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Should quarterly government finance statistics be used for fiscal surveillance in Europe?

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Abstract

We use a newly available dataset of euro area quarterly national accounts fiscal data and construct multivariate state space mixed-frequencies models for the government deficit, revenue and expenditure in order to assess its information content and potential use for fiscal forecasting and monitoring purposes. The models are estimated using annual and quarterly national accounts fiscal data, but also incorporate monthly information taken from the cash accounts of the governments. The results show the usefulness of our approach for real-time fiscal policy surveillance in Europe, given the current policy framework in which the relevant official figures are expressed in annual terms.

Keywords: Fiscal policies; Mixed frequency data; Forecasting; Unobserved components models; State space; Kalman Filter

1. Introduction

The issue addressed in this paper is how to obtain timely estimates of annual government deficits. The operation of the fiscal policy coordination device in the European Union (EU), i.e. the Stability and Growth Pact, is directly related to an annual multilateral assessment of EU countries' latest budgetary figures and fiscal plans, including targets and projections for subsequent years. The relevant official figures used for this assessment are expressed in annual terms, using the European System of Integrated Economic Accounts (ESA95) as a conceptual reference method. The first estimates of annual figures for year $t-1$ are made available by the spring of year t, in line with standard National Accounts compilation practices, while the second estimate is due by the autumn of year t, and is sometimes subject to further revisions in subsequent years (see Bier, Mink, & Rodríguez-Vives, 2004 and Gordo & Nogueira Martins, 2007).

The fact that the multilateral EU system is based solely on annual fiscal data might limit its ability to detect departures from fiscal rules early, and hinder private sector agents and the monetary authority in internalizing fiscal policy shocks in a timely fashion.

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Thus, a number of EU regulations have developed the mandate to compile quarterly ESA95 fiscal data.[1] Following these regulations, Eurostat started to disseminate quarterly budget balance figures for the EU aggregates and for most member countries in April 2006, while the European Central Bank (ECB) has been publishing euro area aggregates since August 2004 (see ECB, 2004). Quarterly general government accounts present some shortcomings in terms of coverage of revenue and expenditure items, sample size (the period starting 1999Q1, with some exceptions), and timeliness (with at least 90 days delay). In addition, there is still some heterogeneity as regards country availability. For example, Germany and France only publish quarterly figures for the four quarters of a given year, in conjunction with the release calendar of the annual accounts of that year.[2] Nevertheless, the euro area aggregate is published in a timely manner, following a regular quarterly publication calendar.

Even considering all these caveats, it is fair to say that the ESA95 quarterly accounts for the general government, as currently disseminated by Eurostat, represent an important improvement in the matter of timeliness with respect to using only annual ESA95 accounts. Thus, the aim of this paper is to analyze the extent to which using this new set of information might help in improving the monitoring and forecasting of annual ESA95 figures within the current year. Fig. 1 (left panel) shows the annual ESA95 euro area government deficit path over the past 20 years, together with the four-quarter moving sum of quarterly ESA95 figures for the period 1999Q4–2007Q4 (the period for which the quarterly figures are available). The reduction in the sampling interval from 1999 onwards is evident by simple visual inspection.

Fig. 1 (right panel, solid line) also displays another measure of the euro area fiscal deficit, based on monthly cash accounts of governments,[3] that traces the profile of annual/quarterly ESA95 figures over the same period of time. Monthly and quarterly revenue and expenditure cash data from central government and other sub-sectors of the general government have recently been shown to contain valuable information for monitoring and forecasting euro area annual ESA95 fiscal deficits (Onorante, Pedregal, Pérez, & Signorini, in press; Pérez, 2007). They are available with a delay of one to three months, and typically cover long periods of the recent history (i.e., it is possible to find deficit series going back to the 1980s or even the 1970s). We add this set of information to the analysis for three reasons. Firstly, to overcome the short sample problem associated with quarterly ESA95 figures (backcasting). Secondly, to assess its potential use for nowcasting quarterly ESA95 figures. Finally, to assess whether including quarterly ESA95 figures would improve the estimation of annual deficit figures within the year, compared to an approach based solely on intra-annual monthly cash data.

An optimal way to use these data is to build a single model that relates data at all frequencies. In this paper we construct multivariate state space mixed-frequencies models for the euro area aggregate fiscal deficit, revenue and expenditure, based on annual and quarterly ESA95 figures, and on monthly information taken from the cash accounts of governments. Our approach is closely related to that of Harvey and Chung (2000), Moauro and Savio (2005), and Proietti and Moauro (2006).[4] These papers use a temporal aggregation method that relies on the information contained in related indicators observed at the desired higher frequency. The statistical treatment of structural time series models is based on the state space form and the Kalman Filter (see Harvey, 1989). In our case, this approach allows the estimation of a monthly model using annual, quarterly and monthly observations, and permits changes over time arising from an increase in the sample size.

[1] European regulations (EC) N° 264/2000, 1500/2000, 1221/2002, 501/2004, and 1222/2004.

[2] For details on cross-country coverage and availability, see European Commission (2007).

[3] Comprising the monthly cash deficit of Belgium, Germany, Spain, France, Italy, the Netherlands, Austria, Ireland, Portugal and Finland. The sum of cash indicators has been done for illustrative purposes, as cross-country definitions are only approximately comparable. For definitions and further details, see the next section of the paper.

[4] Other approaches for modeling data at different sampling intervals include the methods based on regression techniques (Chow & Lin, 1971; Guerrero, 2003), the MIDAS (MIxed DAta Sampling) approach (see Ghysels, Santa-Clara, & Valkanov, 2006, and Clements & Galvão, 2007), the state space approaches of Liu and Hall (2001) and Mariano and Murasawa (2003), and the ARMA model model with missing observations of Hyung and Granger (2008).

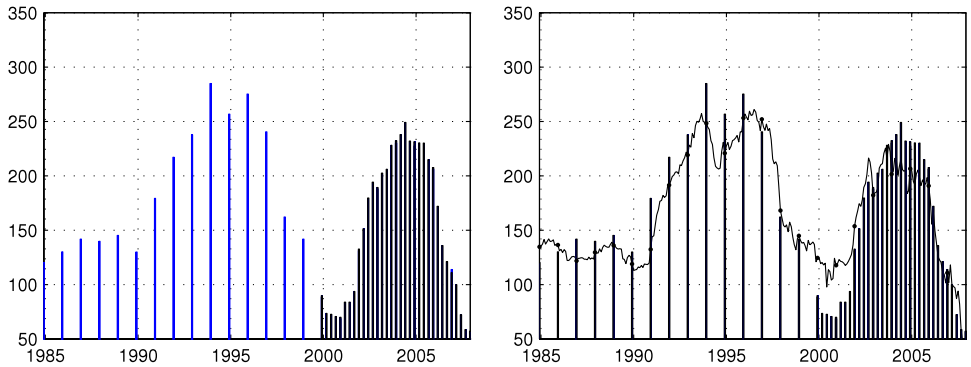

Fig. 1. Euro area deficit (+) / surplus (–), billions of euro: ESA95 annual and quarterly figures (bars, quarterly shown as 4-quarter moving sum) and monthly cash deficits (solid line in right panel, 12-month moving sum).

We move beyond the relevant literature in the following respects: (i) we focus on forecasting, while the motivation of most studies is the estimation of unobserved measurements of certain variables based on measured data, with little interest in the forecasting performance[5]; (ii) we make extensive use of a three frequency setup: annual, quarterly and monthly data; and (iii) we always model and estimate models using non-seasonally-adjusted data.

The analysis focuses on forecasting the quarterly ESA95 general government deficit, total revenue and total expenditure for the euro area aggregate, as published in the Monthly Bulletin of the European Central Bank (based on Eurostat data). The focus on the euro area aggregate stems from its availability in real time (following a quarterly calendar of releases), while in some cases individual country data is only available with a much longer delay, most noticeably in the above-mentioned cases of Germany and France. Monthly public accounts data for Belgium, Germany, Greece, Spain, France, Italy, the Netherlands, Ireland, Austria and Finland for the period 1984–2007 are used as well. The results unambiguously show the potential gains that would be derived from using quarterly ESA95 figures for fiscal surveillance in Europe.

With a focus on forecasting the annual government deficit, we also evaluate the comparative behaviours of approaches that directly forecast the government deficit versus approaches that forecast government revenues and government expenditures, and then compute forecasts for the deficit as a residual variable (revenue minus expenditure).

A valuable by-product of our analysis is that we provide interpolated monthly series of annual fiscal variables based only on intra-annual *fiscal information*. This is a relevant point for further research devoted to the integration of intra-annual fiscal variables in more general macroeconomic studies. A clear advantage of using only intra-annual fiscal data to interpolate annual fiscal variables versus an approach based on quarterly GDP and other macroeconomic variables lies in the circularity that the latter approach might induce in cases where the so-interpolated fiscal series were used with GDP or other macro variables to assess the intra-annual impact of fiscal policies (where the GDP is used to generate intra-annual dynamics in fiscal variables, and then the so-generated fiscal variables are used in turn to assess the intra-annual impact of fiscal policies).[6] An approach like the one presented in our paper, which is based solely on intra-annual fiscal information, is free from this caveat.

The paper is organized as follows. Section 2 presents the data employed and the timing convention used for the main empirical exercise. Section 3

[5] Nevertheless, the models presented here may also be used for the reconstruction of annual fiscal variables in ESA95 terms toward the beginning of the sample at a shorter sampling interval.

[6] Camba-Méndez and Lamo (2004) use the latter approach to provide estimates for quarterly budget balances for Germany and Italy, on the basis of annual general government deficits and quarterly GDP, focusing on the study of structural deficits. For the use of fiscal indicators on a cash basis to interpolate annual ESA95 data, see Estrada, Fernández, Moral, and Regil (2004) for the Spanish economy and Onorante et al. (in press) for a number of euro area countries.

presents our methodological approach. Section 4 describes a thorough forecasting exercise for testing alternative models. Section 5 gives some additional empirical results, especially as regards the value added by the use of quarterly figures rather than an approach based solely on intra-annual monthly information. Section 6 concludes.

2. Data description and timing

2.1. Data sources

The data cover the period 1984–2007. Annual ESA95 data and monthly cash accounts are available for the whole period, while quarterly ESA95 figures are only available for the period 1999Q1–2007Q4. Quarterly and annual ESA95 data have been taken from Eurostat and/or the Monthly Bulletin of the ECB. The impact of one-off proceeds from the allocation of mobile licenses (UMTS) that sizeably distort some years was removed from the relevant series (deficit and expenditure).

Cash data have been taken from various different national sources that are mostly available on the internet. In the case of Germany we use two sources of cash indicators: quarterly General Government cash figures taken from the web page of the Deutsche Bundesbank, and Federal Government fiscal series obtained from the Ministry of Finance. Then, for each pair of deficit, revenue and expenditure cash indicators we use the monthly Federal Government series to interpolate the quarterly General Government cash ones, by means of a mixed frequency model,[7] and take the resulting series as the monthly cash indicators for Germany. In the cases of Greece, France, the Netherlands and Finland we use central government series obtained from the Ministry of Finance. For Spain we use central government series from the National Statistical Institute, and in the case of Italy we use series from Banca d'Italia. For Austria, central government series are available at the quarterly frequency for the period 1984–1987, and monthly for 1988–2007; in order to obtain a monthly indicator series for the whole period (1984–2007) we estimate a mixed frequency model with all of the available information.[8] Ireland presents a similar case, as we were able to obtain quarterly data for the period 1984–1995, and monthly data for the period 1996–2007.

For further details on the sources of the cash indicators used in our paper, see Pérez (2007) and Onorante et al. (in press). For a deep analysis of the detailed accounting rules and conventions involved in the compilation of the Net Borrowing/Net Lending of the General Government, and the differences between National Accounts and Public Accounts (cash indicators), the interested reader can consult Eurostat (1996, 2002a,b) for National Accounts-related matters, and http://dsbb.imf.org for Public Accounts-specific features.

2.2. Transformations of the variables

The mixture of frequencies, and the estimation of models at the monthly frequency, implies the combination of variables that can be considered as stocks at the monthly frequency, with those being pure flows. An annual ESA95 series cast into the monthly frequency is a set of missing observations for the first eleven months of the year (January to November) and the observed value assigned to the last month of each year (December). Theoretically the annual ESA95 series would be obtained from a monthly ESA95 series by the summation of the 12 months of a year (January to December), had they been available. In the same fashion, a quarterly ESA95 series cast at the monthly frequency encompasses missing observations for the first and second months of each quarter, while the quarterly observation is assigned to the last month of each quarter. Theoretically the quarterly ESA95 series would be obtained from a monthly ESA95 series by summation of the 3 months of each quarter, had they been available.

Given this fact, we are interested in two kinds of combinations of variables. On the one hand, the baseline mixed-frequencies models would comprise variables that are included, as they come from the official statistics. The annual ESA95 figure for a given year is assigned to the December of that very year, and the quarterly figure for a given quarter is assigned

[7] The models used are in the vein of Harvey (1989), and are described in detail in the main methodological section of the paper.

[8] Again, the models used are in the vein of Harvey (1989).

Table 1
Timing rules.

	Q1 year t (March)	Q2 year t (June)	Q3 year t (September)	Q4 year t (December)
Available annually (A)	A $t-2$ (March)	A $t-1$ (April)	A$t-1$	A $t-1$
Available quarterly (Q)	Q3 $t-1$	Q4 $t-1$ (April)	Q1 t	Q2 t
Available monthly (M)	Jan t	Jan–April t	Jan–July t	Jan–October t

to the third month of that quarter. Then the model takes care of guaranteeing the accounting constraints between annual, quarterly and monthly data.

The second alternative is to transform monthly and quarterly variables so that they can be considered as "annual stocks". For a given ESA95 variable z_t, we shall denote Z_t at each t as the rolling (moving) sum of monthly observations over the previous 12 months. Thus, when the subindex t equals the December of a given year, Z_t represents the yearly result. In the same fashion, for a given budgetary (cash) variable u_t, we shall denote U_t as the rolling (moving) sum of monthly observations over the previous 12 months.

Thus, we estimate models for the general government budget balance, and general government total revenue and total expenditure, while at the same time exploring two types of data input: (i) input variables expressed as 12-month moving sums; and (ii) input variables expressed as originally obtained. The latter distinction is relevant from a practitioner's viewpoint, as the sum of four consecutive quarters/12 consecutive months generates the annual variable, which is the objective in the current policy framework, and thus rolling summation is a widely used measure in practitioner circles.

At the same time, we will explore two sets of monthly cash information for each data approach: (i) country monthly cash series for the five big euro area countries (Germany, France, Italy, Spain, Netherlands) and an aggregate of smaller countries (Austria, Greece, Ireland, Finland); and (ii) aggregates of individual country indicators.

With all these cases, we will cover quite a rich set of alternatives in our empirical exercises.

2.3. Timing rules

In order to replicate the real-time constraints faced by real-time fiscal policy analysts, we adopt the timing rules displayed in Table 1, following the standard dates of the dissemination of data at the different frequencies. In the table we show the information available in each quarter of a given year. Annual ESA95 figures for the year $t-1$ are first released by Eurostat in March/April of year t, but the validation processes performed by Eurostat on figures reported by national statistical agencies render April/May the actual date at which usable/reliable figures are available to an outside analyst. Thus, from a quarterly observation perspective, it is fair to assume that the annual figure for year $t-1$ is only available in the second quarter of year t. In a related fashion, the quarterly ESA95 figures for the fourth quarter of year $t-1$ are only available in the course of the second quarter of year t. Regarding monthly cash accounts, we follow the assumption of availability with a lag of two months. We also deem this convention as a fair heuristic representation of reality.

Nevertheless, it is worth mentioning that we do not use real-time data, but revised data, as available in November 2008. Of course, the exercise has some counter-factual features, in that data revisions might have affected the lessons drawn from mixed-frequencies models in relation to today's re-creation. For our exercise it is not possible to fully re-create the real-time nominal fiscal series that would have been available at the time, given that the quarterly ESA95 data started to be published for the euro area aggregate only in August 2004. In addition, the different vintages of the euro area quarterly ESA95 figures, as published in the Monthly Bulletin of the European Central Bank, are published as a percentage of the nominal GDP, and not nominal values (this is another caveat linked to the real-time re-creation). In any case, it is worth mentioning that revisions to quarterly fiscal figures were linked to revisions of annual fiscal data (European Commission, 2007).

3. The models

The basic model will be a multivariate Unobserved Components Model which is known as the Basic Structural Model (BSM; Harvey, 1989), and sometimes also as Structural Unobserved Time Series (STUSE). Such models decompose a set of time series into unobserved components which are meaningful from an economic point of view (trend $\mathbf{T}_t$, seasonal $\mathbf{S}_t$, and irregular $\mathbf{e}_t$). A general form is given in Eq. (1), where t is a time sub-index measured in months (and thus models are cast at the monthly frequency), $\mathbf{z}_t$ denotes the variable in ESA95 terms expressed at annual or quarterly sampling intervals (depending on availability) for the deficit (scalar) or revenue and expenditure (vector), and $\mathbf{u}_t$ represents the vector of monthly cash indicators.

$$\begin{bmatrix}\mathbf{z}_t\\ \mathbf{u}_t\end{bmatrix} = \mathbf{T}_t + \mathbf{S}_t + \mathbf{e}_t. \tag{1}$$

The general consensus with respect to this type of models is to allow components of the same type to interact among themselves for different time series, but to be independent of any of the components of different types. For example, trends are interrelated, but are independent of the seasonal components. A model for each of the components has to be set up in a state space framework, and a full model may be built by block concatenation of the individual components. The full model may be written in its state space form as in Eqs. (2)–(4) (see Harvey, 1989):

$$\mathbf{x}_t = \boldsymbol{\Phi}\mathbf{x_{t-1}} + \mathbf{E}\mathbf{w_t} \tag{2}$$

$$\begin{bmatrix}\mathbf{z}_t\\ \mathbf{u}_t\end{bmatrix} = \begin{bmatrix}\mathbf{H}\\ \mathbf{H}^u\end{bmatrix}\mathbf{x}_t + \begin{bmatrix}\boldsymbol{\epsilon}_t\\ \mathbf{v}_t\end{bmatrix} \tag{3}$$

where

$$\mathbf{w}_t \sim N(0, \Sigma_{\mathbf{w}_t}), \qquad \boldsymbol{\epsilon}_t \sim N(0, \Sigma_{\epsilon}),$$
$$\mathbf{v}_t \sim N(0, \Sigma_{\mathbf{v}_t}). \tag{4}$$

The system matrices $\boldsymbol{\Phi}$, $\mathbf{E}$, $\mathbf{H}$ and $\mathbf{H}^u$ in Eqs. (2)–(3) include the particular definitions of the components (see below), and all of the vector noises have the usual Gaussian properties, with zero mean and constant covariance matrices ($\boldsymbol{\epsilon}_t$ and $\mathbf{v}_t$ are correlated, but both are independent of $\mathbf{w}_t$). The particular structure of the covariance matrices of the observed and transition noises defines the structures of correlations among the components across output variables.

The particular structure of the system matrices in system (2)–(3) is as follows. Let m be the number of variables $\mathbf{z}_t$ and $\mathbf{u}_t$ combined; and $\mathbf{I}$ and $\mathbf{0}$ be $m \times m$ identity and zero matrices, respectively. Then $\boldsymbol{\Phi}$ is a matrix formed by the block concatenation of the matrices

$$\boldsymbol{\Phi}_0 = \begin{bmatrix}\mathbf{I} & \mathbf{I}\\ \mathbf{0} & \mathbf{I}\end{bmatrix},$$
$$\boldsymbol{\Phi}_k = \begin{bmatrix}\cos\dfrac{2\pi k}{12} & \sin\dfrac{2\pi k}{12}\\ \sin\dfrac{2\pi k}{12} & \cos\dfrac{2\pi k}{12}\end{bmatrix} \otimes \mathbf{I},$$
$$k = 1, 2, \ldots, 6. \tag{5}$$

$\mathbf{E}$ is an identity matrix of appropriate dimension, and

$$\begin{bmatrix}\mathbf{H}\\ \mathbf{H}^u\end{bmatrix} = \begin{bmatrix}\mathbf{I} & \mathbf{0} & \mathbf{I} & \mathbf{0} & \ldots & \mathbf{I} & \mathbf{0}\end{bmatrix}. \tag{6}$$

An additional modelling difficulty arises in our case from the different sampling intervals of the time series involved. In particular, the annual-quarterly ESA95 data in the moving-sum models are the sum of 12 monthly observations in the time span where only ESA95 annual data are available, and 3 monthly observations in the period where ESA95 quarterly data are available. This temporal aggregation problem will be dealt with differently depending on the nature of $\mathbf{z}_t$ and $\mathbf{u}_t$, i.e. depending on whether these variables are defined as moving sums or flows. It is well-known that, given the structure of system (2) and the information available, the Kalman Filter and fixed interval smoother algorithms provide an optimal estimation of the states $\mathbf{x}_t$. Maximum likelihood in the time domain provides optimal estimates of the unknown system matrices, which in the present context are just the covariance matrices of all of the vector noises involved in the model. See the details in Harvey (1989) or Pedregal and Young (2002), for example.

3.1. Models for the variables expressed as moving sums

The basic model described by Eqs. (2) and (3) is suitable as such for rolling sums. As $\mathbf{z}_t$ and $\mathbf{u}_t$ are rolling sums of the original data, the seasonal

component is not included, since the summation operation washes out the seasonality in the data.

Four versions of the model are estimated:

- **Model MS1**: bivariate version in which $\mathbf{z}_t = Z_t$ refers to the euro area deficit in ESA95 terms (annual data for 1984–1998, quarterly data for 1999–2006), expressed as moving sums of the four previous quarters, and $\mathbf{u}_t = \sum_{i=1}^{6} U_{it}$, $\forall t$, is an aggregate of the cash deficit series (monthly data for 1984–2006, expressed as moving sums of the previous twelve months) for the following countries: U_{1t}: Germany; U_{2t}: France; U_{3t}: Italy; U_{4t}: Spain; U_{5t}: the Netherlands; and U_{6t}: sum of Belgium, Greece, Ireland, Austria and Finland.
- **Model MS2**: multivariate version in which $\mathbf{z}_t$ is defined as in MS1, and $\mathbf{u}_t = [U_{1t}, U_{2t}, \ldots, U_{6t}]$ are cash deficit series (monthly data for 1984–2006, expressed as moving sums of the previous twelve months) for the following countries: U_{1t}: Germany; U_{2t}: France; U_{3t}: Italy; U_{4t}: Spain; U_{5t}: the Netherlands; U_{6t}: sum of Belgium, Greece, Ireland, Austria and Finland.
- **Model MS3**: multivariate version for total revenue and total expenditure. In this case $\mathbf{z_t} = [Z_{1t}, Z_{2t}]^{\mathrm{T}}$, where Z_{1t} and Z_{2t} refer to euro area total revenue and total expenditure respectively, both in ESA95 terms (annual data for 1984–1998, quarterly data for 1999–2006). Regarding the cash variables, $\mathbf{u}_t = [\mathbf{u}_{1t}, \mathbf{u}_{2t}]^{\mathrm{T}}$, where $\mathbf{u}_{1t} = \sum_{i=1}^{5} U_{it}^{1}$, $\forall t$, is an aggregate of total revenue indicators in cash terms (monthly data for the period 1984–2006), and $\mathbf{u}_{2t} = \sum_{i=1}^{5} U_{it}^{2}$, $\forall t$, is an aggregate of total expenditure indicators in cash terms (monthly data for the period 1984–2006). In both cases, the five big euro area countries are covered: Germany (U_{1t}^{j}), France (U_{2t}^{j}), Italy (U_{3t}^{j}), Spain (U_{4t}^{j}) and the Netherlands (U_{5t}^{j}), $\forall j = 1, 2$.
- **Model MS4**: multivariate version for total revenue and total expenditure. In this case $\mathbf{z_t}$ is defined as in MS3. Regarding cash variables, $\mathbf{u}_t = [\mathbf{u}_{1t}, \mathbf{u}_{2t}]^{\mathrm{T}}$, where $\mathbf{u}_{1t} = \left[U_{1t}^{1} \ldots U_{5t}^{1}\right]^{\mathrm{T}}$ refer to total revenue in cash terms (monthly data for 1984–2006) and $\mathbf{u}_{2t} = \left[U_{1t}^{2} \ldots U_{5t}^{2}\right]^{\mathrm{T}}$ refer to total expenditure in cash terms (monthly data for 1984–2006). In both cases, the five big euro area countries are covered: Germany (U_{1t}^{j}), France (U_{2t}^{j}), Italy (U_{3t}^{j}), Spain (U_{4t}^{j}) and the Netherlands (U_{5t}^{j}), $\forall j = 1, 2$.

3.2. Flow models

There are several additional steps to carry out when the original flow variables are to be used, in order to address the time aggregation problem. If the original data are used, then the seasonal component is compulsory, and in our particular case such components are considered to be independent across countries, as it is assumed to reflect country-specific institutional arrangements.[9] In order to set up a model in which the temporal aggregation is taken into account explicitly, a cumulator variable has to be defined.

The first step is to set up model (2)–(3) to include the first observation equation in the state vector. The second step consists of adding a cumulator variable to this model to guarantee accounting consistency within the year. This cumulator variable is defined as:

$$C_t = \begin{cases} 0, & t = \text{every January (monthly data)/} \\ & \quad \text{first quarter (quarterly data)} \\ 1, & \text{otherwise.} \end{cases} \tag{7}$$

Thus, the model turns out to be:

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} = \begin{bmatrix} C_t \otimes \mathbf{I} & \mathbf{H}\boldsymbol{\Phi} \\ \mathbf{0} & \boldsymbol{\Phi} \end{bmatrix} \begin{bmatrix} \mathbf{z}_{t-1} \\ \mathbf{x}_{t-1} \end{bmatrix} + \begin{bmatrix} 1 & \mathbf{H} \\ \mathbf{0} & \mathbf{E} \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \mathbf{w}_t \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{u}_t \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{H}^{u} \end{bmatrix} \begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{I} \end{bmatrix} \mathbf{v}_t. \tag{9}$$

It is worth noticing that this model has one time varying system matrix, due to the introduction of the cumulator variable. Once more, four versions of the model are estimated.

- **Model F1**: bivariate version in which $\mathbf{z}_t = z_t$ refers to the euro area flow deficit in ESA95 terms (annual data for 1984–1998, quarterly data for 1999–2007), and $\mathbf{u}_t = u_t = \sum_{i=1}^{6} u_{it}$, $\forall t$ is an aggregate of cash deficit series (monthly data for 1984–2007) for the following countries: u_{1t}: Germany; u_{2t}: France; u_{3t}: Italy; u_{4t}: Spain; u_{5t}: the Netherlands; and u_{6t}: sum of Belgium, Greece, Ireland, Austria and Finland.
- **Model F2**: multivariate version for total revenue and total expenditure. In this case $\mathbf{z}_t = [z_{1t}\, z_{2t}]^{\mathrm{T}}$, where z_{1t} and z_{2t} refer to euro area total revenue

[9] The empirical tests performed confirm this hypothesis. The results are presented in an Appendix.

and total expenditure respectively, both in ESA95 terms (annual data for 1984–1998, quarterly data for 1999–2007) and as originally reported by Eurostat (i.e. flows). Regarding the cash variables, $\mathbf{u}_t = [\mathbf{u}_{1t}, \mathbf{u}_{2t}]^{\mathrm{T}}$, where $\mathbf{u}_{1t} = \sum_{i=1}^{6} u_{it}^{1}$ is an aggregate of total revenue cash series (monthly data for 1984–2007) and $\mathbf{u}_{2t} = \sum_{i=1}^{6} u_{it}^{2}$ is an aggregate of total expenditure cash series (monthly data for 1984–2007). In both cases, the five big euro area countries are covered: Germany (u_{1t}^{j}), France (u_{2t}^{j}), Italy (u_{3t}^{j}), Spain (u_{4t}^{j}) and the Netherlands (u_{5t}^{j}), $\forall j = 1, 2$.

- **Model F3**: multivariate version in which $\mathbf{z}_t$ is defined as in F1, and $\mathbf{u}_t = [u_{1t}, u_{2t}, \ldots, u_{6t}]$ are cash deficit series (monthly data for 1984–2007) for the following countries: u_{1t}: Germany; u_{2t}: France; u_{3t}: Italy; u_{4t}: Spain; u_{5t}: the Netherlands; and u_{6t}: sum of Belgium, Greece, Ireland, Austria and Finland.
- **Model F4**: multivariate version for total revenue and total expenditure. In this case, $\mathbf{z}_t$ is defined as in F2. Regarding the cash variables, $\mathbf{u}_t = [\mathbf{u}_{1t}, \mathbf{u}_{2t}]^{\mathrm{T}}$, where $\mathbf{u}_{1t} = \left[u_{1t}^{1} \ldots u_{5t}^{1}\right]^{\mathrm{T}}$ refer to total revenue in cash terms (monthly data for 1984–2007) and $\mathbf{u}_{2t} = \left[u_{1t}^{2} \ldots u_{5t}^{2}\right]^{\mathrm{T}}$ refer to total expenditure in cash terms (monthly data for 1984–2007). In both cases, the five big euro area countries are covered: Germany (u_{1t}^{j}), France (u_{2t}^{j}), Italy (u_{3t}^{j}), Spain (u_{4t}^{j}) and the Netherlands (u_{5t}^{j}), $\forall j = 1, 2$.

4. Comparison of alternative models

4.1. Forecasting exercise

As a summary of the discussion of previous sections, with this forecasting exercise we want to test:

1. The information content of the quarterly data;
2. The comparative behaviour of models that use variables expressed as moving sums versus those using flows;
3. The forecasting record of models that use intra-annual information versus a random walk based solely on annual data;
4. The comparative performance of approaches that forecast the government deficit directly versus approaches that forecast government revenues and government expenditures and then compute forecasts for the deficit as a residual variable (revenue minus expenditure); and
5. The nowcasting properties of different models (one-quarter-ahead forecasts).

In order to achieve these goals, we add the following models to the list of models described in the previous section: (i) quarterly random walk (QRW henceforth); and (ii) annual random walk (ARW henceforth). The QRW alternative allows us to test the models against an alternative based purely on quarterly ESA95 information. The ARW alternative is the standard naive benchmark.

We then perform a rolling forecasting exercise in which the selection of the forecast origin and the information set available at each date are carefully controlled for. In particular, we evaluate the forecasts generated from four forecast origins per year from March 2001 to December 2007 (this makes up to 28 projections at each forecast horizon). The first forecast origin is March 2001, and, following the timing convention outlined earlier (see Table 1), the annual information available covers up to the year 1999, the quarterly information up to 2000:Q3, and the monthly information up to January 2001. The second forecast origin is June 2001, with annual information up to 2000, quarterly up to 2000:Q4 and monthly up to January–April 2001. Then we move the forecast origin to September 2001, and so on, until December 2007.

Finally, we present two standard quantitative measures of forecasting performance. Firstly, we use the ratio of the Root Mean Squared Errors (RMSE) of the different alternative models to those of the ARW and/or QRW alternatives. Secondly, we also look at the Diebold and Mariano test (using the finite sample modification of Harvey, Leybourne, and Newbold (1997)), and test for the null hypothesis of no difference in the accuracies of two competing forecasts. The Diebold-Mariano test could be biased when parameter uncertainty is taken into account (see for example Clark and McCraken (2001). We make sure that a reasonable proportion of the sample is employed when the first out-of-sample forecast is computed in order to reduce the bias generated by ignoring parameter uncertainty (the forecasting exercise is performed on the moving window 2001–2007, while the full sample covers 1984–2007).

Table 2
Current-year forecasts (full year forecasts): forecasting quarterly ESA95 figures with the different models. RMSE ratios to the annual random walk and Diebold-Mariano tests.

RMSE ratio of models to the annual random walk

	QRW	Model MS1	Model MS2	Model MS3	Model MS4	Model F1	Model F2	Model F3	Model F4
	0.68	0.48	0.51	0.46	0.48	0.47	0.53	0.71	0.53

Dieblod-Mariano test

	ARW	QRW	MS1	MS2	MS3	MS4	F1	F2	F3
QRW	-3.18^{***}	–	–	–	–	–	–	–	–
Model MS1	-3.41^{***}	-2.24^{**}	–	–	–	–	–	–	–
Model MS2	-3.47^{***}	-1.77^{*}	0.61	–	–	–	–	–	–
Model MS3	-3.56^{***}	-2.61^{**}	−0.58	−0.89	–	–	–	–	–
Model MS4	-3.78^{***}	-2.00^{**}	0.06	−0.36	0.32	–	–	–	–
Model F1	-3.77^{***}	-2.66^{***}	−0.11	−0.52	0.24	−0.20	–	–	–
Model F2	-3.49^{***}	-2.80^{***}	0.87	0.30	1.27	0.64	1.41	–	–
Model F3	-1.70^{*}	0.20	1.27	1.14	1.41	1.29	1.29	1.00	–
Model F4	-3.41^{***}	−1.52	0.67	0.31	1.08	0.67	0.79	−0.02	−1.27

Models:
Model MS1: 2 variables (annual-quarterly ESA95 deficit, monthly deficit cash). Moving sums.
Model MS2: 7 variables (a-q ESA95 deficit, 6 countries monthly deficit cash). Moving sums.
Model MS3: 4 variables (a-q ESA95 rev and exp, monthly revenue and exp cash). Moving sums.
Model MS4: 12 variables (a-q rev and exp ESA95, 5 revenue cash, 5 expenditure cash). Moving sums.
Model F1: 2 variables (a-q ESA95 deficit, monthly deficit cash). Flows.
Model F2: 4 variables (a-q ESA95 rev and exp, monthly revenue and expenditure cash). Flows.
Model F3: 7 variables (a-q ESA95 deficit, 6 countries monthly deficit cash). Flows.
Model F4: 12 variables (a-q rev and exp ESA95, 5 revenue cash, 5 exp cash). Flows.
Notes:
1. Diebold-Mariano test (the Harvey et al., 1997, version) for the null hypothesis of the equal forecast accuracy of two forecast methods. A squared loss function is used. The number in each cell represents the loss differential of the method in the row as compared to the method in the column.
2. We perform a rolling forecasting exercise in which we evaluate the forecasts generated from four forecast origins per year from March 2001 to December 2007, following the timing convention described in Table 1. The first forecast origin is March 2001, and the second is June 2001. We then move the forecast origin to September 2001, and so on until December 2007.
* denotes rejection of the null hypothesis at the 10% level of significance.
** denotes rejection of the null hypothesis at the 5% level of significance.
*** denotes rejection of the null hypothesis at the 1% level of significance.

We focus on the forecast performance at two horizons: (i) annual projections (forecasts generated from each forecast origin for the end of the current year); and (ii) one-quarter-ahead forecasts (forecasts for the next quarter).

4.2. Results

Table 2 shows the results for the end-of-the-year forecasts performed using the alternative models. It shows the RMSE ratios of the different alternative models to the ARW alternative, and the Diebold-Mariano tests of equal forecast accuracy for each pair of models. As regards the RMSE ratios, the results clearly show that all alternatives with intra-annual updating (mixed-frequency models and QRW) beat the ARW. The ratios range from 0.46 for model MS3 to 0.71 for model F3. As regards the ratios between pairs of other alternatives than ARW, all mixed-frequency models beat QRW (with the exception of F3). The ratios of the RMSEs of the mixed frequency models to those of QRW lie in the interval (0.67, 1.05), with a median of 0.73. Regarding the results of the Diebold-

Table 3
One-quarter-ahead forecasts: forecasting quarterly ESA95 figures with the different models. RMSE ratios to the quarterly random walk and Diebold-Mariano tests.

RMSE ratio of a mixed-frequency model to the quarterly random walk

Model MS1	Model MS2	Model MS3	Model MS4	Model F1	Model F2	Model F3	Model F4
0.65	1.14	0.65	0.73	0.61	0.68	0.62	0.74

Diebold-Mariano test

	QRW	Model MS1	Model MS2	Model MS3	Model MS4	Model F1	Model F2	Model F3
Model MS1	−2.57**	–	–	–	–	–	–	–
Model MS2	0.92	3.41***	–	–	–	–	–	–
Model MS3	−2.75**	0.03	−3.65***	–	–	–	–	–
Model MS4	−1.82*	0.94	−3.16***	0.94	–	–	–	–
Model F1	−2.83***	−0.58	−3.61***	−0.64	−1.24	–	–	–
Model F2	−2.63**	0.44	−3.07***	0.53	−0.44	1.29	–	–
Model F3	−2.82***	−0.28	−3.78***	−0.41	−1.11	0.11	−0.67	–
Model F4	−2.08**	0.93	−3.05***	1.31	0.17	1.48	0.76	1.82*

Notes: See footnotes for Table 2.

Mariano test, there is a collection of mixed-frequency models that present a better performance record than QRW (models MS1, MS2, MS3, MS4, F1, F2, F4), while QRW and F3 are not distinguishable from a statistical point of view. At the same time, models MS1 to MS4, F1 to F4, and QRW beat ARW. Mixed-frequency models are not distinguishable according to the Diebold-Mariano test.

Table 3 shows the forecasting record for the one-quarter-ahead horizon. According to the RMSE criterion, most mixed-frequency alternatives beat the QRW alternative (all ratios are below 1, with the exception of F3). The RMSE ratio to the QRW lies in the interval (0.61, 1.14), with a median of 0.66. Except in the cases of models MS2 and MS4, the relative performance of mixed-frequencies models vs QRW improves with respect to the full year projections discussed in the previous paragraph. According to the DM criterion, models MS1, MS3, F1, F2, F3 and F4 beat the QRW, but QRW is less costly than MS2 in terms of forecast loss.

The main lessons to be drawn from Tables 2 and 3 are: (i) all models with intra-annual updating beat ARW; (ii) mixed-frequency models tend to beat QRW; (iii) overall, all mixed-frequency models tend to give fairly similar results, which hints that all of the estimated models make a proper use of the available information; and (iv) thus, models that use variables expressed as moving sums tend to give results similar to those of more complicated and computer-intensive models that incorporate variables expressed as flows.

5. Case analysis and other considerations

5.1. The use of quarterly ESA95 fiscal data vs an approach based solely on monthly cash data

We have shown in the previous section that the estimated mixed-frequency models tend to outperform the simpler alternatives (ARW, QRW). On the intra-annual information front, the models incorporate quarterly ESA95 information and monthly cash information. One question that cannot be clarified with the previous results is, what is the contribution of the quarterly information as compared to the monthly information? Thus, given the aim of the paper, a question worth checking is the following: would an approach based solely on monthly cash data be enough? That is, does the incorporation of quarterly ESA95 figures in the estimation of the mixed-frequency models improve the forecast performance of the models? Table 4 provides some valuable results to support an affirmative answer to these questions.

In the table we show the ratios of the RMSEs of some selected mixed-frequency models estimated using annual, quarterly and monthly information to the RMSEs of the same models estimated with only annual and monthly information. Given the results obtained in the previous section, and for the sake of

Table 4
The value of intra-annual quarterly ESA95 figures vs. an approach based solely on monthly cash-based government figures. Ratios of the RMSEs of the model estimated using annual, quarterly and monthly data (A-Q-M model) to the RMSEs of the model estimated using annual and monthly data (A-M model), with associated Diebold-Mariano tests.

	Annual projections		One-quarter-ahead projections			
	A-Q-M vs A-M model		A-Q-M vs A-M model		QRW vs A-M model	
	RMSE	DM	RMSE	DM	RMSE	DM
Model MS1	0.71	−1.72*	0.64	−2.60**	0.99	−0.06
Model MS2	1.00	−0.67	1.00	−0.39	0.88	−0.92
Model MS3	0.73	−2.11**	0.59	−1.51	0.90	−0.40
Model MS4	0.70	−2.02**	0.59	−2.25**	0.81	−0.95

Notes: See footnotes for Table 2.

brevity, we select 4 of the 8 mixed-frequency models for the exercise. Columns 1 and 3 show that the RMSE ratios are below unity in most selected cases (MS1, MS3, MS4) and equal to 1 in one case (MS2). The improvement is marginally clearer for the one-quarter-ahead projections. The Diebold-Mariano test results confirm the picture (columns 2 and 4).

Finally, columns 5 and 6 show evidence from the exercise of comparing quarterly random walk forecasts (QRW) with the mixed-frequency models estimated with only annual and monthly information, for the one-quarter-ahead case. Even though the RMSEs are slightly below unity, the Diebold-Mariano test results indicate that the two approaches are indistinguishable in statistical terms. These results highlight the information content of the quarterly figures.

5.2. A (pseudo) real time illustration

In a final exercise we look at the qualitative indications that one would have drawn from using intra-annual information explicitly from a real-time perspective. We look at one episode in which the euro area government deficit experienced a turning point. Apart from the models considered, we compare the results with the signals that an independent observer would have derived from looking at the EC projections at the time. As was shown by Artis and Marcellino (2001) and Keereman (1999), the forecasting record of the EC is among the best for international organizations producing regular forecasts of GDP, inflation and government deficits for European countries. The EC forecasts tend to make use of all available information at the time the forecasts are made (rationality), and are based on a bottom-up approach, not forecasting the deficit/surplus directly, but rather computing it as the difference between revenues and expenditures. In addition, EC fiscal forecasts use both macroeconomic models and expert judgment. That is why checking the performance of the mixed-frequency models against EC forecasts should be quite a demanding criterion.

By design, this is a counterfactual exercise, in that data revisions may have affected the lessons drawn from mixed-frequencies models at the time of the episode. For our exercise it is not possible to fully recreate the real-time quarterly fiscal series in nominal terms that would have been available at the time, given that the quarterly ESA95 data only started to be published for the euro area aggregate in August 2004, as was discussed in a previous section. In order to minimize the impact of data revisions on our (pseudo) real-time exercise, we follow the standard, only feasible alternative in our case: we adjust EC annual projections for the effect of ex-post revisions. We do so by applying the changes in the annual deficit-to-GDP ratio projected by the EC in real-time to the final annual deficit-to-GDP figures. Thus, we preserve the sign and direction of the deficit projections made by the EC, while at the same time accounting for the revised base level.

The euro area fiscal deficit suffered a deterioration until 2003, then started to improve again around 2003/2004. This turning point is illustrated in Fig. 2. With the information set available in March 2004 (including the annual figure for 2002 but not the preliminary 2003 outcome), the EC was forecasting a further worsening of the deficit for 2004; the mixed-frequency model would have signalled a similar, albeit slightly more positive figure for 2004, while it would have now-casted the 2003 outcome quite accurately. The EC Spring 2004 issue (panel "June 2004") left the path for the euro area nominal deficit almost

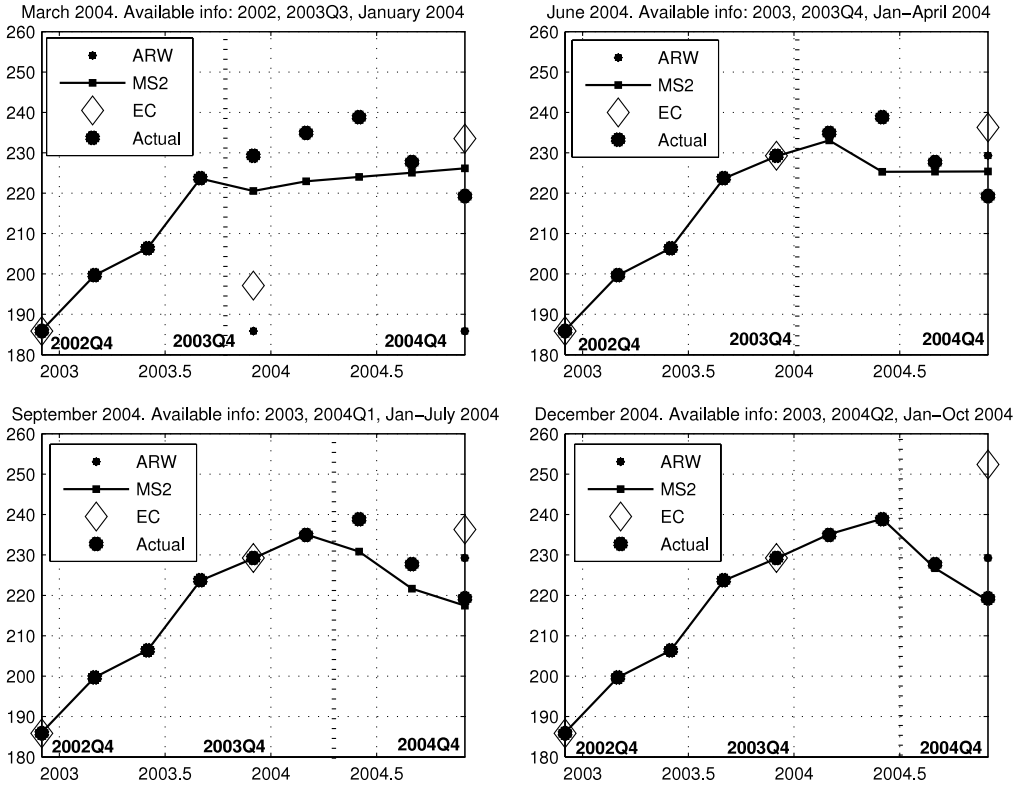

Fig. 2. Euro area deficit (+) / surplus (–), billions of euro: anticipation of the fiscal recovery that started in 2004. Alternative methods: annual random walk (ARW), mixed-frequency model MS2, and EC. Quarterly figures and projections are shown as 4-quarter moving sums.

unchanged, while the Autumn 2004 EC projections (panel "December 2004") showed an additional worsening in nominal terms; the intra-annual information, had it been available in "June 2004", would at that time have captured the improvement in the deficit figures, which is subsequently fully confirmed in the updated projections shown in the "September 2004" and "December 2004" panels.

6. Conclusions

In this paper we construct multivariate state space mixed-frequencies models for the euro area aggregate fiscal deficit, total revenue and total expenditure, based on annual and quarterly ESA95 figures and monthly cash government country data. The three frequencies structure of the models allows us to highlight the advantages of using quarterly ESA95 figures as a source of intra-year information, and also to explore their properties in conjunction with monthly cash fiscal figures.

In particular, we can summarize the main points highlighted in the paper as follows: (i) the mixed-frequency models present a reasonable forecasting record compared to simple alternatives (annual random walk, quarterly random walk); (ii) the three frequency structure of the models allows us to now-cast quarterly figures using monthly fiscal figures, and in turn to use quarterly and monthly figures to now-cast annual fiscal variables; (iii) approaches that forecast the government deficit directly and approaches that forecast government revenues and expenditures and then compute forecasts for the deficit as a residual variable are not significantly different; (iv) we provide models to interpolate (back-cast) annual fiscal variables by means of only intra-annual fiscal information, with quarterly figures playing a key role; (v) quarterly ESA95 data contain valuable information that is

Revenue:

	Germany	*France*	*Italy*	*Spain*	*Netherlands*
Germany	–	1.6035	0.4785	0.2071	0.0193
France	−0.3960	–	1.6832	2.7582	1.9599
Italy	0.3299	−0.5353	–	1.6013	1.3411
Spain	−0.0772	−0.4280	0.4849	–	2.2791
Netherlands	0.0677	−0.5069	0.4512	0.4826	–

Expenditure:

	Germany	*France*	*Italy*	*Spain*	*Netherlands*
Germany	–	0.1175	0.2185	2.8033	0.1871
France	0.0689	–	1.0177	0.2820	0.0070
Italy	−0.1056	0.3674	–	0.1414	3.2738
Spain	−0.3361	0.1087	0.0916	–	1.7097
Netherlands	−0.0856	−0.0182	0.4654	0.2726	–

Deficit/surplus:

	Germany	*France*	*Italy*	*Spain*	*Netherlands*
Germany	–	0.6477	0.6486	1.6882	0.1205
France	−0.4445	–	2.8422	0.8146	0.4845
Italy	−0.2166	0.2623	–	2.2351	0.3170
Spain	−0.4538	0.1215	0.2426	–	0.1716
Netherlands	−0.1809	−0.0240	0.2081	−0.0279	–

Box I.

not fully covered by the available monthly cash data; and (vi) intra-annual fiscal information might provide valuable insights for turning point detection in real-time.

These results confirm the unambiguous potential gains that would be derived from using quarterly ESA95 figures for real-time fiscal surveillance in Europe.

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Appendix

In this Appendix we provide several tests for the independence of the seasonal components of the variables included in the models. We present several likelihood ratio tests in three tables, one for each type of variable included in our analysis (revenues, expenditures and deficits). All tests are based on multivariate monthly SUTSE basic structural models of the type included in the paper (see Eqs. (2)–(4)) for the five big euro countries. In each table, the lower triangle indicates the point estimates of correlations between the seasonal components. The upper triangle shows the value of the likelihood ratio $\lambda = L(\boldsymbol{\Psi}_0)/L(\boldsymbol{\Psi})$, where $L(\boldsymbol{\Psi}_0)$ and $L(\boldsymbol{\Psi})$ stand for the constrained

and unconstrained likelihoods, respectively (see Harvey, 1989, chapter 5). Each constrained estimation is the full model with one single covariance set to zero (i.e. the one in the same row and column). The distributions of all of the statistics are χ_1^2, since the test is on one single parameter. All results show unambiguously that the seasonal components are uncorrelated with each other, since the critical value for the χ_1^2 for a 95% confidence level is 3.8415 (see Box I).

Similar LR tests were also carried out for simultaneous checks of the independence of the seasonal components (i.e., the seasonal components have a diagonal covariance matrix). Therefore, we are testing for ten constraints in these cases, and the likelihood ratio statistics are 12.0913, 13.3347 and 9.8038 for revenues, expenditures and deficit/surplus, respectively. The conclusion is that there is no joint correlation, since the critical value for the χ_{10}^2 for a 95% confidence level is 18.30.

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