Short-run GDP forecasting in G7 countries: temporal disaggregation techniques and bridge models
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SHORT-RUN GDP FORECASTING IN G7 COUNTRIES:
TEMPORAL DISAGGREGATION TECHNIQUES AND BRIDGE MODELS

by

Giuseppe Bruno ('), Tommaso Di Fonzo (’’), Roberto Golinelli (’’’), Giuseppe Parigi (’)

Abstract

Both temporal disaggregation techniques and bridge models are tools to analyse the GDP dynamics in the very short run (the current quarter), though their methodological approaches differ on how to exploit the available monthly information. The aim of this paper is to propose a way to merge the information sources of the two approaches. In doing so, we use forecast ability statistics to validate the appropriateness of some temporal disaggregation techniques by related series. The results for the GDP of the G7 countries suggest that the information about the list of the coincident indicators in the bridge models can be often useful to select the related series to be used in the temporal disaggregation procedures. In particular, the monthly disaggregation of the quarterly Euro area GDP may be improved thanks to the information content of the French, German and Italian models.

Index

1. Introduction ...................................................................................................................... 2
2. The specification of the temporal disaggregation models ................................................ 4
3. Preliminary inspection of the relationships at the observable frequency ......................... 7
4. The GDP temporal disaggregation exercises for the G7 countries................................. 11
5. A deeper look at Euro area GDP temporal disaggregation............................................ 13
6. Conclusions ....................................................................................................................... 14
References .............................................................................................................................. 16

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() Bank of Italy, Research Department; giuseppe.bruno@bancaditalia.it and giuseppe.parigi@bancaditalia.it
(’’) University of Padova, Department of Statistics; difonzo@stat.unipd.it
(’’’) University of Bologna, Department of Economics; golinell@spbo.unibo.it
1. Introduction

The delayed release of quarterly National Account data for GDP is an impediment to the early understanding of the current economic situation. However, during the reference quarter, a number of monthly short-run indicators are available. In order to get a picture of the evolution of the current economic activity, alternative tools can be used.

Among possible approaches, the Bridge Models (BM), i.e. dynamic quarterly models, can “bridge the gap” outlined above between GDP and indicators release times, and can provide reliable one-quarter ahead GDP estimates, as shown in Baffigi et al. (2004), and in Golinelli and Parigi (2004). In the BM approach the basic aim is to forecast the unknown GDP quarterly figure when some indicators are already known. In this case the computation of the GDP figures is not a proper forecast, but an estimate (similar to a “flash” estimate) or a “nowcast”. The fact that the indicators are generally available at a higher frequency, e.g. monthly, may suggest that it should not be difficult to compute a monthly version of the GDP. In this context, a possibility is to use some temporal disaggregation techniques (TD), where an estimate of the monthly GDP, coherent with the corresponding quarterly figure, is obtained from the relationship of GDP itself and some related series (see the original, static approach by Chow and Lin, 1971, and its dynamic extension by Santos Silva and Cardoso, 2001, Salazar et. al., 1997, Di Fonzo, 2003, and Proietti, 2004).

Given the strong similarity of the BM and TD approaches, it seems natural to think to a combination of the two procedures, which should deliver the “best” one-step ahead quarterly GDP estimate (i.e. the BM one) as well as a “reliable” higher frequency (monthly) GDP representation (i.e. TD one).

The crucial steps in both BM and TD techniques are the specification search and the choice of the indicator series. With the BM a parsimonious specification and the more suitable indicators are chosen according to the researchers’ experience and several testing procedures. In the TD procedure there is no specification search and only few (actually, very often only one) indicators are used on the basis of their supposed logical and/or economic

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link with GDP. This implies that the relationship between GDP and the chosen indicator(s) is necessarily far simpler than that of the BM and, most importantly, that it is not properly tested. The only statistical checks are very simple statistics, such as t-statistics on the coefficient estimate(s) of the indicator(s) in the lower frequency relationship, which are valid only if the chosen functional specification is valid\(^2\). What is really striking is the absence of a general criterion to assess the plausibility of the whole set of choices, functional specification and indicators, underlying the TD procedures. To fill this gap we propose to apply some testing procedure widely used in the BM context, such as the analysis of the out-of-sample forecasting performance.

Once a BM is estimated its validity is assessed by comparing the root mean square error (RMSE) of the one-step-ahead forecasts with that of some benchmark models, i.e. univariate and/or multivariate autoregressive representations of the variable of interest\(^3\). One could say that a specification is a BM only if its forecasting performance is better or at least similar to that of the best benchmark model. A similar exercise can be advocated for the validation of a specific TD procedure. More specifically, when the indicator set is known over the whole quarter, the TD procedure may be used to compute the three months ahead GDP figures that once aggregated may be interpreted as an estimate (a “nowcast”) of the corresponding unknown quarterly figure. The RMSE of these estimates can be used to compare the performance of different TD procedures and/or indicator choices. In this context, the RMSE of the different temporal disaggregation procedures is almost surely higher than that of a BM model, which can therefore be interpreted as a sort of lower bound of the results. The intuition is that the high frequency external information should be a satisfactory representation of the GDP dynamics, with a reasonably stable relationship. A bad forecasting performance, due for instance to breaks of the relationship between GDP and its indicator(s), should be interpreted as a sign of unreliability of the chosen interpolation model.

In the present paper, this approach has been applied to both single countries of the G7 group (United States, Japan, Germany, France, United Kingdom, Italy, and Canada), and the Euro area over the period from 1985 to 2000, leaving the period 2001-2003, characterised by

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\(^2\) First interesting results about specification searches in the context of temporal disaggregation using standard econometric tools can be found in Proietti (2004).

\(^3\) The choice of the RMSE criterion is essentially based on its wide application in the context of economic analysis but nothing prevents the use of other criteria, such as for instance the mean absolute error.
special events and different cyclical phases, for the out-of-sample forecasting performance analysis.\textsuperscript{4}

The paper is organised as follows. Section 2 reviews the alternative temporal disaggregation techniques used in our experiments. Section 3 investigates the relationships between GDP and indicators at the observable quarterly frequency. Section 4 reports the results of the forecast performance comparison among different approaches to temporal disaggregation and different indicator choices for the G7 countries. Section 5 focuses on the monthly disaggregation of the Euro area GDP. Section 6 concludes.

2. The specification of the temporal disaggregation models

In this section we briefly describe the temporal disaggregation models used to extrapolate the variable of interest at the desired (monthly) temporal frequency. We do not discuss here the distinctive features of each model – that, apart the data-based benchmarking procedure by Guerrero (1990), comes from a very similar regression framework – rather we stress the simplified specification ‘philosophy’ behind those models, which in any case assume an \textit{ad-hoc} monthly relationship between the target variable and a set of related indicators.

We adopt the following notation convention. Single observations of quarterly data are denoted by a single subscript, \textit{i.e.} \( y_t, \ t=1,\ldots,T \). Our aim is to derive an estimate of the underlying monthly series, whose unknown values are denoted by a double-subscript, so that \( y_{tu} \) denotes the value of \( Y \) in month \( u \) of quarter \( t \). We assume that there exists a summation constraint linking quarterly and monthly data given by:

\[ y_t = \sum_{u=1}^{r} y_{tu}, \ t=1,\ldots,T. \]

Let \( y_t = (y_{1t}, y_{2t}, \ldots, y_{Tt})' \) be the \((T \times 1)\) vector of quarterly data, while the \((n \times 1)\) vector of unknown monthly data is denoted by \( y_h \). If \( n = 3T \), then \( y_h = (y_{1h}, \ldots, y_{T,h})' \) and we face a problem of distribution (Chow and Lin, 1971). In our case, however, we explicitly assume \( n > 3T \), so that an extrapolation issue has to be considered.

We express (1) in matrix terms as \( y_t = Cy_h \), where \( C \) is a \((T \times n)\) matrix that links the (observed) quarterly vector \( y_t \) to the corresponding (unknown) monthly series \( y_h \). If \( n = 3T \),

\[ \]

\textsuperscript{4} Canada, the only G7 country where the monthly GDP is published together with other main indicators, is included in our experiments in order to draw results from an additional case.
the aggregation matrix \( C \) has a block-diagonal structure:

\[
C = \begin{bmatrix}
1 & 1 & 1 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 & 0 & 1 & 1 & 1 \\
0 & 0 & 0 & 1 & 1 & 1 & \cdots & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 & 1 & 1 & 1
\end{bmatrix} = I_T \otimes I_3
\]

where \( \otimes \) denotes the Kronecker product. When, as in our case, an extrapolation problem is also present, \( n - 3T \) columns of zeroes must be added to matrix \( C \).

The Best Linear Unbiased approach to temporal disaggregation by Chow and Lin (1971) postulates that quarterly observations for the target variable \( y_t \) are available, and that the following regression model, linking the unknown monthly variable \( Y \) and \( K \) observed monthly related indicators, holds:

\[
y_h = X_h \beta + u_h
\]

where \( y_h \) is a \((n \times 1)\) unobserved monthly vector, \( X_h \) is a \((n \times K)\) matrix of observed monthly indicators, \( \beta \) is a \((K \times 1)\) vector of unknown coefficients and \( u_h \) is a stochastic error with

\[
E(u_h | X_h) = 0 \quad \text{and} \quad E(u_h u'_h | X_h) = V_h,
\]

assumed to be known.

The BLUE solution found by Chow and Lin (1971) can be expressed as:

\[
\hat{y} = X_h \hat{\beta} + V_h (CV_h C')^{-1} \left( y_f - X_h \hat{\beta} \right)
\]

\[
\hat{\beta} = \left[ X_f (CV_h C')^{-1} X_f \right]^{-1} X_f (CV_h C')^{-1} y_f
\]

where \( X_f = CX_h \) is the \((T \times K)\) matrix of quarterly aggregated indicators. It is interesting to notice that the estimator \( \hat{y}_h \) is obtained by correcting the linear combination of the monthly indicators series, \( X_h \hat{\beta} \), by distributing the quarterly residuals of the GLS regression

\[
y_f = X_f \beta + u_f,
\]

where \( u_f = \text{Cu}_h \), among the months. The covariance matrix of \( \hat{y}_h \) is given by (Bournay and Laroque, 1979)

\[
E(\hat{y}_h - y_h)(\hat{y}_h - y_h)' = (I_n - LC)V_h + (X_h - LX_f)(X_f V_f^{-1} X_f)' (X_h - LX_f)'
\]

where \( L = V_h C' V_f^{-1} \).

From a practical point of view, when one is interested in applying the disaggregation procedure presented so far, the key issue lies in identifying the covariance matrix \( V_h \) from \( V_f \). This latter can be estimated, possibly by imposing an \textit{ARIMA} structure, but, in general,
the covariance matrix of the monthly disturbances cannot be uniquely identified from the relationship \( V = CV_h C' \). When indicators are available, several restrictions on the data generating process of \( u_{t,u} | X_h \) have been proposed in order to simplify the problem (Eurostat, 1999):

- Chow and Lin (1971): \( u_{t,u} | X_h \sim AR(1) \);
- Fernández (1981): \( u_{t,u} | X_h \sim \text{random walk} \);
- Litterman (1983): \( u_{t,u} | X_h \sim ARIMA(1,1,0) \).

A dynamic extension to this approach is due to Salazar et al. (1997, see also Mitchell et al., 2005) and Santos Silva and Cardoso (2001). In this case the basic monthly model on which the disaggregation procedure grounds is

\[
y_i = \phi y_{i-1} + x' \beta + \epsilon_i,
\]

where now, for notation convenience, suffix \( t \) denotes the months, \( |\phi| < 1 \) and \( \epsilon_i \) is a white noise. This specification is more flexible than those previously considered and is more attractive from an economic modelling point of view (for details, Di Fonzo, 2003; Proietti, 2004). However, we have considered a more general dynamic specification given by:

\[
y_i = \phi y_{i-1} + x' \beta + x_{t-1}' \gamma + \epsilon_i,
\]

known as the first order autoregressive distributed lag (henceforth, ADL) specification.

In his 1990 paper, Guerrero proposed an ARIMA based approach for estimating the high frequency values of a time series observed only at a lower frequency. The method is based on the use of the ARIMA model characterising a preliminary estimate obtained, for instance, from a linear regression on indicators observed at the desired high frequency.

Following the same convention as before \( y_i \) \((l=1,2,\ldots,T)\) is the series observed at low frequency while \( y_h \) \((h=1,2,\cdots,mT)\) is the unobserved series at a higher frequency; finally \( \hat{\hat{y}}_t \) \((t=1,2,\cdots,mT)\) is a preliminary estimate of \( y_h \).

The same ARIMA model fitted for the preliminary estimate:

\[
\phi(B)d(B)\hat{\hat{y}}_t = \tau(B)a_{u,t}
\]

is assumed for \( y_h \), the series to be estimated. For computational purposes, the ARIMA model (8) is converted into its pure moving average providing the following matrix formulation:

\[
y_h - \hat{\hat{y}} = \theta u
\]
where:
\[
\theta = \begin{bmatrix}
1 & 0 & \cdots & \cdots & 0 \\
\theta_1 & 1 & 0 & \cdots & 0 \\
\theta_2 & \theta_1 & 1 & 0 & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
\theta_h & \theta_{h-1} & \cdots & \theta_1 & 1
\end{bmatrix}
\]

is the matrix containing the sequence of weights of the moving average representation of preliminary estimate \( \hat{\mathbf{W}} \); \( u \) is a \( \text{IID}(0, P) \) random innovations vector.

Once achieved the preliminary estimate \( \hat{\mathbf{W}} \), the linear Minimum Mean Square Error (MMSE) of \( y_h \) subject to the aggregation constraints \( y_i = C y_h \) is given by:

\[
y_h = \hat{\mathbf{W}} + \hat{A} (y_i - C \hat{\mathbf{W}})
\]
\[
\hat{A} = \theta P \theta^T (C \theta P \theta^T C)^{-1}
\]

From a computational standpoint the algorithm can be broken down in the following steps:

a) Choose an indicator and estimate its ARIMA model (e.g. with TRAMO/SEATS).

b) Compute a first estimate of the disaggregated values assuming innovations with \( P=I \) in the equations (11) and (10).

c) Evaluate the innovations \( u = \theta^{-1} (\hat{y}_h - \hat{\mathbf{W}}) \) and check whether they are white noise:
   - if it is white noise \( \hat{y}_h \) is the final disaggregated series;
   - if it is not a white noise estimate, set an ARIMA model for the innovations and estimate the variance covariance matrix \( P \) of the innovations vector.

d) Make the final estimate by using this estimate of \( P \) and the equations (11) and (10) once again.

As a closing remark, it can be said that this method provides the integration of the signal extraction and the temporal disaggregation techniques by adopting the ARIMA model of the suitably chosen linearly related series (the indicator).

3. Preliminary inspection of the relationships at the observable frequency

The aim of this section is to assess the nature of the relationship between quarterly GDP and a list of country-specific monthly indicators that can be used in the temporal disaggregation procedure, as suggested by the BM specification. BM uses all the indicator information to obtain the “best” one-quarter-ahead GDP forecasts in terms of RMSE. In this
context, we essentially refer to the nowcast case, when the indicators are known over the whole quarter. Though still useful, the BM is a slightly worse forecaster when some indicators are not available for all the months (see Golinelli and Parigi, 2004 for detailed results) stressing the relevance for the BM of the coincident information, which is the basic ingredient of the TD techniques.

The BM is found through the general-to-specific methodology that allows obtaining a valid reduction of the starting multivariate system (a data congruent VAR model). The result is usually a very complex model that cannot be easily employed in the TD procedure given the limitation of the dynamic specification.

The analyses of this section are articulated in three steps, accomplished at the aggregated quarterly frequency when all the variables of interest (GDP and indicators) are observable. Initially, a subset of monthly coincident indicators is extracted from the specification of a BM as suitable candidates for the GDP temporal disaggregation models. Then, since with short spans of data the persistence of many time series is well represented by integrated univariate stochastic processes, all the variables are tested for the presence of unit roots. Finally, a number of tests of cointegration are accomplished in order to assess for the existence of level relationships between the GDP and its indicators.

The whole analysis is conducted over the period 1985.1 to 2000.4, i.e. the period used below for the identification and estimation of the temporal disaggregation models.

Unit root test results about both GDP and the selected indicators are reported along the different rows of Table 1. A pair of columns corresponds to each country because the test statistics are computed for both levels and log-levels of the variables of interest. As far as the number of GDP indicators is concerned, we have selected four indicators for Germany; three indicators for France, Italy, the United Kingdom, and Japan; two indicators for Canada and the United States. The industrial production index is the only variable in all the country indicator sets. The services production index (or, when not available, close substitutes like the retail sales index or the consumption of manufactured goods) is another relevant coincident indicator (in Italy and the United States such a role is however played by the interest rates). Other country-specific indicators are drawn from qualitative surveys, manufacturing sub-sectors or the labour market.

*Table 1 here*
The unit-root test statistics reported in Table 1 are based on the Dickey-Fuller Generalised Least Squares approach, (DF-GLS; see Elliott et al. 1996). The results are quite clear-cut: at quarterly frequency, all variables are first-order integrated, or I(1), with the only exception of job vacancies in Japan and the index of households and firms confidence in Italy, whose levels and log-levels are generated by stationary mean-reverting stochastic processes, and the consumer price index in the United Kingdom, that is trend stationary.

These data features lead to the problem of the specification of the temporal disaggregation models: whether to induce stationarity by differencing the I(1) variables, or to model the relationships in levels to avoid the loss of potentially relevant information. A statistically founded answer can come from the cointegration analysis. Unfortunately, the empirical application of this technique entails a number of drawbacks due to the small sample, the lack of theoretical guidance and the heterogeneous nature of the GDP and indicators data generation process. In particular, in small samples cointegration tests are often problematic (e.g. lack of power). Moreover, without a theoretical model we cannot impose long run over-identification restrictions because cointegrating vectors are unknown mixtures of reduced form parameters (see Wickens, 1996). Finally, GDP levels are estimated within the NA cross-validating procedures, while indicators are index numbers aggregated with constant weights for subperiods. Such heterogeneity may imply parameter instability and forecasting failure due to shifts of the level relationships (see Clements and Hendry, 1999).

Three general approaches are widely used for testing whether non-stationary variables are cointegrated: single-equation static regressions (Engle and Granger, 1987); single-equation conditional error correction models and vector autoregressions (Johansen, 1995). Given that all three approaches have their advantages and disadvantages (see Ericsson and MacKinnon, 2002), Table 2 reports the results from each approach in order to assess their robustness and to ease their comparative interpretation (see Gonzalo and Lee, 1998).

Table 2 here

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5 Elliott et al. (1996) find that local GLS detrending of the data yields substantial power gains with respect to alternative approaches, such as the seminal Dickey and Fuller (1979) test. Ng and Perron (2001) show that size and power of the DF-GLS test may be further improved when truncation lag is selected by their Modified AIC selection rule. In our case, we set the maximum lags equal to five.
The first row of Table 2 lists the names of the country-indicators (the same tested for unit roots along the rows of Table 1) used in the cointegration analysis. As in the unit root case, the statistics are computed for both levels and log-levels.

As discussed in Lupi and Parigi (2002), there should be a link between the outcome of cointegration tests and the specification of the model for GDP temporal disaggregation. In fact, under the null of no cointegration, the approaches of Fernández (1981) and Litterman (1983) are more adequate specifications because both get rid of levels by differencing the variables. On the other side, under the alternative of cointegration, the approaches of Chow and Lin (1971) and more general ADL specifications, as in (7) above, are more valid representations of the level relationship between GDP and indicators. However, Chow and Lin (1971) approach entails a specific dynamic relationship in levels that could be rejected because it implies a common factor restriction to the general dynamics of the ADL model.

Engle and Granger (1987) test statistics for cointegration are reported in the first two rows of data of Table 2: CRDW and CRDF tests (respectively the Durbin-Watson and the DF tests) are based on the residuals of the static regression between GDP and its indicators. In addition, the estimate of the AR(1) coefficient from the residuals is reported in the third row: the closer to one the coefficient, the less likely the cointegration. Results do not reject the null of no cointegration in almost all cases, and AR(1) coefficient estimates are in the 0.75-0.95 range, with the only exception of Japan.

This testing approach often imposes invalid common factor restrictions to the dynamic model and arbitrarily assumes the cointegration rank being equal to either zero or one. The first of these two untested assumptions is relaxed by the dynamic (error correction) approach, reported in the middle part of Table 2. In this context, the no-cointegration test is based on the significance of the estimate of the parameter measuring the speed of adjustment of GDP towards its long run (target) level. Finite sample p-values of the test are computed according to Ericsson and MacKinnon (2002). Results show valid (cointegrated) relationships for France, Italy and the United States (when variables are in log-levels), while results for Germany, the United Kingdom, and Canada strongly reject cointegration.

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6 Litterman (1983) proposes a more general representation of the relationship in differences than Fernández (1981) because it allows for AR(1) errors. However, given the constraints on the available information, it sometimes provides bad estimation results, see Proietti (2004).

7 At the price of assuming that the indicators are weakly exogenous.
Being based on the maximum likelihood of the full system, the VAR approach advocated by Johansen (1995) is even more general and allows computing significance tests for the long run parameters. The trace test of the cointegration rank delivers results broadly in line with those from the error-correction approach above. France, Italy and the United States VAR models are cointegrated with rank equal to one, the indicator variables are weakly exogenous for the parameters of interest, and the GDP equation loading parameter (the GDP speed of adjustment towards the target, in the error-correction jargon) has always the right sign. Germany, the United Kingdom, and Canada VAR models either are not cointegrated, or weak exogeneity is rejected, or loading parameters are not significantly negative as expected \textit{a priori}. The Japanese VAR model is characterised by two long run relationships, and the VAR model in levels is affected by the absence of weak exogeneity.

Overall, as expected given the drawbacks outlined above, the outcomes from alternative cointegration tests are not robust enough to deliver a clear answer about the best specification of the TD procedure (either levels or differences).

4. The GDP temporal disaggregation exercises for the G7 countries

The TD procedures described in Section 2 are used in a number of estimation and extrapolation exercises articulated in two steps: 1) models are estimated at the quarterly (observable) frequency from 1985.1 to 2000.4, thus leaving twelve quarters (up to 2003.4) for out-of-sample forecasting exercises; 2) three-months ahead GDP forecasts are obtained from (disaggregated) monthly models with a rolling procedure over the period 2001.1-2003.12, where both the model specification and the dimension of the estimation sample is kept fixed (see Stock and Watson, 1996, Tashman, 2000, and more recently, Pesaran and Timmerman, 2004). Three-months ahead GDP forecasts are converted into quarterly figures before the calculation of forecast evaluation statistics.

Table 3 reports the root mean squared error (RMSE) over the 2001.1-2003.4 period: along the columns there are the G7 countries, along the rows the TD procedures used in the forecasting exercises under the hypothesis that all three months of indicator data of the...

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8 This approach may suffer from spurious cointegration in presence of relevant specification errors, such as incorrect specification of either the deterministic components or the VAR lag length (Gonzalo and Lee, 1998).

9 In the US case only when the variables are in log-levels.

10 Results from the recursive procedure are qualitatively similar.
quarter are known (nowcast). For each country, disaggregation models have been built by using data both in levels and log-levels (only logs for Guerrero’s approach); in the log case, the estimation has been performed according to Di Fonzo (2003) in order to fulfil the temporal aggregation constraint (see also Salazar et al., 1997 and Aadland, 2000; for an alternative approach, see Proietti, 2004).

Table 3 here

The implementation of the TD procedure according to Guerrero’s method requires some general decisions for the ARIMA modelling of the time series used as indicators and observable at the high frequency. In fact, the use of the TRAMO/SEATS program for the identification and maximum-likelihood estimation of the ARIMA model entails some practical decisions to be taken by choosing a number of parameters inside the input file of the TRAMO/SEATS program. With these options\(^{11}\) we have been able to identify all the indicators.

The different GDP temporal disaggregations have been obtained under alternative sets of indicators. The higher part of Table 3, labelled “one indicator”, reports the results referring to models that use only the industrial production index for all countries, while in the lower part, labelled “many indicators”, there appear the results obtained with models based on several coincident indicators drawn from the specification of the corresponding BM (see Golinelli and Parigi, 2004, table 1), that is the same variables analysed in Tables 1 and 2.

Finally, the RMSEs from monthly “BM search” temporal disaggregation models and from the quarterly BM forecasts of Golinelli and Parigi (2004, table 2) are reported in the last two rows; the latter results are only available for the log-transformed data and refer to the nowcast case. As far as the “BM search” models are concerned, their specification is the outcome of a reduction of quarterly dynamic models of the first order based on both the Johansen and the error-correction results in Section 3.

\(^{11}\) The parameters of the TRAMO/SEATS procedure are: IATIP=0 (the program doesn’t make any search for outliers); IDIF=3 (the program searches for regular differences up to order 2 and for seasonal differences up to order 1; then it continues with the identification of an ARMA model for the differenced series); INIC=2 (the program searches for regular polynomials up to order 2, and for seasonal polynomials up to order 1); LAM=1 (the program uses a model on the level of the input variables).
First of all, we note that the level and the log-level results are basically the same, as in Tables 1 and 2. Almost all the cases reported in Table 3 suggest the Chow and Lin (1971) results (in the “COMFAC” lines) are improved by the other approaches: this is the sign of the effectiveness of the extensions to the seminal methodology introduced by the literature on this topic. More specifically, the ADL and Guerrero’s specifications provide the best results in terms of RMSE thanks to their richer dynamics.

Given the list of indicators entering the long run relationships of the Johansen cointegration approach in the last row of Table 2, TD models with IP as the only related series (upper panel of Table 3) seems to be not correctly specified. In this case, the lower RMSE often corresponds to the ADL model because its general dynamics is probably able to proxy for the excluded indicators. All other TD procedures (except for Guerrero’s one) are nested in the general ADL specification and this should reduce the risks of large ADL forecast errors due to wrong dynamics restrictions.

The inclusion, alongside IP, of other indicators improves the forecasting ability of GDP (with respect to the previous one-indicator case) in countries, such as Japan and Canada, where IP-levels are not relevant coincident indicators.

Despite the non-cointegration results in Table 3, the United Kingdom ADL model with IP-only levels shows the lower RMSE. On this regard, Golinelli and Parigi (2004) note that the very simple AR(4) model is the best performer in forecasting the UK GDP; in such a situation, it seems quite difficult to derive useful suggestions from BM.

The failure of the monthly “BM search” model in catching-up with the quarterly BM RMSE, or simply its difficulties in improving the forecasting ability over the other TD cases, suggests that the search with quarterly data of the specific model to be used at the monthly frequency is not very useful. In other terms, we cannot improve the TD forecast performance by imposing simplifying restrictions, on the basis of quarterly outcomes, to the specification of disaggregated (monthly) models. In fact, though relatively low, the RMSE of the BM-search model in each country is almost never the lowest of the column.

5. A deeper look at Euro area GDP temporal disaggregation

The quarterly GDP for the Euro area (EA) may be disaggregated by using either a single indicator for each of the three countries, or only one aggregate indicator obtained by averaging (summing) the three indicators above.
In Table 4, different rows correspond to different TD models (only log-transformed cases are reported). To ease comparisons, the first three columns report the same results as in Table 3 for France, Germany and Italy, while the last two columns show the results for, respectively, the TD procedures using disaggregated (by country) and aggregated (area-wide) indicators, that is the industrial production index and the monthly GDP (monthly GDP series for the three countries are obtained by using either IP or many country-specific indicators; details are in the previous section).

Table 4 here

From the comparison of upper panel with middle panel results in Table 4, it appears that the EA GDP forecasting ability of TD models using IP is almost always better than that using monthly GDP (obtained by using the IP only) because the indicator dataset is always the same (i.e. the monthly IP by country). Things however improve if the disaggregation is based on monthly GDP series obtained by using many indicators (see the lower panel of Table 4): in this case the RMSEs are the lowest, irrespective of the TD model used.

Overall, the area-wide RMSE is always well below those corresponding to each GDP of the three European countries, indicating the advantage of aggregating single countries in the area when the forecasting performance of the country models is not good (about this point, see also Baffigi et al., 2004). On the other hand, parsimony of TD models using only the average indicator leads to RMSEs that are lower than models using three separate indicators.

Finally, it is worth noting that the performance of the ADL model using the sum of three monthly GDP (obtained with many indicators) is very close to that of the BM for the EA reported in Golinelli and Parigi (2004), though the TD single-country results were significantly worse than the BM ones in the last row of Table 3.

6. Conclusions

In this paper we show that the forecasting ability statistics can be used to assess the appropriateness of the selection of the related series to estimate monthly GDP from quarterly data. In fact, the traditional statistics of the TD lower frequency estimates (such as the t-statistics) simply test the null of absence of a related series from the model specification, without any valid insight about its appropriateness in explaining GDP dynamics.
Our results suggest that at quarterly frequency the forecasting ability in nowcast exercises with TD models is, as expected, worse than that of the corresponding BM for all the countries of the G7 group. However, the preliminary analyses of data (to assess the integration-cointegration properties of the variables of interest), together with the use of the most appropriate BM coincident indicators, may shed some light about the selection caveat of the (monthly) related series to be used in the TD approaches. On the other side, the short span of available data at the lower frequency prevents the integration-cointegration tests to act, per se, as clear guidelines about the more appropriate TD method. In the TD model selection field, the better RMSE performance of models generalising the seminal Chow and Lin (1971) approach is the only robust outcome.

Therefore, the joint use of BM and TD sources of information prevents the worst results for the countries where the “classical” industrial production index is not an appropriate description of the GDP pattern. In our examples, this is the case of Japan and Canada. In the aggregate Euro area GDP case, the use of monthly GDP data of the three biggest countries allows for large improvements over the performance of TD models based on industrial production data.

As far as the usefulness of the BM specifications are concerned, we found that a deep fine tuning of the TD model specification (such as transforming in differences some indicators on the basis of the BM structure) does not ensure clear improvements over the explanatory power of TD models that simply use the list of the BM coincident indicators.

The results of the present paper could be extended in the near future by using other TD techniques, such as the state-space model-based approach, see Harvey and Chung (2000), Casals at al. (2004), and Moauro and Savio (2005).
References


Eurostat (1999), Handbook of quarterly national accounts, Luxembourg, European Commission.


### Table 1


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(1) Elliott, Rothemberg and Stock (1996) DFGLS test critical values for models with trend: -3.717, -3.15, and -2.85 at 1%, 5% and 10% respectively, and for models without trend (variables in differences): -2.602, -1.946 and -1.614 at 1%, 5% and 10% respectively. (1) Δ (first-differences); GDP (Gross Domestic Product at constant prices); IP (index of production, manufacturing); IPIT (index of production, intermediate goods); ICT (index of production, construction);CONS (consumption of manufactured goods); RET (retail sales index); IPSE (index of production, services); JOB (unemployment rate for Germany, and job vacancies for Japan); R (real interest rate for Italy, and nominal interest rate for the US); CLI (index of households and firms confidence); CPI (consumer price index).
### Table 2

#### COINTEGRATION ANALYSIS, 1985.1-2000.4

<table>
<thead>
<tr>
<th>Indicators (1)</th>
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<th>United States</th>
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(1) Definitions are in Table 1. (2) Cointegration tests based on single-equation static regressions. CRDW (cointegrating regression Durbin-Watson) critical values for a sample size of 50 and 2 variables: 1.00 (1.49), 0.78 (1.03) and 0.69 (0.83) at 1%, 5% and 10% respectively (Engle and Yoo, 1987, table 4). CRDF (cointegrating regression Dickey-Fuller) critical values with four I(1) indicators and trend are: -5.677, -4.992 and -4.649; with three indicators: -5.332, -4.661 and -4.325, with two indicators: -4.968, -4.309 and -3.979 at 1%, 5% and 10% respectively (from the PC programs provided by MacKinnon, 1996). (3) Estimate of the AR(1) coefficient from the residuals of the static regression. (4) Cointegration tests based on single-equation conditional error correction models, H0: γ1=0 in equation (16) of Ericsson and MacKinnon (2002), p. 289. (5) From the computer program of Ericsson and MacKinnon (2002). (6) Cointegration rank trace tests based on vector autoregressions (Johansen, 1995). (7) Names of the indicators that significantly enter in the long relationship with GDP.
<table>
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<th>United States</th>
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(\(\hat{\phi}\)) Each model is extrapolated three months ahead by using the historical values of the monthly explanatory indicators, then the monthly forecasts are aggregated in quarterly figures before to compute the RMSE. (\(\hat{\phi}\)) Definitions are in Table 1. (\(\hat{\phi}\)) Chow and Lin (1971). (\(\hat{\phi}\)) Fernandez (1981). (\(\hat{\phi}\)) Litterman (1983). (\(\hat{\phi}\)) First order autoregressive distributed lag specification; see equation (7). (\(\hat{\phi}\)) Specific models that are valid reductions of the general quarterly ADL(1,1) model defined on the basis of the outcomes in section 3; in Germany, UK and Canada they coincide with the “DIFF” TD approach. (\(\hat{\phi}\)) Computed from one-quarter ahead bridge model forecasts, supposing that all simultaneous indicator data are available, see the nowcast case in Golinelli and Parigi (2004, table 2).

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(1) See the corresponding note in Table 3. All data are in logarithms. Results for France, Germany and Italy are reported from Table 3 in order to ease comparisons with Euro area outcomes. (3) Definitions are in Table 1. (4) Chow and Lin (1971). (5) Fernandez (1981). (6) Litterman (1983). (7) First order autoregressive distributed lag specification; see equation (7). (8) Computed from one-quarter ahead bridge model forecasts, supposing that all simultaneous indicator data are available, see the nowcast case in Golinelli and Parigi (2004, table 2). (9) Monthly data for France, Germany and Italy are used as three separate indicators. (10) Monthly data for France, Germany and Italy are first aggregated in a single indicator and then used to disaggregate the Euro area GDP. The monthly GDP, obtained from the previous three columns, is used for the monthly disaggregation of quarterly Euro area GDP.