STUDIECENTRUM VOOR ECONOMISCH EN SOCIAAL ONDERZOEK

VAKGROEP MACRO-ECONOMIE

Computing Quarterly GDP Data : a question of economics ?

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report 96/340

December 1996

I wish to thank J. Jacobs and the other participants of the 1996 EEA Meeting in Istanbul for their helpful comments on an earlier draft of this paper. Remaining errors are my own responsibility.

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D/1996/1169/11

Abstract

The first part of the paper reviews some procedures to distribute an annual time series across a quarterly one, either by using information from the annual totals only, or by using information from both the annual totals and one or more related quarterly series. In the second part of the paper the various procedures are applied to compute both real and nominal quarterly GDP series for a number of (larger) countries. The estimates are then compared with the actual quarterly real and nominal GDP data of these countries. Although the results are far more clear for real GDP than they are for nominal GDP, we recommend to use one of the procedures proposed by Denton to distribute both real and nominal annual GDP data.

Keywords: data disaggregation, data distribution
quarterly real GDP, quarterly nominal GDP

1 Introduction

There are two reasons why we would like to disaggregate a time series. The first one relates to the inconsistency in the observation frequencies of macroeconomic variables. When we consider the European countries we see that for most (smaller) countries GDP is only reported on an annual basis, while many other variables are reported every quarter or even every month[1]. Instead of aggregating these quarterly variables to annual totals (and thus losing a lot of information), it is more reasonable to disaggregate the GDP time series into quarterly observations. The need for time series disaggregation also arises from a possible change in the observation frequency of a given variable as is e.g. the case for the GNP series of the United States. Since 1957 US GNP is reported on a quarterly basis, but annual observations of this series are available from 1900 onwards. Instead of omitting the annual observations prior to 1957 from the analysis, we should try to disaggregate them into quarterly figures and then use the entire sample period. In this paper we are mainly concerned with the first reason.

A preliminary exploration of the empirical literature - primarily on money demand - leads us to conclude that many authors are very vague as to the method they use to disaggregate their annual data. Kremers and Lane (1990, p.784) e.g. state that "annual data are interpolated according to the quarterly pattern of industrial production" without further reference to the exact procedure used. Similarly, Fase and Winder (1992, p.31) state that their "quarterly data are constructed by means of data on industrial output". This could lead to the false impression that there exists only one method to obtain quarterly data from the annual totals.

Therefore a thorough investigation of possible disaggregation procedures seems worthwile to try and answer the following question: should we compute quarterly GDP data by purely mathematical smoothing procedures or should we rely on economic theory and use information from related series that are observed on a quarterly basis ?

[1] Recently, most European countries have started to develop quarterly GDP series. These data are collected in the databank of the Bank for International Settlements, but are not publicly available.

This paper extends a previous one[2] in three ways. Firstly, we no longer restrict ourselves to real GDP, but now investigate the performance of the various disaggregation procedures both for real and nominal GDP. Secondly, we include two more disaggregation methods, i.e. the Kalman filter and the method proposed by Ginsburgh (1973). Finally, we extend the observation period to include all available data from the first quarter of 1957 to the fourth quarter of 1994.

The paper is organised as follows. We start in section 2 by reviewing some of the proposed methods for the distribution of a time series[3]. In section 3 we construct the resulting quarterly series for both real (1990 prices) and nominal GDP for a set of thirteen countries. In order to be able to select one (or more) procedure(s) we compare the estimated quarterly GDP growth rates with the actual ones by means of the correlation coefficients on the one hand and the mean absolute error, the root mean squared error, and Theil's inequality coefficient on the other. Finally, the results are summarized in section 4.

2 A review of some distribution procedures

To the purpose of the distribution of time series several procedures have been developed. They can be divided into two broad categories: the data-based procedures and the model-based procedures. We define *data-based procedures* as those procedures which only use information from the annual totals[4]. The disaggregated values are then the result of some smoothing algorithm. The *model-based procedures* rely on one or more equations linking at least two variables and can themselves be subdivided into two subgroups. A first subgroup

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[2] Bruggeman, A. (1995), *'Disaggregating annual real GDP data into quarterly figures'*, SESO Report, 95/331, 46 p.

[3] The *distribution* problem relates to the disaggregation of flow variables. Given the values of a flow variable (e.g. GDP) during n years, the distribution problem is to estimate 4n quarterly values of GDP which satisfy the condition that the four quarterly values relating to the same year add up to the annual total. The *interpolation* problem relates to the disaggregation of stock variables. Given the values of a stock variable (e.g. the money supply) at the end of n years, the interpolation problem is to estimate the remaining 3n quarterly values.

[4] This definition of data-based procedures does include distribution procedures that use ARIMA-models, since in these models no other information is used but information on the variable itself (and its lagged values).

comprises the procedures which not only use information from the annual totals, but also rely on additional information from other related series. The 'model' is thus constructed only for the purpose of estimating the disaggregated values of the dependent variable. The second subgroup comprises the structural models in which the estimates of the disaggregated data are obtained as a by-product of the parameter estimates of the structural model. In this paper we will not retain the procedures in this second subgroup. Table 1 summarizes the various distribution procedures that will be discussed in this paper.

Table 1:

An outline of the various distribution methods described in the paper

Data-based procedures i.e. procedures which only use information from the annual totals
Lisman and Sandee (1964) Boot, Feibes, and Lisman (1967) Stram and Wei (1986)
Model-based procedures i.e. procedures which use information from both the annual totals and related quarterly series
Chow and Lin (1971) Denton (1971) Ginsburgh (1973) Fernandez (1981) Litterman (1983)

Every procedure will be described for a periodicity $m=4$ (i.e. to distribute an annual series across a quarterly one). In this section the annual series will be denoted X_t (for t=1, 2, ..., n) while y_q and z_q (for q=1, 2, ..., 4n) will denote the quarterly series to be estimated and the quarterly related series, respectively.

2.1 Procedures which only use information from the annual totals

The performance of the procedures belonging to the first category has already been discussed by Chan (1993). Relying on his conclusions we only select the procedures developed by Lisman and Sandee (1964), Boot, Feibes, and Lisman (1967), and Stram and Wei (1986). Finally, we consider the 'data-based' Kalman filter procedure.

2.1.1 Lisman and Sandee

In Lisman and Sandee (1964) a very simple procedure is given to compute a quarterly time series if no assumption about its pattern can be made. In their approach the quarterly values for year *t* (for t=2, 3, ..., n-1) are weighted averages of the annual totals of the years *t-1*, *t*, and *t+1* or in matrix notation:

$$\begin{bmatrix} y_{4t-3} \\ y_{4t-2} \\ y_{4t-1} \\ y_t \end{bmatrix} = \begin{bmatrix} a & e & i \\ b & f & j \\ c & g & k \\ d & h & l \end{bmatrix} \cdot \begin{bmatrix} X_{t-1} \\ X_t \\ X_{t-1} \end{bmatrix} \qquad \text{for } t=2, 3, \ldots, n\text{-}1 \qquad (1)$$

To determine the value of the coefficients *a* through *l*, Lisman and Sandee impose the following conditions: (1) there should be a logical symmetry in time[5], (2) during each year the quarterly figures should add up to the annual total, (3) if the annual totals *X* remain constant, the quarterly figures should necessarily be equal to *X/4*, (4) if the annual figures increase by a constant amount *p*, the quarterly figures should increase by a constant amount *p/16*, and (5) if

[5] If the annual totals in three successive years are X_1, X_2, and X_3, then the quarterly values for year 2 should be the same but in reverse order from what they would have been had the annual totals been X_3, X_2, and X_1.

the annual figures alternate, the trend should be a sinusoid.

Lisman and Sandee then show that these five requirements lead to the following quarterly values:

$$\begin{aligned} y_{4t-3} &= 0.0728X_{t-1} + 0.1983X_t - 0.0210X_{t+1} \\ y_{4t-2} &= -0.0103X_{t-1} + 0.3018X_t - 0.0415X_{t+1} \\ y_{4t-1} &= -0.0415X_{t-1} + 0.3018X_t - 0.0103X_{t+1} \\ y_{4t} &= -0.0210X_{t-1} + 0.1983X_t + 0.0728X_{t+1} \end{aligned} \qquad \text{for t=2, 3, ..., n-1} \qquad (2)$$

This very simple procedure has however two important drawbacks. Firstly, no quarterly values can be computed for the first and the last year of the time series. Secondly, it is a very arbitrary procedure.

2.1.2 Boot, Feibes, and Lisman

Boot, Feibes, and Lisman (1967) introduce two smoothing criteria in order to correct for these defects. The first criterion is to minimize the sum of squares of the first differences between the successive quarterly values y_q, subject to the constraint that during each year the sum of the quarterly figures equals the annual total.

$$\begin{aligned} &\min_{y} \sum_{q=2}^{4n} \left(y_q - y_{q-1}\right)^2 \\ &s.t. \sum_{q=4t-3}^{4t} y_q = X_t \end{aligned} \qquad \text{for t=1, 2, ..., n} \qquad (3)$$

From the Lagrangean expression

$$L = \sum_{q=2}^{4n} \left(y_q - y_{q-1}\right)^2 + 2\sum_{t=1}^{n} \lambda_t \left(\sum_{q=4t-3}^{4t} y_q - X_t \right) \qquad (4)$$

the first order conditions with respect to each y_q and the Lagrangean multipliers λ_t amount to:

$$\begin{bmatrix} \mathbf{y} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{C}_n' \\ \mathbf{C}_n & \mathbf{0}_{nxn} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \mathbf{0}_{4nx1} \\ \mathbf{X} \end{bmatrix} \qquad (5)$$

where[6]: **y** is a columnvector of 4n quarterly figures, **λ** is a columnvector of n Lagrangean multipliers, **A** is a matrix of order 4n x 4n containing the coefficients of the y_q 's in the partial derivatives of the Lagrangean expression with respect to these y_q 's, $\mathbf{C_n}$ is a convertor matrix of order n x 4n which converts the quarterly values into annual figures, **0** is a nullmatrix, and **X** is a columnvector of n annual figures.

Although this is still a very simple method, it is less arbitrary than the one used by Lisman and Sandee (1964). Furthermore with this procedure we can compute quarterly values for all the years in the sample including the first and the last one. However, if the annual observations exhibit a linear trend, the computed quarterly values will lie on a long-stretched 'S' instead of on a straight line. Therefore the authors themselves suggest to use another criterion that remedies this defect.

The new criterion is to minimize the sum of squares of the second differences between the successive quarterly values y_q , subject to the same constraint that during each year the sum of the quarterly figures equals the annual total.

$$\begin{aligned} &\underset{y}{Min} \quad \sum_{q=2}^{4n-1}\left(\Delta y_q - \Delta y_{q-1}\right)^2 \\ &s.t. \quad \sum_{q=4t-3}^{4t} y_q = X_t \end{aligned} \qquad \text{for t=1, 2, ..., n} \qquad (6)$$

where Δy_q is defined as $y_{q+1} - y_q$.

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$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 0 & 0 & \dots & 0 & 0 & 0 & 0 \\ -1 & 2 & -1 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & -1 & 2 & -1 & \dots & 0 & 0 & 0 & 0 \\ . & . & . & . & & & & & \\ 0 & 0 & 0 & 0 & \dots & -1 & 2 & -1 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & -1 & 2 & -1 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & -1 & 1 \end{bmatrix} \text{ and } \mathbf{C_n} = \mathbf{I}_n \otimes \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & \dots & 0 & 0 & 0 & 0 \\ . & . & . & & & & & & \\ 0 & 0 & 0 & 0 & \dots & 1 & 1 & 1 & 1 \end{bmatrix}$$

The first order conditions with respect to each y_q and the Lagrangean multipliers λ_t are now:

$$\begin{bmatrix} \mathbf{y} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{B} & \mathbf{C}_n' \\ \mathbf{C}_n & \mathbf{0}_{nxn} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \mathbf{0}_{4nx1} \\ \mathbf{X} \end{bmatrix} \tag{7}$$

where[7] **B** is a matrix of order 4n x 4n containing the coefficients of the y_q 's in the partial derivatives of the Lagrangean expression with respect to these y_q 's.

Compared to the previous procedure of Boot, Feibes, and Lisman this procedure has the advantage that the quarterly values will lie on a straight line if the annual observations exhibit a linear trend.

2.1.3 Stram and Wei

Stram and Wei (1986) develop a procedure based on ARIMA modelling to transform an aggregate time series into a disaggegrate time series of periodicity *m*. In the following paragraph we will apply their general procedure to the case of distributing an annual time series across a quarterly one (i.e. m=4).

Let y_q be a quarterly series whose d*th* differences $w_q = (1\text{-}B)^d\, y_q$ follow a stationary Gaussian process and X_t an aggregate annual series whose d*th* differences $U_t = (1\text{-}B)^d\, X_t$ equally follow a stationary Gaussian process.

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$$\mathbf{B} = \begin{bmatrix} 1 & -2 & 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ -2 & 5 & -4 & 1 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & -4 & 6 & -4 & 1 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -4 & 6 & -4 & 1 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & & & & & & & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 1 & -4 & 6 & -4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 1 & -4 & 6 & -4 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 1 & -4 & 5 & -2 \\ 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 1 & -2 & 1 \end{bmatrix}$$

Their generalized least squares approach to the distribution problem can be stated as:

$$\underset{y}{Min} \quad \mathbf{w}'\mathbf{V}_{\mathbf{w}}^{-1}\mathbf{w}$$

$$s.t. \quad \sum_{q=4t-3}^{4t} y_q = X_t \qquad \text{for } t=1, 2, \dots, n \tag{8}$$

where: **w** is a columnvector of 4n-d stationary quarterly figures after differencing d times and $\mathbf{V}_\mathbf{w}$ is the covariance matrix of the quarterly differenced series w_q of order (4n-d) x (4n-d).

Wei and Stram (1990) propose to solve this problem in three steps.

Firstly, they fit an ARIMA model to the annual series X_t such that the residuals from this model are white noise. This model is then used to obtain an estimate of the covariance matrix $\mathbf{V}_\mathrm{U}$ of the annual differenced series U_t.

The next step consists of distributing this model across an ARIMA model for the quarterly series y_q to be estimated, the residuals of which are again white noise. That model is also used to estimate the covariance matrix $\mathbf{V}_\mathbf{w}$ of the quarterly differenced series w_q.

Finally, the quarterly values y_q can then be estimated by the following formula:

$$\mathbf{y} = \left[\frac{\Delta^{\mathbf{d}}_{\mathbf{4n}}}{\mathbf{0}_{\mathbf{dx4(n-d)}} \,|\, \mathbf{C}_\mathbf{d}}\right]^{-1} \cdot \left[\frac{\mathbf{V}_\mathbf{w}\mathbf{F}'\mathbf{V}_\mathbf{U}^{-1}\Delta^{\mathbf{d}}_{\mathbf{n}}}{\mathbf{0}_{\mathbf{dx(n-d)}} \,|\, \mathbf{I}_\mathbf{d}}\right] \cdot \mathbf{X} \tag{9}$$

where[8]: Δ^{d}_{4n} is a matrix of order (4n-d) x 4n, $\mathbf{C}_d$ is a convertor matrix of order d x 4d, **F** is a block matrix of order (n-d) x (4n-d), and $\mathbf{V}_\mathrm{U}$ is the covariance matrix of the annual differenced series U_t of order (n-d) x (n-d).

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$$\Delta^{\mathbf{d}}_{\mathbf{4n}} = \begin{bmatrix} \delta_0 & \delta_1 & . & . & . & \delta_d & 0 & 0 & 0 & 0 & 0 & . & . & . & 0 \\ 0 & \delta_0 & \delta_1 & . & . & . & \delta_d & 0 & 0 & 0 & 0 & . & . & . & 0 \\ . & . & . & & & & & & & & & & & & \\ 0 & 0 & 0 & . & . & . & 0 & 0 & 0 & \delta_0 & \delta_1 & . & . & . & \delta_d \end{bmatrix}$$

where δ_i is the coefficient of B^i in $(B-1)^d$

$$\text{and } \mathbf{F} = \begin{bmatrix} \mathbf{f} & | \mathbf{0} & | \mathbf{0} & | \mathbf{0} | & \dots & | \mathbf{0} \\ \mathbf{0} & | \ \mathbf{f} & | \mathbf{0} & | \mathbf{0} | & \dots & | \mathbf{0} \\ \mathbf{0} & | \ \mathbf{0} | & \mathbf{f} & | \mathbf{0} | & \dots & | \mathbf{0} \\ . & . & . & & & \\ \mathbf{0} & | \ \mathbf{0} | & \mathbf{0} | & \dots & | \mathbf{0} \ | & \mathbf{f} \end{bmatrix}$$

where **0** is a rowvector of 4 ones and $\mathbf{f}=(f_0, f_1, \dots, f_{3(d+1)})$ with f_i the coefficient of B^i in $(1+B+B^2+B^3)^{(d+1)}$.

The major advantage of the Stram and Wei procedure is that it uses information on the data generating process of both the aggregate and the disaggregated variable, whereas the previous procedures do not use such information. However, there are two practical limitations encountered in using this procedure. Firstly, the fitting of a well specified aggregate ARIMA model to X_t remains a difficult and fairly subjective task. Secondly, the procedure does not work when m is even (as in our application) and some real roots of the autoregressive polynomial of the estimated aggregate ARIMA model are negative.

2.1.4 The Kalman Filter

When we want to use the Kalman filter we first have to find a state space representation of the underlying data generating process. A state space model always consists of two parts.
The first part is the *measurement equation* linking the unobservable state variables y_t to one or more directly observable variables X_t:

$$\mathbf{X}_t = \beta_t \mathbf{y}_t + \mathbf{S}_t \varepsilon_t \qquad \varepsilon \sim N(0, \mathbf{H}_t) \tag{10}$$

where $\mathbf{X}_t$ is a vector of observable variables, β_t is a matrix of coefficients, $\mathbf{y}_t$ is the vector of state variables, and ε_t is a vector of disturbances.
The second part of the state space model is formed by the *transition equation*:

$$\mathbf{y}_t = \mathbf{T}_t \mathbf{y}_{t-1} + \mathbf{R}_t \eta_t \qquad \eta \sim N(0, \mathbf{Q}_t) \tag{11}$$

where $\mathbf{T}_t$ and $\mathbf{R}_t$ are matrices of coefficients and η_t is a vector of disturbances.

The Kalman filter technique is a recursive procedure for inference about the state variables α_t applying both the prediction and the updating equations.
The *prediction equations* are used to predict at time *t-1* the value of $\mathbf{y}_t$ and $\mathbf{P}_t$ (the covariance matrix of the prediction errors $\mathbf{y}_t - \hat{\mathbf{y}}_t$) using all available information at that time:

$$\begin{aligned} \hat{y}_{t|t-1} &= \mathbf{T}_t \, y_{t-1} \\ \mathbf{P}_{t|t-1} &= \mathbf{T}_t \mathbf{P}_{t-1} \mathbf{T}_t' + \mathbf{R}_t \mathbf{Q}_t \mathbf{R}_t' \end{aligned} \tag{12}$$

The *updating equations* are used to update the predictions by using the information that becomes available at time t:

$$\hat{y}_t = \hat{y}_{t|t-1} + \mathbf{P}_{t|t-1}\mathbf{Z}_t^{'}\mathbf{F}_t^{-1}\left(\mathbf{X}_t - \mathbf{Z}_t\hat{y}_{t|t-1}\right)$$
$$\mathbf{P}_t = \mathbf{P}_{t|t-1} - \mathbf{P}_{t|t-1}\mathbf{Z}_t^{'}\mathbf{F}_t^{-1}\mathbf{Z}_t\mathbf{P}_{t|t-1} \qquad (13)$$

where $\mathbf{F}_t = \mathbf{Z}_t\mathbf{P}_{t|t-1}\mathbf{Z}_t^{'} + \mathbf{S}_t\mathbf{H}_t\mathbf{S}_t^{'}$

Applied to our problem of distributing annual data across quarterly figures and assuming that the quarterly figures follow an AR(1) process the state space model to be estimated becomes:

$$\mathbf{X}_t = \begin{bmatrix}1 & 1 & 1 & 1\end{bmatrix}\cdot\begin{bmatrix}\mathbf{y}_{1,t}\\ \mathbf{y}_{2,t}\\ \mathbf{y}_{3,t}\\ \mathbf{y}_{4,t}\end{bmatrix}$$
$$\begin{bmatrix}\mathbf{y}_{1,t}\\ \mathbf{y}_{2,t}\\ \mathbf{y}_{3,t}\\ \mathbf{y}_{4,t}\end{bmatrix} = \begin{bmatrix}0 & 0 & 0 & \rho\\ 0 & 0 & 0 & \rho^2\\ 0 & 0 & 0 & \rho^3\\ 0 & 0 & 0 & \rho^4\end{bmatrix}\cdot\begin{bmatrix}\mathbf{y}_{1,t-1}\\ \mathbf{y}_{2,t-1}\\ \mathbf{y}_{3,t-1}\\ \mathbf{y}_{4,t-1}\end{bmatrix} + \begin{bmatrix}1 & 0 & 0 & 0\\ \rho & 1 & 0 & 0\\ \rho^2 & \rho & 1 & 0\\ \rho^3 & \rho^2 & \rho & 1\end{bmatrix}\cdot\begin{bmatrix}\eta_{1,t}\\ \eta_{2,t}\\ \eta_{3,t}\\ \eta_{4,t}\end{bmatrix} \qquad (14)$$

where **X** is a columnvector of n annual data, $\mathbf{y}_i$ are columnvectors of n quarterly figures for the *ith* quarter, ρ is a columnvector of the first order autocorrelation coefficient of the quarterly figures (obtained via the second method of Boot, Feibes, and Lisman), **0** is a columnvector of n zeros, **1** is a columnvector of n ones, and η_i are columnvectors of n quarterly disturbances for the *ith* quarter.

2.2 Procedures which use information from both the annual totals and related quarterly time series

A common feature of all but one of the procedures in this category is that they estimate the quarterly series *y* using information on one or more related quarterly series, subject to the constraint that during each year the sum of the quarterly figures equals the annual total. In practice, the quarterly related series is converted into an annual series (by premultiplying the matrix **Z** by the convertor matrix **C**), the annual series X is then regressed upon the computed annual related series CZ, and the resulting annual residuals are distributed across the quarterly series to be estimated y. We could make a distinction between the procedures that use the best linear unbiased estimator approach (Chow and Lin (1971), Fernandez (1981), and Litterman (1983)) and those that rely on the quadratic loss function approach (Denton (1971) and Fernandez (1981)). However, since Fernandez has demonstrated that the quadratic loss function approach also provides best linear unbiased estimators if the classical assumptions of the regression model are met by the quarterly residuals, we will present the various methods in a chronological order.

2.2.1 Chow and Lin

Chow and Lin (1971) discuss the problem of distribution for a periodicity $m=3$, i.e. estimating a monthly series given its quarterly data and monthly data on related series. The same procedure - mutatis mutandis - applies to the problem of estimating a quarterly series given its annual data and quarterly data on related series.

Following Chow and Lin (1971) we assume that the quarterly observations of the series to be estimated y satisfy a regression relationship with a number p of related series $z_1, \ldots, z_p$ which can be written as:

$$y = \mathbf{Z}\beta + \varepsilon \tag{15}$$

where: **Z** is a matrix of order 4n x p with p columns of quarterly observations on related series, β is a columnvector of p coefficients, and ε is a columnvector of 4n error terms.

The first step consists of converting the quarterly observations of the related series into annual observations by summing those quarterly observations that belong to the same year or in matrix formulation by premultiplying **Z** and ε by the n x 4n convertor matrix[9] **C**.

[9] Chow and Lin (1971) premultiply their convertor matrix **C** with 1/3, which leaves them with quarterly data that are the average of the monthly data. In this paper we will not premultiply **C** with 1/4, since we imposed the constraint that during each year the sum of the quarterly figures equals the annual total. This same procedure was followed by Denton (1971) and Fernandez (1981).

We now have a new regression model with annual data:

$$\mathbf{X} = \mathbf{C}\mathbf{y} = \mathbf{C}\mathbf{Z}\beta + \mathbf{C}\varepsilon \tag{16}$$

The best linear unbiased estimator y then becomes:

$$\begin{aligned} \mathbf{y} &= \mathbf{Z}\hat{\beta} + \left[\mathbf{V}\mathbf{C}'(\mathbf{C}\mathbf{V}\mathbf{C}')^{-1}\right]\cdot\left[\mathbf{X} - \mathbf{C}\mathbf{Z}\hat{\beta}\right] \\ \hat{\beta} &= \left[\mathbf{Z}'\mathbf{C}'(\mathbf{C}\mathbf{V}\mathbf{C}')^{-1}\mathbf{C}\mathbf{Z}\right]^{-1}\mathbf{Z}'\mathbf{C}'(\mathbf{C}\mathbf{V}\mathbf{C}')^{-1}\mathbf{X} \end{aligned} \tag{17}$$

The intuition behind this solution is that the quarterly estimates are based on two components, the first of which is a linear function of the quarterly values of the related series, while the second is a distribution of the annual residuals across the four quarters.

This estimator requires knowledge of the covariance matrix **V**. In practice however, this matrix is unknown and has to be estimated by assuming some structure in the residuals ε. Chow and Lin discuss two possibilities, namely serially uncorrelated residuals and residuals that follow an AR(1) process. In the next section we will refer to these procedures as CHO1 and CHO2, respectively.

If the quarterly residuals are serially uncorrelated, each with variance σ^2, the estimator in equation (17) reduces to[10]:

$$\begin{aligned} \mathbf{y} &= \mathbf{Z}\hat{\beta} + \mathbf{0.25}\,\mathbf{C}'\hat{\varepsilon} \\ \hat{\beta} &= (\mathbf{Z}'\mathbf{C}'\mathbf{C}\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{C}'\mathbf{X} \end{aligned} \tag{18}$$

which means that the annual residuals will be equally distributed across the four quarters within the year. The problem with this procedure is that it might introduce spurious discontinuities between the last quarter of one year and the first quarter of the next year, since the annual residuals are not necessarily uniformly distributed.

[10] In that case $\mathbf{V} = \sigma^2\mathbf{I}$ and $\mathbf{CVC'} = 4\sigma^2\mathbf{I}$.

If the quarterly residuals follow a first order autoregression ($\varepsilon_q = \alpha\varepsilon_{q-1} + e_q$) the covariance matrix will depend on the value of the autoregressive parameter α and on the value of the variance of the residuals e which is unknown. However the matrix $\boldsymbol{VC'(CVC')^{-1}}$ only depends on the value of the (quarterly) autoregressive parameter α. To obtain a consistent estimate of this parameter α Chow and Lin propose to use an iterative procedure based on the knowledge that the first-order (annual) autocorrelation coefficient q is in fact the ratio of the off-diagonal element to the diagonal element of the matrix $\sigma^2\mathbf{CVC'}$.

Using this iterative procedure for the problem of distributing annual totals across quarterly values, the relevant equation becomes:

$$q = \frac{\alpha^7 + 2\alpha^6 + 3\alpha^5 + 4\alpha^4 + 3\alpha^3 + 2\alpha^2 + \alpha}{2\alpha^3 + 4\alpha^2 + 6\alpha + 4} \qquad (19)$$

Starting with an initial guess of q the corresponding value of α can be calculated. We can then compute the annual residuals $\mathbf{X} - \mathbf{CZ}\hat{\beta}$, calculate their first-order autocorrelation coefficient as the next guess of q and proceed as before. Once convergence is reached, equation (17) can be used to estimate the quarterly series y.

2.2.2 Denton

Denton (1971) considers the adjustment problem, i.e. the fact that the sum of the quarterly values y_q for each year (obtained from another source or from a regression on related series) does not necessarily equal the annual total X_t. As the adjustment problem is narrowly related to the distribution problem we will discuss Denton's method here as an alternative procedure to distribute an annual series across a quarterly one.

To solve this adjustment problem Denton minimizes a quadratic loss function or penalty function $p(\mathrm{y}, \mathbf{Z}\hat{\beta})$ in the differences between the quarterly values to be estimated y_q and the quarterly values of the regression $(Z\hat{\beta})_q$, subject to the constraint that during each year the sum of the quarterly figures equals the annual total.

More formally, the problem can be stated as:

$$\underset{y}{Min}\ p(\mathbf{y},\mathbf{Z}\hat{\beta}) = (\mathbf{y}-\mathbf{Z}\hat{\beta})'\mathbf{G}(\mathbf{y}-\mathbf{Z}\hat{\beta})$$

$$s.t. \quad \sum_{q=4t-3}^{4t} y_q = X_t \qquad \text{for } t=1, 2, \ldots, n \tag{20}$$

This results in the following first order conditions with respect to each y_q and the Lagrangean multipliers λ_t :

$$\begin{bmatrix} \mathbf{y} \\ \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{G} & \mathbf{C}_n' \\ \mathbf{C}_n & \mathbf{0}_{nxn} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \mathbf{G} & \mathbf{0}_{4nxn} \\ \mathbf{C}_n & \mathbf{I}_n \end{bmatrix} \cdot \begin{bmatrix} \mathbf{Z}\hat{\beta} \\ \mathbf{X}-\mathbf{C}\mathbf{Z}\hat{\beta} \end{bmatrix} \tag{21}$$

From (21) we can then calculate the vector of the quarterly figures **y** as:

$$\mathbf{y} = \mathbf{Z}\hat{\beta} + \left[\mathbf{G}^{-1}\mathbf{C}'\left(\mathbf{C}\mathbf{G}^{-1}\mathbf{C}'\right)^{-1}\right]\cdot\left[\mathbf{X}-\mathbf{C}\mathbf{Z}\hat{\beta}\right]$$

$$\hat{\beta} = \left[\mathbf{Z}'\mathbf{C}'\left(\mathbf{C}\mathbf{G}^{-1}\mathbf{C}'\right)^{-1}\mathbf{C}\mathbf{Z}\right]^{-1}\mathbf{Z}'\mathbf{C}'\left(\mathbf{C}\mathbf{G}^{-1}\mathbf{C}'\right)^{-1}\mathbf{X} \tag{22}$$

The specific solution will depend on the choice of the matrix **G**. The three possibilities considered by Denton are: (1) **G** equal to the identity matrix $\mathbf{I}_{4n}$, (2) **G** equal to **D'D** where **D** is a matrix that transforms a series into first differences[11], and (3) **G** equal to **D'D'DD** where **DD** transforms a series into second differences. In the next section we will refer to these procedures as DEN1, DEN2, and DEN3, respectively.

[11] The matrix **D** is a matrix of order 4n x 4n that transforms a series into its first differences, assuming that the first quarterly value to be estimated y_0 is equal to the first quarterly value of the regression $(Z\beta)_0$:

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & \ldots & 0 & 0 \\ -1 & 1 & 0 & \ldots & 0 & 0 \\ 0 & -1 & 1 & \ldots & 0 & 0 \\ \cdot & \cdot & \cdot & & & \\ 0 & 0 & 0 & \ldots & -1 & 1 \end{bmatrix}$$

If we simply want to minimize the sum of squares of the differences between the quarterly values to be estimated y and the quarterly values of the regression $Z\hat{\beta}$, we choose **G** to be the identity matrix $\mathbf{I}_{4n}$. In that case $\mathbf{G}^{-1}\mathbf{C}'(\mathbf{C}\mathbf{G}^{-1}\mathbf{C}')^{-1}$ simplifies to 0.25 **C'**. Since this solution is identical to the one of Chow and Lin (1971) with homoscedastic and serially uncorrelated residuals it suffers from the same defects.

If we want to minimize the sum of squares of the differences between the first differences of the series y and the first differences of the series $Z\hat{\beta}$, we choose **G** equal to **D'D**. This procedure reduces to the first procedure of Boot, Feibes, and Lisman (1967) in cases where there exist no related quarterly series.

If we want to minimize the sum of squares of the differences between the second differences of the series y and the second differences of the series $Z\hat{\beta}$, we choose **G** equal to **D'D'DD**. This procedure reduces to the second procedure of Boot, Feibes, and Lisman (1967) in cases where there exist no related quarterly series.

2.2.3 Ginsburgh

Ginsburgh (1973) proposes to use a three step procedure that combines the second method of Boot, Feibes, and Lisman (1967) with the estimation of an annual model relating the annual totals to be distributed to the annualized totals of some related series.

The first step consists of using the second method of Boot, Feibes, and Lisman (1967) on both the annual totals of the series to be distributed and the annualized totals of the related series. This results in consistent quarterly estimates $\hat{y}$ and $\hat{z}$, in that the four quarters of the same year add up to the annual total.

According to Ginsburgh these quarterly estimates $\hat{y}$ should be 'modulated' to incorporate the advantage of using additional information from a related quarterly series. Therefore, the second step consists of estimating the annual model:

$$\mathbf{X} = \beta_0 + \beta_1 \mathbf{Cz} + \mathbf{C}\varepsilon \quad (23)$$

Finally, the estimated parameter $\hat{\beta}_1$ is used to modulate the former estimates $\hat{y}$ in the following way:

$$\mathbf{y} = \hat{\mathbf{y}} + \hat{\beta}_1 (\mathbf{z} - \hat{\mathbf{z}}) \quad (24)$$

In the next section we will refer to this series as GINS.

2.2.4 Fernandez

Fernandez (1981) in fact combines two of the procedures described above. He starts from the regression model $\mathbf{y} = \mathbf{Z}\beta + \varepsilon$ in which the error term follows a random walk[12]. He then transforms the whole model into first differences (to obtain stationary variables) and applies a procedure similar to the one of Chow and Lin. Finally he shows that this leads to the same result as using the Denton model with **G** equal to **D'D**.

In general he proposes the following procedure for distributing annual totals across quarterly values. As a first step, find a (simple) transformation that converts the residuals of the quarterly regression model ε to a serially uncorrelated and stationary random variable. Then, given the adequate transformation, β may be estimated by generalized least squares and the annual residuals distributed as indicated by equation (22).

12 The error term can be modelled as: $\varepsilon_q = \varepsilon_{q-1} + e_q$.

2.2.5 Litterman

Litterman (1983) proposes a method to estimate monthly values of a variable such that their average is equal to the quarterly value. We will discuss his procedure - mutatis mutandis - for the problem of estimating quarterly values of a variable such that their sum equals the annual value.

In fact, Litterman proposes a special case of the general procedure of Fernandez in that he assumes that the quarterly residuals follow an ARIMA(1,1,0) model:

$$\begin{aligned} \varepsilon_q &= \varepsilon_{q-1} + e_q \\ e_q &= \alpha\, e_{q-1} + v_q \end{aligned} \qquad \text{for q=2, 3, ..., 4n} \qquad (25)$$

In that case the best linear unbiased estimator **y** becomes:

$$\begin{aligned} \mathbf{y} &= \mathbf{Z}\hat{\beta} + (\mathbf{D'H'HD})^{-1}\mathbf{C'}\left[\mathbf{C}(\mathbf{D'H'HD})^{-1}\mathbf{C'}\right]^{-1}\left[\mathbf{X} - \mathbf{CZ}\hat{\beta}\right] \\ \hat{\beta} &= \left\{\mathbf{Z'C'}\left[\mathbf{C}(\mathbf{D'H'HD})^{-1}\mathbf{C'}\right]^{-1}\mathbf{CZ}\right\}^{-1}\mathbf{Z'C'}\left[\mathbf{C}(\mathbf{D'H'HD})^{-1}\mathbf{C'}\right]^{-1}\mathbf{X} \end{aligned} \qquad (26)$$

where[13] **H** is a 4n x 4n matrix.

We now need an estimate of the parameter α in order to be able to calculate the estimator **y**. Litterman proposes to use a three step procedure: (1) use the DEN2 procedure to generate annual residuals, (2) calculate the first-order autocorrelation coefficient of the first differences of the annual residuals, and (3) calculate the parameter α knowing that the first-order (annual) autocorrelation coefficient q is in fact the ratio of the off-diagonal element to the diagonal element of the covariance matrix σ^2**D'H'HD**.

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$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ -\alpha & 1 & 0 & \dots & 0 & 0 \\ 0 & -\alpha & 1 & \dots & 0 & 0 \\ . & . & . & & & \\ 0 & 0 & 0 & \dots & -\alpha & 1 \end{bmatrix}$$

For the problem of distributing annual totals across quarterly values, the relevant equation then becomes:

$$q = \frac{\alpha^{10} + 4\alpha^{9} + 10\alpha^{8} + 20\alpha^{7} + 31\alpha^{6} + 40\alpha^{5} + 44\alpha^{4} + 40\alpha^{3} + 32\alpha^{2} + 24\alpha + 10}{2\alpha^{6} + 8\alpha^{5} + 20\alpha^{4} + 40\alpha^{3} + 62\alpha^{2} + 80\alpha + 44} \qquad (27)$$

Equation (26) can then be used to estimate the quarterly series y. In the next section we will refer to this series as LIT.

3 An empirical comparison of the various procedures considered above

In this section we use the various distribution methods described above to construct disaggregated quarterly series for real (1990 prices) and nominal GDP for thirteen countries[14]. For most countries the data cover the period 1957.1-1994.4. For some countries, however, one or more data series are only available for a shorter observation period. As a consequence the samples vary across countries.

All data are taken from the *International Financial Statistics* of the IMF. For the estimation of quarterly real GDP data we use seasonally adjusted industrial production as the related series, whereas both seasonally adjusted industrial production and a price index (respectively producer prices (PPI) and consumer prices (CPI)) are used for the estimation of quarterly nominal GDP data[15].

For each of the countries considered and for the longest possible sample we calculate 11 quarterly series of real GDP and 18 quarterly series of nominal GDP following the

[14] These countries are selected by means of two criteria. First, the country should be a member of either the European Union (EU) since January 1 1995 or the G-7. Second, there should exist national quarterly data on GDP for a sufficiently long observation period (at least 60 observations, i.e. 15 years). This resulted in the following group of countries: Austria, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the United States.

[15] For Portugal only CPI data are available.

procedures outlined above[16]. Table 2 summarizes the abbreviations used for the various distribution procedures.

Table 2:

The distribution procedures used in the empirical part of the paper

LIS	Lisman and Sandee (1964)
BFL1	Boot, Feibes, and Lisman (1967) with first differences
BFL2	Boot, Feibes, and Lisman (1967) with second differences
KAL	Kalman filter
GINS	Ginsburgh (1973)
CHO1	Chow and Lin (1971) with serially uncorrelated residuals
CHO2	Chow and Lin (1971) with AR(1) residuals
DEN2	Denton (1971) with **G=D'D**
DEN3	Denton (1971) with **G=D'D'DD**
DEN4	Denton (1971) with **G=D'D'D'DDD**
LIT	Litterman (1983)

For nominal GDP we calculate two quarterly series using the procedures GINS, CHO1, CHO2, DEN2, DEN3, DEN4, and LIT, one with the PPI (GINS1, CHO11, CHO21, ...) and one with the CPI (GINS2, CHO12, CHO22, ...) as the price index.

[16] We did not apply the method proposed by Stram and Wei (1986, 1990) because of the practical limitations discussed above. When the periodicity is even the disaggregation of the aggregate ARIMA model into an ARIMA model for the quarterly series is either impossible (if some real roots of the AR polynomial of the aggregate model are negative) or not unique. Neither did we use the Fernandez-procedure in the empirical part of this paper since the 'simple' transformations proposed by Fernandez never led to stationary serially uncorrelated quarterly residuals.

3.1 Testing for nonstationarity[17]

We first test for the nonstationarity of the quarterly GDP series[18]. To test the null hypothesis of a unit root we use the (adjusted) Dickey-Fuller test statistic[19]. The number of lags (k) is selected in the following way: we start from a regression with 8 lags and each time eliminate the last insignificant lag. We both test for nonstationarity of the levels and of the growth rates. For *real GDP* both a constant and a trend are included in the ADF-regression of the levels, whereas in the ADF-regression of the growth rates we only include a constant. For *nominal GDP* we start by including both a constant and a trend in the ADF-regression of the levels. However, we eliminate the trend when some of the obtained test statistics are positive[20]. In the ADF-regression of the growth rates again only a constant is included.

Based on the ADF-test statistics for *real GDP* we can conclude that all actual quarterly real GDP series can be assumed to have one unit root. For the calculated series 96 out of 143 also have one unit root, whereas 45 series have two unit roots. Only CHO1 for the United Kingdom and GINS for Portugal are stationary series. Thus, the majority of the calculated quarterly growth rates of real GDP are stationary, although about one third still has a unit root. Since the majority of the computed series are therefore I(1), we concentrate on comparing the evolution of the *quarterly growth rates of real GDP* instead of the levels.

[17] The results of the nonstationarity tests are not included to save space, but can be obtained from the author on request.

[18] To this end we use the unit root tests of Hendry's software package PcGive Professional 8.00.

[19] We start from the most general ADF-regression:

$$\Delta y_q = \alpha + \beta \, Trend + (\gamma - 1) y_{q-1} + \sum_{i=1}^{k} \delta_i \Delta y_{q-i}$$

The null hypothesis of a unit root is $\gamma = 1$ (an insignificant test statistic $t_{\gamma-1}$) and the alternative hypothesis is $\gamma < 1$ (or a negative test statistic $t_{\gamma-1}$). The critical values of these test statistics are taken from McKinnon (1991).

[20] A positive test statistic is excluded, because this would mean that the series is exploding.

Table 3: The order of integration of quarterly series of real GDP

Furthermore, table 3 shows that especially the procedures which only use the information from the annual totals lead to I(2) series for real GDP and thus a poorer approximation of the actual quarterly real GDP data. Based on this criterion CHO1 is the best performing procedure (12 out of 13), followed by DEN3 (11 out of 13) and the group consisting of CHO2, DEN2, DEN4, LIT, and KAL (10 out of 13).

Based on the ADF-test statistics for *nominal GDP* we conclude that most actual quarterly nominal GDP series can be assumed to have two unit roots. Only Italian, Dutch, and Portugese nominal GDP only have one unit root. For the calculated series only 100 out of 228 are of the same order of integration as the actual quarterly nominal GDP series. Although the evidence is not as clear as for real GDP, we will also concentrate on comparing the evolution of the *quarterly growth rates of nominal GDP* instead of the levels: more than 90% of the computed series are not I(0) and about 30% is indeed I(1).

Table 4: The order of integration of quarterly series of nominal GDP

Furthermore, table 4 shows that especially the procedures which only use the information from the annual totals lead to I(2) series for nominal GDP and thus a better approximation of the actual quarterly nominal GDP data. Based on this criterion LIS, BFL2, and KAL are the best performing procedures (9 out of 13), followed by BFL1 (8 out of 13).

3.2 Correlation coefficients vis-à-vis the actual growth rates

Table 5 summarizes the correlation coefficients (ρ) of the growth rates computed using the various procedures vis-à-vis the actual quartely *real GDP* growth rates. From this table three conclusions can be drawn.

Table 5: The correlation coefficients (ρ) of the computed growth rates vis-à-vis the actual quarterly real GDP growth rates

Firstly, these correlation coefficients enable us to distinguish three groups of distribution procedures. The first group consists of LIS, BFL1, BFL2, and GINS. The procedures CHO2, DEN2, DEN3, DEN4, and LIT comprise the second group. Within this second group we can further distinguish two subgroups: (1) CHO2 and DEN2 and (2) DEN3, DEN4, and LIT. Finally, the third group consists of the three methods that do not show a close correlation with any of the other procedures (i.e. CHO1 and KAL).

Secondly, we see that for some countries all distribution procedures perform poorly. Therefore, we distinguish three groups of countries: (1) countries where the three best performing procedures are highly correlated ($\rho > 0.74$) with the actual real GDP series, (2) countries where the three best performing procedures are moderately correlated ($0.49 < \rho < 0.74$) with the actual real GDP series, and (3) countries where the three best performing procedures are badly correlated ($\rho < 0.45$) with the actual real GDP series. The first group (G1R) consists of Canada, France, Germany, the United Kingdom, and the United States. The second group (G2R) includes Austria, Italy, and Japan. Finally, Finland, the Netherlands, Portugal, Spain, and Sweden comprise the third group (G3R).

Thirdly, it becomes clear that based on this criterion the procedures of the second subgroup of the second group (i.e. DEN3, DEN4, and LIT) outperform the others.

Table 6 summarizes the correlation coefficients (ρ) of the growth rates computed using the various procedures vis-à-vis the actual quartely *nominal GDP* growth rates. From this table three similar conclusions can be drawn as for real GDP.

Table 6: The correlation coefficients (ρ) of the computed growth rates vis-à-vis the actual quarterly nominal GDP growth rates

Firstly, these correlation coefficients enable us to distinguish four groups of distribution procedures. The first group consists of BFL1, BFL2, and to a lesser extent LIS. The procedures CHO2 and DEN2 comprise the second group. The third group consists of DEN3, DEN4, and to a lesser extent LIT. Finally, the fourth group consists of the three methods that do not show a systematic correlation with any of the other procedures (i.e. CHO1, KAL, and GINS).

Secondly, we see that for some countries all distribution procedures perform poorly. Therefore, we again distinguish three groups of countries: (1) countries where the three best performing procedures are highly correlated ($\rho > 0.75$) with the actual nominal GDP series, (2) countries where the three best performing procedures are moderately correlated ($0.45 < \rho < 0.75$) with the actual nominal GDP series, and (3) countries where the three best performing procedures are badly correlated ($\rho < 0.44$) with the actual nominal GDP series. The first group (G1N) consists of Canada, France, Germany, Japan, Spain, the United Kingdom, and the United States. The second group (G2N) includes Austria, Italy, and the Netherlands. Finally, Finland, Portugal, and Sweden comprise the third group (G3N). Compared to the results for real GDP the results for nominal GDP are thus considerably better for Spain, the Netherlands, and to a lesser extent Japan.

Thirdly, it becomes clear that based on this criterion the procedures DEN3 and DEN4 outperform the others.

3.3 A further comparison with the actual quarterly GDP growth rates

As a final test, we compare our computed quarterly growth rates of both real and nominal GDP with the actual ones by calculating the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), and Theil's Inequality Coeffcient (U)[21].

We first calculate the sum of both the MAEs, the RMSEs, and the Us for the growth rates of *real GDP* across the countries of the first two groups (G1R and G2R). From the results in table 7 we conclude that the procedure DEN3 seems to outperform the other distribution procedures, both in terms of the MAE and the RMSE, whereas the procedure LIT outperforms the others in terms of the U. Furthermore, the table shows that the differences between the procedures DEN3, DEN4, and LIT are relatively small.

Table 7: The summed Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for real GDP growth rates

[21] We are well aware that this is a 'second best' solution, since the 'actual' quarterly GDP data are derived from some quarterly model and are no real observations. In spite of this we calculate the following three test statistics where y_q is the computed series and z_q the actual one.

$$MAE=\frac{\sum_{q=1}^{N}\left|y_q-z_q\right|}{N}$$

$$RMSE=\sqrt{\frac{\sum_{q=1}^{N}\left(y_q-z_q\right)^2}{N}}$$

$$U=\frac{\sqrt{\sum_{q=1}^{N}\left(y_q-z_q\right)^2/N}}{\sqrt{\sum y_q^2/N}+\sqrt{\sum z_q^2/N}}$$

Secondly, in table 8 we report the three best performing procedures for each test statistic for *real GDP* growth rates. Then we rank the three best procedures from 3 to 1 and add these ranks across the countries considered. This leads to a score of 50 for the best performing procedure DEN3 (19, 17, and 14 for MAE, RMSE, and U respectively), whereas the second best performing procedure DEN4 only scores 39 (15, 13, and 11 for MAE, RMSE, and U respectively) and the third best performing LIT only 37 (12, 14 and 11 for MAE, RMSE, and U respectively). Now, the method DEN3 seems to outperform the others, based on all three criteria. We therefore recommend to use the DEN3 procedure for distributing annual real GDP data across quarterly figures.

Table 8: The three best performing distribution procedures in terms of Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for real GDP growth rates

For the growth rates of *nominal GDP* we proceed in the same way.

We first calculate the sum of both the MAEs, the RMSEs, and the Us for the growth rates of *nominal GDP* across the countries of the first two groups (G1N and G2N). From the results in table 9 we see that the conclusions for *nominal GDP* are not as evident as for *real GDP*. Although the procedure DEN42 seems to outperform the other distribution procedures both in terms of the RMSE and the U, it scores rather badly in terms of the MAE. Therefore, we base our choice on the total rank of each procedure across the three criteria. This leads us to the conclusion that the procedure DEN42 does indeed outperform the other distribution procedures (total rank of 8, whereas the second best procedures BFL1 and DEN31 have a total rank of 10).

Table 9: The summed Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for nominal GDP growth rates

Secondly, in table 10 we report the three best performing procedures for each test statistic for the *nominal GDP* growth rates. Then we rank the three best procedures from 3 to 1 and add these ranks across the countries considered. This leads to a score of 30 for the best performing procedure DEN31 (11, 9, and 10 for MAE, RMSE, and U respectively), whereas the second best performing procedure DEN42 only scores 24 (7, 10, and 7 for MAE, RMSE, and U respectively) and the third best performing DEN41 only 23 (8, 8 and 7 for MAE, RMSE, and U respectively). Again we see that the conclusions for *nominal GDP* are not as evident as for *real GDP* since the scores are much lower and no procedure outperforms the others on all three criteria. Still, based on this evidence we conclude that the best method to use is the DEN31 procedure.

Table 10: The three best performing distribution procedures in terms of Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for nominal GDP growth rates

Taking all evidence on nominal GDP growth rates together, we recommend to use the DEN31 procedure for three reasons. The first reason is that this method yields the highest score when we look at the individual countries. Secondly, we learned from the correlation coefficients that the procedures DEN3 and DEN4 are highly correlated with one another. Using DEN31 instead of DEN42 which came out best from the results in table 9 is therefore justified. Finally, when we use the same distribution method for both nominal and real GDP, we can easily derive the implicit GDP deflator at a quarterly frequency.

4 Conclusions

Unfortunately we do not dispose of a theoretical basis to discriminate between the various disaggregation procedures outlined above, since many of them rest on assumptions concerning the underlying data. As a consequence we cannot formulate a conclusion to cover all countries or all observation periods.

A preliminary exploration of the empirical literature - primarily on money demand - leads us to conclude that many authors are very vague as to the method they use to disaggregate their annual data. Kremers and Lane (1990, p.784) e.g. state that "annual data are interpolated according to the quarterly pattern of industrial production" without further reference to the exact procedure used. Similarly, Fase and Winder (1992, p.31) state "quarterly data are constructed by means of data on industrial output". If we restrict ourselves to those authors that do mention (but not motivate the choice of) the procedure used, the method of Chow and Lin[22] (1971) clearly is the most popular one (Campbell (1991), Hoffmaister (1992), Butkiewicz and Yohe (1993), Artis, Bladen-Hovell, and Zhang (1994), ...). Hoffmaister (1992) also uses the method of Litterman (1983) to distribute nontraditional exports, Fernandez's (1981) method is used by Chowdhury (1993) to obtain quarterly estimates of government spending, and Duffy (1991) uses the second method of Boot, Feibes, and Lisman (1967) to distribute his annual population data across quarterly figures.

Since neither theory nor the empirical literature can provide a definite answer as to which disaggregation method is the 'best' one, we apply 11 of them to calculate quarterly real and nominal GDP data for 13 different countries. We test for nonstationarity of the levels and the growth rates and then calculate the correlation coefficients between the growth rates of the estimated quarterly GDP data and the actual ones. Based on these results, we can divide the 11 distribution procedures used into four groups: (1) the first three methods that only use information from the annual totals of GDP (i.e. LIS, BFL1, and BFL2), (2) the method of Chow and Lin with serially correlated residuals and the method of Denton with first

[22] However, they do not specify whether they use CHO1 or CHO2.

differences (i.e. CHO2 and DEN2), (3) the methods of Denton with second differences and with third differences and the method proposed by Litterman (i.e. DEN3, DEN4, and LIT), and (4) the other procedures (i.e. KAL, GINS, and CHO1). Finally, we compare the computed quarterly growth rates with the actual growth rates for a number of countries by means of the Mean Absolute Error, the Root Mean Squared Error, and Theil's inequality coefficient.

Although we are well aware that our results might be influenced by the choice of the periods and countries in our sample, we do recommend to compute both real and nominal quarterly GDP data by the method DEN3. For real GDP this means regressing annual real GDP data on annual industrial production data and minimizing the second differences between the quarterly real GDP data to be estimated and the quarterly regression outcomes. For nominal GDP we suggest regressing annual nominal GDP data on annual industrial production and annual producer prices and again minimizing the second differences between the quarterly nominal GDP data to be estimated and the quarterly regression outcomes.

The answer to the question raised in the title is therefore affirmative. It is indeed better to use the additional information from related quarterly series suggested by economic theory, than to simply apply a smoothing algorithm to the annual data.

Table 3: The order of integration of quarterly series of real GDP

	LIS	BFL1	BFL2	KAL	GINS	CHO1	CHO2	DEN2	DEN3	DEN4	LIT	ACT
score *	7	2	5	**10**	9	**12**	**10**	**10**	**11**	**10**	**10**	
Austria	1	2	2	1	2	1	1	1	1	1	1	1
Canada	1	2	1	1	1	1	1	1	1	1	1	1
Finland	2	2	1	1	1	1	1	1	1	1	1	1
France	2	2	2	2	1	1	1	1	1	1	1	1
Germany	1	1	2	1	1	1	1	1	1	1	1	1
Italy	1	2	1	1	1	1	1	1	1	1	1	1
Japan	2	2	2	2	2	1	2	2	2	2	2	1
Netherlands	1	2	2	1	1	1	1	1	1	1	1	1
Portugal	2	2	2	1	0	1	2	2	1	2	2	1
Spain	2	2	2	2	2	1	2	2	2	2	2	1
Sweden	2	2	2	1	1	1	1	1	1	1	1	1
U.K.	1	2	1	1	1	0	1	1	1	1	1	1
U.S.	1	1	1	1	1	1	1	1	1	1	1	1

* number of countries for which that distribution procedure generates a quarterly series of real GDP which is of the same order of integration as the actual one

Table 4: The order of integration of quarterly series of nominal GDP

	LIS	BFL 1	BFL 2	KAL	GINS 1	GINS 2	CHO 11	CHO 12	CHO 21	CHO 22	DEN 21	DEN 22	DEN 31	DEN 32	DEN 41	DEN 42	LIT 1	LIT 2	ACT
score *	9	8	9	9	6	7	5	6	5	4	5	3	5	3	5	3	6	2	
Austria	2	2	2	2	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2
Canada	2	2	2	2	1	2	1	1	2	1	2	1	2	1	1	1	2	1	2
Finland	2	1	2	2	2	1	1	2	1	2	1	1	1	1	1	1	1	1	2
France	2	2	2	2	1	2	1	2	1	1	1	1	1	1	1	1	1	1	2
Germany	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	0	2
Italy	2	2	2	2	1	2	1	2	2	2	2	2	2	2	2	2	1	2	1
Japan	2	2	2	2	2	2	0	2	2	2	2	2	2	0	2	0	2	0	2
Netherlands	2	2	2	2	1	2	1	2	1	2	1	2	2	2	2	2	0	2	1
Portugal	2	2	2	1	2	2		2		2		2		1		2		2	1
Spain	2	2	2	2	2	2	2	2	1	2	1	2	2	2	2	2	2	2	2
Sweden	2	2	2	2	0	1	2	1	2	1	2	1	0	1	2	2	2	1	2
U.K.	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
U.S.	2	2	2	1	1	2	1	1	1	1	1	1	2	1	2	1	1	1	2

* number of countries for which that distribution procedure generates a quarterly series of nominal GDP which is of the same order of integration as the actual one

Table 5: The correlation coefficients (ρ) of the computed growth rates vis-à-vis the actual quarterly real GDP growth rates

	LIS	BFL1	BFL2	KAL	GINS	CHO1	CHO2	DEN2	DEN3	DEN4	LIT
average	0.372	0.407	0.404	0.250	0.385	0.362	0.499	0.500	0.524	0.521	0.519
average good *	0.505	0.544	0.539	0.318	0.563	0.510	0.704	0.705	0.732	0.728	0.727
Austria	0.045	0.038	0.051	-0.168	-0.014	0.490	**0.494**	**0.494**	**0.494**	0.493	0.494
Canada	0.563	0.651	0.651	0.373	0.616	0.506	0.737	**0.739**	**0.747**	0.738	**0.746**
Finland	0.147	0.148	0.152	0.093	0.125	**0.159**	0.142	0.142	**0.152**	**0.163**	0.149
France	0.665	0.708	0.709	0.468	0.589	0.475	0.716	0.723	**0.805**	**0.796**	**0.782**
Germany	0.503	0.465	0.443	0.325	0.773	0.671	**0.815**	**0.815**	**0.818**	0.815	**0.818**
Italy	0.531	0.583	0.576	0.334	0.553	0.449	0.638	0.638	**0.682**	**0.685**	**0.678**
Japan	0.621	0.682	0.689	0.358	0.555	0.277	0.670	0.670	**0.703**	**0.692**	**0.704**
Netherlands	0.157	0.218	0.218	0.129	0.195	0.221	0.221	0.223	**0.252**	**0.256**	**0.235**
Portugal	0.270	**0.292**	**0.277**	**0.318**	0.005	0.118	0.253	0.253	0.271	0.241	0.277
Spain	0.187	**0.232**	**0.241**	0.128	0.110	0.104	0.159	0.159	0.201	**0.206**	0.193
Sweden	0.043	0.043	0.053	0.037	0.068	0.028	0.076	0.076	**0.076**	**0.082**	**0.076**
U.K.	0.526	0.557	0.528	0.393	0.669	0.592	0.737	0.739	**0.765**	**0.764**	**0.754**
U.S.	0.584	0.669	0.664	0.461	0.764	0.622	0.824	0.826	**0.843**	**0.844**	**0.837**

* average of those countries where the three best performing procedures are moderately correlated with the actual real GDP series (ρ>0.49), i.e. Austria, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

Table 6: The correlation coefficients (ρ) of the computed growth rates vis-à-vis the actual quarterly nominal GDP growth rates

	LIS	BFL 1	BFL 2	KAL	GINS 1	GINS 2	CHO 11	CHO 12	CHO 21	CHO 22	DEN 21	DEN 22	DEN 31	DEN 32	DEN 41	DEN 42	LIT 1	LIT 2
average *	0.493	0.513	0.510	0.177	0.368	0.307	0.290	0.201	0.539	0.567	0.541	0.567	0.606	0.613	0.591	0.607	0.607	0.579
average good **	0.558	0.587	0.581	0.253	0.422	0.352	0.317	0.219	0.613	0.645	0.616	0.646	0.696	0.703	0.681	0.695	0.694	0.661
Austria	0.075	0.085	0.088	-0.441	-0.114	-0.103	**0.487**	-0.157	0.458	0.450	0.458	0.450	**0.480**	0.475	**0.483**	0.474	0.478	0.458
Canada	0.786	0.818	**0.819**	0.382	0.644	0.676	0.461	0.481	0.711	0.719	0.717	0.719	0.799	**0.827**	0.810	**0.826**	0.777	0.736
Finland	**0.223**	0.211	**0.214**	-0.384	0.061	0.007	0.147	0.084	0.202	0.194	0.203	0.189	0.211	0.177	**0.215**	0.196	0.208	0.186
France	0.498	0.468	0.464	0.219	0.719	-0.152	0.553	-0.095	0.835	0.861	0.838	0.861	**0.872**	**0.870**	**0.880**	0.869	0.870	0.856
Germany	0.481	0.476	0.449	0.420	0.703	0.385	0.224	0.031	0.752	0.665	0.755	0.667	**0.780**	0.774	**0.776**	0.730	**0.782**	0.695
Italy	0.595	0.642	0.631	0.434	-0.065	0.038	0.001	0.069	0.586	0.663	0.586	0.663	**0.727**	**0.697**	0.662	0.693	**0.718**	0.673
Japan	0.696	0.709	0.720	0.310	0.464	0.609	0.133	0.349	0.650	0.650	0.653	0.651	0.764	**0.796**	**0.772**	**0.810**	0.765	0.757
Netherlands	0.273	0.313	0.280	0.193	0.263	0.341	0.114	0.274	0.373	**0.460**	0.375	**0.460**	0.398	**0.446**	0.380	0.431	0.379	0.445
Portugal	0.373	**0.395**	**0.374**	0.432		0.137		0.125		0.226		0.226		0.311		0.263		0.240
Spain	**0.920**	**0.954**	**0.958**	0.353	0.351	0.562	0.283	0.416	0.465	0.653	0.465	0.653	0.537	0.569	0.455	0.567	0.658	0.585
Sweden	0.111	0.080	0.095	-0.017	0.132	**0.161**	**0.170**	0.134	0.138	**0.163**	0.138	0.159	0.105	0.150	0.067	0.139	0.139	0.152
U.K.	0.646	0.715	0.716	0.301	0.655	0.420	0.523	0.345	0.636	0.587	0.637	0.588	**0.808**	**0.786**	**0.799**	0.766	0.740	0.641
U.S.	0.608	0.687	0.687	0.357	0.599	0.740	0.389	0.479	0.667	0.745	0.672	0.745	**0.794**	**0.793**	**0.790**	0.789	0.776	0.761

* average of all countries but Portugal

** average of those countries where the three best performing procedures are moderately correlated with the actual nominal GDP series (ρ>0.44), i.e. Austria, Canada, France, Germany, Italy, Japan, the Netherlands, Spain, the United Kingdom, and the United States.

Table 7: The summed Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for real GDP growth rates

MAE		RMSE		U	
DEN3	0.1036	DEN3	0.1289	LIT	2.4591
DEN4	0.1038	LIT	0.1295	DEN3	2.4896
LIT	0.1060	DEN4	0.1302	DEN4	2.5376
DEN2	0.1118	DEN2	0.1364	DEN2	2.5758
CHO2	0.1121	CHO2	0.1369	CHO2	2.5906
BFL1	0.1191	BFL1	0.1497	BFL1	3.3932
BFL2	0.1193	BFL2	0.1500	BFL2	3.3964
LIS	0.1217	LIS	0.1526	LIS	3.4741
KAL	0.1424	KAL	0.1796	GINS	3.6455
GINS	0.1564	GINS	0.2115	KAL	4.0361
CHO1	0.1750	CHO1	0.2230	CHO1	4.0735

Table 8: The three best performing distribution procedures in terms of Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for real GDP growth rates

	MAE	RMSE	U
Austria	DEN4 0.0679 DEN3 0.0683 LIT 0.0697	LIT 0.0796 CHO2 0.0800 DEN2 0.0800	CHO1 0.5057 CHO2 0.5481 DEN2 0.5481
Canada	DEN3 0.0052 LIT 0.0052 DEN4 0.0053	DEN3 0.0068 LIT 0.0068 DEN4 0.0069	LIT 0.2601 DEN3 0.2605 DEN2 0.2635
France	DEN3 0.0031 DEN4 0.0033 LIT 0.0033	DEN3 0.0043 DEN4 0.0044 LIT 0.0047	DEN3 0.2338 DEN4 0.2385 LIT 0.2469
Germany	DEN3 0.0049 LIT 0.0049 CHO2 0.0052	DEN3 0.0062 LIT 0.0062 CHO2 0.0065	CHO2 0.2715 DEN2 0.2716 LIT 0.2717
Italy	DEN4 0.0058 DEN3 0.0059 LIT 0.0060	DEN4 0.0096 DEN3 0.0097 LIT 0.0099	DEN4 0.3155 DEN3 0.3177 LIT 0.3211
Japan	LIT 0.0066 DEN3 0.0066 BFL1 0.0067	LIT 0.0092 DEN3 0.0092 DEN4 0.0094	LIT 0.2474 DEN3 0.2485 DEN4 0.2528
United Kingdom	DEN4 0.0054 DEN3 0.0055 LIT 0.0059	DEN4 0.0072 DEN3 0.0072 LIT 0.0078	DEN3 0.3042 DEN4 0.3098 LIT 0.3100
United States	DEN4 0.0041 DEN3 0.0041 LIT 0.0042	DEN4 0.0051 DEN3 0.0052 LIT 0.0053	DEN4 0.2233 DEN3 0.2240 LIT 0.2268

Table 9: The summed Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for nominal GDP growth rates

MAE		RMSE		U	
BFL2	0.1307	DEN42	0.1779	DEN42	2.5870
BFL1	0.1309	BFL1	0.1832	DEN32	2.6495
DEN31	0.1343	BFL2	0.1834	DEN31	2.6510
LIT1	0.1348	DEN31	0.1850	LIT1	2.6686
LIS	0.1353	DEN32	0.1860	DEN41	2.6756
DEN42	0.1358	LIT1	0.1873	BFL1	2.9375
DEN32	0.1373	DEN41	0.1883	BFL2	2.9392
DEN41	0.1388	LIS	0.1887	LIS	2.9913
LIT2	0.1545	LIT2	0.2189	LIT2	3.0472
CHO22	0.1661	CHO22	0.2394	CHO22	3.2737
DEN22	0.1661	DEN22	0.2397	DEN22	3.2765
GINS2	0.1753	GINS2	0.2540	DEN21	3.4429
DEN21	0.1873	DEN21	0.2831	CHO21	3.4869
CHO21	0.1898	CHO21	0.2900	GINS2	3.7675
KAL	0.2127	KAL	0.2933	KAL	4.3147
CHO12	0.2362	CHO12	0.3316	GINS1	4.4387
GINS1	0.2438	GINS1	0.3689	CHO12	4.6607
CHO11	0.4470	CHO11	0.6221	CHO11	5.5259

Table 10: The three best performing distribution procedures in terms of Mean Absolute Error, Root Mean Squared Error, and Theil's Inequality Coefficient for nominal GDP growth rates

	MAE		RMSE		U	
Austria	DEN42	0.0582	DEN42	0.0702	CHO21	0.5148
	DEN32	0.0585	DEN41	0.0703	DEN21	0.5148
	LIT2	0.0585	DEN32	0.0704	LIT1	0.5186
Canada	BFL2	0.0052	BFL2	0.0073	BFL2	0.1536
	BFL1	0.0053	BFL1	0.0073	BFL1	0.1542
	DEN32	0.0055	DEN42	0.0076	DEN32	0.1558
France	LIS	0.0075	DEN42	0.0111	DEN42	0.1770
	BFL1	0.0075	DEN41	0.0133	DEN41	0.2035
	BFL2	0.0076	LIS	0.0161	DEN32	0.2715
Germany	LIT1	0.0053	LIT1	0.0069	LIT1	0.2135
	DEN31	0.0054	DEN31	0.0070	DEN41	0.2144
	DEN41	0.0055	DEN41	0.0070	DEN31	0.2160
Italy	BFL2	0.0097	LIT1	0.0173	DEN31	0.2206
	BFL1	0.0100	DEN31	0.0177	LIT1	0.2221
	LIT1	0.0107	BFL1	0.0189	DEN42	0.2520
Japan	DEN42	0.0079	DEN42	0.0111	DEN42	0.1797
	DEN32	0.0082	DEN32	0.0116	DEN32	0.1861
	DEN41	0.0082	DEN41	0.0120	DEN41	0.1971
Netherlands	DEN31	0.0104	DEN22	0.0148	CHO22	0.4207
	DEN41	0.0104	CHO22	0.0148	DEN22	0.4209
	BFL1	0.0104	LIT2	0.0149	LIT2	0.4300
Spain	BFL2	0.0024	BFL2	0.0037	BFL2	0.0524
	BFL1	0.0025	BFL1	0.0039	BFL1	0.0550
	LIS	0.0036	LIS	0.0051	LIS	0.0706
United Kingdom	DEN31	0.0074	DEN31	0.0094	DEN31	0.1710
	DEN41	0.0076	DEN41	0.0095	DEN41	0.1744
	DEN32	0.0076	DEN32	0.0098	DEN32	0.1798

United States	DEN31 0.0053 DEN41 0.0054 DEN42 0.0054	GINS2 0.0073 DEN31 0.0076 BFL1 0.0078	DEN31 0.1765 GINS2 0.1773 DEN32 0.1805

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