = 1, \ldots, 12$, and the year by m, $m = 1, \ldots, M = [n/12]$, so that the time index is written $t = j + 12m, t = 1, \ldots, n$. We are interested in estimating the monthly values of GDP at basic and market prices, which are, respectively, the sum of the value added of the six branches, and this sum plus taxes less subsidies (or the sum of expenditure components), by aggregating the monthly estimates of sectoral value added and expenditure components. If the estimates were expressed at current prices, then no consistency problem would arise, as the monthly disaggregated estimates would be perfectly additive.

For a particular component of GDP let us denote by y_{jm} the value at current prices of month j in year m, $y_{.m} = \sum_j y_{jm}$ the annual total, $\bar{y}_m = y_{.m}/12$ the annual average. The chain-linked volume estimate with reference year b (the year 1995 in our case) will be denoted $y_{jm}^{(b)}$. The temporal disaggregation methods described in the previous section are applyed to the quarterly chained-linked volume series with reference year b and yield estimates that add up to the quarterly and annual totals (temporal consistency), but are not additive in a horizontal (that is cross-sectional) sense.

The following multistep procedure enables the computation of volume measures expressed at the prices of the previous year that are additive.

1. Transform the monthly estimates into Laspayres type quantity indices with reference year b (volumes are evaluated at year b average prices), by computing

$$I_{jm}^{(b)} = \frac{y_{jm}}{y_{.b}}, j = 1, \ldots, 12, m = 1, \ldots, M,$$

   where the denominator is the annual total of year b at current prices. In our case $b = 1$ (year 1 is the calendar year 1995).

2. Change the reference year to $m = 2$, the second year of the series (1996 in our case), by computing:

$$I_{jm}^{(2)} = \frac{I_{jm}^{(b)}}{\bar{I}_2^{(b)}}, j = 1, \ldots, 12, m = 1, \ldots, M,$$

   where $\bar{I}_2^{(b)} = \sum_j I_{j2}^{(b)}/12$ is the average quantity index for year 2.

3. Transform the quantity indices for year $m = 2, 3 \ldots, M$, into indices with reference year $m-1$ (the previous year), by rescaling $I_{jm}^{(2)}$ as follows:

$$I_{jm}^{(m-1)} = \frac{I_{jm}^{(2)}}{\bar{I}_{m-1}^{(2)}}, j = 1, \ldots, 12, m = 2, \ldots, M,$$

where

$$\bar{I}_{m-1}^{(2)} = \begin{cases} \frac{1}{12}\sum_j I_{j,m-1}^{(2)}, & m = 3, \ldots, M \\ \frac{y_{.2}^{(b)}}{y_{.b}}, & m = 2 \end{cases}$$

4. Compute the series at the average prices of the previous year as:

$$y_{jm}^{(m-1)} = I_{jm}^{(m-1)} \bar{y}_{m-1}, \quad j = 1, \ldots, 12, m = 2, \ldots, M,$$

5. *Aggregation step*: the values $y_{i,jm}^{(m-1)}$ for the i-th component series (the index $i = 1, \ldots, N$ was omitted in the previous steps for notation simplicity) are additive and can be summed up to produce the aggregate GDP measure,

$$Y_{jm}^{(m-1)} = \sum_{i=1}^{N} y_{i,jm}^{(m-1)}, \quad j = 1, \ldots, 12, m = 2, \ldots, M.$$

6. *Chain-linking* (annual overlap):

   (a) Convert the aggregated volume measures into Laspeyres-type quantity indices with respect to the previous year:

   $$\mathcal{I}_{jm}^{(m-1)} = \frac{Y_{jm}^{(m-1)}}{\bar{Y}_{m-1}}, \quad j = 1, \ldots, 12, m = 2, \ldots, M,$$

   where $\bar{Y}_{m-1} = \sum_j Y_{j,m-1}/12$ is the average GDP of the previous year at current prices.

   (b) Chain-link the indices using the recursive formula (the first year is the reference year):

   $$\mathcal{I}_{jm}^{(1)} = \mathcal{I}_{jm}^{(m-1)} \bar{\mathcal{I}}_{m-1}^{(b)}, \quad j = 1, \ldots, 12, m = 2, \ldots, M,$$

   where

   $$\bar{\mathcal{I}}_{m-1}^{(1)} = \frac{1}{12}\sum_j \mathcal{I}_{j,m-1}^{(b)}.$$

   (c) If $b > 1$ then change the reference year to year b:

   $$\mathcal{I}_{jm}^{(b)} = \frac{\mathcal{I}_{jm}^{(1)}}{\bar{\mathcal{I}}_b^{(1)}} \quad j = 1, \ldots, 12, m = 2, \ldots, M.$$

   (This is not needed in our case, since $b = 1$).

(d) Compute the chain-linked volume series with reference year b:

$$Y_{jm}^{(b)} = \mathcal{I}_{jm}^{(b)} \bar{Y}_b \quad j = 1, \ldots, 12, m = 2, \ldots, M,$$

where $\bar{Y}_b = \frac{1}{12} \sum_j Y_{jb}$ is the value of GDP (at basic or market prices) at current prices of the reference year.

The multistep procedure just described enables to obtain estimates of monthly GDP in volume such that the values $Y_{jm}^{(m-1)}$ expressed at the average prices of the previous year add up to their quarterly and annual totals published by Eurostat and to sum of the values of the component series. Moreover, the chain-linked volumes $Y_{jm}^{(b)}$ with reference year b are temporally consistent (they add up to the quarterly and monthly totals published by Eurostat for the GDP), but are not horizontally consistent (cross-sectional additivity cannot be retained).

5 Empirical results: temporal disaggregation of GDP

The estimates of monthly value added and GDP presented in this Section cover the sample period January 1995 – December 2006, where model specification and estimation are based on data up to the third quarter of 2006. Therefore, the last three monthly estimates, concerning the fourth quarter of 2006, can be considered as genuine out of sample forecasts, whereas the estimates for September 2006 can be considered as "nowcasts", as they exploit the preliminary Eurostat estimate of quarterly value added for the third quarter of GDP and the timely monthly indicators (industrial production, turnover, and so forth).

Two important model specification issues concern whether or not we should assume cointegration between the temporally aggregated flow and the indicator variables, and whether or not we should apply the logarithmic transformation to GDP. As mentioned, the Appendix provides evidence in favour of not imposing cointegration, and also of working with the raw data rather than logs. Maintaining these two assumptions, the estimation of GDP at market prices is carried out both from the output side (first subsection) and the expenditure side (second subsection). Regressors accounting for calendar effects (trading days, Easter and length of the month) were included in the equations to provide working day adjustment. We also report results for each of the output sectors and demand components, which can be of interest by themselves.

The results from the output and demand sides are later balanced by combining the estimates using optimal weights (third subsection). Finally, a truly real time implementation and evaluation is conducted for 2007 (fourth subsection).[3]

[3] All the algorithms and procedures used in the paper are implemented in Ox, the matrix programming language by Doornik (2001), version 3.3

5.1 The output side

The smoothed estimates of the coincident index, μ_t, and of monthly value added are presented in figure 1, along with their 95% confidence interval. In the same plot we report also the original quarterly value added series while the maximum likelihood estimates of the parameters of the model are presented in table 3.

According to the NACE classification the GDP at basic price is obtained by summing up the following branch of activities:A–B: Agriculture, hunting, forestry and fishing; C–D–E: Industry, incl. Energy; F: Construction ; G–H–I: Trade, transport and communication services; J–K: Financial services and business activities; L–P: Other services.

As mentioned before the branch Agriculture is characterised by the lack of coincident indicators available at the monthly frequency. We thus proceeded to the temporal disaggregation of the value added at constant prices according to the Fernàndez (1981) method, i.e. assuming a random walk with constant drift for the unobserved underlying monthly series.

As far as Industry is concerned six monthly indicators are selected. Among them three are quantitative indicators - the index of industrial production, employment and hours worked- and the remaining three are business survey indicators compiled in the form of balances of opinions by the European Commission- the industrial confidence indicator, the production trend observed in recent months and the assessment of order book levels.

For the quantification of surveys and their role in econometric analysis see Pesaran and Weale (2007). We found their inclusion in the dynamic factor model and thus in the disaggregation of value added problematic, as we argument below, and we propose to investigate the issue further in future research.

Business surveys are supposed to be stationary (see also the evidence arising from stationarity tests in Proietti and Frale, 2007), so that we can postulate a relationship only with the changes in the coincident index, $\Delta\mu_t$, plus a further idiosyncratic stationary component. As a consequence, survey variables have been included in our models in integrated form so as to preserve the level specification of the regression and the dynamic factor models.

The SW dynamic factor model was estimated for the seven series, the six monthly indicators plus quarterly value added, by specifying an AR(2) process for the common component $\Delta\mu_t$ and the idiosyncratic components of the monthly indicators. For value added, the idiosyncratic component is formulated as a random walk with drift. This restricted specification is motivated by the fact that there are identification problems of the kind that have been discussed by Proietti (2006a) with reference to the Litterman model, which affect the estimation of autoregressive effects.

The estimation results are such that the common factor μ_t is driven mostly by the business survey variables, which dominate in variation the other quantitative variables. Moreover, the factor loading of industry's value added is not significant.

When the business survey indicators are removed from the analysis, the estimation results are much more satisfactory as the common factor is strongly related to the dynamics of industrial

production and value added. Therefore, after some additional experimentation, we focused on a trivariate model with two monthly indicators - Industrial production and hours worked- and the quarterly value added. For hours worked we also considered the possibility of a lagged relationship with the common factor, which however did not result significant.

As well as for Industry, for the Constructions sector six candidate monthly indicators were selected (see table 1) and two business survey indicators (Construction Confidence Indicator and Trend of activity over recent months). However, survey data were dismissed after a preliminary analysis, for similar reasons to those exposed about Industry: essentially when they are included in the SW factor model, they drive the common factor so that value added does not load significantly on the common factor and it is fully idiosyncratic.

The main evidence is that the index of production in construction is highly significant. Value added presents sharp drops at the beginning of the sample, in correspondence to January and February. These are well reflected in the indicators, in particular the index of production and hours worked and thus there is no need for particular interventions. The SW dynamic factor model was estimated for a five variable system consisting of production in constructions, building permits, employment, hours worked and value added.

It is interesting to notice (see table 3) that all the variables, including value added, load significantly on the common factor, except for building permits.

The third branch of activity- Trade, transport and communication services- accounts for about 22% of total value added at constant prices. It includes wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods; hotels and restaurants; transport, storage and communication. While for industry and construction it is possible to find a very good indicator of value added, the production index, the relationship with the monthly indicators becomes more blurred for this sector.

Seven indicators were considered, see table 1, and after preliminary analysis based among others on Fernàndez univariate method, the SW dynamic factor model was formulated as a trivariate system including the industrial production index for consumption goods, the number of registered cars (both available at the monthly frequency) and value added (quarterly).

Value added loads significantly on the coincident single index. The coincident index, plotted in figure 1, is highly coherent with the same index estimated for the industry sector.

For the branch of financial intermediation, real estate, renting and business activities, we select two monthly indicators, which are provided by the European Central Bank, and that measure the liabilities and the loans of the monetary and financial institution. Both series were deflated using the harmonised consumer price index. Two intervention variables were included so as to account for a level shift in the January 2001, presumably due to the fact that the previous data referred to 11 countries excluding Greece.

The estimation results for the trivariate dynamic factor model are reported in table **??**. The loading of value added on the common factor is not significant and most variation is captured by

the idiosyncratic random walk.

Nevertheless, the monthly disaggregated estimates of monthly value added appear to be very reliable (see Figure 1).

Finally, the last branch of NACE classification (labelled L-P) gathers a variety of economic activities (public administration and defence, compulsory social security; education; health and social work; other community, social and personal service activities; private households with employed persons) for which it is not easy to find reliable and timely monthly indicators of value added. For our disaggregation exercise we tried several macroeconomic aggregates related to the state of the economy, such as the unemployment rate, the index of industrial production. We ended up selecting a single monthly indicator, the total amount of debt securities issued by central government, deflated by the harmonised consumer price index.

5.2 The Expenditure side

So far we have dealt with the disaggregation of GDP into branch of activities. Nevertheless, the quarterly value added might be obtained from the main National account identity: GDP (market prices) = Final consumption expenditure + Gross capital formation + External balance. Final consumption expenditure is made up of households and non-profit institutions serving households expenditure, as well as government expenditure. While for the latter no monthly indicator is available, for private consumption the most plausible indicators are those referring to the final demand, among which we select retail trade and new cars registration. The index of industrial production for consumer goods may also provide useful information. Furthermore, we include in the set of indicators some soft variables from Consumer Surveys, such as the confidence indicator, the assessment of the financial situation, and price trend, to capture economic agents expectations and feelings. The specification adopted for the coincident indicator and the idiosyncratic components is AR(1), rather than AR(2), which produces smoother estimates. Both indicators and the national accounts aggregate load positively and significantly on the coincident index. On the contrary, the loading coefficient of the survey variables was not significant. This motivated the use of only car registration and retail trade as regressors in the final model, whose estimation results are presented in table 4 and in Figure 2.

Gross capital formation is mainly the result of investments in the industry and construction sectors. The monthly indicators preliminary selected featured industrial production, also for capital goods, building permits and the survey variables listed in Table 2.

As well as in former exercises, we tentatively conclude that survey data do not play a significant role, whereas the general industrial production index resulted strongly significant. The coincident index is specified as an AR(1) process as in the case of final consumption.

As far as the external balance is concerned, we first point out that quarterly imports and exports have to be disaggregated separately since the chain-linking mechanism cannot be performed directly on variables that can take both negative and positive values.

As indicators we use the monthly volume indices of Imports and Exports produced by Eurostat; these are published with a delay of more than 40 days. We also include the real exchange rate of the euro, and survey variables concerning orders (internal and external demand). From a preliminary Fernàndez model we obtained that volume monthly indexes, Exchange Rate and industrial production for intermediate goods are significant, while in the SW dynamic model, Exchange Rate looses its explanatory power. Survey data are not relevant in both univariate and multivariate models. We also consider some quarterly information from the Business Survey questionnaire, in particular the questions about production capacity and export expectations. Unfortunately neither helped in estimating the coincident index. We ended up to a model with only two indicators- volume index and industrial production of intermediate goods- whose results are listed in table 4 and shown in Figure 2.

To conclude, it is worth to comment upon "Taxes less subsidies on products". This aggregate is the gap between the GDP at market price, obtained by the expenditure side, and the value added at basic price, computed from the output side. The temporal disaggregation of Taxes less subsidies at chained 1995 prices was carried out using a trivariate dynamic factor model for monthly industrial production, deflated turnover and quarterly Taxes less subsidies. The latter does not load significantly on the monthly indicators and thus the disaggregation method is not different from the Fernàndez univariate method with a constant drift.

5.3 Monthly gross domestic product

The estimation of the monthly indicator of the Euro area GDP at basic and market prices was carried out using the methodology outlined in section 4. The components series (the estimated monthly sectoral value added and taxes less subsidies, the estimated expenditure components), expressed as chain-linked volume with reference year 1995, were de-chained and expressed at the average prices of the previous year, and then contemporaneously aggregated. The corresponding GDP measures are fully additive and are later chain-linked to express the volume measure with a common reference year, which is 1995.

As it is well known, as a result of chain-linking the GDP estimates fail to be additive in a horizontal sense. Thus, the sum of components (for the six branches, or expenditure components) differs from GDP at basic prices and market prices, respectively. However, the discrepancy is very small.

As far as the standard errors are concerned, these are obtained as the square root of the sum of the estimation error variances of the individual components time series, made available by the Kalman filter and smoother. Strictly speaking they do not represent the estimation standard errors for GDP at basic and market prices, as the latter arises from the elaborate procedure described in section 4. The latter involves a sequence of multiplicative transformations, which makes the computation of the standard errors prohibitive. Nevertheless, the statistical discrepancy is negligible because it never overcomes 0.1%.

Figure 3 plots the percent coefficient of variation of the estimates (100 times the standard error relative to the GDP estimate) both from the output side and from the demand side for 2006. This increases rapidly for the last three estimates, which concern the last quarter of 2006 and, as mentioned, constitute out of sample predictions. The right top graph of each panel is a fan plot of the level of GDP at market prices, and the two subsequent plots show the point estimates and the 95% interval estimates of the monthly and yearly growth rates.

The estimates of GDP at market prices from the expenditure side are slightly more volatile and are characterised by a higher estimation error variance. Their quarterly sum is nevertheless equal to that obtained from the disaggregated estimates from the output side.

The two estimates, obtained respectively from the output side, here denoted Y_t^o, and from the expenditure side, Y_t^e, are combined with time-invariant weights $w_o = 0.88$ and $w_e = 0.12$, $0 < w_o < 1$ and $w_e = 1 - w_o$, so as to form the estimate

$$Y_t^c = w_o Y_t^o + w_e Y_t^e. \tag{12}$$

If S_t^{2o} and S_t^{2e} denote respectively the estimation error variance of the output and expenditure estimates, then w_o is the sample average of the relative precision of the output estimates, namely,

$$w_o = \frac{1/S_t^{2o}}{1/S_t^{2o} + 1/S_t^{2e}}. \tag{13}$$

The combined estimates, with standard error $(w_o^2 S_t^{2o} + w_e^2 S_t^{2e})^{1/2}$ are obviously more precise than the individual estimates Y_t^o and Y_t^e. The percent reduction in variance with respect to Y_t^o is about 12%. Finally, the combined estimates of the level of GDP and its monthly and annual growth are displayed in figure 4, along with their approximate 95% confidence region.

5.4 Revisions

Macroeconomic data published by Eurostat are revised every time a new observation is released. As a consequence, also our estimates are subject to the revision process. In figure 5 we report the estimates of monthly GDP as obtained running the model for all months in the year 2007. It is quite visible that the more relevant change in the estimates occurs when a new observation for the quarterly GDP is published, or in the third month of the quarter. Altogether, the estimates are characterised by a high degree of reliability.

There are two different source of variability affecting our results. First, the revision of the monthly indicators as well as of the quarterly GDP, which is a source of uncertainty completely outside our control. Second, every time the model is run to produce an additional estimate the parameters are re-estimated according to the new information set. A rough attempt to split those two effects is to compare the results obtained by running the model with fixed parameter and using the real time data. In Figure 6 we show the percentage discrepancy between the estimates with fixed parameters and time varying parameters, i.e., reestimated as a new observation becomes

available. Apart from February, whose pattern is idiosyncratic, the evidence is in line with the above conclusions, namely that the most relevant changes in the estimates occur when quarterly GDP is released. This suggests that variability in our results is mainly driven by the revisions of the information set, rather than by the estimation process.

The total monthly GDP is obtained combining the estimates from the expenditure and output side, according to their relative precision. It is worth to analyze the contribution of each sectors/components to the final uncertainty, as plotted in figure 8 and 7. It is evident that standard errors are basically stable month by month, and therefore the period in which the model is run does not affect the composition of uncertainty of the estimates. Among sectors, the highest volatility is found in the services sector, which is also broadly considered one of the most difficult to estimate. Among components of expenditure, the biggest contribution to the final GDP uncertainty is due to Gross fixed capital formation. When nowcast observations are added, the feature does not change: the total level of uncertainty increases, but the relative position of sectors and components of expenditure remains the same.

6 Conclusions

In this paper we have presented a monthly indicator of Euro area gross domestic product, based prominently on an extension of the Stock and Watson (1991) dynamic factor model of coincident indicators. We have proposed a multivariate approach that alleviates the drawbacks of univariate treatments.

The model is cast in state space form and a convenient statistical treatment is carried out to handle mixed frequency data -monthly and quarterly- and the temporal constraint -the quarterly GDP is the sum over three consecutive monthly values. In addition, a suitable procedure to compute the chain-linked values for the total GDP at market price is presented.

The application of the model to the sectoral data is satisfactory and as a by-product we obtain estimates of monthly sectoral value added, which can in turn be aggregated into an estimate of gross domestic product. The disaggregation exercise is also conducted on the expenditure side. The estimates from this approach are less reliable, due to the higher volatility of national accounts aggregate such as gross capital formation and exports and imports. The greater sectional disaggregation and the relative stability of output of industry and services provides an explanation for the greater precision of the output side estimates. The combination of the estimates obtained from the two approaches, with weights reflecting their relative precision, leads to a more accurate final estimate of monthly GDP.

We also present a set of post-estimation diagnostics, focusing on the contribution of sectors and components to the total precision of the monthly GDP estimates, and on the impact of data revisions for the indicators.

One of the benefits of our approach is that approximate measures of reliability concerning the

estimated levels and growth rates of the indicator of monthly GDP are available. Furthermore, by using the Kalman filter we solve endogenously the problem of the unbalanced sample due to different delay of released data, and we can handle data irregularities in a unified framework.

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

Label	*Quarterly Aggregate*	*Label*	*Monthly Indicators*	*Delay*
A–B	Agriculture, hunting and fishing			
C–D–E	Industry, incl. Energy			
		prod	Monthly production index (CDE)	45
		empl	Number of persons employed	70
		howk	Volume of work done (hours worked)	60
		EA99	Industrial Confidence Indicator (Dg Ecfin)	15
		EA.1	Production trend observed in recent months (Dg Ecfin)	15
		EA.2	Assessment of order-book levels (Dg Ecfin)	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 (Dg Ecfin)	15
		EA.1	Trend of activity over recent months (Dg Ecfin)	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 (Dg Ecfin)	15
		EA.1	Business activity over recent months (Dg Ecfin)	15
		EA.2	Assessment of stocks (Dg Ecfin)	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 (A6)			
	Taxes less subsidies on products			
		prod	Monthly production index (CDE)	45
		tovv	Index of deflated turnover	35

Table 2: Monthly indicators employed for the disaggregation of GDP from expenditure side

Label	*Quarterly Aggregate*	*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 (Dg Ecfin)	15
		EA.1	Financial situation (Dg Ecfin)	15
		EA.3	General Economic situation(Dg Ecfin)	15
		EA.5	Price trends (Dg Ecfin)	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_F	Construction Confidence Indicator (Dg Ecfin)	15
		EA.1_F	Assessment of order in construction (Dg Ecfin)	15
		EA99	Industrial Confidence Indicator (Dg Ecfin)	15
		EA.1	Production trend observed in recent months (Dg Ecfin)	15
		EA.2	Assessment of order-book levels (Dg Ecfin)	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.3	Assessment of export order-book levels (CDE) (Dg Ecfin)	15
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 export order-book levels (CDE) (Dg Ecfin)	15

Table 3: Output side: parameter estimates and asymptotic standard errors, when relevant

C-D-E-INDUSTRY

Parameters	*prod*	*howk*	*Value added*
θ_{i0}	0.576	0.191	0.708
	(0.119)	(0.064)	(0.191)
θ_{i1}		0.000	
		(0.054)	
δ_i	0.317	-0.153	0.186
	(0.073)	(0.028)	(0.040)
d_{i1}	-0.664	-0.295	
d_{i2}	-0.305	-0.078	
σ_{η^*}	0.160	0.077	0.001
$\left(1+0.394L+0.104L^2\right)\Delta\mu_t=\eta_t, \quad \eta_t \sim N\left(0,1\right)$			

F-CONSTRUCTIONS

Parameters	*c_pro_m*	*Building permits*	*empl*	*howk*	*Value added*
θ_{i0}	2.371	-0.168	0.207	1.290	0.436
	(0.315)	(0.607)	(0.051)	(0.277)	(0.071)
θ_{i1}			-0.095	-0.080	
			(0.028)	(0.158)	
δ_i	0.149	-0.086	0.015	-0.188	0.022
	(0.313)	(0.308)	(0.014)	(0.103)	(0.023)
d_{i1}	-0.831	-0.224	0.453	-0.313	
d_{i2}	-0.770	-0.341	0.256	0.069	
σ_{η^*}	0.540	3.607	0.162	0.760	0.097
$\left(1+0.496L+0.191L^2\right)\Delta\mu_t=\eta_t, \quad \eta_t \sim N\left(0,1\right)$					

GHI-TRADE AND COMMUNICATIONS

Parameters	*prod_cons*	*car_reg*	*Value added*
θ_{i0}	0.286	1.014	0.536
	(0.140)	(0.596)	(0.114)
δ_i	0.104	0.173	0.211
	(0.064)	(0.263)	(0.031)
d_{i1}	-0.462	-0.430	
σ_{η^*}	0.700	2.939	0.001
$\left(1+0.462L\right)\Delta\mu_t=\eta_t, \quad \eta_t \sim N\left(0,1\right)$			

JKI-FINANCIAL SERVICES

Parameters	*M3*	*Loans*	*Value added*
θ_{i0}	0.182	0.198	0.059
	(0.022)	(0.033)	(0.068)
θ_{i1}			θ_{i1}
δ_i	0.348	0.064	0.275
	(0.047)	(0.012)	(0.035)
d_{i1}	-0.357	0.441	
d_{i2}	-0.457	0.324	
σ_{η^*}	0.093	0.123	0.399
$\left(1-0.301L-0.101L^2\right)\Delta\mu_t=\eta_t, \quad \eta_t \sim N\left(0,1\right)$			

LP-OTHER SERVICES

Parameters	*Debt*	*Value added*
θ_{i0}	0.137	0.023
	(0.009)	(0.024)
θ_{i1}	0.022	
		(0.045)
δ_i	0.077	0.125
	(0.012)	(0.011)
d_{i1}	0.970	
d_{i2}	-0.987	
σ_{η^*}	0.008	0.123
$\left(1+0.005L-0.031L^2\right)\Delta\mu_t=\eta_t, \quad \eta_t \sim N\left(0,1\right)$		

Note: standard errors in parenthesis.

Table 4: Expenditure side: parameter estimates and asymptotic standard errors, when relevant

CONSUMPTION				**INVESTMENTS**			
Parameters	*prod_cons*	*tovv*	*Value added*	*Parameters*	*prod*	*c_prod_m*	*Value added*
θ_{i0}	1.526	0.481	1.155	θ_{i0}	0.362	0.869	1.850
	(0.540)	(0.162)	(0.219)		(0.134)	(0.432)	(0.331)
δ_i	0.188	0.179	0.631	δ_i	0.215	0.064	0.244
	(0.256)	(0.067)	(0.067)		(0.060)	(0.208)	(0.108)
d_{i1}	-0.414	-0.490		d_{i1}	-0.382	-0.485	
σ_{η^*}	2.661	0.626	0.0004	σ_{η^*}	0.618	2.301	8.74e-005
$(1-0.461L)\,\Delta\mu_t = \eta_t, \quad \eta_t \sim N(0,1)$				$(1-0.454L)\,\Delta\mu_t = \eta_t, \quad \eta_t \sim N(0,1)$			
IMPORTS				**EXPORTS**			
Parameters	*Mimp*	*prod_int*	*Value added*	*Parameters*	*Mexp*	*prod_int*	*Value added*
θ_{i0}	1.185	0.681	1.923	θ_{i0}	0.915	0.806	1.434
	(0.296)	(0.173)	(0.616)		(0.189)	(0.177)	(0.546)
δ_i	0.512	0.220	0.863	δ_i	0.380	0.216	0.874
	(0.163)	(0.087)	(0.130)		(0.084)	(0.090)	(0.153)
d_{i1}	-0.507	-0.375		d_{i1}	-0.078	-0.348	
σ_{η^*}	1.448	0.786	0.686	σ_{η^*}	0.647	0.676	1.443
$(1-0.404L)\,\Delta\mu_t = \eta_t, \quad \eta_t \sim N(0,1)$				$(1-0.318L)\,\Delta\mu_t = \eta_t, \quad \eta_t \sim N(0,1)$			

Note: standard errors in parenthesis.

Figure 1: Quarterly National Account, Monthly estimates with standard errors and Coincident Index- Output approach.

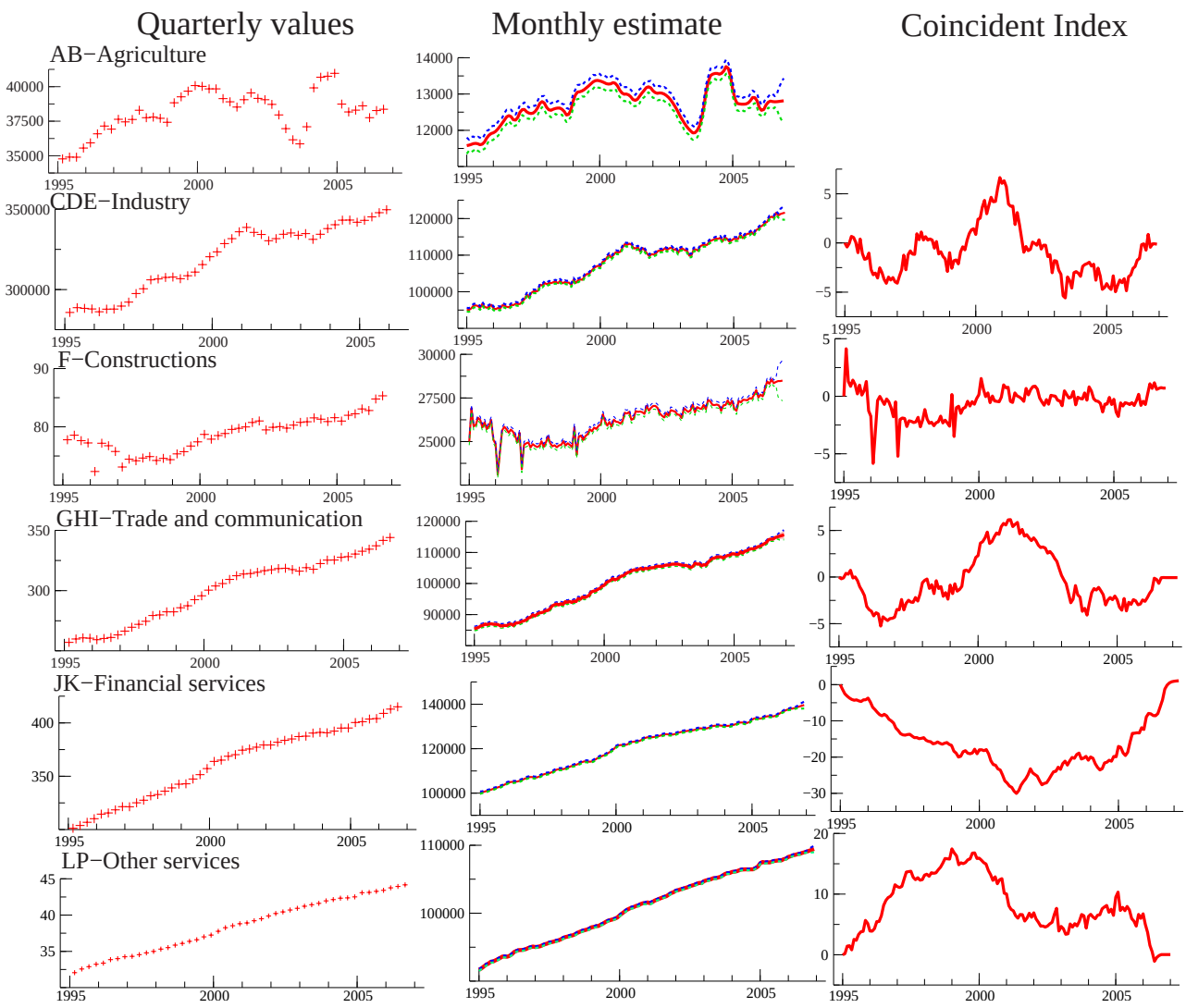


Figure 2: Quarterly National Account, Monthly estimates with standard errors and Coincident Index- Expenditure approach.

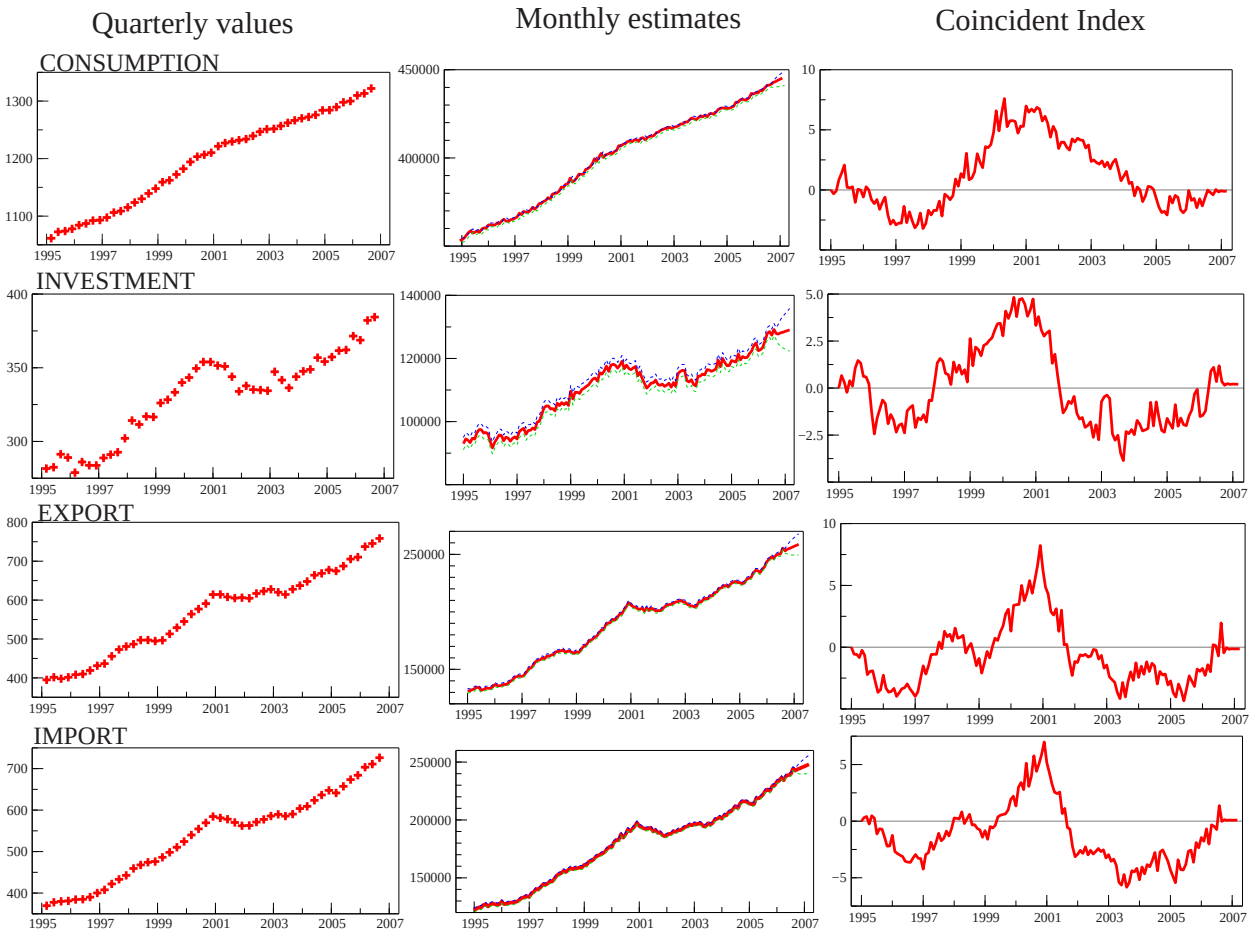


Figure 3: Monthly gross domestic product estimates for the Euro Area (eurozone12)

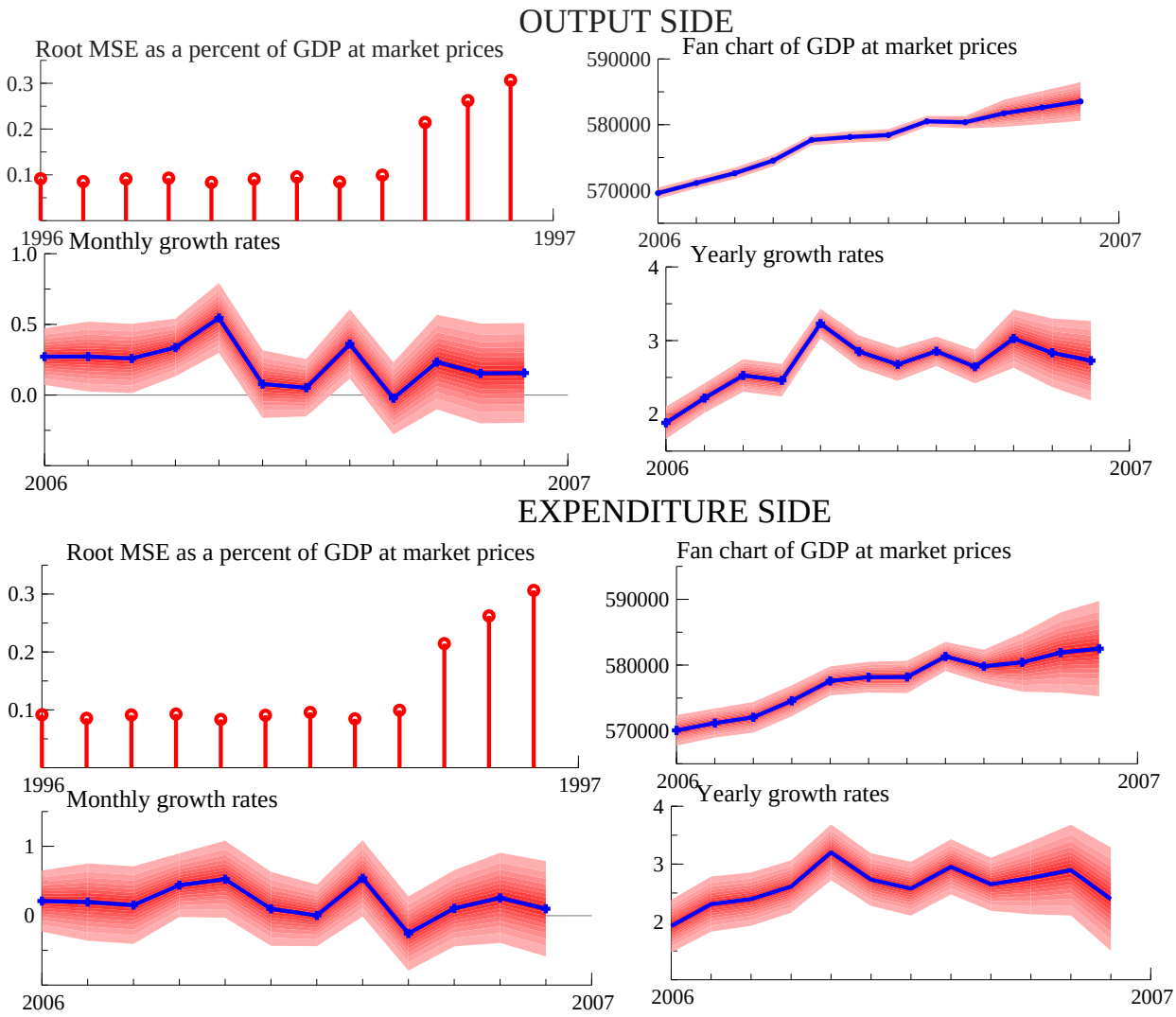


Figure 4: Combined monthly estimates of gross domestic product at market prices.

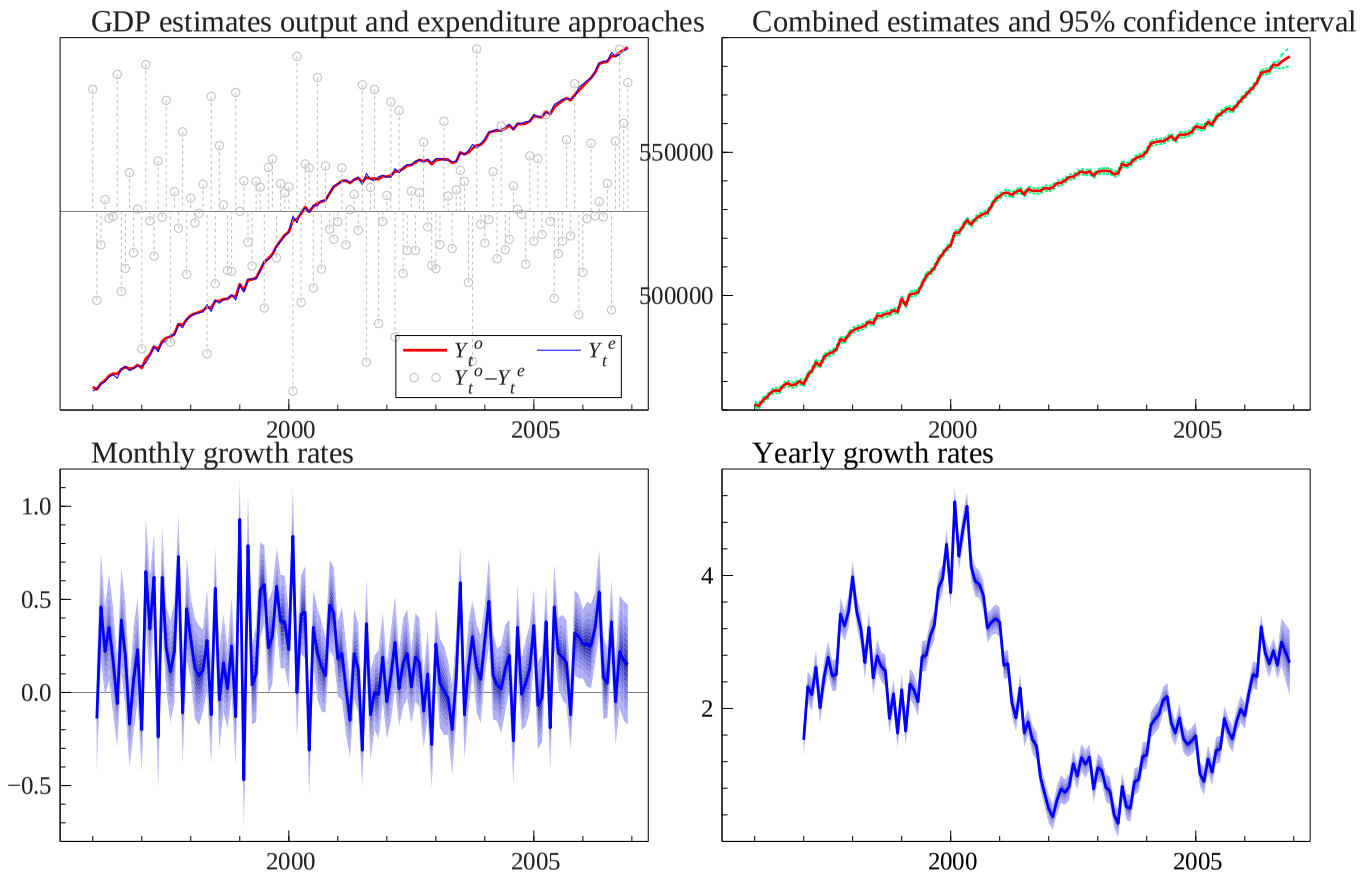


Figure 5: Estimates of Euro Area Monthly GDP in levels and growth rates - 13 vintages December 2006 - December 2007

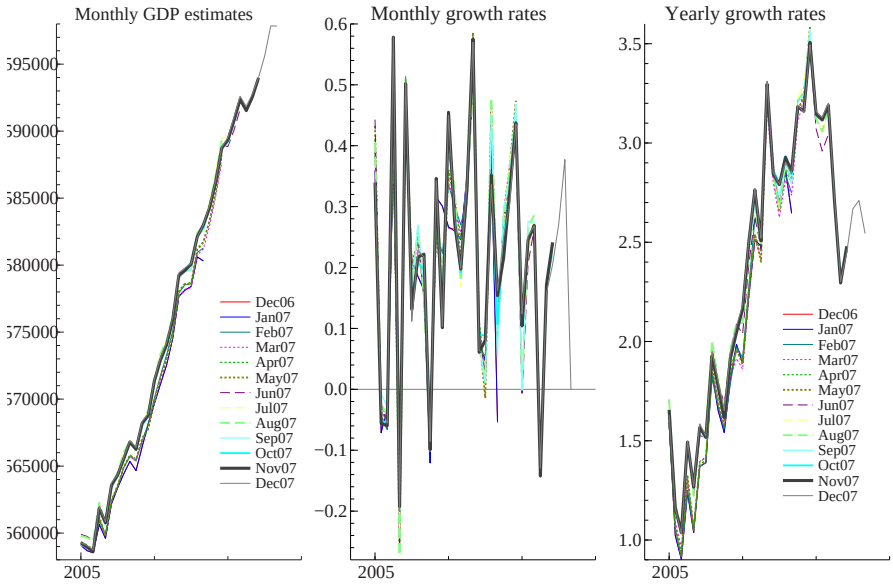


Figure 6: GDP estimates with constant parameters and estimated parameters

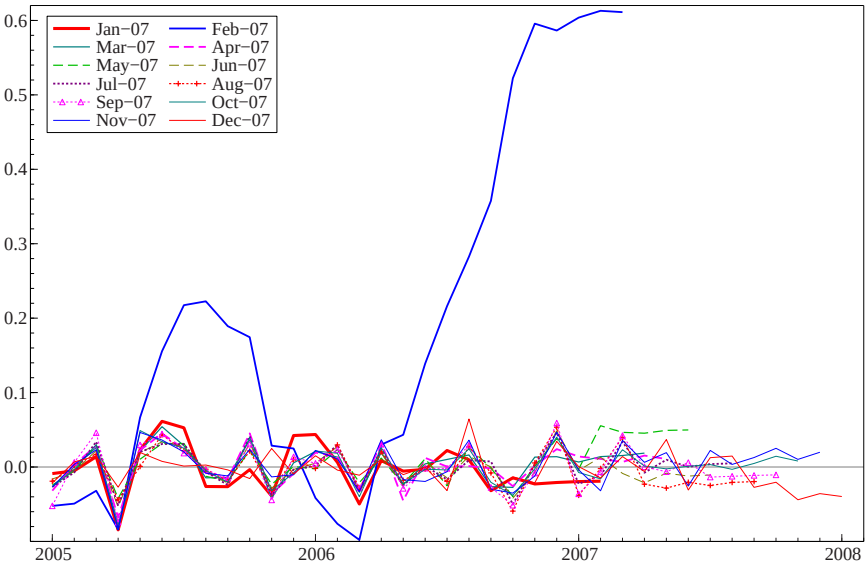


Figure 7: Standard errors by sectors, output side

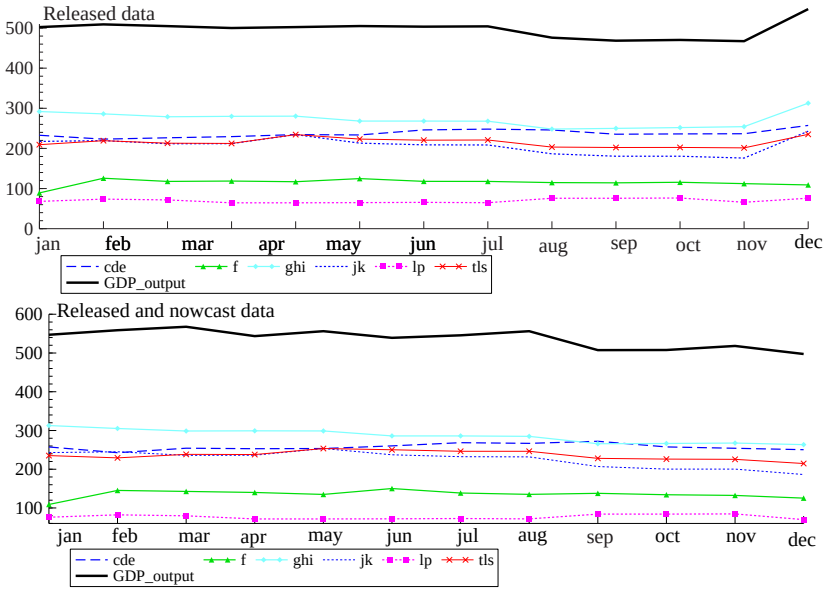
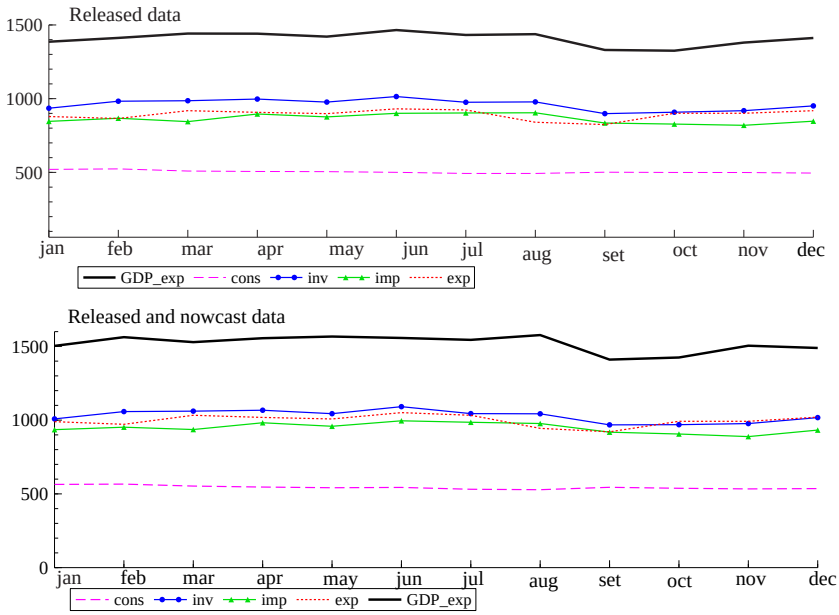


Figure 8: Standard errors by components, expenditure side



Appendix - Cointegration and the logarithmic transformation

In this Appendix we report some empirical evidence concerning a few important model specification issues. The first concerns whether we should assume cointegration between the temporally aggregated flow and the indicator variables. The multivariate dynamic factor model with $I(1)$ idiosyncratic factors, does not assume cointegration - see the discussion in section 3.4. The second is whether the linear Gaussian models considered in the previous sections can be assumed to hold only after all the variables are transformed into logarithms.

Our previous experience, dealing with the temporal disaggregation of the Italian national accounts and with the the dynamic factor model for the U.S. and Euro area economy (reported in Istat, 2005, Proietti, 2006a, and Proietti and Moauro, 2006), is that it is usually safer to assume that cointegration is not present. In particular, the univariate disaggregation of the Italian value added series with the Fernàndez (1981) method were more satisfactory with respect to those obtained by the Chow-Lin methodology (see Chow and Lin, 1971), as the results of out-of sample rolling forecast exercises and in sample diagnostics indicated. The Litterman (1983) model was ruled out instead due to a fundamental identifiability problem.

Secondly, the logarithmic transformation was found to be most suitable when a long time series is available and the growth rate of the series is sustained and homoscedastic, as it occurs in the U.S. case. For the Euro area the time series are short and growth is not sustained, so that disaggregating the time series on the original scale is usually appropriate.

These a priori considerations are reinforced by the empirical evidence originating from a rolling forecast experiment for the Industrial sector that we report below. The experiment is based on the comparison of the revision histories that characterise four alternative univariate methods of disaggregating the total value added of the branches C-D-E. For brevity, we do not report the results for the other branches, that confirm anyway our findings.

The four methods are the following:

1. Chow-Lin with regression effects represented by a constant and the indicators (see table 1 for a list of the indicators).

2. Chow-Lin with a linear trend and the indicator.

3. The double-logarithmic Chow-Lin model, featuring both value added and the indicators in logarithms. This poses a non-linear temporal disaggregation problem.

4. The Fernández (1981) model with a constant and the indicator.

The revision histories are generated as follows: starting from 2001 we perform a rolling forecast experiment such that at the beginning of each subsequent quarter we make predictions for the three months using the information available up to the beginning of the quarter and revise the

estimates concerning the three months of the previous quarter. This assumes that the quarterly aggregate at time τ accrues between the end of the month 3τ and the beginning of month $3\tau + 1$. At the end of the experiment 23 sets of predictions are available for three horizons (one month to three months); these are compared with the revised estimates, which incorporate the quarterly aggregate information. The models are re-estimated as a new quarterly observation becomes available.

The decision between alternative methods should be based on a careful assessment of the revision of the estimates as the new total, sometimes referred to as the quarterly benchmark, becomes available. Hence, revision histories are a diagnostic tool, referring to the discrepancy between the estimates not using the last aggregate data and those incorporating it, that complies with the criterion proposed by the European System of National and Regional Accounts (par. 12.04).

> *The choice between the different indirect procedures must above all take into account the minimisation of the forecast error for the current year, in order that the provisional annual estimates correspond as closely as possible to the final figures.*

The following table presents summary statistics pertaining to the revision histories at the three horizons considered: the mean revision error, also as a percentage of the final estimate, the mean absolute and square revision errors. Obviously the performance of the methods deteriorates with the horizons. More importantly, the random walk model (Fernández) outperforms the three CL specifications according to all the measures presented, including the specification in logarithms.

As far as the latter is concerned, the profile likelihood with respect to the Box-Cox tranformation parameter λ for the Fernández model

$$y_t(\lambda) = \mathbf{x}_t(\lambda)'\boldsymbol{\beta} + u_t, \quad \Delta u_t = \epsilon_t.$$

where

$$y_t(\lambda) = \begin{cases} \frac{y_t^\lambda - 1}{\lambda}, & \lambda \neq 0, \\ \ln y_t, & \lambda = 0. \end{cases}$$

takes the following values:

λ	0.0	0.2	0.4	0.6	0.8	1.0
Likelihood	-1.6316	-1.6207	-1.6104	-1.6008	-1.5919	-1.5836

Hence, the likelihood ratio test of the hypothesis that $\lambda = 1$ (no transformation) against the alternative $\lambda = 0$ is not significant.

Table 5: Revision history for Industrial value added (years 2002-2006).

Model	*Mean percentage revision error*		
	1 step	2 steps	3 steps
Chow-Lin (constant)	0.18	0.24	0.24
Chow-Lin (trend)	0.08	0.09	0.09
CL Logarithms	0.06	0.07	0.06
Fernández	-0.00	-0.00	-0.00
	Mean revision error		
	1 step	2 steps	3 steps
Chow-Lin (constant)	204.67	268.71	266.52
Chow-Lin (trend)	91.86	106.20	99.38
CL Logarithms	71.95	79.99	63.86
Fernández	-2.18	-2.87	-1.11
	Mean absolute revision error		
	1 step	2 steps	3 steps
Chow-Lin (constant)	284.75	382.66	389.93
Chow-Lin (trend)	248.86	320.96	316.22
CL Logarithms	245.09	312.42	305.40
Fernández	217.20	314.22	367.10
	Mean square revision error		
	1 step	2 steps	3 steps
Chow-Lin (constant)	149255.27	253934.56	246612.17
Chow-Lin (trend)	117564.20	186504.38	176205.58
CL Logarithms	115590.47	183408.05	169103.50
Fernández	68264.69	142244.25	194418.59