Luiss Libera Università Internazionale degli Studi Sociali Guido Carli

Luiss Lab of European Economics

LLEE Working Document no.58

The role of European Business Surveys for the estimation of GDP

Cecilia Frale

January 2008

Outputs from LLEE research in progress, as well contributions from external scholars and draft reports based on LLEE conferences and lectures, are published under this series. Comments are welcome. Unless otherwise indicated, the views expressed are attributable only to the author(s), not to LLEE nor to any institutions of affiliation.

The role of European Business Surveys for the estimation of GDP

Cecilia Frale*

LLEE Working Document No.58 January 2008

Abstract

This paper explores the potential of the European Business Survey for the estimation and disaggregation of macroeconomic variables at higher frequency. We propose a multivariate approach which is an extension of the Stock and Watson (1991) dynamic factor model, considering more than one common factor and low-frequency cycles. The multivariate model is cast in State Space Form and the temporal aggregation constraint is converted into a problem of missing values. An application in real time for the value added of the Industry sector in the Euro area is presented.

Keywords: Temporal Disaggregation. Multivariate State Space Models. Dynamic factor Models. Kalman filter and smoother. Survey data

JEL Classification: E32, E37, C53

(*) Dipartimento S.E.F. e ME.Q., University of Rome "Tor Vergata'" and Ministry of Economy and Finance and LUISS "Guido Carli"; E-mail: cecilia.frale@uniroma2.it.
This paper has appeared in the working paper series of the Department of the Treasury-Ministry of Economy and Finance-Italy. The analysis presented has been developed inside the Eurostat project "Principal European Economic Indicators", headed by Tommaso Proietti to whom I am grateful for supervision and great advises. I also wish to express my thanks to Massimiliano Marcellino and Gianluca Cubadda for discussion on several issues about forecasting and to an anonymous referee for his suggestions. Routines are coded in Ox 3.3 by Doornik (2001) and provide an extension of the programs realized by Proietti T. as part of the mentioned Eurostat project.

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 business cycle and the conduct of the economic policy. As matter of fact official data are released with delay by statistical offices (e.g. GDP of the Euro Area arrives about 60 days later the referring quarter) and therefore at each point in time we have information about the state of the economy as it was two or three months ago, not actually as it is at present. This is the so-called issue of "nowcasting", or the estimation of the current level of a variable not yet released officially, which is different from the concept of "forecasting" that concerns the future value of a time series. This paper deals with both these sorts of topics. The main idea is that using the statistical methodology and the recent advances in the literature on temporal disaggregation we can indirectly disaggregate macroeconomic variables (e.g. GDP and other aggregates of National Accounts) by using indicators available at higher frequency (monthly indicators of economic activity) and released earlier.

Our methodology is based on variants of Stock and Watson (1991) dynamic factor model cast in State Space form. The model postulates that a multivariate time series is driven by one (or few), possibly nonstochastic, factors, which are responsible for the comovements of the series. Each individual indicator is also driven by idiosyncratic dynamics. Starting from the standard SW model, to address the potential of Business Survey data, we consider for the coincident indicators a re-parametrization of the standard autoregressive model(AR), suitable for low frequency cycle (Morton and Tunnicliffe-Wilson (2004)).

Let us disentangle the procedure in more details considering the case of quarterly National Accounts. Due to temporal aggregation, the series are not observable at monthly frequency, and the quarterly release is considered as the sum of 3 consecutive monthly unknown values. This approach, proposed by Harvey (1989, sec. 6.3), converts the disaggregation problem into a problem of missing values, that can be addressed in a State Space set up by skipping certain updating operations in the filtering and smoothing equations. The multivariate model is implemented by using the univariate statistical treatment by Anderson and Moore (1979), which 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). The multivariate vectors, containing indicators and the quarterly series, 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.

We claim that our method as many appealing advantages. First of all a model based approach allows figuring out an interpretation of the coincident index and idiosyncratic components in terms of the original variables, preserving the economic meaning of the series and of their relationship. Secondly, we deal with mixed frequencies, including information about past values of the GDP in addition to the monthly indicators. Third, the Kalman filter and smoother is an efficient way to solve the unbalanced sample issue induced by different delays in the released series. Last, the inclusion of a low-frequency cycle autoregressive component allows capturing the feature of survey data.

An application for Euro Area value added of Industry is provided and the model is evaluated in term of forecast ability and estimation accuracy trough real time experiments. As a benchmark we estimate the monthly value added for Industry by univariate Autoregressive Distributed Lag (ADL) models. Particular attention is devoted to understand the information and the news content of survey data. Via similar models it is possible to compute the value added of each sector and obtain the monthly GDP by summing up. This procedure is in general preferable to a direct estimate of GDP, because allows the use of specific indicators for each sector. However we show only the estimation for Industry.

The paper is structured as follows. After a review of the univariate treatment (section 2), Section 3 introduces the Stock and Watson dynamic factor model with the mentioned extension. In particular, we present the State Space parametrization in section 3.1 and discuss the temporal aggregation of the monthly estimates in section 3.2. A comprehensive presentation of the filtering and smoothing procedure is reported in the Appendix.

Section 4 summarizes the main estimation results as applied to the disaggregation of quarterly Euro Area Value Added of Industry, with particular focus on news content and timeliness of Survey data trough real time experiments. Finally, some conclusions are presented.

2 Autoregressive Distributed Lags Models

The delay of official National Accounts data has led business cycle analyst to find an alternative way to produce nowcasts and forecasts. The most common approach is based on the idea of building "bridge" equations from high frequency to quarterly GDP (or his components) trough monthly indicators (survey and/or hard data). Models of this sort, known as Bridge Models, generally outperform traditional models, such as ARIMA, VAR or BVAR. Typically they are derived from an initial unrestricted Autoregressive Distributed Lag (ADL(p,s)) equation, estimated using aggregated data. For instance, real GDP growth on a quarterly basis is regressed on monthly indicators aggregated to a quarterly frequency.

In this paper, following Proietti (2004), we cast the ADL models in State Space Form (SSF) and we disaggregate endogenously the National Account components at monthly level, by using the Kalman filter and Smoother in a mixed frequency univariate model.

Let us start from a simple Autoregressive Distributed Lag first order model, ADL(1,1), and suppose for simplicity to use only one indicator to disaggregate at higher frequency the series y_t. The model takes the form:

$$y_t = \phi y_{t-1} + m + gt + x_t'\beta_0 + x_{t-1}'\beta_1 + \epsilon_t \qquad \epsilon_t \sim NID(0; \sigma_t^2), \tag{1}$$

where x_t is the indicator at time t. It is possible to find a corresponding state space representation, which is a useful tool to decompose a series into unobservable components such as trend, cycle, seasonality. In a standard SSF the observed data y_t are expressed as a function of a "state" variables α_t not directly observable, for which it is possible to define the data generating process. For this application the SSF is:

$$\begin{aligned} y_t &= \alpha_t \\ \alpha_t &= \phi \quad \alpha_{t-1} + \mathbf{W}_t \boldsymbol{\beta} + \epsilon_t \end{aligned}$$

where the matrix $\mathbf{W}_t = [1, t, x'_t, x'_{t-1}]$ includes the drift, the trend and the exogenous variable x_t. To start the system some initial condition are needed and several initializations are possible. Among them one can assume that the process started in the indefinite past or consider y_1 as a fixed value or assume that y_1 is random and the process is supposed to have started at time t = 0 with a value which is fixed, but unknown. The hypothesis of stationarity might be relaxed (see Proietti (2004)) and the ADL model could be estimated in first differences:

$$\Delta y_t = \psi \Delta y_{t-1} + x'_t \beta_0 + x'_{t-1} \beta_1 + \epsilon_t \quad \epsilon_t \sim NID(0; \sigma_t^2).$$

The transition equation is $\boldsymbol{\alpha}_t = \mathbf{T}_{t-1} \boldsymbol{\alpha}_{t-1} + \mathbf{W}_t \boldsymbol{\beta} + \boldsymbol{\epsilon}_t$, with state element $\boldsymbol{\alpha}_t = [y_{t-1}, \Delta y_t]'$ and transition matrix $\mathbf{T} = [1, 1\vdots 0, \psi]$, and regression effects in the matrix $\mathbf{W}_t$. The measurement equation $y_t = [1, 1]\boldsymbol{\alpha}_t$ complete the SSF.

The model is formulated at the frequency level of the indicators x_t (e.g. monthly), therefore due to temporal aggregation, y_t (e.g. GDP) is not observed. The data arise, instead, as the sum of s (equal to 3 in our case) consecutive values, $\sum_{j=0}^{s-1} y_{\tau s - j}$, and are available at times $\tau = 1, 2, \ldots [n/s]$ (e.g. representing the quarters), where $[n/s]$ denotes the integral part of n/s.

In order to handle temporal aggregation, a new state space representation is derived, by augmenting the state vector of the original state space representation with a cumulator variable that is only partially observed:

$$y_t^c = \psi_t y_{t-1}^c + y_t, \quad \psi_t = \begin{cases} 0, & t = s(\tau - 1) + 1, \tau = 1, \ldots, [n/s] \\ 1, & \text{otherwise} \end{cases} \tag{2}$$

Extensions to higher order ADL(p,q)D could be derived in a similar way.

The statistical treatment is based upon the augmented Kalman filter due to de Jong (1991), suitably modified to take into account the presence of missing values, which is easily accomplished by skipping certain updating operations. For a comprehensive treatment of the statistical univariate treatment see Proietti (2004).

There are two main related sources of criticism that arise with respect to the univariate disaggregation methods. The first concerns the exogeneity assumption, according to which the indicator is considered as an explanatory variable in a regression model. Actually there is no a priori reason to say that a monthly indicator Granger cause the GDP, just they represent different aspects of the same phenomenon, the state of the economy. The second is that the regression based methods assume that the indicators are measured without error. Considering how much macroeconomic data, such as Industrial production, are revised by Statistical Offices is hard to support this hypothesis.

A multivariate framework is in general more realistic.

3 The Dynamic Factor Model

There are relatively few examples of multivariate disaggregation methods in the literature. Harvey and Chung (2000) use a bivariate unobserved components model, while Moauro and Savio (2005) propose multivariate disaggregation methods based on the class of Sutse models. Starting from the original work of Stock and Watson (1991, SW henceforth) several papers develop an explicit probability model for the composite index of coincident economic indicators. They consider a dynamic factor model to figure out a common difference-stationary factor which is assumed to be the value of a single unobservable variable, the state of the economy. This represents by assumption the only source of the co-movements of few relevant time series: industrial production, sales, employment, and real incomes. Although it is available only quarterly, GDP is perhaps the most important coincident indicator. This consideration motivate Mariano and Murasawa (2003) to extend the SW model with the inclusion of quarterly real GDP growth, proposing a linear state space model defined at the monthly observation frequency, with a time aggregation constraint. The model is formulated in terms of the logarithmic changes in the variables, and the nonlinear nature of the temporal aggregation constraint is addressed just considering a geometric mean relation between monthly and quarterly data. A more technical solution of the nonlinear constraint is presented in Proietti and Moauro (2006).

The recent interest in Survey data and some evidence of their relevance in macroeconomic forecast (Giannone *et al.* 2005, Altissimo *et al.* 2007) suggests a possible extension of the information set on which is based the SW model to include survey data. Results from companion applications (Proietti and Frale (2007)) have provided evidence on the inadequacy of the standard formulation of the model to include soft data. Therefore a modification of the SW standard formalization that considers the specific nature of survey data is achieved. We propose to address this issue in two directions: first considering more than one common factor, secondly including in the common index a predefined Moving Average (MA) part, suitable for processes with peaks in the spectral density at low frequencies. Morton and Tunnicliffe-Wilson find evidence of improving forecast ability for a standard AR(p) by using the above modification:

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

where $\phi(L)$ is a lag polynomial of the form $(1+\phi_1 L+\phi_2 L^2+...+\phi_p L^p)$ and θ is a specified parameter in the interval [0.4-0.7] (mostly $\theta = 0.5$). This re-parametrization for the AR(p), called ZAR(p), squeezes the spectrum in the fraction $(1-\theta)/(1+\theta)$ of frequencies at the lower end of the range and therefore accounts for low frequency cycles. In the sequel we present how to extend the SW model in these two directions.

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 $\Delta y_{it}, i = 1,\dots,N$, has a stationary and invertible representation. The extended SW 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 an idiosyncratic component, $\boldsymbol{\gamma}_t$, 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 level:

$$\begin{array}{lcll}
\mathbf{y}_t & = & \boldsymbol{\vartheta}_0\mu_t + \boldsymbol{\vartheta}_1\mu_{t-1} + \widetilde{\boldsymbol{\vartheta}}_0\widetilde{\mu}_t + \widetilde{\boldsymbol{\vartheta}}_1\widetilde{\mu}_{t-1} + \boldsymbol{\gamma}_t + \mathbf{X}_t\boldsymbol{\beta}, & t = 1, ..., n, \\
\phi(L)\Delta\mu_t & = & (1-\theta L)^p\eta_t, & \eta_t \sim \text{NID}(0, \sigma^2_\eta), \\
\widetilde{\phi}(L)\Delta\widetilde{\mu}_t & = & \widetilde{\eta}_t, & \widetilde{\eta}_t \sim \text{NID}(0, \sigma^2_{\tilde{\eta}}), \\
\mathbf{D}(L)\Delta\boldsymbol{\gamma}_t & = & \boldsymbol{\delta} + \boldsymbol{\xi}_t, & \boldsymbol{\xi}_t \sim \text{NID}(\mathbf{0}, \boldsymbol{\Sigma}_\xi),
\end{array} \tag{3}$$

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. 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 $\boldsymbol{\Sigma}_\xi = \text{diag}(\sigma^2_1, \ldots, \sigma^2_N)$.
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 exogenous variables that are used to incorporate k calendar effects (trading day regressors, Easter, length of the month) and intervention variables (level shifts, additive outliers, etc.).

Although the SW model was originally presented in difference, we prefer the specification of the model in level because this is a very convenient formalization to deal with missing observations and the disaggregation temporal constraint. Notice that the first equation

$$\mathbf{y}_t = \boldsymbol{\vartheta}_0\mu_t + \boldsymbol{\vartheta}_1\mu_{t-1} + \widetilde{\boldsymbol{\vartheta}}_0\widetilde{\mu}_t + \widetilde{\boldsymbol{\vartheta}}_1\widetilde{\mu}_{t-1} + \boldsymbol{\gamma}_t + \mathbf{X}_t\boldsymbol{\beta}$$

could be rewritten as

$$\mathbf{y}_t = \boldsymbol{\theta}_0\mu_t + \boldsymbol{\theta}_1\Delta\mu_{t-1} + \widetilde{\boldsymbol{\theta}}_0\widetilde{\mu}_t + \Delta\widetilde{\boldsymbol{\theta}}_1\widetilde{\mu}_{t-1} + \boldsymbol{\gamma}_t + \mathbf{X}_t\boldsymbol{\beta},$$

where $\theta_0 = \vartheta_0 + \vartheta_1$ and $\theta_1 = -\vartheta_1$ and similarly for the other coefficients. We continue the discussion about the model in the next section showing how to cast it in SSF.

3.1 State Space Form

To make exposition clear we present the state space of every component of the model 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) in difference, $\Delta\mu_t$, using the following SSF:

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

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 (3) is express in level, therefore we need to derive the corresponding SSF in level, that is 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

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

where $\mathbf{H}_\mu = [1, \mathbf{h}']'$.
A similar approach could be follow 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:

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

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

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

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:

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

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:

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

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

$$\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}'_{\mu,t}, \boldsymbol{\alpha}'_{\tilde{\mu},t}, \boldsymbol{\alpha}'_{\mu_1,t}, \ldots, \boldsymbol{\alpha}'_{\mu_N,t}]'. \tag{4}$$

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

$$\mathbf{y}_t = \mathbf{Z}\boldsymbol{\alpha}_t + \mathbf{X}_t\boldsymbol{\beta}, \quad \boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \mathbf{W}\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t, \tag{5}$$

where $\boldsymbol{\epsilon}_t = [\eta_t, \tilde{\eta}_t, \xi_{1t}, \ldots, \xi_{Nt}]'$ and the system matrices are given below:

$$\begin{array}{l} \mathbf{Z} = \left[\boldsymbol{\theta}_0, \vdots\, \boldsymbol{\theta}_1 \;\; \vdots\, \mathbf{0} \vdots\, \tilde{\boldsymbol{\theta}}_0, \vdots\, \tilde{\boldsymbol{\theta}}_1 \;\; \vdots\, \mathbf{0} \vdots\, \text{diag}(\mathbf{e}'_{p_1+1}, \ldots, \mathbf{e}'_{p_N+1})\right], \\ \mathbf{T} = \text{diag}(\mathbf{T}_\mu, \mathbf{T}_{\tilde{\mu}}, \mathbf{T}_1, \ldots, \mathbf{T}_N), \\ \mathbf{H} = \text{diag}(\mathbf{H}_\mu, \mathbf{H}_{\tilde{\mu}}, \mathbf{H}_1, \ldots, \mathbf{H}_N). \end{array} \tag{6}$$

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

The first $2N$ elements of the vector $\boldsymbol{\beta}$ are the pairs $\{(\gamma_{i0}, \delta_i, i = 1, \ldots, N\}$, 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 k 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 $\mathbf{W}_t$ is time invariant and selects the drift δ_i for the appropriate state element:

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

whereas $\mathbf{W}_1$

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

3.2 Temporal Aggregation

The estimation of the monthly GDP is an exercise of disaggregation in time, where the quarterly value added is divider in three monthly values. The main idea is to make use of informative monthly indicator to perform this disaggregation. We follow the multivariate disaggregation method proposed by Proietti and Frale (2007), as reported in the sequel.

Suppose that the set of coincident indicators, $\mathbf{y}_t$, can be partitioned into two groups, $\mathbf{y}_t = [\mathbf{y}'_{1t}, \mathbf{y}'_{2t}]'$, of dimension $N1$ and $N2$, where the second block gathers the flows that are subject to temporal aggregation, so that

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

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

The strategy proposed by Harvey (1989) consists of operating a suitable augmentation of the state vector (4) using an appropriately defined cumulator variable. In particular, the SSF (4)-(6) need to be augmented by the $N_2 \times 1$ vector $\mathbf{y}^c_{2t}$, generated as follows

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

where ψ_t is the cumulator variable, defined as follows:

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

and $\mathbf{Z}_2$ is the $N_2 \times m$ block of the measurement matrix $\mathbf{Z}$ corresponding to the second set of variables, $\mathbf{Z} = [\mathbf{Z}'_1, \quad \mathbf{Z}'_2]'$ and $\mathbf{y}_{2t} = \mathbf{Z}_2 \boldsymbol{\alpha}_t + \mathbf{X}_2 \boldsymbol{\beta}$, 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:

$$\boldsymbol{\alpha}^*_t = \begin{bmatrix} \boldsymbol{\alpha}_t \\ \mathbf{y}^c_{2t} \end{bmatrix}, \quad \mathbf{y}^\dagger_t = \begin{bmatrix} \mathbf{y}_{1t} \\ \mathbf{y}^c_{2t} \end{bmatrix}$$

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

$$\mathbf{y}^\dagger_t = \mathbf{Z}^* \boldsymbol{\alpha}^*_t + \mathbf{X}_t \boldsymbol{\beta}, \quad \boldsymbol{\alpha}^*_t = \mathbf{T}^* \boldsymbol{\alpha}^*_{t-1} + \mathbf{W}^* \boldsymbol{\beta} + \mathbf{H}^* \boldsymbol{\epsilon}_t, \tag{7}$$

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

$$\mathbf{Z}^* = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{N_2} \end{bmatrix}, \quad \mathbf{T}^* = \begin{bmatrix} \mathbf{T} & \mathbf{0} \\ \mathbf{Z}_2 \mathbf{T} & \psi_t \mathbf{I} \end{bmatrix}, \mathbf{W}^* = \begin{bmatrix} \mathbf{W} \\ \mathbf{Z}_2 \mathbf{W} + \mathbf{X}_2 \end{bmatrix}, \quad \mathbf{H}^* = \begin{bmatrix} \mathbf{I} \\ \mathbf{Z}_2 \end{bmatrix} \mathbf{H}. \tag{8}$$

The state space model (7)-(8) 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 $\mathbf{y}_{2t}^c$ can be estimated, which need to be "decumulated", using $\mathbf{y}_{2t} = \mathbf{y}_{2t}^c - \psi_t \mathbf{y}_{2,t-1}^c$, so as to be converted into estimates of $\mathbf{y}_{2t}$. In order to provide the estimation standard error, however, the state vector must be augmented of $\mathbf{y}_{2t} = \mathbf{Z}_2\boldsymbol{\alpha}_t + \mathbf{X}_2\boldsymbol{\beta} = \mathbf{Z}_2\mathbf{T}\boldsymbol{\alpha}_{t-1} + [\mathbf{X}_2 + \mathbf{Z}_2\mathbf{W}]\boldsymbol{\beta} + \mathbf{H}\boldsymbol{\epsilon}_t$.

4 Empirical Application

4.1 Estimation of the Monthly Value Added for Industry

We present an application on the estimation of the Value Added for Industry carried out using the methodology outlined in section 3. The construction of the monthly indicator is based on the temporal disaggregation of the quarterly values by using monthly indicators. We consider preferable to figure out the total GDP estimation summing up sectorial estimates in order to exploit specific indicators for each sector, although we carry out the estimation only for the Industry sector leaving to future work the treatment of all the other sectors.

At the time of writing the series of quarterly Value Added are available by Eurostat from the begin of 1995 to the third quarter of 2006. Observations are seasonally adjusted and working day adjusted and refer to the Euro Area. The series are relatively short because of a major structural break concerning the statistical allocation of Financial Intermediation Services Indirectly Measured (FISIM).

After a set of preliminary analysis for variable selection, we consider as monthly indicators five series, shown in the top left panel of figure 1. Two 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: the industrial confidence indicator (EA.clim), the production trend observed in recent months (EA.prod) and the assessment of order–book levels (EA.ord). As matter of fact, any variable selection is arbitrary. There are literally hundreds of papers on variable selection methods and some recent studies show that the smaller set of indicators are often yet satisfactory or even better than large dataset. (se Boivin and Ng (2006) and Bańbura M. and R$\ddot{u}$nstler (2007)).

However, the aim of this paper is to investigate whether the inclusion of survey data improve the performance of the model, producing more accurate estimates and forecasts, not to address the issue of variable selection. Therefore we start from the same information set for all the competitor models, that includes the most widely used hard data for Industry (industrial production, employment, hours work) and all survey data coming from the Business Survey. Hence we proceed from the general to the particular model eliminating variables that result not significant. We consider also Likelihood based criteria, AIC and Akaike lag selection procedures, to discriminate among different models.

As far as survey data are concerned, see Pesaran and Weale (2006) for a discussion on the quantification of surveys and their role in econometric analysis. Business cycle indicators are supposed to be stationary at the long run frequency (see also stationarity tests in Proietti and Frale, 2006), therefore 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. We leave to future research the investigation of alternative specifications and quantifications for survey data.

We estimate three benchmark models: starting from the traditional ADLD we move to the SW single index and finally we conclude with the double index SW with modification (SW2-ZAR henceforth). We first present estimation results for each of these models, then, in the next paragraph, we compare their forecast ability.

The ADLD model is estimated according to the framework presented in section 2. Among alternative specifications in terms of components (drift, trend), in terms of lags and in terms of initialization options, we found that the ADL(1,1)D with trend is the best model, as also suggested by BIC and Akaike lag selection procedures. The estimated regression coefficients, along with their standard error and the t-statistic are reproduced in table 1.

Although industrial production remains the most relevant indicator, survey data matter, both contemporaneously than with lag. On the contrary the series of hours worked does not enter at any lags. Figure 1 shows the original quarterly series along with smoothed and filtered estimation.

As mentioned before multivariate models are a more appropriate solution, therefore we estimate a dynamic SW factor model with single common factor. The maximum likelihood estimates of the parameters of the model along with asymptotic standard errors are presented in table 2. The coincident index, which is an AR(2), seems to be strongly related to both industrial production and hours worked. Nevertheless indicators do not enter with lags. Survey data appears not significant, neither contemporaneously neither with lag, therefore results for the SW single index are presented as estimated without survey data. The smoothed estimates of the common factor, μ_t, and of monthly value added are shown in the left column of figure 2.

Finally we estimate a SW model with two common factors and correction for low frequency cycles whose results are reported in table 3. For the first coincident index we propose a ZAR(2), meanwhile for the second one we use an AR(2) specification. This is the best model in term of significativeness of coefficients and Likelihood, in a set of alternative parametrization, accounting for: numbers of common factors, combination of indicators and combination of lags.

It is relevant to notice that firstly survey data enter in the model and secondly that there is a clear separation between indicators: hard data load in the first coincident index, survey data in the second one. This confirms our a priori that allowing for more than one coincident indicator might point out the relevance of soft data, although the loading of GDP in the second common index is not significant. We consider that variables could enter in the model with lag, nevertheless we have not found evidence on it.

The right column of Figure 2 shows the estimated monthly value added and the two coincident indexes, along with their first difference. The inclusion of a second coincident index has an evident effect on the first common component (see the central left and right panels of figure 2), which appears more volatile and dampened in the SW2-ZAR model. The second coincident index in differences seems to reproduce the cyclical behavior of the survey data with a positive shift for stocks and negative for the others indicators (compare with the pattern of Indicators in figure 1).

Some diagnostics and goodness of fit measures for the SSF might be based on the one step ahead forecast errors, that are given by $\tilde{v}_{t,i} = v_{t,i} - \mathbf{V}'_{t,i}\mathbf{S}_{t,i}^{-1}\mathbf{s}_{t,i}$, with variance $\tilde{f}_{t,i} = f_{t,i} + \mathbf{V}'_{t,i}\mathbf{S}_{t,i}^{-1}\mathbf{V}_{t,i}$. The standardised innovations, $\tilde{v}_{t,i}/\sqrt{\tilde{f}_{t,i}}$ can be used to check for residual autocorrelation and departure from the normality assumption. However, on the goal of the paper we base the comparison of the competitor models in terms of nowcasting and forecasting ability, which is done in the next section.

4.2 Comparative Performance of Rolling Forecasts

Bridge models and in general model for monthly GDP has been widely used to produce forecasts, which are an important requirement for the economic analysis and the conduct of the economic policy. As a consequence, it might be worth to evaluate the three competitor models under consideration, the ADLD, the SW single index and the SW2-ZAR, in terms of forecast accuracy. As common in the literature we use a rolling experiment as an out-of-sample exercise. This corresponds to split the sample period in two parts, the first of which is used for the estimation and the second for evaluation, considering a measure of distance between forecasts and realized observations.

In this context a well known issue is how to split the series between the pre-forecast and the test period. There is not a fixed rule, but considering that the sample starts from 1995 and that we are interested in short term forecast, we run the rolling experiment over 54 consecutive observations in the sample 2001M1-2005M6. Hence, starting from January 2001, the three models are estimated at monthly level and quarterly forecasts of the value added are computed up to 3 step-ahead summing up the monthly data. Then, the forecast origin is moved one step forward and the process is repeated until the end of sample is reached, or 54 times. 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. As a benchmark, we run as baseline the same exercise taking the parameters constant, as estimated using the information set available at the end of the sample.

All forecast experiments are made in "pseudo" real-time, so as to consider at each observation in time the last release for monthly and quarterly indicators that produce a non balanced sample. Therefore distinction is made regarding the position of the month inside the quarter, to account for different delay in the indicators releases. In particular, for the third month in the quarter, we should incorporate in the forecast the anticipated release of the quarterly value added. No account is made at this step for data revisions which is considered in details in the next section.

In table 4 and 5 we report a few basic statistics upon which forecasting accuracy will be addressed, for the model with constant parameters and re-estimated parameters. Monthly estimates are aggregated at quarterly frequency before computing any measure of errors, being our benchmark the national account Value Added. Denoting the l-step ahead forecast by $\widehat{y}_{t+l|t}$ and the true realized value by y_t, we compute for the three competitor models: the average of the forecast mean error (ME), ($\widehat{y}_{t+l|t} - y_{t+l}$); 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; 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. Finally, we add the mean square forecast error (MSFE).

For the ADL(1,1)D, the SW2-ZAR and the SW model, these statistics are reported with distinction of the month in the quarter, and the forecast horizon as resulted from the rolling experiment.

The ADLD model is almost always encompassed by the multivariate models, between which the SW2-ZAR model makes the lowest forecast error, unless in few exceptions and in terms of ME. This evidence is stronger as the forecast horizon goes forward and the information set goes smaller (1st month). In the re-estimated results, this evidence is even stronger and the SW2-ZAR models appears to get better performance especially for 2 and 3 step ahead forecast.

The forecast accuracy of pairwise models could be test formally by using the Diebold-Mariano test. It is worth to clarify that although the SW and SW2-ZAR models are nested, the real time nature of the rolling experiment validates the applicability of the Diebold-Mariano test (see Giacomini and White 2003). In table 6 we report the p-values test for the three models, with distinction of the month in the quarter and the horizon forecast, which intend to be compared with the usual threshold of 5%. There is strong evidence of significant different forecasts between multivariate SW and univariate ADLD model. Nevertheless the hypothesis of equal forecast accuracy of the single and the double SW model is not overall rejected. This is particularly relevant for models with re-estimated parameters. In line with the previous forecast error analysis, the SW2-ZAR model seems to be preferable for 3 step ahead forecast. Although this could not be considered as a general result, for this empirical application the evidence is in favor of multivariate models, among which the SW2-ZAR is preferable for long horizon forecast.

4.3 Revisions and Contribution to the Estimation

In this section we attempt isolating the news content of each block of series used in the estimation of GDP, namely survey data rather than hard data. For this task we present some forecast exercises using real time data from the Euro area Real Time database, providing vintages of time series of several macroeconomic variables. The revision process is supposed to incorporate the more recent information available and therefore could not be neglected in our purpose. In particular, in order to address the issue of timeliness and news of content of data, we consider how much estimates change when a new block of series is released. We wish to figure out whether survey data matter for the estimation of GDP because their timeliness and/or because their content.

As for the forecast exercise, we consider 54 rolling forecasts staring from 2001M1. The last estimated quarter is 2005Q2. At each period in time the input in the model are the quarterly revised value added along with the revised indicators, unless for the series of hours worked because of the lack of the data. The model is run more than once per month, and in particular every time a block of indicators is made available. Because 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.

In table 7 are displayed the results for the models with both constat and re-estimated parameters. As expected the most relevant change in the estimate occurs when Industrial Production is released, and this evidence is amplified for the SW2-ZAR model (0.38% on average). Nevertheless contribution of survey data seems to play a role, the more the horizon goes ahead and the more the information set is small. As expected the impact is higher in the first month of the quarter, because of the lack of hard data information. The results are even stronger in the re-estimated model. In particular the impact of survey on the prevision of GDP 3-step ahead made in the 1 month of the quarter (0.39%) is higher than the corresponding of Industrial production (0.38%). The evidence suggests that the more the forecast horizon increase the more timeliness of data is relevant. This is in line with the findings of Giannone *et al.*(2005).

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

5 Conclusions

This paper mainly deals with the issue of macroeconomic variables disaggregation and estimation. The aim is to explore if the inclusion of high frequency data might improve estimation accuracy and forecast ability. The methodology proposed for the estimation at monthly level is based prominently on the Stock and Watson (1991) dynamic factor model, with the inclusion in the model of the quarterly GDP subject to temporal disaggregation. An extension to a model with more than one common factor and a correction for low frequency cycle is presented. We propose an application to the valued added for Industry of the Euro Area and we compare the extended model versus the original SW formulation in term of the forecast ability. The issue of data revisions and content of news in each block of series, survey and hard data, is also analyzed. In conclusion we found evidence for better performance of a model including also survey data, especially in term of forecast errors. As far as the news content of data is concerned, information from survey is related to the lack of hard data. This evidence is more persistent as the information set is small (first month in the quarter) and as the horizon forecast increase (three step ahead).

References

Altissimo, F., Cristadoro , R., Forni M.,Lippi M.,Veronese G. (2007). *New Eurocoin: Tracking Economic Growth in real time*,Bank of Italy working paper n. 631.

Anderson, B.D.O., and Moore, J.B. (1979). *Optimal Filtering*, Englewood Cliffs NJ: Prentice-Hall.

Bańbura M., Rünstler (2007), A look into the factor model black box: publication lags and the role of hard and soft data in forecasting GDP, European Central Bank working paper no. 751.

Bloem, A., Dippelsman, R.J. and Maehle, N.O. (2001), *Quarterly National Accounts Manual Concepts, Data Sources, and Compilation*, International Monetary Fund.

Boivin J. and Ng S. (2006),Are more data always better for factor analysis?, *Journal of Econometrics* 132, 169-194

Chow, G., and Lin, A. L. (1971). Best Linear Unbiased Interpolation, Distribution and Extrapolation of Time Series by Related Series, *The Review of Economics and Statistics*, 53, 4, 372-375.

Eurostat (1999). Handbook on quarterly accounts. Luxembourg.

de Jong, P. (1989). Smoothing and interpolation with the state space model, *Journal of the American Statistical Association*, 84, 1085-1088.

de Jong, P. (1991). The diffuse Kalman filter, *Annals of Statistics*, 19, 1073-1083.

de Jong, P., and Chu-Chun-Lin, S. (1994). Fast Likelihood Evaluation and Prediction for Nonstationary State Space Models, *Biometrika*, 81, 133-142.

Di Fonzo T. (2003), Temporal disaggregation of economic time series: towards a dynamic extension, European Commission (Eurostat) Working Papers and Studies, Theme 1, General Statistics.

Doornik, J.A. (2001). *Ox 3.0 - An Object-Oriented Matrix Programming Language*, Timberlake Consultants Ltd: London.

Durbin J., and Koopman, S.J. (2001). *Time Series Analysis by State Space Methods*, Oxford University Press: New York.

Fernández, P. E. B. (1981). A methodological note on the estimation of time series, *The Review of Economics and Statistics*, 63, 3, 471-478.

Geweke J. (1977). The dynamic factor analysis of economic time series models. In *Latent Variables in Socio-Economic Models*, Aigner DJ, Goldberger AS (eds); North Holland: New York.

Giacomini R., and White, H. (2006), Tests of conditional predictive ability, Econometrica, Econometric Society, vol 74(6),pp 1545-1578.

Giannone, D., Reichlin, L., and Small, D.(2005) Nowcasting GDP and Inflation: The Real-Time Informational Content of Macroeconomic Data Releases Finance and Economics Discussion Series 42.

Harvey, A.C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press: Cambridge.

Harvey, A.C. and Chung, C.H. (2000) Estimating the underlying change in unemployment in the UK. Journal of the Royal Statistics Society, Series A, 163, 303-339.

Harvey, A.C., Koopman, S.J., and Penzer, J. (1998). Messy time series. In *Advances in Econometrics*, Vol 13, pp. 103-143, Cambridge University Press.

Harvey, A.C., and Pierse R.G. (1984). Estimating Missing Observations in Economic Time Series. *Journal of the American Statistical Association*, 79, 125-131.

Harvey, A.C. and Proietti, T. (2005). *Readings in unobserved components models*. Oxford University Press.

Koopman, S.J. (1997). Exact initial Kalman filtering and smoothing for non-stationary time series models, *Journal of the American Statistical Association*, 92, 1630-1638.

Koopman, S.J., and Durbin, J. (2000). Fast filtering and smoothing for multivariate state space models, *Journal of Time Series Analysis*, 21, 281–296.

Litterman, R. B. (1983). A random walk, Markov model for the distribution of time series, *Journal of Business and Economic Statistics*, 1, 2, pp. 169-173.

Mitchell, J., Smith, R.J., Weale, M.R., Wright, S. and Salazar, E.L. (2004). An Indicator of Monthly GDP and an Early Estimate of Quarterly GDP Growth. Discussion Paper 127 (revised) National Institute of Economic and Social Research.

Mariano, R.S., and Murasawa, Y. (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics*, 18, 427-443.

Mohanan, J.F. (1984). A note on enforcing stationarity in autoregressive-moving average models. *Biometrika*, 71, 403–404.

Morton A.S. and Tunnicliffe-Wilson G.(2004) A class of modified high-order autoregressive models with improved resolution of low-frequency cycles, Journal of Time Series Analysis, 25 (2), 235-250

Sargent T.J. and Sims CA. (1977). Business cycle modelling without pretending to have too much a-priori economic theory. In *New Methods in Business Cycle Research*, Sims C, et al (eds); Federal Reserve Bank of Minneapolis: Minneapolis.

Moauro F. and Savio G. (2005). Temporal Disaggregation Using Multivariate Structural Time Series Models. Econometrics Journal, 8, 214-234.

Pesaran, M.H & Weale, M. (2005), Survey Expectations, in Handbook of Economic Forecasting, G. Elliott, C.W.J. Granger, and A.Timmermann (eds.), North-Holland (forthcoming 2006).

Proietti, T. (2004). Temporal Disaggregation by State Space Methods: Dynamic Regression Methods Revisited. Eurostat Working Papers and Studies, Luxembourg: Office for Official Publications of the European Communities. Forthcoming in the *Econometric Journal*.

Proietti, T. (2006). On the estimation of nonlinearly aggregated mixed models. *Journal of Computational and Graphical Statistics*, Vol. 15, 1–21.

Proietti T. and Frale C. (2006). New proposal for the Quantification of Business Survey data. Mimeo.

Proietti, T. and Frale C. (2007). A Monthly Indicator of the Euro Area GDP - Technical Report, Eurostat project on the ”Principal European Economic Indicators”, January 2007.

Proietti T. and Moauro F. (2006). Dynamic Factor Analysis with Nonlinear Temporal Aggregation Constraints. Journal of the Royal Statistical Society, series C (Applied Statistics), 55, pp. 281300.

Rosenberg, B. (1973). Random coefficient models: the analysis of a cross-section of time series by stochastically convergent parameter regression, *Annals of Economic and Social Measurement*, 2, 399-428.

Rnstler, G. (2004), Modelling phase shifts among stochastic cucles, *Econometric Journal*, volume 7, pp. 232-248.

Shephard, N.G., and Harvey, A.C. (1990). On the probability of estimating a deterministic component in the local level model, *Journal of Time Series Analysis*, 11, 339-347.

Shumway, R.H., and Stoffer, D. (2000). *Time Series Analysis and Its Applications*, Springer-Verlag, New York.

Stock, J.H., and Watson M.W. (1991). A probability model of the coincident economic indicators. In *Leading Economic Indicators*, Lahiri K, Moore GH (eds), Cambridge University Press, New York.

Tunnicliffe-Wilson, G. (1989). On the use of marginal likelihood in time series model estimation, *Journal of the Royal Statistical Society, Series B*, 51, 15-27.

APPENDIX-Univariate treatment of filtering and smoothing for multivariate models

This section is taken from Proietti and Frale (2006).

The univariate statistical treatment of multivariate models was considered by Anderson and Moore (1979). It 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 (1990).

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:

$$y_{t,i}^\dagger = \mathbf{z}_i^{*'}\boldsymbol{\alpha}_{t,i}^* + \mathbf{x}_{t,i}'\boldsymbol{\beta}, \quad t = 1, \ldots, n, \quad i = 1, \ldots, N, \tag{9}$$

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

$$\text{Var}(\boldsymbol{\epsilon}_{1,1}) = \text{Var}(\boldsymbol{\epsilon}_{t,1}) = \text{diag}(1, \sigma_1^2, \ldots, \sigma_N^2) = \boldsymbol{\Sigma}_\epsilon.$$

The augmented Kalman filter, taking into account the presence of missing values, is given by the following definitions and recursive formulae. Setting the initial values $\mathbf{a}_{1,1} = \mathbf{0}, \mathbf{A}_{1,1} = \mathbf{W}_1^*, \mathbf{P}_{1,1} = \mathbf{H}_1\boldsymbol{\Sigma}_\epsilon\mathbf{H}_1', q_{1,1} = 0, \mathbf{s}_{1,1} = \mathbf{0}, \mathbf{S}_{1,1} = \mathbf{0}$, for $t = 1, \ldots, n$, $i = 1, \ldots, N-1$, if $y_{t,i}t^\dagger$ is available:

$$\begin{array}{lcllcl}
v_{t,i} & = & y_{t,i}^\dagger - \mathbf{z}_i^{*'}\mathbf{a}_{t,i}^*, & \mathbf{V}_{t,i}' & = & -\mathbf{x}_{t,i}' - \mathbf{z}_i^{*'}\mathbf{A}_{t,i}^*, \\
f_{t,i} & = & \mathbf{z}_i^{*'}\mathbf{P}_{t,i}^*\mathbf{z}_i^{*'}, & \mathbf{K}_{t,i} & = & \mathbf{P}_t^*\mathbf{z}_i^{*'}/f_{t,i} \\
\mathbf{a}_{t,i+1}^* & = & \mathbf{a}_{t,i}^* + \mathbf{K}_{t,i}v_{t,i}, & \mathbf{A}_{t,i+1}^* & = & \mathbf{A}_{t,i}^* + \mathbf{K}_{t,i}\mathbf{V}_{t,i}', \\
\mathbf{P}_{t,i+1}^* & = & \mathbf{P}_{t,i}^* - \mathbf{K}_{t,i}\mathbf{K}_{t,i}'f_t, & & & \\
q_{t,i+1} & = & q_{t,i} + v_{t,i}^2/f_{t,i}, & \mathbf{s}_{t,i+1} & = & \mathbf{s}_{t,i} + \mathbf{V}_{t,i}v_{t,i}/f_{t,i} \\
\mathbf{S}_{t,i+1} & = & \mathbf{S}_{t,i} + \mathbf{V}_{t,i}\mathbf{V}_{t,i}'/f_{t,i} & d_{t,i+1} & = & d_{t,i} + \ln f_{t,i} \\
cn & = & cn + 1 & & &
\end{array} \tag{10}$$

Else, if $y_{t,i}t^\dagger$ is missing, which occurs for the second block of variables $\mathbf{y}_{2t}^c$ systematically for $t \neq \tau s$:

$$\begin{array}{lcl}
\mathbf{a}_{t,i+1}^* & = & \mathbf{a}_{t,i}^*, \quad \mathbf{A}_{t,i+1}^* = \mathbf{A}_{t,i}^*, \\
\mathbf{P}_{t,i+1}^* & = & \mathbf{P}_{t,i}^*, \\
q_{t,i+1} & = & q_{t,i}, \quad \mathbf{s}_{t,i+1} = \mathbf{s}_{t,i}, \quad \mathbf{S}_{t,i+1} = \mathbf{S}_{t,i}, \quad d_{t,i+1} = d_{t,i}.
\end{array} \tag{11}$$

Then for $i = N$

$$\begin{array}{rclrcl} \mathbf{a}^*_{t+1,1} & = & \mathbf{T}^*_{t+1}\mathbf{a}^*_{t,N}, & \mathbf{A}^*_{t+1,1} & = & \mathbf{W}^* + \mathbf{T}^*_{t+1}\mathbf{A}^*_{t,N}, \\ \mathbf{P}^*_{t+1,1} & = & \mathbf{T}^*_{t+1}\mathbf{P}^*_{t,N}\mathbf{T}^{*\prime}_{t+1} + \mathbf{H}^*\mathbf{\Sigma}_\epsilon\mathbf{H}^{*\prime}, & & & \\ q_{t+1,1} & = & q_{t,N}, \quad \mathbf{s}_{t+1,1} = \mathbf{s}_{t,N}, & \mathbf{S}_{t+1,1} & = & \mathbf{S}_{t,N}, \quad d_{t+1,1} = d_{t,N}. \end{array} \tag{12}$$

Here, $\mathbf{V}_{t,i}$ is a vector with $2N + k$ elements, $\mathbf{A}^*_{t,i}$ is $m \times (2N + k)$, cn counts the number of observations.

Under the fixed effects model maximising the likelihood with respect to $\boldsymbol{\beta}$ and σ^2 yields:

$$\hat{\boldsymbol{\beta}} = -\mathbf{S}^{-1}_{n+1,1}\mathbf{s}_{n+1,1}, \text{Var}(\hat{\boldsymbol{\beta}}) = \mathbf{S}^{-1}_{n+1,1}, \quad \hat{\sigma}^2 = \frac{q_{n+1,1} - \mathbf{s}'_{n+1,1}\mathbf{S}^{-1}_{n+1,1}\mathbf{s}_{n+1,1}}{cn}, \tag{13}$$

The profile likelihood is

$$\mathcal{L}_c = -0.5\left[d_{n+1,1} + cn\left(\ln\hat{\sigma}^2 + \ln(2\pi) + 1\right)\right]. \tag{14}$$

When $\boldsymbol{\beta}$ is diffuse (de Jong, 1991), the maximum likelihood estimate of the scale parameter is

$$\hat{\sigma}^2 = \frac{q_{n+1,1} - \mathbf{s}'_{n+1,1}\mathbf{S}^{-1}_{n+1,1}\mathbf{s}_{n+1,1}}{cn - 2N - k},$$

and the diffuse profile likelihood, denoted $\mathcal{L}_\infty$, takes the expression:

$$\mathcal{L}_\infty = -0.5\left[d_{n+1,1} + (cn - 2N - k)\left(\ln\hat{\sigma}^2 + \ln(2\pi) + 1\right) + \ln|\mathbf{S}_{n+1,1}|\right]. \tag{15}$$

Table 1: Autoregressive Distributed Lag model for Industry ADL(1,1)D with trend: parameter estimates and asymptotic standard errors, when relevant

Variables	*coef.*	*StDev*	*t-stat*
Drift	22.81	9.35	2.44
Trend	-0.02	0.02	-1.18
production	1.01	0.16	6.40
hours worked	0.20	0.36	0.55
EA.climate	-2.31	0.92	-2.51
EA.production	1.78	0.68	2.62
EA.orders	0.67	0.33	2.01
production(1)	-1.00	0.15	-6.48
hours worked (1)	-0.41	0.35	-1.17
EA.climate(1)	2.28	0.96	2.36
EA.production(1)	-1.72	0.70	-2.45
EA.orders(1)	-0.68	0.34	-1.97

Note: The label EA indicates that the variable comes from the Business Survey on firms. The script (1) stands for one lag of the variable.

Table 2: Dynamic factor model for Industry (SW): parameter estimates and asymptotic standard errors, when relevant

Parameters	*prod*	*howk*	*Value added*
θ_{i0}	0.603	0.218	0.745
	(0.087)	(0.053)	(0.121)
δ_i	0.297	-0.164	0.187
	(0.066)	(0.032)	(0.039)
d_{i1}	-0.587	-0.357	
d_{i2}	-0.231	-0.089	
$\sigma^{\mathbf{2}}{}_{\eta}$	0.140	0.099	3.45E-07

Common Index Equation

$$(1 - 0.44L - 0.196L^2)\,\Delta\mu_t = \eta_t, \quad \eta_t \sim N(0,1)$$

Note: standard errors in parenthesis.

Table 3: Dynamic factor model with 2 factor and modification for low frequency cycles (SW2-ZAR): parameter estimates and asymptotic standard errors, when relevant

Parameters	*prod*	*howk*	*EA.clim*	*EA.prod*	*EA.ord*	*Value added*
θ_{i0}	0.651	0.199	0.005	0.015	0.006	0.679
	(0.115)	(0.076)	(0.021)	(0.048)	(0.187)	(0.136)
$\widetilde{\theta_{i0}}$	0.026	0.013	0.207	0.197	0.173	0.024
	(0.020)	(0.011)	(0.037)	(0.036)	(0.031)	(0.020)
δ_i	0.025	0.022	0.033	0.061	0.025	0.251
	(0.034)	(0.009)	(0.049)	(0.087)	(0.034)	(0.090)
d_{i1}	0.449	-0.636	0.294	0.790	0.637	
d_{i2}	0.456	-0.133	0.642	0.099	0.312	
$\sigma^{\mathbf{2}}{}_{\eta}$	0.059	0.101	0.003	0.036	0.009	0.097

$$(1 - 0.55L - 0.36L^2)\,\Delta\mu_t = (1 + 0.5L)^2\eta_t, \quad \eta_t \sim N(0,1)$$
$$(1 - 1.42L + 0.44L^2)\,\Delta\widetilde{\mu_t} = \widetilde{\eta}_t, \quad \widetilde{\eta}_t \sim N(0,1)$$

Table 4: Statistics on forecast performance with constant parameters for 54 rolling estimates (2001M1-2005M6).

		ADL(1,1)D Model			**SW Model**			**SW2-ZAR Model**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	175	<u>-483</u>	<u>-930</u>	137	1,265	2,408	<u>-126</u>	503	1,235
	2^{nd}	620	<u>201</u>	<u>-352</u>	<u>-45</u>	933	2,055	-232	349	1,156
	3^{thd}	<u>-246</u>	<u>-774</u>	<u>-1,574</u>	661	1,926	2,727	303	1,179	1,634
MAE	1^{st} Month	1,508	2,738	3,372	<u>836</u>	2,488	3,894	878	<u>2,223</u>	<u>3,546</u>
	2^{nd}	1,746	3,211	4,255	<u>726</u>	2,221	3,966	765	<u>1,999</u>	<u>3,497</u>
	3^{thd}	2,024	3,239	4,116	1,323	3,103	4,124	<u>1,246</u>	<u>2,478</u>	<u>3,569</u>
MAPE	1^{st} Month	0.45	0.81	1.00	<u>0.25</u>	0.74	1.15	0.26	<u>0.66</u>	<u>1.05</u>
	2^{nd}	0.52	0.95	1.26	<u>0.22</u>	0.66	1.17	0.23	<u>0.59</u>	<u>1.03</u>
	3^{thd}	0.60	0.96	1.22	0.39	0.92	1.22	<u>0.37</u>	<u>0.73</u>	<u>1.05</u>
RMSFE	1^{st} Month	1,226	2,260	2,809	<u>737</u>	2,048	3,381	810	<u>1,728</u>	<u>3,325</u>
	2^{nd}	1,384	2,300	<u>2,912</u>	595	1,881	3,665	<u>580</u>	<u>1,764</u>	3,507
	3^{thd}	1,987	2,680	4,573	868	3,390	3,556	<u>872</u>	<u>2,291</u>	<u>3,095</u>
mRAE	1^{st} Month				<u>0.5</u>	<u>0.9</u>	1.3	<u>0.5</u>	<u>0.9</u>	1.2
	2^{nd}				<u>0.4</u>	<u>0.6</u>	<u>0.8</u>	<u>0.4</u>	<u>0.5</u>	<u>0.8</u>
	3^{thd}				<u>0.7</u>	1.1	1.3	<u>0.7</u>	<u>0.6</u>	<u>0.8</u>

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

Table 5: Statistics on forecast performance with estimated parameters for 54 rolling estimates (2001M1-2005M6).

		ADL(1,1)D Model			**SW Model**			**SW2-ZAR Model**		
		1-step	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*	*1-step*	*2-step*	*3-step*
ME	1^{st} Month	133	-507	-954	131	1,002	2,100	-407	-26	836
	2^{nd}	121	-450	-1,000	-9	701	1,774	-454	-200	622
	3^{thd}	-593	-1,038	-1,886	524	1,628	2,398	206	1,059	1,739
MAE	1^{st} Month	1,827	3,258	3,871	780	2,486	4,009	1,259	2,297	3,295
	2^{nd}	2,199	3,859	4,772	700	2,446	4,112	1,179	2,156	3,551
	3^{thd}	2,349	3,105	4,260	1,351	2,911	3,883	1,552	2,717	3,689
MAPE	1^{st} Month	0.54	0.97	1.15	0.23	0.74	1.19	0.38	0.68	0.98
	2^{nd}	0.65	1.15	1.42	0.21	0.73	1.22	0.35	0.64	1.05
	3^{thd}	0.70	0.92	1.26	0.40	0.86	1.15	0.46	0.81	1.09
RMSFE	1^{st} Month	1,771	2,947	3,239	480	2,137	3,715	876	2,113	2,545
	2^{nd}	1,963	4,283	4,246	442	2,107	3,694	1,042	1,837	3,710
	3^{thd}	2,282	2,719	4,323	837	3,101	3,213	1,370	2,244	2,850
mRAE	1^{st} Month				0.4	0.8	1.5	0.9	0.6	1.0
	2^{nd}				0.5	0.6	0.8	0.8	0.5	0.6
	3^{thd}				0.4	0.9	1.1	0.6	1.0	0.0

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

Table 6: Diebold-Mariano test (p-values) of equal forecast accuracy:

Constant parameters			
	1-step	*2-step*	*3-step*
SW *vs* ADLD	0.001	0.023	0.470
SW2-ZAR *vs* ADLD	0.001	0.000	0.026
SW2-ZAR *vs* SW	0.688	0.001	0.005
	1^{st} *Month*	2^{nd} *Month*	3^{thd} *Month*
SW *vs* ADLD	0.590	0.001	0.414
SW2-ZAR *vs* ADLD	0.066	0.000	0.064
SW2-ZAR *vs* SW	0.059	0.066	0.043
Estimated parameters			
	1-step	*2-step*	*3-step*
SW *vs* ADLD	0.000	0.000	0.176
SW2-ZAR *vs* ADLD	0.001	0.000	0.008
SW2-ZAR *vs* SW	1.000	0.163	0.039
	1^{st} *Month*	2^{nd} *Month*	3^{thd} *Month*
SW *vs* ADLD	0.188	0.002	0.258
SW2-ZAR *vs* ADLD	0.009	0.000	0.151
SW2-ZAR *vs* SW	0.203	0.219	0.223

Table 7: Averaged size of the news in the estimation, real time data for 54 rolling forecasts - (2001M1-2005M6).

Constant parameters

		SW2-ZAR Model			**SW Model**		
News in Ω		1-step	2-step	3-step	1-step	2-step	3-step
Surveys	1^{st} Month	0.03	0.14	0.27			
	2^{nd}	0.02	0.11	0.24			
	3^{thd}	0.00	0.06	0.14			
IP	1^{st} Month	0.40	0.44	0.41	0.35	0.40	0.41
	2^{nd}	0.27	0.43	0.41	0.27	0.41	0.43
	3^{thd}	0.12	0.51	0.44	0.09	0.43	0.40

Estimated parameters

		SW2-ZAR Model			**SW Model**		
News in Ω		1-step	2-step	3-step	1-step	2-step	3-step
Surveys	1^{st} Month	0.15	0.29	0.39			
	2^{nd}	0.10	0.33	0.41			
	3^{thd}	0.04	0.30	0.32			
IP	1^{st} Month	0.31	0.38	0.38	0.31	0.38	0.39
	2^{nd}	0.27	0.47	0.47	0.23	0.43	0.44
	3^{thd}	0.15	0.43	0.45	0.09	0.45	0.43

The news is measured by the Mean Absolute Relative difference between two consecutive vintages : $100 * abs[(Y1 - Y0)/Y0]$

Figure 1: Temporal disaggregation of value added of Industry: Eurozone12, 1995.1-2006.9. ADL(1,1)D with trend.

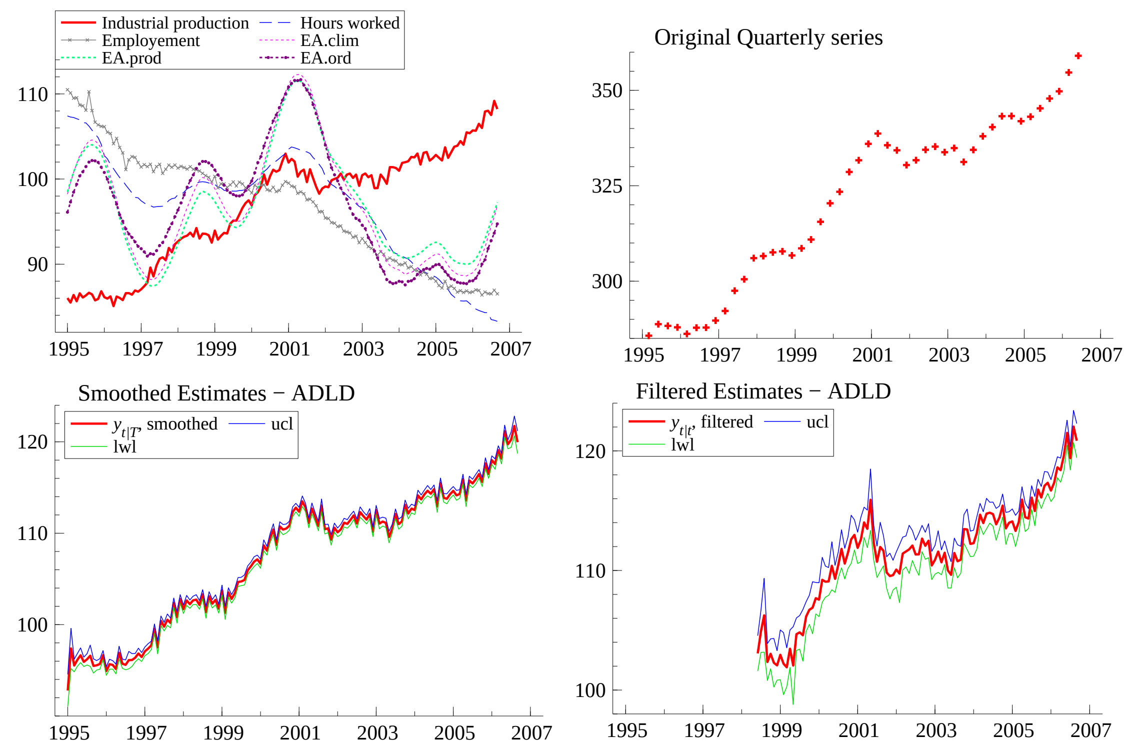

Figure 2: Temporal disaggregation of value added of Industry: Eurozone12, 1995.1-2006.9. Dynamic SW factor model.