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**Benchmarking systems of
seasonally adjusted time
series according**

T. Di Fonzo, M. Martini

2003.9

**Dipartimento di Scienze Statistiche
Università degli Studi
Via C. Battisti 241-243
35121 Padova**

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**Benchmarking systems of
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movement preservation
principle**

T. Di Fonzo and M. Marini

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Abstract

When a system of time series is seasonally adjusted, generally the accounting constraints originally linking the series are not fulfilled. To overcome this problem, we discuss an extension to a system of series linked by an accounting constraint of the classical univariate benchmarking procedure due to Denton (1971), which is founded on a movement preservation principle very appreciable in this case. The presence of linear dependence between the variables makes it necessary to conveniently deal with the whole set of contemporaneous and temporal aggregation relationships. The cases of one-way classified (e.g., by regions *or* by industries) and of two-ways classified (e.g., by regions *and* by industries) systems of series are studied. Moreover, simplified expressions of the matrices involved in the calculations are presented, which turn out useful in practical implementation of benchmarking for large systems of series. An empirical application to the Canadian retail trade series by province (12 series) and trade groups (18 series) is finally considered to show the capability of the proposed procedures.

Keywords: benchmarking; systems of time series; accounting constraints; Denton's movement preservation principle.

Benchmarking systems of seasonally adjusted time series according to Denton's movement preservation principle

Tommaso Di Fonzo
Dipartimento di Scienze Statistiche
Università di Padova

Marco Marini
Istituto Nazionale di Statistica
Roma

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Summary

When a system of time series is seasonally adjusted, generally the accounting constraints originally linking the series are not fulfilled. To overcome this problem, we discuss an extension to a system of series linked by an accounting constraint of the classical univariate benchmarking procedure due to Denton (1971), which is founded on a movement preservation principle very appreciable in this case. The presence of linear dependence between the variables makes it necessary to conveniently deal with the whole set of contemporaneous and temporal aggregation relationships. The cases of one-way classified (e.g., by regions *or* by industries) and of two-ways classified (e.g., by regions *and* by industries) systems of series are studied. Moreover, simplified expressions of the matrices involved in the calculations are presented, which turn out useful in practical implementation of benchmarking for large systems of series. An empirical application to the Canadian retail trade series by province (12 series) and trade groups (18 series) is finally considered to show the capability of the proposed procedures.

Keywords: benchmarking; systems of time series; accounting constraints; Denton's movement preservation principle.

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1. Introduction

Laniel and Fyfe (1989, pp. 464-465) write:

Most economic sub-annual surveys produce series of estimates for a number of industrial activities within a number of geographical regions. These are published sub-annually in the form of tables, where the cells as well as the marginals and the grand totals need to be benchmarked.

If one applies a benchmarking method independently on each cell series, each marginal series and the grand total series, the results will be a series of benchmarked sub-annual estimates where the sums of the cell totals are not equal to the marginal totals, and the sum of the marginal totals are not equal to the grand total. In other words, a series of inconsistent tables will be produced. To avoid this problem, a number of strategies can be adopted. Amongst these strategies, the first that comes to mind is the following simple approach. First, the cell series are independently benchmarked. Then, the benchmarked cell totals are summed up to get the benchmarked marginal totals and benchmarked grand totals. With this method one might get benchmarked margins and grand totals with chronological patterns which look more noisy than if they were directly benchmarked (this is a problem well known in seasonal adjustment). If this is the case one would be better to use the following method:

i) First benchmark the series of grand totals.

ii) Then, independently benchmark each series of marginal totals and then for each sub-annual period separately adjust the benchmarked margins by a constant factor so that they add up to the benchmarked grand totals.

iii) Finally, independently benchmark each series of cell totals and then for each sub-annual period separately adjust the benchmarked cells using the raking ratio algorithm (also called iterative proportional fitting, see Deming and Stephan, 1940) so that they add up to the adjusted benchmarked margins.

This method assumes that the series of grand totals is the most important series of the table in terms of preserving month-to-month trends, the series of marginal totals are the second most important and the series of cell totals are the least important. An inconvenient with this method is that the month-to-month trends of the cells can be very much disturbed (...)

One can also think of benchmarking simultaneously the cell series with the margin series and the grand total series. Then the problem can become very large in terms of the number of parameters to estimate and even difficult to handle with a computer. This has been addressed by Cholette (1988b) in the case where series are to be benchmarked with Denton's method.

In this paper we start just from the last point quoted by Laniel and Fyfe, that is the paper by Cholette (1988), which presents a wide review of the problems which a researcher faces when systems of time series, rather than only one, are to be benchmarked in order to simultaneously fulfil temporal and contemporaneous (longitudinal, geographical) aggregation constraints.

Benchmarking systems of time series is a typical problem for data producers. Different classifications for the same phenomenon often lead to different total aggregates, so that an adjustment to the estimates is needed to give a coherent picture to the users. In what follows we will refer to benchmarking systems of (or tables of two-ways classified)¹ individually seasonally

¹ In this paper we deal exclusively with benchmarking of more than one series. At univariate level, references to more sophisticated - and statistically well founded - procedures are Hillmer and Trabelsi (1987), Cholette and Dagum (1994), Durbin and Quenneville (1997), Dagum *et al.* (1998).

adjusted series, but the results are more general and apply to any context in which accounting constraints hold (Chen and Dagum, 1997, Eurostat, 1999, Di Fonzo, 2002).

We will consider benchmarking according to Denton's movement preservation principle, dealing with both binding and unbinding constraints². Particular attention will be given to the computational aspects which, as seen before, represented up to now a major problem for a massive application of this kind of procedures.

As we shall see, by a thorough analysis of the matrices involved in the various benchmarking expressions, we can formulate solutions very easy to implement in a computer program and whose processing times dramatically decrease as compared to those necessary if no simplification is performed.

The paper is organized as follows. Section 2 is devoted to problem formulation, while in section 3 the problem of benchmarking one system of series when a binding accounting constraint is available is presented. An approach to solve this problem is developed in section 4, and simplified benchmarking formulae, obtained by taking into account the partitioned nature of the matrices involved when two classic variants (additive and proportional) of Denton's movement preservation principle are used, are shown in section 5. We consider also the case of a system of series with an unbinding accounting constraint, while the benchmarking of two systems of series linked by the same accounting constraint (either binding or unbinding) is described in section 6. We then deal with two enlargements of the simultaneous benchmarking problem. Firstly (section 7) we develop a benchmarking procedure according to a movement preservation principle explicitly operating on period-to-period rates of change, based on suitable log-transformations of the variables. Secondly (section 8), we discuss the more general problem of benchmarking a two-ways classified table of time series, giving a solution in two cases generally encountered in practice. In section 9 we take a look on the computational times needed to perform multivariate benchmarking. Finally, practical applications of the various procedures presented are performed on individually seasonally adjusted monthly Canadian retail trade series, classified by province and trade groups.

2. Statement of the problem and some notation

We assume that the available information is given by:

- $M+1$ monthly raw series $\{x_{it}\}$, $i=1, \dots, M+1$, $t=1, \dots, n$, linked by the accounting constraints

$$\sum_{i=1}^M x_{it} = x_{M+1,t}, \quad t=1, \dots, n; \quad (1)$$

- $M+1$ monthly unbenchmarked SA series $\{y_{it}\}$, $i=1, \dots, M+1$, $t=1, \dots, n$, such that, in general, neither contemporaneous (between SA series) nor temporal (with the annual sums of the raw series) aggregation links are fulfilled, that is

$$\sum_{i=1}^M y_{it} \neq y_{M+1,t}, \quad t=1, \dots, n;$$

$$\sum_{s=1}^{12} y_{i,(T-1)12+s} \neq \sum_{s=1}^{12} x_{i,(T-1)12+s}, \quad i=1, \dots, M+1, \quad T=1, \dots, N.$$

We want to estimate benchmarked SA monthly series, say $y_{i,t}^*$, $i=1, \dots, M+1$, $t=1, \dots, n$, such that all the aggregation constraints be simultaneously fulfilled:

² Multivariate benchmarking of one system of time series with a binding contemporaneous constraint has been dealt with in Eurostat(1999) and Di Fonzo (2002).

$$\sum_{i=1}^M y_{i,t}^* = y_{M+1,t}^*, \quad t=1, \dots, n; \quad (2)$$

$$\sum_{s=1}^{12} y_{i,(T-1)12+s}^* = \sum_{s=1}^{12} x_{i,(T-1)12+s}, \quad i=1, \dots, M+1, \quad T=1, \dots, N. \quad (3)$$

In what follows we consider the situation, often encountered in practice, in which one series (generally the one representing the total, $y_{M+1,t}$) constitutes a *binding* constraint³, and thus must not be benchmarked. Furthermore, we deal with other two cases: the one in which the whole set of $M+1$ series must be benchmarked (*unbinding* constraint) and the contemporaneous benchmarking of two systems of time series linked by an accounting constraint, either binding or not.

3. One system of series and a binding accounting constraint

Let us denote with \mathbf{x}_i , $i=1, \dots, M$, the $(n \times 1)$ vectors of raw data for the M component series, with \mathbf{y}_i the SA unbenchmarked counterparts, with \mathbf{y}_i^* the benchmarked vectors to be derived and, finally, with $\mathbf{z} = \mathbf{y}_{M+1} = \mathbf{y}_{M+1}^*$ the aggregate series to be assumed as a binding constraint to be fulfilled by the benchmarked series.

Denoting $\mathbf{1}_M = (1, \dots, 1, \dots, 1)'$ and \mathbf{J} the $(N \times n)$ matrix performing temporal aggregation of a single monthly vector⁴, the whole set of aggregation constraints can be expressed in matrix form as follows:

$$\begin{bmatrix} \mathbf{1}'_M \otimes \mathbf{I}_n \\ \mathbf{I}_M \otimes \mathbf{J} \end{bmatrix} \mathbf{y}^* = \begin{bmatrix} \mathbf{z} \\ \mathbf{x}_0 \end{bmatrix}, \quad (4)$$

where $\mathbf{y}^* = (\mathbf{y}_1^*, \dots, \mathbf{y}_i^*, \dots, \mathbf{y}_M^*)'$, $\mathbf{x}_0 = (\mathbf{I}_M \otimes \mathbf{J}) \mathbf{x}$ is the $((M \cdot N) \times 1)$ vector containing the yearly sums of the M component raw series, and $\mathbf{x} = (\mathbf{x}'_1, \dots, \mathbf{x}'_i, \dots, \mathbf{x}'_M)'$.

The accounting constraints (4) can be written in compact form as

$$\mathbf{H} \mathbf{y}^* = \mathbf{x}_a, \quad (5)$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{1}'_M \otimes \mathbf{I}_n \\ \mathbf{I}_M \otimes \mathbf{J} \end{bmatrix} \quad (6)$$

has dimension $((n+M \cdot N) \times M \cdot n)$ and

³ In this case, $y_{M+1,t} \equiv y_{M+1,t}^*$ and $\sum_{s=1}^{12} y_{M+1,(T-1)12+s} = \sum_{s=1}^{12} x_{M+1,(T-1)12+s}$, $T=1, \dots, N$.

⁴ For example, assuming that the first monthly data in the series has been observed on January, and assuming $n=12 \cdot N$, \mathbf{J} takes the form $\mathbf{J} = \mathbf{I}_N \otimes \mathbf{1}'_{12}$. Matrix \mathbf{J} can be simply modified such as to deal with cases in which for the starting year and/or the last year not all monthly data are available.

$$\mathbf{x}_a = \begin{bmatrix} \mathbf{z} \\ \mathbf{x}_0 \end{bmatrix}$$

is a $((n+M\cdot N)\times 1)$ vector containing the contemporaneous and temporal aggregates.

Notice that a contemporaneous accounting constraint holds for the yearly sums too:

$$\sum_{i=1}^M x_{0i,T} = x_{0M+1,T} = \sum_{s=1}^{12} z_{(T-1)12+s}, \quad T=1, \dots, N, \quad (7)$$

that is, in matrix form,

$$\begin{bmatrix} \mathbf{J} & \vdots & -(\mathbf{1}'_M \otimes \mathbf{I}_N) \end{bmatrix} \mathbf{x}_a = \mathbf{0}. \quad (8)$$

Relationship (8) states that N linear restrictions of the $n+M\cdot N$ established by expression (5) are superfluous, and then matrix \mathbf{H} has not full row rank. To clarify this fact, partition \mathbf{H} in such a way as to distinguish the temporal aggregation constraints linking \mathbf{y}_M^* to $\mathbf{x}_{0,M} = \mathbf{J}\mathbf{x}_M$ from the remainder⁵:

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_w \\ \cdots \\ \mathbf{H}_M \end{bmatrix}, \quad (9)$$

where $\mathbf{H}_w = \begin{bmatrix} \mathbf{1}'_{M-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_{M-1} \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix}$ and $\mathbf{H}_M = [\mathbf{0} \quad \vdots \quad \mathbf{J}]$ are matrices $(r \times M \cdot n)$ and $(N \times M \cdot n)$, respectively, with $r = n + (M-1) \cdot N$, such that

$$\mathbf{H}_w \mathbf{y}^* = \begin{bmatrix} \mathbf{z} \\ \mathbf{J}\mathbf{x}_1 \\ \vdots \\ \mathbf{J}\mathbf{x}_{M-1} \end{bmatrix} = \begin{bmatrix} \mathbf{z} \\ \mathbf{x}_{01} \\ \vdots \\ \mathbf{x}_{0M-1} \end{bmatrix} = \mathbf{w}$$

and

$$\mathbf{H}_M \mathbf{y}^* = \mathbf{J}\mathbf{x}_M = \mathbf{x}_{0M}.$$

Denoting \mathbf{W} the $(N \times r)$ matrix,

$$\mathbf{W} = \begin{bmatrix} \mathbf{J} & \vdots & -(\mathbf{1}'_{M-1} \otimes \mathbf{I}_N) \end{bmatrix} \quad (10)$$

and \mathbf{R} the $((r+N) \times r)$ matrix

$$\mathbf{R} = \begin{bmatrix} \mathbf{I}_r \\ \mathbf{W} \end{bmatrix}, \quad (11)$$

⁵ As we shall see, contrary to what Chen and Dagum (1997) state, the results are invariant with respect to the choice of one of the M vectors \mathbf{x}_{0i} forming \mathbf{x}_0 .

the following relationships hold:

$$\mathbf{H}_M = \mathbf{W}\mathbf{H}_w, \quad \mathbf{H} = \mathbf{R}\mathbf{H}_w, \quad (12)$$

$$\mathbf{R}\mathbf{w} = \begin{bmatrix} \mathbf{I}_r \\ \mathbf{W} \end{bmatrix} \begin{bmatrix} \mathbf{z} \\ \mathbf{x}_{01} \\ \vdots \\ \mathbf{x}_{0M-1} \end{bmatrix} = \begin{bmatrix} \mathbf{z} \\ \mathbf{x}_{01} \\ \vdots \\ \mathbf{x}_{0M-1} \\ \mathbf{J}\mathbf{z} - \sum_{i=1}^{M-1} \mathbf{x}_{0i} \end{bmatrix} = \begin{bmatrix} \mathbf{w} \\ \mathbf{x}_{0M} \end{bmatrix} = \mathbf{x}_a. \quad (13)$$

Thus, constraints (4) can be expressed as:

$$\mathbf{R}\mathbf{H}_w \mathbf{y}^* = \mathbf{R}\mathbf{w}. \quad (14)$$

4. The benchmarking formula

We assume that the following models hold for the unknown series to be benchmarked, \mathbf{y}_i^* , $i=1, \dots, M$, and the unbenchmarkd SA series \mathbf{y}_i , $i=1, \dots, M$:

$$\mathbf{y}_i^* = \mathbf{y}_i + \mathbf{e}_i, \quad i=1, \dots, M, \quad (15)$$

where \mathbf{e}_i are $(n \times 1)$ zero-mean random disturbances, with $E(\mathbf{e}_i \mathbf{e}_j') = \mathbf{\Omega}_{ij}$, $i, j=1, \dots, M$, and $\mathbf{\Omega}_{ij}$ are $(n \times n)$ known matrices⁶. Putting together the M relationships (15) we have the complete model

$$\mathbf{y}^* = \mathbf{y} + \mathbf{e}, \quad (16)$$

with $E(\mathbf{e}) = \mathbf{0}$ and $E(\mathbf{e}\mathbf{e}') = \mathbf{\Omega}$.

The simultaneously benchmarked series can be obtained by solving the following quadratic-linear minimization problem:

$$\min_{\mathbf{y}^*} (\mathbf{y}^* - \mathbf{y})' \mathbf{\Omega}^{-1} (\mathbf{y}^* - \mathbf{y}) \quad \text{subject to } \mathbf{H}\mathbf{y}^* = \mathbf{x}_a. \quad (17)$$

However, the constraints (5) being linearly dependent, particular attention has to be given to the rank of the matrices involved in the procedure.

Let us consider the lagrangean

$$L = (\mathbf{y}^* - \mathbf{y})' \mathbf{\Omega}^{-1} (\mathbf{y}^* - \mathbf{y}) + 2\boldsymbol{\lambda}' (\mathbf{H}\mathbf{y}^* - \mathbf{x}_a), \quad (18)$$

where $\boldsymbol{\lambda}$ is a $((r+N) \times 1)$ vector of Lagrange multipliers. The first order conditions are given by the system

⁶ For the time being, we assume that this matrix has full rank (see footnote 9).

$$\begin{cases} \frac{\partial L}{\partial \mathbf{y}^*} = \mathbf{0} \\ \frac{\partial L}{\partial \boldsymbol{\lambda}} = \mathbf{0} \end{cases} \Leftrightarrow \begin{cases} \boldsymbol{\Omega}^{-1} \mathbf{y}^* + \mathbf{H}' \boldsymbol{\lambda} = \boldsymbol{\Omega}^{-1} \mathbf{y} \\ \mathbf{H} \mathbf{y}^* = \mathbf{x}_a \end{cases}, \quad (19)$$

that is

$$\begin{bmatrix} \boldsymbol{\Omega}^{-1} & \mathbf{H}' \\ \mathbf{H} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{y}^* \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Omega}^{-1} \mathbf{y} \\ \mathbf{x}_a \end{bmatrix}. \quad (20)$$

Using a well known matrix result (Magnus and Neudecker, 1988, pp. 60-61), the solution to system (20) is actually given by

$$\hat{\mathbf{y}}^* = \mathbf{y} + \boldsymbol{\Omega} \mathbf{H}' (\mathbf{H} \boldsymbol{\Omega} \mathbf{H}')^{-} (\mathbf{x}_a - \mathbf{H} \mathbf{y}), \quad (21)$$

where $(\mathbf{H} \boldsymbol{\Omega} \mathbf{H}')^{-}$ denotes the Moore-Penrose generalized inverse of $\boldsymbol{\Omega}_a = \mathbf{H} \boldsymbol{\Omega} \mathbf{H}'$.

A solution, equivalent to (21), and which does not involve singular matrices to be inverted, can be expressed in terms of r 'free' observations. In fact, using expression (12), the singular matrix $\mathbf{H} \boldsymbol{\Omega} \mathbf{H}'$ can be written as $\mathbf{R} \mathbf{H}_w \boldsymbol{\Omega} \mathbf{H}_w' \mathbf{R}' = \mathbf{R} \boldsymbol{\Omega}_w \mathbf{R}'$, where $\boldsymbol{\Omega}_w = \mathbf{H}_w \boldsymbol{\Omega} \mathbf{H}_w'$ is a full rank ($r \times r$) matrix. Furthermore, it can be readily checked⁷ that $\boldsymbol{\Omega}_a^{-}$ is univocally given by

$$\boldsymbol{\Omega}_a^{-} = (\mathbf{H} \boldsymbol{\Omega} \mathbf{H}')^{-} = \mathbf{R} (\mathbf{R}' \mathbf{R})^{-1} \boldsymbol{\Omega}_w^{-1} (\mathbf{R}' \mathbf{R})^{-1} \mathbf{R}'. \quad (22)$$

By substituting (22) into (21), and taking into account that $\mathbf{R}' \mathbf{H} = \mathbf{R}' \mathbf{R} \mathbf{H}_w$, after a bit of algebra we find the more feasible benchmarking formula

$$\hat{\mathbf{y}}^* = \mathbf{y} + \boldsymbol{\Omega} \mathbf{H}_w' \boldsymbol{\Omega}_w^{-1} (\mathbf{w} - \mathbf{H}_w \mathbf{y}). \quad (23)$$

The benchmarked estimates are thus obtained by distributing a linear combination of the discrepancies pertaining to r unconstrained observations of the aggregated vector \mathbf{x}_a over the original unbenchmarking data. It should be noted that expression (23) (i) involves the inversion only of full rank matrices and (ii) fulfils both temporal and contemporaneous constraints:

$$\begin{aligned} \mathbf{H} \hat{\mathbf{y}}^* &= \mathbf{H} \mathbf{y} + \mathbf{H} \boldsymbol{\Omega} \mathbf{H}_w' \boldsymbol{\Omega}_w^{-1} (\mathbf{w} - \mathbf{H}_w \mathbf{y}) \\ &= \mathbf{H} \mathbf{y} + \mathbf{R} \mathbf{H}_w \boldsymbol{\Omega} \mathbf{H}_w' \boldsymbol{\Omega}_w^{-1} (\mathbf{w} - \mathbf{H}_w \mathbf{y}) \\ &= \mathbf{H} \mathbf{y} + \mathbf{R} (\mathbf{w} - \mathbf{H}_w \mathbf{y}) = \mathbf{H} \mathbf{y} + \mathbf{x}_a - \mathbf{H} \mathbf{y} = \mathbf{x}_a \end{aligned}$$

⁷ See the appendix.

5. The choice of Ω : Denton's movement preservation principle

A natural way of proceeding in the choice of Ω is to reconsider the 'movement preservation principle' stated by Denton (1971)⁸. According to that principle, additive and proportional variants of the multivariate extension of Denton's benchmarking procedure should operate focusing on, respectively, the simple period-to-period change,

$$(y_{i,t}^* - y_{i,t-1}^*) - (y_{i,t} - y_{i,t-1}) \equiv (y_{i,t}^* - y_{i,t}) - (y_{i,t-1}^* - y_{i,t-1}), \quad i=1, \dots, M,$$

or the proportional period-to-period change,

$$\frac{y_{i,t}^* - y_{i,t}}{y_{i,t}} - \frac{y_{i,t-1}^* - y_{i,t-1}}{y_{i,t-1}} \equiv \frac{y_{i,t}^*}{y_{i,t}} - \frac{y_{i,t-1}^*}{y_{i,t-1}}, \quad i=1, \dots, M.$$

The objective functions to be minimized for the first differences case are thus given by

$$\sum_{i=1}^M \sum_{t=1}^n [(y_{i,t}^* - y_{i,t}) - (y_{i,t-1}^* - y_{i,t-1})]^2$$

and

$$\sum_{i=1}^M \sum_{t=1}^n \left(\frac{y_{i,t}^*}{y_{i,t}} - \frac{y_{i,t-1}^*}{y_{i,t-1}} \right)^2,$$

respectively. Using matrix notation, Ω can be expressed as (Eurostat, 1999, Di Fonzo, 2002):

$[\mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D})]^{-1} = \mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D})^{-1}$	Denton additive first differences
$[\mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D}'\mathbf{D}\mathbf{D})]^{-1} = \mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D}'\mathbf{D}\mathbf{D})^{-1}$	Denton additive second differences
$\mathbf{Y}(\mathbf{I}_M \otimes \mathbf{D}'\mathbf{D})^{-1} \mathbf{Y} = \mathbf{Y}[\mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D})^{-1}] \mathbf{Y}$	Denton proportional first differences
$\mathbf{Y}(\mathbf{I}_M \otimes \mathbf{D}'\mathbf{D}'\mathbf{D}\mathbf{D})^{-1} \mathbf{Y} = \mathbf{Y}[\mathbf{I}_M \otimes (\mathbf{D}'\mathbf{D}'\mathbf{D}\mathbf{D})^{-1}] \mathbf{Y}$	Denton proportional second differences

where \mathbf{D} is the $(n \times n)$ matrix⁹ performing first differences:

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ -1 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 & 1 \end{bmatrix} \quad (26)$$

⁸ See also Cholette (1988).

⁹ For computational convenience, we present the original difference matrix used by Denton (1971). As Cholette (1984) pointed out, at univariate level the computational reasons behind this specification, which involves $y_{i,0}^* - y_{i,0} = 0$ and $y_{i,0}^* - y_{i,0} = y_{i,-1}^* - y_{i,-1} = 0$ for AFD and ASD variants, respectively, have become obsolete. We are currently engaged in working out simplified multivariate benchmarking formulae which correctly deal with the first observation of each series.

and

$$\mathbf{Y} = \begin{bmatrix} \text{diag}(\mathbf{y}_1) & \mathbf{0} & \cdots & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \text{diag}(\mathbf{y}_2) & \cdots & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \text{diag}(\mathbf{y}_i) & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \cdots & \text{diag}(\mathbf{y}_M) \end{bmatrix}.$$

The dimensions of the matrices involved in the calculations can be considerable in practical situations, giving raise to high computational times. However, it is possible to obtain a sensible safe of time by exploiting the particular form of the matrices involved, as shown in what follows.

Let us denote $\mathbf{Q} = (\mathbf{D}'\mathbf{D})^{-1}$ or $\mathbf{Q} = (\mathbf{D}'\mathbf{D}'\mathbf{D}\mathbf{D})^{-1}$ the matrices involved in the calculation for the first differences or second differences variants of the benchmarking procedure, respectively. The aggregated covariance matrix $\mathbf{\Omega}_w$ for the additive variant of the procedure can be expressed in terms of partitioned matrices as:

$$\mathbf{\Omega}_w = \mathbf{H}_w \mathbf{\Omega} \mathbf{H}_w' = \begin{bmatrix} \mathbf{1}'_{M-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_{M-1} \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{I}_{M-1} \otimes \mathbf{Q} & \vdots & \mathbf{0} \\ \mathbf{0} & \vdots & \mathbf{Q} \end{bmatrix} \begin{bmatrix} \mathbf{1}_{M-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_{M-1} \otimes \mathbf{J}' \\ \mathbf{I}_n & \vdots & \mathbf{0} \end{bmatrix}.$$

Thus, we have

$$\mathbf{\Omega}_w = \begin{bmatrix} M\mathbf{Q} & \vdots & \mathbf{1}'_{M-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{1}_{M-1} \otimes \mathbf{J}\mathbf{Q} & \vdots & \mathbf{I}_{M-1} \otimes \mathbf{J}\mathbf{Q}\mathbf{J}' \end{bmatrix} \quad \text{and} \quad \mathbf{\Omega}\mathbf{H}_w' = \begin{bmatrix} \mathbf{1}_{M-1} \otimes \mathbf{Q} & \vdots & \mathbf{I}_{M-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{Q} & \vdots & \mathbf{0} \end{bmatrix}.$$

For the proportional variant of the procedure, matrix $\mathbf{\Omega}$ has the form $\mathbf{\Omega} = \mathbf{Y}(\mathbf{I}_M \otimes \mathbf{Q})\mathbf{Y}'$, that is:

$$\mathbf{\Omega} = \begin{bmatrix} \mathbf{Y}_1\mathbf{Q}\mathbf{Y}_1' & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{Y}_2\mathbf{Q}\mathbf{Y}_2' & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{Y}_M\mathbf{Q}\mathbf{Y}_M' \end{bmatrix}, \quad \text{with} \quad \mathbf{Y}_i = \begin{bmatrix} y_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & y_{in} \end{bmatrix}, \quad i=1, \dots, M.$$

Then, in this case we have

$$\mathbf{\Omega}_w = \begin{bmatrix} \mathbf{I}_n & \cdots & \mathbf{I}_n & | & \mathbf{I}_n \\ - & - & - & - & - \\ \mathbf{J} & \cdots & \mathbf{0} & | & \mathbf{0} \\ \vdots & \ddots & \vdots & | & \vdots \\ \mathbf{0} & \cdots & \mathbf{J} & | & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{Y}_1\mathbf{Q}\mathbf{Y}_1' & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{Y}_2\mathbf{Q}\mathbf{Y}_2' & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{Y}_M\mathbf{Q}\mathbf{Y}_M' \end{bmatrix} \begin{bmatrix} \mathbf{I}_n & | & \mathbf{J}' & \cdots & \mathbf{0} \\ \vdots & | & \vdots & \ddots & \vdots \\ \mathbf{I}_n & | & \mathbf{0} & \cdots & \mathbf{J}' \\ - & | & - & - & - \\ \mathbf{I}_n & | & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

↓

$$\Omega_w = \begin{bmatrix} \sum_{i=1}^M Y_i Q Y_i & | & Y_1 Q Y_1 J' & \cdots & Y_{M-1} Q Y_{M-1} J' \\ - & - & - & - & - \\ J Y_1 Q Y_1 & | & J Y_1 Q Y_1 J' & \cdots & \mathbf{0} \\ \vdots & | & \vdots & \ddots & \vdots \\ J Y_{M-1} Q Y_{M-1} & | & \mathbf{0} & \cdots & J Y_{M-1} Q Y_{M-1} J' \end{bmatrix}$$

and

$$\begin{aligned} \Omega H'_w &= \begin{bmatrix} Y_1 Q Y_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & Y_2 Q Y_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & Y_M Q Y_M \end{bmatrix} \begin{bmatrix} \mathbf{I}_n & | & J' & \cdots & \mathbf{0} \\ \vdots & | & \vdots & \ddots & \vdots \\ \mathbf{I}_n & | & \mathbf{0} & \cdots & J' \\ - & | & - & - & - \\ \mathbf{I}_n & | & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix} \\ &= \begin{bmatrix} Y_1 Q Y_1 & | & Y_1 Q Y_1 J' & \cdots & \mathbf{0} \\ \vdots & | & \vdots & \ddots & \vdots \\ Y_{M-1} Q Y_{M-1} & | & \mathbf{0} & \cdots & Y_{M-1} Q Y_{M-1} J' \\ - & | & - & - & - \\ Y_M Q Y_M & | & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix} \end{aligned}$$

5.1. One system of series and an unbinding accounting constraint

In this case the series y_{M+1} has to be benchmarked together with the other M component series. As a consequence, the aggregation constraints, expressed as to distinguish the 'free' links from the redundant ones, are given by

$$\begin{bmatrix} \mathbf{1}'_M \otimes \mathbf{I}_n & \vdots & -\mathbf{I}_n \\ \mathbf{I}_M \otimes \mathbf{J} & \vdots & \mathbf{0} \\ \mathbf{0} & \vdots & \mathbf{J} \end{bmatrix} \mathbf{y}^* = \begin{bmatrix} \mathbf{0} \\ \mathbf{x}_0 \end{bmatrix}, \quad (27)$$

where, with a slight change of notation with respect to the previous sections, $\mathbf{y}^* = (y_1^*, \dots, y_i^*, \dots, y_M^*, y_{M+1}^*)'$, $\mathbf{x}_0 = (\mathbf{I}_{M+1} \otimes \mathbf{J}) \mathbf{x}$ and $\mathbf{x} = (x_1', \dots, x_i', \dots, x_M', x_{M+1}')'$.

We can easily deal with this case by a re-parameterization which transforms the problem in hand into a standard benchmarking with binding constraint, as the one considered in section 3. In fact, it is sufficient to consider $\mathbf{g} = (y_1', \dots, y_i', \dots, y_M', -y_{M+1}')'$, $\mathbf{g}^* = (y_1^*, \dots, y_i^*, \dots, y_M^*, -y_{M+1}^*)'$, $\mathbf{v} = (x_1', \dots, x_i', \dots, x_M', -x_{M+1}')'$, $\mathbf{v}_0 = (x_{01}', \dots, x_{0M}', -x_{0M+1}')'$, and re-write (27) in the equivalent form

$$\mathbf{H} \mathbf{g}^* = \mathbf{v}_a,$$

where, in this case,

$$\mathbf{H} = \begin{bmatrix} \mathbf{1}'_{M+1} \otimes \mathbf{I}_n \\ \mathbf{I}_{M+1} \otimes \mathbf{J} \end{bmatrix} \quad (28)$$

has dimension $((n+(M+1) \cdot N) \times (M+1) \cdot n)$, and

$$\mathbf{v}_a = \begin{bmatrix} \mathbf{0} \\ \mathbf{v}_0 \end{bmatrix}.$$

The benchmarked estimates are thus given by

$$\hat{\mathbf{g}}^* = \mathbf{g} + \mathbf{\Omega} \mathbf{H}'_u \mathbf{\Omega}_u^{-1} (\mathbf{u} - \mathbf{H}_u \mathbf{g}), \quad (29)$$

where

$$\mathbf{H}_u = \begin{bmatrix} \mathbf{1}'_M \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_M \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix},$$

$\mathbf{\Omega}_u = \mathbf{H}_u \mathbf{\Omega} \mathbf{H}'_u$, and

$$\mathbf{u} = \mathbf{H}_u \mathbf{g}^* = \begin{bmatrix} \mathbf{0} \\ \mathbf{J} \mathbf{x}_1 \\ \vdots \\ \mathbf{J} \mathbf{x}_M \end{bmatrix}.$$

The final benchmarked estimates are thus given by $\hat{\mathbf{y}}_i^* = \hat{\mathbf{g}}_i^*$, $i = 1, \dots, M$, and $\hat{\mathbf{y}}_{M+1}^* = -\hat{\mathbf{g}}_{M+1}^*$.

6. Benchmarking two systems of time series linked by an accounting constraint

Consider the situation in which the same aggregate can be broken down according to two different single classification schemes¹⁰ (e.g., the former by regions and the latter by economic activity sectors). If the component series of both systems have been seasonally adjusted individually, it is likely that the 'geographically' aggregated series be different from the aggregate obtainable from the 'sector side', and eventually from a directly seasonally adjusted aggregate series too.

In the following we will consider three cases, corresponding respectively to situations in which

1. a binding contemporaneous constraint is available;
2. no preliminary estimate of the constraint series is available;
3. a preliminary estimate of the constraint series is available and has to be benchmarked together (and coherently) with the component series of both systems.

6.1. Binding constraint

In this case the available data are given by

¹⁰ Notice that we are not dealing with a two-ways classification scheme (see Cholette, 1988, and section 8).

$\mathbf{a}_i, i=1, \dots, R:$	component unbenchmarked SA series of the first system;
$\mathbf{b}_j, j=1, \dots, S:$	component unbenchmarked SA series of the second system;
$\mathbf{a}_{0i}, i=1, \dots, R:$	annual sums of the first system's component series;
$\mathbf{b}_{0j}, j=1, \dots, S:$	annual sums of the second system's component series;
$\mathbf{z}:$	binding constraint series.

Notice that, in this as in the following two cases considered in this section, the temporally aggregated component series must satisfy the accounting relationship

$$\sum_{i=1}^R \mathbf{a}_{0i} = \sum_{j=1}^S \mathbf{b}_{0j}.$$

The estimated benchmarked series $\hat{\mathbf{a}}_i^*$ and $\hat{\mathbf{b}}_j^*$ must be such that:

$$\sum_{i=1}^R \hat{\mathbf{a}}_i^* = \mathbf{z}, \quad \sum_{j=1}^S \hat{\mathbf{b}}_j^* = \mathbf{z} \quad (\text{that is, } \sum_{i=1}^R \hat{\mathbf{a}}_i^* - \sum_{j=1}^S \hat{\mathbf{b}}_j^* = \mathbf{0}),$$

$$\mathbf{J}\hat{\mathbf{a}}_i^* = \mathbf{a}_{0i}, \quad i=1, \dots, R \quad \text{and} \quad \mathbf{J}\hat{\mathbf{b}}_j^* = \mathbf{b}_{0j}, \quad j=1, \dots, S.$$

The vector containing all the available aggregated data, considered in a way which helps in writing the aggregation matrix referred only to the 'free' information, is

$$\mathbf{y}_a = \begin{bmatrix} \mathbf{z} \\ \mathbf{a}_{01} \\ \vdots \\ \mathbf{a}_{0R-1} \\ \mathbf{z} \\ \mathbf{b}_{01} \\ \vdots \\ \mathbf{b}_{0S-1} \\ \mathbf{a}_{0R} \\ \mathbf{b}_{0S} \end{bmatrix}.$$

In fact, $2N$ observations are 'redundant', in the sense that for each system the N annually sums for a variable are automatically determined by the difference between the annually sums of the binding series and the sums of the remaining $M-1$ annually component series, so that the whole set of aggregation constraints can be expressed as $\mathbf{H}_w \mathbf{y}^* = \mathbf{y}_w$, where

$$\mathbf{H}_w = \begin{bmatrix} \mathbf{1}'_{R-1} \otimes \mathbf{I}_n & \mathbf{I}_n & \mathbf{0} & \mathbf{0} \\ \mathbf{I}_{R-1} \otimes \mathbf{J} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1}'_{S-1} \otimes \mathbf{I}_n & \mathbf{I}_n \\ \mathbf{0} & \mathbf{0} & \mathbf{I}_{S-1} \otimes \mathbf{J} & \mathbf{0} \end{bmatrix},$$

$$\mathbf{y}^* = \begin{bmatrix} \mathbf{a}_1^* \\ \vdots \\ \mathbf{a}_M^* \\ \mathbf{b}_1^* \\ \vdots \\ \mathbf{b}_M^* \end{bmatrix} \quad \text{and} \quad \mathbf{y}_w = \begin{bmatrix} \mathbf{z} \\ \mathbf{a}_{01} \\ \vdots \\ \mathbf{a}_{0R-1} \\ \mathbf{z} \\ \mathbf{b}_{01} \\ \vdots \\ \mathbf{b}_{0S-1} \end{bmatrix}.$$

Now, remember that for the additive variant of the benchmarking procedure (see section 5), it is $\mathbf{\Omega} = \mathbf{I}_{R+S} \otimes \mathbf{Q}$. Intuitively, the block-diagonal structure of both \mathbf{H}_w and $\mathbf{\Omega}$ should notably simplify the benchmarking formulae. In fact, it can be easily checked that

$$\mathbf{\Omega}_w = \begin{bmatrix} \mathbf{\Omega}_w^a & \mathbf{0} \\ \mathbf{0} & \mathbf{\Omega}_w^b \end{bmatrix},$$

with

$$\mathbf{\Omega}_w^a = \begin{bmatrix} R\mathbf{Q} & \vdots & \mathbf{1}'_{R-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{1}_{R-1} \otimes \mathbf{J}\mathbf{Q} & \vdots & \mathbf{I}_{R-1} \otimes \mathbf{J}\mathbf{Q}\mathbf{J}' \end{bmatrix} \quad \text{and} \quad \mathbf{\Omega}_w^b = \begin{bmatrix} s\mathbf{Q} & \vdots & \mathbf{1}'_{S-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{1}_{S-1} \otimes \mathbf{J}\mathbf{Q} & \vdots & \mathbf{I}_{S-1} \otimes \mathbf{J}\mathbf{Q}\mathbf{J}' \end{bmatrix}.$$

Now, denoting $\hat{\mathbf{y}}^* = [\hat{\mathbf{a}}^*, \hat{\mathbf{b}}^*]'$ and $\mathbf{y} = [\mathbf{a}', \mathbf{b}']'$, the benchmarking formula

$$\hat{\mathbf{y}}^* = \mathbf{y} + \mathbf{\Omega}\mathbf{H}'_w\mathbf{\Omega}_w^{-1}(\mathbf{y}_w - \mathbf{H}_w\mathbf{y}),$$

reduces to

$$\begin{aligned} \hat{\mathbf{a}}^* &= \mathbf{a} + \mathbf{\Omega}^a\mathbf{H}_w^{a'}(\mathbf{\Omega}_w^a)^{-1}(\mathbf{a}_w - \mathbf{H}_w^a\mathbf{a}) \\ \hat{\mathbf{b}}^* &= \mathbf{b} + \mathbf{\Omega}^b\mathbf{H}_w^{b'}(\mathbf{\Omega}_w^b)^{-1}(\mathbf{b}_w - \mathbf{H}_w^b\mathbf{b}) \end{aligned}$$

where, with obvious notation, it is

$$\mathbf{\Omega}^a = \mathbf{I}_R \otimes \mathbf{Q}, \quad \mathbf{\Omega}^b = \mathbf{I}_S \otimes \mathbf{Q},$$

$$\mathbf{H}_w^a = \begin{bmatrix} \mathbf{1}'_{R-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_{R-1} \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix}, \quad \mathbf{H}_w^b = \begin{bmatrix} \mathbf{1}'_{S-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_{S-1} \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix}$$

and, finally,

$$\mathbf{a}_w = \begin{bmatrix} \mathbf{z} \\ \mathbf{a}_{01} \\ \vdots \\ \mathbf{a}_{0R-1} \end{bmatrix}, \quad \mathbf{b}_w = \begin{bmatrix} \mathbf{z} \\ \mathbf{b}_{01} \\ \vdots \\ \mathbf{b}_{0S-1} \end{bmatrix}.$$

In conclusion, when a contemporaneous binding constraint is available, the benchmarked estimates for the component series of both systems are exactly those obtained by separately benchmarking each system of series with a binding constraint. Given the form of the matrices involved, this result holds for the proportional variant of the benchmarking procedure too.

6.2. Unbinding (and unavailable preliminary estimate) constraint

In this case the available data are given by

- $\mathbf{a}_i, i=1, \dots, R$: component unbenchmarked SA series of the first system;
- $\mathbf{b}_j, j=1, \dots, S$: component unbenchmarked SA series of the second system;
- $\mathbf{a}_{0i}, i=1, \dots, R$: annual sums of the first system's component series;
- $\mathbf{b}_{0j}, j=1, \dots, S$: annual sums of the second system's component series.

As to the accounting constraints, the estimated benchmarked series $\hat{\mathbf{a}}_i^*$ and $\hat{\mathbf{b}}_j^*$ must be such that:

$$\sum_{i=1}^R \hat{\mathbf{a}}_i^* - \sum_{j=1}^S \hat{\mathbf{b}}_j^* = \mathbf{0},$$

$$\mathbf{J}\hat{\mathbf{a}}_i^* = \mathbf{a}_{0i}, i=1, \dots, R \quad \text{and} \quad \mathbf{J}\hat{\mathbf{b}}_j^* = \mathbf{b}_{0j}, j=1, \dots, S.$$

It is immediate to recognize that we can turn to a standard benchmarking of a system with a binding constraint (see section 3) by means of the following re-parameterization:

$$M=R+S \quad \mathbf{z}=\mathbf{0} \quad \mathbf{y} = \begin{bmatrix} \mathbf{a} \\ -\mathbf{b} \end{bmatrix} \quad \mathbf{x}_a = [\mathbf{0}', \mathbf{a}'_{01}, \dots, \mathbf{a}'_{0R}, \mathbf{b}'_{01}, \dots, \mathbf{b}'_{0S}]',$$

according to which the final estimates of the second system's component series are obtained after a change of sign.

6.3. Unbinding constraint with an available preliminary estimate

In this case, besides the aggregated data considered in the previous sub-section, we assume that a $(n \times 1)$ vector \mathbf{v} is available, which is the unbenchmarked SA series for the aggregate. This new information is such that, in general, no aggregation constraint is fulfilled, that is:

$$\sum_{i=1}^R \mathbf{a}_i \neq \mathbf{v}, \quad \sum_{j=1}^S \mathbf{b}_j \neq \mathbf{v}, \quad \sum_{i=1}^R \mathbf{a}_{0i} \neq \mathbf{J}\mathbf{v} \quad \text{and} \quad \sum_{j=1}^S \mathbf{b}_{0j} \neq \mathbf{J}\mathbf{v}.$$

We want to get benchmarked estimates that preserve as much as possible the dynamic profiles of the original unbenchmark series while fulfilling all the aggregation constraints.

Let $\mathbf{y}^* = [\mathbf{a}^*, \mathbf{b}^*, \mathbf{v}^*]'$ be the $((R+S+1)nx1)$ vector of unknown benchmarked SA series and $\hat{\mathbf{y}}^* = [\hat{\mathbf{a}}^*, \hat{\mathbf{b}}^*, \hat{\mathbf{v}}^*]'$ the benchmarked estimates, which have to fulfil the constraints

$$\sum_{i=1}^R \hat{\mathbf{a}}_i^* - \hat{\mathbf{v}}^* = \mathbf{0}, \quad \sum_{j=1}^S \hat{\mathbf{b}}_j^* - \hat{\mathbf{v}}^* = \mathbf{0} \quad (\text{that is, } \sum_{i=1}^R \hat{\mathbf{a}}_i^* - \sum_{j=1}^S \hat{\mathbf{b}}_j^* = \mathbf{0}),$$

$$\mathbf{J}\hat{\mathbf{a}}_i^* = \mathbf{a}_{0i}, \quad i=1, \dots, R \quad \text{and} \quad \mathbf{J}\hat{\mathbf{b}}_j^* = \mathbf{b}_{0j}, \quad j=1, \dots, S.$$

As done in section 5.1, it is convenient to express the vector containing all the available aggregated data in such a way as to easily write the aggregation matrix referred only to the 'free' information:

$$\mathbf{y}_a = \begin{bmatrix} \mathbf{0} \\ \mathbf{a}_{01} \\ \vdots \\ \mathbf{a}_{0R-1} \\ \mathbf{0} \\ \mathbf{b}_{01} \\ \vdots \\ \mathbf{b}_{0S-1} \\ \mathbf{a}_{0R} \\ \mathbf{b}_{0S} \end{bmatrix}.$$

Again, $2N$ observations are 'redundant', in the sense that for each system the N annually sums for a variable are automatically determined by the difference between the yearly sums of $R-1$ variables of the first system and the yearly sums of $S-1$ variables of the second system. The whole set of aggregation constraints can thus be expressed as $\mathbf{H}_w \mathbf{y}^* = \mathbf{y}_w$, where

$$\mathbf{H}_w = \begin{bmatrix} \mathbf{1}'_{R-1} \otimes \mathbf{I}_n & \mathbf{I}_n & \mathbf{0} & \mathbf{0} & -\mathbf{I}_n \\ \mathbf{I}_{R-1} \otimes \mathbf{J} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1}'_{S-1} \otimes \mathbf{I}_n & \mathbf{I}_n & -\mathbf{I}_n \\ \mathbf{0} & \mathbf{0} & \mathbf{I}_{S-1} \otimes \mathbf{J} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

and

$$\mathbf{y}_w = \begin{bmatrix} \mathbf{0} \\ \mathbf{a}_{01} \\ \vdots \\ \mathbf{a}_{0R-1} \\ \mathbf{0} \\ \mathbf{b}_{01} \\ \vdots \\ \mathbf{b}_{0S-1} \end{bmatrix}.$$

Denoting with $\mathbf{y} = [\mathbf{a}', \mathbf{b}', \mathbf{v}']'$ the vector containing all the unbenchmarked SA series, the benchmarked estimates are then given by

$$\hat{\mathbf{y}}^* = \mathbf{y} + \mathbf{\Omega} \mathbf{H}'_w \mathbf{\Omega}_w^{-1} (\mathbf{y}_w - \mathbf{H}_w \mathbf{y}).$$

Simplified expressions using partitioned matrices

The aggregated covariance matrix $\mathbf{\Omega}_w$ for the additive variant of the benchmarking procedure can be expressed as a partitioned matrix of the form:

$$\mathbf{\Omega}_w = \begin{bmatrix} {}^{(R+1)}\mathbf{Q} & \mathbf{1}'_{R-1} \otimes \mathbf{Q}\mathbf{J}' & \mathbf{Q} & \mathbf{0} \\ \mathbf{1}_{R-1} \otimes \mathbf{J}\mathbf{Q} & \mathbf{I}_{R-1} \otimes \mathbf{J}\mathbf{Q}\mathbf{J}' & \mathbf{0} & \mathbf{0} \\ \mathbf{Q} & \mathbf{0} & {}^{(S+1)}\mathbf{Q} & \mathbf{1}'_{S-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{0} & \mathbf{0} & \mathbf{1}_{S-1} \otimes \mathbf{J}\mathbf{Q} & \mathbf{I}_{S-1} \otimes \mathbf{J}\mathbf{Q}\mathbf{J}' \end{bmatrix}.$$

Moreover, it is

$$\mathbf{\Omega} \mathbf{H}'_w = \begin{bmatrix} \mathbf{1}_{R-1} \otimes \mathbf{Q} & \mathbf{I}_{R-1} \otimes \mathbf{Q}\mathbf{J}' & \mathbf{0} & \mathbf{0} \\ \mathbf{Q} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1}_{S-1} \otimes \mathbf{Q} & \mathbf{I}_{S-1} \otimes \mathbf{Q}\mathbf{J}' \\ \mathbf{0} & \mathbf{0} & \mathbf{Q} & \mathbf{0} \\ -\mathbf{Q} & \mathbf{0} & -\mathbf{Q} & \mathbf{0} \end{bmatrix}.$$

As far as the proportional variant is concerned, we start by considering

$$\mathbf{\Omega} = \begin{bmatrix} \mathbf{\Omega}_a & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{\Omega}_b & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{V}\mathbf{Q}\mathbf{V} \end{bmatrix},$$

where

$$\mathbf{\Omega}_a = \mathbf{A}(\mathbf{I}_R \otimes \mathbf{Q})\mathbf{A}, \quad \mathbf{\Omega}_b = \mathbf{B}(\mathbf{I}_S \otimes \mathbf{Q})\mathbf{B},$$

with

$$\mathbf{A} = \begin{bmatrix} a_{11} & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & \ddots & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & a_{1n} & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & a_{R1} & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & a_{Rn} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} b_{11} & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & \ddots & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & b_{1n} & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & b_{S1} & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & b_{Sn} \end{bmatrix}$$

and

$$\mathbf{V} = \begin{bmatrix} v_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & v_n \end{bmatrix}.$$

Then, it is immediately verified that

$$\Omega \mathbf{H}'_w = \begin{bmatrix} \mathbf{A}_1 \mathbf{Q} \mathbf{A}_1 & \mathbf{A}_1 \mathbf{Q} \mathbf{A}_1 \mathbf{J}' & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{R-1} \mathbf{Q} \mathbf{A}_{R-1} & \mathbf{0} & \cdots & \mathbf{A}_{R-1} \mathbf{Q} \mathbf{A}_{R-1} \mathbf{J}' & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{A}_R \mathbf{Q} \mathbf{A}_R & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{B}_1 \mathbf{Q} \mathbf{B}_1 & \mathbf{B}_1 \mathbf{Q} \mathbf{B}_1 \mathbf{J}' & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{B}_{S-1} \mathbf{Q} \mathbf{B}_{S-1} & \mathbf{0} & \cdots & \mathbf{B}_{S-1} \mathbf{Q} \mathbf{B}_{S-1} \mathbf{J}' \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{B}_S \mathbf{Q} \mathbf{B}_S & \mathbf{0} & \cdots & \mathbf{0} \\ -\mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{0} & \cdots & \mathbf{0} & -\mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{0} & \cdots & \mathbf{0} \end{bmatrix}$$

and

$$\Omega_w = \begin{bmatrix} \sum_{i=1}^R \mathbf{A}_i \mathbf{Q} \mathbf{A}_i + \mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{A}_1 \mathbf{Q} \mathbf{A}_1 \mathbf{J}' & \cdots & \mathbf{A}_{R-1} \mathbf{Q} \mathbf{A}_{R-1} \mathbf{J}' & \mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{J} \mathbf{A}_1 \mathbf{Q} \mathbf{A}_1 & \mathbf{J} \mathbf{A}_1 \mathbf{Q} \mathbf{A}_1 \mathbf{J}' & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{J} \mathbf{A}_{R-1} \mathbf{Q} \mathbf{A}_{R-1} & \mathbf{0} & \cdots & \mathbf{J} \mathbf{A}_{R-1} \mathbf{Q} \mathbf{A}_{R-1} \mathbf{J}' & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{0} & \cdots & \mathbf{0} & \sum_{j=1}^S \mathbf{B}_j \mathbf{Q} \mathbf{B}_j + \mathbf{V} \mathbf{Q} \mathbf{V} & \mathbf{B}_1 \mathbf{Q} \mathbf{B}_1 \mathbf{J}' & \cdots & \mathbf{B}_{S-1} \mathbf{Q} \mathbf{B}_{S-1} \mathbf{J}' \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{J} \mathbf{B}_1 \mathbf{Q} \mathbf{B}_1 & \mathbf{J} \mathbf{B}_1 \mathbf{Q} \mathbf{B}_1 \mathbf{J}' & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{J} \mathbf{B}_{S-1} \mathbf{Q} \mathbf{B}_{S-1} & \mathbf{0} & \cdots & \mathbf{J} \mathbf{B}_{S-1} \mathbf{Q} \mathbf{B}_{S-1} \mathbf{J}' \end{bmatrix}$$

7. Benchmarking while preserving period-to-period growth rates

The proportional adjustment of a system of time series mostly alters those component series having greater magnitude. As we will see in section 10, the ranges of corrections present (quasi perfect correlation with the ranking (by mean) of the variables. Such a result might be in contrast with the fact that the most reliable series of a survey are generally the greater ones (and *viceversa*).

An attempt to overcome this kind of problem could be made by considering benchmarking according to a movement preservation principle referred to the growth rates and in presence of a binding constraint. In this case, the criterion to be minimised would be

$$\sum_{i=1}^M \left[\sum_{t=2}^n \left(\frac{y_{it} - y_{it-1}}{y_{it-1}} - \frac{p_{it} - p_{it-1}}{p_{it-1}} \right)^2 \right] \equiv \sum_{i=1}^M \left[\sum_{t=2}^n \left(\frac{y_{it}}{y_{it-1}} - \frac{p_{it}}{p_{it-1}} \right)^2 \right]. \quad (30)$$

At univariate level, many authors (Helfand *et al.*, 1977, Bozik and Otto, 1988, Bloem *et al.*, 2001) consider this criterion as ‘the ideal objective formulation’ (Bloem *et al.*, 2001, p. 100), but it is not generally pursued¹¹ because of the inherent nonlinearity of the problem and because the proportional variant of Denton’s procedure has been generally considered a good approximation (Helfand *et al.*, 1977).

In what follows we work out a solution to the minimization problem defined so far, moving from an approximation of (30) through the log-transformed expression

$$\sum_{i=1}^M \left\{ \sum_{t=2}^n [(\ln y_{it} - \ln y_{it-1}) - (\ln p_{it} - \ln p_{it-1})]^2 \right\}. \quad (31)$$

For notational convenience, let us denote with $y_{iT,h}$, $i=1,\dots,M$, $T=1,\dots,N$, $h=1,\dots,s$, the unknown

series to be estimated, with $y_{iT} = \sum_{h=1}^s y_{iT,h}$ the available temporal aggregates (flow variable) and with

$z_{T,h} = \sum_{i=1}^M y_{iT,h}$ the high-frequency contemporaneous aggregate (which is a binding constraint).

Temporal aggregation and approximate expression for $\ln y_{iT,h}$

Let us consider the Taylor series expansion (truncated at the first order term) of $\ln y_{iT,h}$ around its

low-frequency-period-average, $\bar{y}_{iT} = \frac{1}{s} \sum_{h=1}^s y_{iT,h} = \frac{y_{iT}}{s}$:

$$\ln y_{iT,h} \approx g_{iT,h} = \ln \bar{y}_{iT} + \frac{1}{\bar{y}_{iT}} (y_{iT,h} - \bar{y}_{iT}) = \ln y_{iT} - \ln s + \frac{sy_{iT,h}}{y_{iT}} - 1.$$

Summing up over $h=1,\dots,s$ we have

$$\sum_{h=1}^s \ln y_{iT,h} \approx g_{iT} = \sum_{h=1}^s g_{iT,h} = s \ln y_{iT} - s \ln s + \frac{s \sum_{h=1}^s y_{iT,h}}{y_{iT}} - s = s \ln y_{iT} - s \ln s. \quad (32)$$

Summing up over $i=1,\dots,M$ we have

$$\sum_{i=1}^M \ln y_{iT,h} \approx \sum_{i=1}^M g_{iT,h} = \sum_{i=1}^M \ln y_{iT} - M \ln s + s \sum_{i=1}^M \frac{y_{iT,h}}{y_{iT}} - M. \quad (33)$$

It should be noted that expression (33) is an unfeasible approximation, because $y_{iT,h}$ is obviously unknown. However, for our purposes, $y_{iT,h}$ can be substituted by a temporally benchmarked value, say $\tilde{y}_{iT,h}$, such that

$$\sum_{h=1}^s \tilde{y}_{iT,h} = y_{iT}, \quad i=1,\dots,M, \quad t=1,\dots,N.$$

¹¹ An exception is Bozik and Otto (1988).

For, the complete transformation we consider is the following:

$$\ln y_{iT,h} \approx g_{iT,h} = \ln y_{iT} - \ln s + \frac{s\tilde{y}_{iT,h}}{y_{iT}} - 1, \quad i=1,\dots,M, \quad T=1,\dots,N, \quad h=1,\dots,s$$

$$\ln y_{it} \approx g_{it} = \ln \tilde{y}_{it}, \quad t < I \text{ and/or } t = Ns+1, Ns+1,\dots,$$

where the second expression permits to derive benchmarked estimates also for those high-frequency periods in which low-frequency benchmarks are not available (constrained extrapolation or preliminary benchmarking).

As it can be easily shown, relationship (32) is still valid and, furthermore, it is:

$$\sum_{i=1}^M \ln y_{iT,h} \approx \sum_{i=1}^M g_{iT,h} = \sum_{i=1}^M \ln y_{iT} - M \ln s + s \sum_{i=1}^M \frac{\tilde{y}_{iT,h}}{y_{iT}} - M, \quad T=1,\dots,N, \quad h=1,\dots,s.$$

Now, we have

$$\sum_{i=1}^M g_{iT} = \sum_{i=1}^M (s \ln y_{iT} - s \ln s) = s \sum_{i=1}^M \ln y_{iT} - sM \ln s, \quad T=1,\dots,N$$

and

$$\sum_{h=1}^s \sum_{i=1}^M g_{iT,h} = s \sum_{i=1}^M \ln y_{iT} - sM \ln s + s \sum_{h=1}^s \sum_{i=1}^M \frac{\tilde{y}_{iT,h}}{y_{iT}} - sM = s \sum_{i=1}^M \ln y_{iT} - sM \ln s, \quad T=1,\dots,N.$$

In other words the chosen approximation for $\ln y_{iT,h}$ satisfies a low-frequency temporal aggregation constraint analogous to that found in the quadratic-linear minimization approach.

Now, denoting $w_{i,Th} = \ln p_{i,Th}$, let us minimise the objective function

$$\sum_{i=1}^M \left\{ \sum_{t=2}^n [(g_{it} - g_{it-1}) - (w_{it} - w_{it-1})]^2 \right\} \quad (34)$$

constrained by

$$\sum_{h=1}^s g_{i,Th} = g_{i,T} \quad \text{and} \quad \sum_{i=1}^M g_{i,Th} = z_{Th}^* \quad T=1,\dots,N, \quad h=1,\dots,s.$$

where

$$z_{Th}^* = \sum_{i=1}^M \ln y_{iT} - M \ln s + s \sum_{i=1}^M \frac{\tilde{y}_{iT,h}}{y_{iT}} - M, \quad T=1,\dots,N, \quad h=1,\dots,s.$$

Thus, we can get benchmarked estimates of $g_{i,Th}$, say $g_{i,Th}^*$, using Denton's AFD procedure on the log-transformed data. A 'natural' estimate of the benchmarked series is given by $\tilde{y}_{i,Th} = \exp\{g_{i,Th}^*\}$. However, due to the approximations involved in the calculations, $\tilde{y}_{i,Th}$ needs to be further adjusted

(for example, through Denton's PFD procedure) in order to get the final benchmarked estimates fulfilling both contemporaneous and temporal constraints.

8. Benchmarking a system of two-ways classified series

Let us consider the following table, containing $R \times S$ elementary (and unknown) series y_{ij} , $i=1, \dots, R, j=1, \dots, S$, classified by (say) R regions and S industries.

Region	Industry					Total
	1	...	j	...	S	
1	y_{11}	...	y_{1j}	...	y_{1S}	\mathbf{a}_1
\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots
i	y_{i1}	...	y_{ij}	...	y_{iS}	\mathbf{a}_i
\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots
R	y_{R1}	...	y_{Rj}	...	y_{RS}	\mathbf{a}_R
Total	\mathbf{b}_1	...	\mathbf{b}_j	...	\mathbf{b}_S	\mathbf{z}

Each vector in the table has dimension $(n \times 1)$, and the links between the component series and the totals (by region, by industry and general) are the following:

$$\mathbf{a}_i = \sum_{j=1}^S y_{ij}, \quad i=1, \dots, R, \quad \mathbf{b}_j = \sum_{i=1}^R y_{ij}, \quad j=1, \dots, S, \quad \mathbf{z} = \sum_{i=1}^R \sum_{j=1}^S y_{ij} = \sum_{i=1}^R \mathbf{a}_i = \sum_{j=1}^S \mathbf{b}_j.$$

Using a matrix notation, let us denote

$$\mathbf{Y} = \begin{bmatrix} y_{11} & \cdots & y_{1j} & \cdots & y_{1S} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{i1} & \cdots & y_{ij} & \cdots & y_{iS} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{R1} & \cdots & y_{Rj} & \cdots & y_{RS} \end{bmatrix},$$

matrix $(Rn \times S)$, and define as $\mathbf{y} = \text{vec}(\mathbf{Y})$, the $(RSn \times 1)$ vector containing the observations stacked by column of the $R \times S$ component series. With obvious notation, let us define the vectors containing the totals by region (\mathbf{a}) and by industry (\mathbf{b}), respectively:

$$\mathbf{a} = [\mathbf{a}'_1 \dots \mathbf{a}'_i \dots \mathbf{a}'_R] (Rn \times 1) \quad \mathbf{b} = [\mathbf{b}'_1 \dots \mathbf{b}'_j \dots \mathbf{b}'_S] (Sn \times 1).$$

The aggregation constraints can thus be expressed as

$$\mathbf{a}_i = \sum_{j=1}^S y_{ij}, \quad i=1, \dots, R, \quad \Leftrightarrow \quad (\mathbf{1}'_S \otimes \mathbf{I}_{Rn}) \mathbf{y} = \mathbf{a}$$

$$\mathbf{b}_j = \sum_{i=1}^R \mathbf{y}_{ij}, \quad j=1, \dots, S, \quad \Leftrightarrow \quad [\mathbf{I}_S \otimes (\mathbf{1}'_R \otimes \mathbf{I}_n)] \mathbf{y} = \mathbf{b}$$

$$\mathbf{z} = \sum_{i=1}^R \sum_{j=1}^S \mathbf{y}_{ij} = \sum_{i=1}^R \mathbf{a}_i = \sum_{j=1}^S \mathbf{b}_j \quad \Leftrightarrow \quad \begin{cases} (\mathbf{1}'_{RS} \otimes \mathbf{I}_n) \mathbf{y} = \mathbf{z} \\ (\mathbf{1}'_R \otimes \mathbf{I}_n) \mathbf{a} = \mathbf{z} \\ (\mathbf{1}'_S \otimes \mathbf{I}_n) \mathbf{b} = \mathbf{z} \end{cases}$$

Moreover, we assume that $R \times S$ temporally aggregated component series are available such that $\mathbf{Jy}_{ij} = \mathbf{y}_{0,ij}$, $i=1, \dots, R, j=1, \dots, S$, where \mathbf{J} is the $(N \times n)$ temporal aggregation matrix defined in section 3.

We assume that $R \times S$ preliminary series \mathbf{p}_{ij} , $i=1, \dots, R, j=1, \dots, S$, are available, which have to be benchmarked in such a way that all the aggregation (both temporal and contemporaneous) constraints be fulfilled by the benchmarked estimates $\tilde{\mathbf{y}}_{ij}$, $i=1, \dots, R, j=1, \dots, S$. Moreover, in many practical situations the total series, either by regions or by industry, are available in preliminary form (i.e., unbinding constraint to be benchmarked together the component series) and/or as fully reliable (binding constraint) to be fulfilled by the benchmarked estimates.

In general, $3^3 = 27$ different cases are theoretically possible, as shown in the following table.

Case	\mathbf{z}	\mathbf{a}	\mathbf{b}	'equivalent' to case
1	y	y	y	
2	y	y	p	
3	y	y	n	
	y	p	y	2
4	y	p	p	
5	y	p	n	
	y	n	y	3
	y	n	p	5
6	y	n	n	
*	p	y	y	
*	p	y	p	
*	p	y	n	
*	p	p	y	
7	p	p	p	
8	p	p	n	
*	p	n	y	
	p	n	p	8
9	p	n	n	
*	n	y	y	
*	n	y	p	
*	n	y	n	
*	n	p	y	
10	n	p	p	
11	n	p	n	
*	n	n	y	
	n	n	p	11
12	n	n	n	

Legenda

y: a binding (yet benchmarked) series is available;

p: a preliminary (to be benchmarked) series is available;

n: neither a binding (yet benchmarked), nor a preliminary (to be benchmarked) series is available.

*: practically uninteresting, because from either \mathbf{a} or \mathbf{b} it is possible to recover \mathbf{z} .

In practice, 12 of 27 cases are really interesting, 7 being unrealistic (either \mathbf{a} or \mathbf{b} available with \mathbf{z} unavailable), and 5 practically equivalent (for symmetry between \mathbf{a} and \mathbf{b}) to 5 of the 12 numbered cases in the table.

In what follows we consider the two polar cases, namely 1 and 12: in the former, R regional and S industry series are available and considered as (fully reliable) binding constraints, in the latter no total series (neither binding nor preliminary) is available.

8.1. A system of two-ways classified series with binding constraints

As previously shown, the crucial point to develop feasible benchmarking formulae according to Denton's movement preservation movement principle is to write down the whole set of (temporal and contemporaneous) aggregation constraints in such a way as to distinguish the redundant (superfluous) relations from the remaining. In this case, the links between the series to be estimated, \mathbf{y} , and the available benchmarks can be expressed as follows:

$$\mathbf{y} = \mathbf{H}_w \mathbf{y}_w$$

where

$$\mathbf{H}_w = \begin{bmatrix} \mathbf{1}'_{S-1} \otimes \mathbf{I}_{Rn} & \vdots & \mathbf{I}_{Rn} \\ \mathbf{I}_{S-1} \otimes \mathbf{A} & \vdots & \mathbf{0} \end{bmatrix}$$

has $r=Rn+(S-1)n+(S-1)(R-1)N$ rows and RSn columns, with

$$\mathbf{A} = \begin{bmatrix} \mathbf{1}'_{R-1} \otimes \mathbf{I}_n & \vdots & \mathbf{I}_n \\ \mathbf{I}_{R-1} \otimes \mathbf{J} & \vdots & \mathbf{0} \end{bmatrix},$$

which has dimension $(n+(R-1)N \times Rn)$, and

$$\mathbf{y}_w = [\mathbf{a}', \mathbf{b}'_1 \mathbf{y}'_{0,11} \quad \cdots \quad \mathbf{y}'_{0,R-1,1} \quad \cdots \quad \mathbf{b}'_{S-1} \mathbf{y}'_{0,1,S-1} \quad \cdots \quad \mathbf{y}'_{0,R-1,S-1}]'$$

is the vector containing the 'free' available observations, re-organized in a convenient way for expressing the benchmarking formulae.

The components of vector \mathbf{y}_w have been chosen as follows:

- given that $\mathbf{z} = \sum_{i=1}^R \mathbf{a}_i = \sum_{j=1}^S \mathbf{b}_j$, the n observations of \mathbf{z} are superfluous (in the sense that they can be derived from either \mathbf{a}_i or \mathbf{b}_j);
- moreover, $\sum_{i=1}^R \mathbf{a}_i = \sum_{j=1}^S \mathbf{b}_j$ means that other n observations are superfluous; without loss of generality, we do not consider \mathbf{b}_S (which can be derived from the remaining \mathbf{a}_i and \mathbf{b}_j as $\sum_{i=1}^R \mathbf{a}_i - \sum_{j=1}^{S-1} \mathbf{b}_j$);
- given that $\sum_{i=1}^R \mathbf{y}_{0,ij} = \mathbf{J} \mathbf{b}_j$, $j=1, \dots, S$, there are SN superfluous observations contained, for example, in the vectors $\mathbf{y}_{0,Rj}$, $j=1, \dots, S$;

- equivalently, as regards 'regional' series \mathbf{a}_i , we have $\sum_{j=1}^S \mathbf{y}_{0,ij} = \mathbf{J}\mathbf{a}_i$, $i=1, \dots, R$, so that RN observations are redundant, here chosen as those contained in the vectors $\mathbf{y}_{0,iS}$, $i=1, \dots, R$ (as it is obvious, the N observations contained in vector $\mathbf{y}_{0,RS}$ must be accounted for only once).

At this point, simultaneous benchmarking of the whole set of $R \times S$ series can be achieved by applying the benchmarking formulae developed so far. Obviously, the dimensions of the matrices implied in the calculations could be really prohibitive¹². For example, if two-ways classified monthly series by 12 regions and 18 industries are considered, 216 elementary monthly series have to be benchmarked. Assuming annual benchmarks available for 10 years, the simultaneous benchmarking formula

$$\hat{\mathbf{y}}^* = \mathbf{y} + \mathbf{\Omega}\mathbf{H}'_w\mathbf{\Omega}^{-1}(\mathbf{y}_w - \mathbf{H}_w\mathbf{y})$$

involves the calculation of $\mathbf{\Omega}\mathbf{H}'_w$, which has 25,920 rows and 5,350 columns, and the inversion of $\mathbf{\Omega}_w = \mathbf{H}_w\mathbf{\Omega}\mathbf{H}'_w$, which has dimension (5,350 x 5,350).

We are currently evaluating the feasibility of benchmarking formulae exploiting the partitioned nature of the involved matrices.

8.2. A system of two-ways classified series with neither binding nor preliminary constraints

In this case the benchmarked estimates $\tilde{\mathbf{y}}_{ij}$ must be such that

$$\sum_{i=1}^R \tilde{\mathbf{a}}_i = \sum_{j=1}^S \tilde{\mathbf{b}}_j,$$

where $\tilde{\mathbf{a}}_i = \sum_{j=1}^S \tilde{\mathbf{y}}_{ij}$, $i=1, \dots, R$, and $\tilde{\mathbf{b}}_j = \sum_{i=1}^R \tilde{\mathbf{y}}_{ij}$, $j=1, \dots, S$.

The available aggregated 'observations' are thus given by the $((n+RSN) \times 1)$ vector

$$\mathbf{y}_w = \begin{bmatrix} \mathbf{0} \\ \mathbf{y}_{0,11} \\ \vdots \\ \mathbf{y}_{0,RS} \end{bmatrix},$$

linked to the unknown series to be estimated by the relation

$$\mathbf{H}_w\mathbf{y} = \mathbf{y}_w,$$

where \mathbf{H}_w is the $((n+RSN) \times RSn)$ matrix

¹² Cholette (1987, p. 45) states: "Practical experience with simultaneous benchmarking may show that very similar results can be achieved with some combination of individual benchmarking with raking (...) However, simultaneous benchmarking does provide a standard, i.e. a norm, against which alternative and simplex approaches may be assessed".

$$\mathbf{H}_w = \begin{bmatrix} (\mathbf{1}'_R \otimes \mathbf{I}_n)(\mathbf{1}'_S \otimes \mathbf{I}_{Rn}) - (\mathbf{1}'_S \otimes \mathbf{I}_n) [\mathbf{I}_S \otimes (\mathbf{1}'_R \otimes \mathbf{I}_n)] \\ \mathbf{I}_{RS} \otimes \mathbf{J} \end{bmatrix}.$$

When benchmarking a table of monthly series classified by 12 regions and 18 industries using 10 annual benchmarks, the dimensions of matrices $\mathbf{\Omega}\mathbf{H}'_w$ and $\mathbf{\Omega}_w = \mathbf{H}_w\mathbf{\Omega}\mathbf{H}'_w$ are (25,920 x 2,280) and (2,280 x 2,280), respectively. Even for this case, we are currently evaluating the feasibility of benchmarking formulae exploiting the partitioned nature of the involved matrices.

9. An evaluation of computational times on simulated data

The main advantage in using partitioned matrices is the reduction of time needed to complete multivariate temporal disaggregation. Let us rewrite the disaggregation formula (23), that is

$$\hat{\mathbf{y}}^* = \mathbf{y} + \mathbf{\Omega}\mathbf{H}'_w\mathbf{\Omega}_w^{-1}(\mathbf{w} - \mathbf{H}_w\mathbf{y}).$$

Two operations in the above expression depend sensibly from both M , N and, consequently, n . One is the computation of the $(r \times r)$ matrix $\mathbf{\Omega}_w^{-1} = (\mathbf{H}_w\mathbf{\Omega}\mathbf{H}'_w)^{-1}$, where $r = n + N(M-1)$; the other is the product $\mathbf{\Omega}\mathbf{H}'_w\mathbf{\Omega}_w^{-1}$, which involves large and sparse matrices, with even larger dimensions, as $(nM \times nM)$ for $\mathbf{\Omega}$ and $(nM \times r)$ for \mathbf{H}_w .

For the time being, our procedures have been generalized in order to get simultaneously benchmarked estimates from both single and double systems of time series, with or without binding contemporaneous constraints. Moreover, we recover both additive and proportional Denton's variants¹³.

To evaluate the time saving that can be achieved by exploiting the partitioned nature of the involved matrices, we compare the computational times needed by procedures based on both not partitioned (table 1) and partitioned (table 2) matrices for $M = 3, \dots, 10$ and $N = 5, \dots, 20$. The elapsed times (in seconds) are obtained by means of simulated data. Annual benchmarks $(\mathbf{x}_{01}, \dots, \mathbf{x}_{0M})$ are derived from stationary first-order autoregressive processes; monthly preliminary estimates $(\mathbf{y}_1, \dots, \mathbf{y}_M)$ are first computed as univariate disaggregation of the benchmarks using a linear trend and then are noised with unit variance Gaussian white noise processes. Proportional first differences benchmarking is then made using partitioned and not partitioned formulations¹⁴.

As can be noted, the use of partitioned matrices becomes essential when M , the number of variables, grows, but significant improvements are found even in case of small systems to adjust. Table 3 shows the ratios of time using partitioned matrices in terms of that obtained using no partitioned matrices: it is evident that the reduction of time depends much more on the number of variables M than on the number of low-frequency observations N .

Table 1: Elapsed time to derive benchmarked estimates using no partitioned matrices (seconds)

¹³ The calculations are performed using an approximate first differences matrix (see footnote 9 above). All procedures have been coded in GAUSS language, taking back and improving the routines of the software ECOTRIM (Barcellan, 2002). At the moment we write, simultaneous benchmarking according to the multivariate extension of Denton's procedure for a single system can also be performed using the routine *DENTON.m* in the MATLAB toolbox *XTRIMEST* (Quilis, 2002), although only the additive variants are available to the user.

¹⁴ The test was made under GAUSS version 4.0 by using an ACER notebook with Intel Pentium III processor 850 MHz and 128 Mb of RAM.

<i>M</i>	<i>N</i>																		
	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20			
3	1	1	2	3	4	6	7	10	12	15	19	23	28	33	39	45			
4	1	2	4	6	9	12	16	21	26	33	40	49	59	70	83	96			
5	2	5	8	11	16	22	29	38	48	61	75	91	109	128	150	175			
6	4	8	13	19	27	37	49	63	81	101	123	149	178	211	248	290			
7	7	12	20	29	41	57	76	98	123	154	189	229	275	326	385	447			
8	10	18	29	43	60	83	109	142	180	225	276	335	401	481	574	671			
9	15	25	40	60	85	115	153	198	252	314	386	470	573	684	826	1036			
10	20	34	54	81	114	156	207	269	342	426	531	649	789	1018	1328	1612			

Table 2: Elapsed time to derive benchmarked estimates using partitioned matrices (seconds)

<i>M</i>	<i>N</i>																		
	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20			
3	0	0	0	0	0	1	1	1	1	2	3	5	6	7	8	10			
4	0	0	0	0	1	1	1	1	2	2	4	7	8	10	12	14			
5	0	0	0	1	1	1	1	2	2	3	5	9	11	13	15	18			
6	0	0	1	1	1	1	2	2	3	4	7	11	13	16	18	22			
7	0	0	1	1	1	2	2	3	4	5	8	13	16	19	22	26			
8	0	0	1	1	2	2	3	4	4	6	10	15	19	23	26	31			
9	0	1	1	1	2	2	3	4	6	7	12	18	22	26	31	36			
10	0	1	1	2	2	3	4	5	7	8	14	21	26	30	36	42			

Table 3: Reduction of time using partitioned matrices (percentage of elapsed time using no partitioned matrices)

<i>M</i>	<i>N</i>																		
	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20			
3	7.9	8.0	7.9	9.4	10.1	10.1	10.1	9.9	10.1	10.8	15.6	22.1	22.3	22.0	21.9	22.1			
4	5.2	5.2	6.3	6.9	6.8	6.8	6.7	6.6	6.6	7.2	10.1	14.1	14.3	14.1	14.1	14.2			
5	3.6	4.4	5.1	5.1	4.9	4.8	4.9	4.7	4.7	5.1	7.3	9.7	10.0	9.9	9.9	10.0			
6	3.4	4.1	3.9	3.9	3.8	3.8	3.7	3.7	3.7	3.9	5.5	7.3	7.5	7.4	7.5	7.5			
7	3.2	3.3	3.2	3.1	3.1	3.0	3.0	2.9	3.0	3.2	4.3	5.6	5.9	5.8	5.8	5.8			
8	2.9	2.6	2.7	2.7	2.5	2.5	2.5	2.5	2.5	2.7	3.5	4.6	4.8	4.7	4.6	4.6			
9	2.3	2.3	2.3	2.2	2.1	2.2	2.2	2.1	2.1	2.2	3.0	3.8	3.9	3.9	3.8	3.5			
10	2.1	2.0	2.0	1.9	1.9	1.9	1.9	1.9	1.9	2.0	2.7	3.2	3.3	2.9	2.7	2.6			

To better evaluate the performance of our procedures, we compared them with the MATLAB routine *DENTON.m*, which uses the benchmarking formula (23) without considering the partitioned nature of the matrices involved (the tests have been made working with the additive first differences variant¹⁵, the only available in *DENTON.m*). We noticed that the MATLAB routine outperforms the GAUSS procedure implementing (23) without partitioning the matrices (for example, with $M=10$ and $N=10$ the complete disaggregation takes about 19 seconds against 27¹⁶). Anyway, the solution exploiting the partitioned nature of the matrices is the fastest one (8 seconds for the same case). It would thus be interesting to appreciate the times needed by a MATLAB routine (including the proportional variant and) exploiting partitioned matrices.

¹⁵ We run *DENTON.m* in MATLAB version 6.5.

¹⁶ The poorer results of the procedure written in GAUSS can probably be explained by a more efficient usage of RAM by MATLAB in manipulating large sparse matrices.

10. An application: benchmarking Canadian retail trade seasonally adjusted series by province and trade groups

In this section we test the adjustment methods described so far with the Canadian retail trade series, released by Statistics Canada¹⁷. Monthly raw series (expressed in millions of Canadian dollars) are available according two (single) breakdowns, i.e. by 18 trade groups (TG system) and by 12 provinces (PR system).

Each component series and the Total Canada aggregate have been directly seasonally adjusted using X11-ARIMA. Seasonal adjustment procedures often generate two undesirable effects for a statistical office. Firstly, the annual totals of the SA series do not agree with those of the raw series. Second, the monthly contemporaneous sum from different systems does not comply with the monthly SA total series. As shown before, both the discrepancies can be straightforwardly removed by multivariate benchmarking techniques.

According to the nature of the data, we face a problem of one-way classification adjustment: the component series of each system must be adjusted so that they add up to the same Total Canada series. The latter can be considered either as a binding or unbinding constraint. The aim of this exercise is to evaluate the performance of different adjustments for PR and TG breakdowns in terms of discrepancies between (corrections of) benchmarked and (to) unbenchmarked series.

Both systems are composed by series of different magnitude (see Table 4). Province PR300321 represents about 37% of the total Canadian retail sales, whilst the sum of provinces PR300601 and PR300641 does not reach even one percentage point. As far as trade group breakdown is concerned, nearly half of the total sales are achieved by the two items 010001 and 100001. Such diversity strongly reduces the performance of additive variants of Denton's multivariate procedure. To avoid such unpleasant outcomes, benchmarking has thus been accomplished according to the proportional variant (Proportional First Differences, PFD).

ADF statistics, reported in the last column of Table 4, test on the presence of unit root in the series (3 lags are considered in the ADF regression). The unit root hypothesis is not rejected at 5% level in all cases; a common source of non-stationarity is likely to affect the whole system of retail sales.

Table 5 shows some descriptive statistics on both temporal and contemporaneous discrepancies between the SA unbenchmarked monthly series and the relevant (temporal or contemporaneous) constraint¹⁸. From this table it clearly emerges that the discrepancies are negligible in all cases but for the monthly sum of PR component series, which shows large deviations from the Canada Total aggregate (see Figure 1). The largest distance is found in December 1997, which is more than 8 times larger than the mean absolute discrepancy. A seasonal pattern seems to dominate the sub-annual discrepancies: its behaviour cannot be thus classified as constant or erratic in time (Cholette, 1988)¹⁹.

¹⁷ We thank B. Quenneville, from Statistics Canada, who kindly made the SA series available to us.

¹⁸ Statistics on the discrepancies with respect to the temporal constraints are derived as average of the discrepancies of the single variables.

¹⁹ Dependencies from the past such those found in this case should be taken into account in some sort of 'data-based benchmarking' exploiting the idea of Guerrero and Nieto (1999). We are currently working around this extension.

Table 4: Descriptive statistics for Canadian retail trade series according to TG and PR breakdowns (SA unbenchmarked series, 1991.01-2001.01)

Trade Group	Mean	St. dev.	Min	Max	Range	ADF test [5% c.v.]
TG010001	4,162,300	337,533	3,560,975	4,880,131	1,319,156	-0.064 [-2.886]
TG020001	335,966	39,654	254,507	386,634	132,127	-0.861 [-2.886]
TG030001	1,002,352	93,201	792,671	1,168,250	375,579	-1.145 [-2.886]
TG040001	138,831	7,698	120,603	154,953	34,350	-1.987 [-2.886]
TG050001	134,597	7,886	119,708	156,544	36,836	-2.266 [-2.886]
TG060001	348,012	27,598	288,205	407,955	119,750	-0.406 [-2.886]
TG070001	450,122	97,062	300,829	649,648	348,819	0.966 [-2.886]
TG080001	771,265	126,882	540,947	1,117,685	576,738	1.663 [-2.886]
TG090001	190,415	23,219	146,660	257,167	110,507	1.112 [-2.886]
TG100001	4,555,360	1,029,007	3,034,552	6,323,391	3,288,839	-0.078 [-2.886]
TG110001	1,355,285	214,443	1,146,144	1,981,460	835,316	1.683 [-2.886]
TG120001	1,049,627	156,652	833,242	1,350,548	517,306	0.332 [-2.886]
TG131001	1,190,377	174,007	969,904	1,555,479	585,575	0.473 [-2.886]
TG132001	865,874	153,611	674,546	1,192,825	518,279	1.458 [-2.886]
TG140001	624,673	75,289	475,735	755,247	279,512	-0.879 [-2.886]
TG150001	492,345	74,305	389,483	644,373	254,890	0.602 [-2.886]
TG161001	527,567	55,679	460,871	658,551	197,680	0.715 [-2.886]
TG162001	400,494	46,191	311,122	503,897	192,775	-0.520 [-2.886]

Province	Mean	St. dev.	Min	Max	Range	ADF test [5% c.v.]
PR300101	309,597	33,210	274,969	383,481	108,512	1.324 [-2.886]
PR300111	79,635	12,761	60,462	106,020	45,558	0.974 [-2.886]
PR300121	587,000	72,382	473,966	731,827	257,861	0.557 [-2.886]
PR300131	460,852	64,271	370,680	595,039	224,359	1.271 [-2.886]
PR300221	4,382,203	534,915	3,534,316	5,393,719	1,859,403	0.606 [-2.886]
PR300321	6,929,302	1,064,662	5,522,751	9,150,612	3,627,861	1.483 [-2.886]
PR300421	647,807	92,850	513,478	809,824	296,346	0.147 [-2.886]
PR300471	561,345	84,943	429,425	693,946	264,521	-0.232 [-2.886]
PR300481	2,038,662	357,028	1,560,450	2,783,023	1,222,573	1.315 [-2.886]
PR300521	2,538,252	340,222	1,900,230	3,091,321	1,191,091	-0.924 [-2.886]
PR300601	21,771	5,006	13,219	30,123	16,904	-1.211 [-2.886]
PR300641	38,783	5,840	28,051	51,778	23,727	0.072 [-2.886]
300001 – Total Canada	18,595,462	2,623,083	14,816,800	23,756,760	8,939,960	1.680 [-2.886]

Figure 1 here

Different adjustments are devised to get benchmarked estimates in the two systems. The following four cases are considered (benchmarking of the TG system alone is not an interesting case given the small sub-annual and contemporaneous discrepancies²⁰):

²⁰ We present a variety of alternatives in order to appreciate how the methods work. However it should be stressed that, from a practical point of view, in this particular case it would probably reasonable (i) to benchmark TG system using Total Canada as either binding or unbinding constraint, and (ii) adjust PR component series using Total Canada series of step (i) as binding constraint. For all practical purposes, the estimates of PR component series obtained by this way are equivalent to the results of case (2).

- (1) PR system with no binding constraint (12 component series + Total Canada series are benchmarked);
- (2) PR system with Canada total aggregate used as a binding constraint (only 12 component series are benchmarked) using both Denton's PFD variant and the benchmarking procedure working on growth rates described in section 7;
- (3) PR and TG systems with no binding constraint (12 + 18 component series are benchmarked, while the unbenchmarked SA Total Canada series remains unused);
- (4) PR and TG systems with still unbinding constraint, but using the unbenchmarked SA Total Canada as a preliminary series.

Table 5: Temporal and contemporaneous discrepancies for the unbenchmarked SA series according to TG and PR breakdown - Descriptive statistics

	Contemporaneous discrepancies		Temporal discrepancies	
	Trade groups	Province	Trade groups	Province
Median	-1	5172	-1	-1
Standard deviation	3	62,811	1	1
Min	-8	181,535	-2	-2
Max	8	-347,024	1	1

Figure 1 here

The performance of the benchmarking procedure for each adjustment is evaluated by considering the proportional corrections c_{it}^p , defined as

$$c_{it}^p = \frac{\hat{y}_{it}^*}{y_{it}} \text{ for } i=1, \dots, M$$

and the additive corrections c_{it}^a , given by

$$c_{it}^a = \hat{y}_{it}^* - y_{it} \text{ for } i=1, \dots, M,$$

where M is equal to 13, 12, 30 and 31 for cases (1), (2), (3) and (4), respectively. The additive corrections have been kept into considerations also for the monthly growth rates.

Annual benchmarks, given by the sums of monthly raw series, are available for the period 1991-2000, while the unbenchmarked SA series cover the period 1991:01-2001:01 (the benchmarked estimate for the last month is then obtained by extrapolation²¹). In our notation we have $R=12$, $S=18$, $n=121$, $N=10$. The computational times required in our cases (Table 6) are in line with those found with simulated data.

In the following we present a set of tables summarizing the corrections made to levels and growth rates (%) of the unbenchmarked series. To better appreciate changes, we also plot corrections for each variable: by this way we get a graphical picture of the corrections and, eventually, we can disclose undesirable patterns. Although Denton's PFD variant preserves at best the levels, we have chosen to evaluate also rates of change because they can be considered as the "real" short-term information of a monthly series (see section 7).

²¹ Notice that preliminary benchmarked estimates must still fulfil a contemporaneous aggregation constraint.

Table 6: Elapsed time needed for benchmarking PR and TG systems (seconds)

	Number of variables	No partitioned matrices	Partitioned matrices
Province (binding - case 2)	12	273	4
Province (unbinding - case 1)	13	371	7
Trade groups (binding)	18	1,190	9
Trade groups (unbinding)	19	1,351	10
Trade groups and province (unbinding - case 3)	30	2,581	31
Trade groups and province (unbinding* - case 4)	31	2,819	49

* Using unbenchmarked SA Total Canada as a preliminary series.

10.1. Benchmarking series by province

As regards case (1), provincial data are adjusted without a binding constraint according to the procedure described in section 5.1. In this case the benchmarked Total Canada series is forced to comply with the sum of the 12 benchmarked provincial series. The range of the proportional corrections to the levels (Table 7) is 2.34%; the largest absolute correction occurred for January 1992 (-1.44%), due to the correction of opposite sign to December 1992, where the unbenchmarked Canada total aggregate was 181,535 millions of dollars higher than the sum of provincial unbenchmarked data. Other significant adjustments are found to the provinces PR300221 and PR300321, whereas the other provinces show corrections much lower than 0.2% (see Figure 2).

Table 7: Proportional corrections (levels) and additive corrections (growth rates) made by benchmarking PR component series and Total Canada without binding constraint - Descriptive statistics

Variable*	Levels					Growth rates (%)				
	Median	Min	Max	Range	St. dev	Med.	Min	Max	Range	St. dev
PR300321 (1)	0.99989	0.99634	1.00478	0.00844	0.00102	-0.01	-0.43	0.54	0.97	0.14
PR300221 (2)	0.99997	0.99738	1.00320	0.00582	0.00066	-0.01	-0.24	0.33	0.57	0.09
PR300521 (3)	0.99997	0.99868	1.00179	0.00311	0.00037	0.00	-0.16	0.19	0.35	0.05
PR300481 (4)	0.99997	0.99900	1.00147	0.00247	0.00030	0.00	-0.14	0.15	0.29	0.04
PR300421 (5)	0.99999	0.99965	1.00046	0.00081	0.00010	0.00	-0.04	0.05	0.09	0.01
PR300121 (6)	0.99999	0.99971	1.00039	0.00068	0.00009	0.00	-0.04	0.05	0.09	0.01
PR300471 (7)	0.99999	0.99973	1.00041	0.00068	0.00008	0.00	-0.04	0.04	0.08	0.01
PR300131 (8)	1.00000	0.99976	1.00031	0.00055	0.00007	0.00	-0.03	0.04	0.07	0.01
PR300101 (9)	1.00000	0.99981	1.00021	0.00039	0.00005	0.00	-0.02	0.03	0.05	0.01
PR300111 (10)	1.00000	0.99996	1.00006	0.00010	0.00001	0.00	0.00	0.01	0.01	0.00
PR300641 (11)	1.00000	0.99998	1.00003	0.00005	0.00001	0.00	0.00	0.00	0.01	0.00
PR300601 (12)	1.00000	0.99999	1.00002	0.00003	0.00001	0.00	0.00	0.00	0.00	0.00
Canada	1.00021	0.98628	1.00968	0.02340	0.00278	0.03	-1.44	1.15	2.59	0.37

* Provinces are ordered by range of levels' correction; ranking by mean is indicated in parentheses.

Figure 2 here

If the Canada total aggregate is in turn considered fully reliable we fall into case (2), where the Canada total aggregate is used as a binding constraint which provincial data must fulfil. From Table 8 it emerges that provinces PR300321 and PR300221 show again the largest corrections

(about 5.2% and 3.1% of range for month-to-month rates of change, respectively), but also PR300521 and PR300481 are visibly corrected (see Figure 3).

Figure 3 here

Table 8: Proportional corrections (levels) and additive corrections (growth rates) made by benchmarking PR component series with binding constraint - Descriptive statistics

Variable*	Levels					Growth rates (%)				
	Median	Min	Max	Range	St. dev	Med.	Min	Max	Range	St. dev
PR300321 (1)	0.99946	0.98128	1.02722	0.04594	0.00555	-0.06	-2.31	2.92	5.23	0.74
PR300221 (2)	0.99984	0.98655	1.01815	0.03160	0.00360	-0.04	-1.30	1.78	3.07	0.46
PR300521 (3)	0.99988	0.99323	1.01018	0.01695	0.00200	-0.02	-0.88	1.00	1.89	0.27
PR300481 (4)	0.99988	0.99487	1.00836	0.01350	0.00163	-0.02	-0.75	0.83	1.58	0.22
PR300421 (5)	0.99997	0.99820	1.00263	0.00443	0.00052	-0.01	-0.23	0.27	0.50	0.07
PR300121 (6)	0.99996	0.99853	1.00224	0.00370	0.00048	-0.01	-0.20	0.27	0.47	0.06
PR300471 (7)	0.99997	0.99862	1.00231	0.00369	0.00045	-0.01	-0.21	0.23	0.45	0.06
PR300131 (8)	0.99998	0.99878	1.00176	0.00298	0.00037	0.00	-0.16	0.20	0.36	0.05
PR300101 (9)	0.99999	0.99905	1.00118	0.00212	0.00025	0.00	-0.10	0.14	0.25	0.03
PR300111 (10)	1.00000	0.99978	1.00032	0.00054	0.00006	0.00	-0.03	0.03	0.06	0.01
PR300641 (11)	1.00000	0.99990	1.00016	0.00026	0.00003	0.00	-0.01	0.02	0.03	0.00
PR300601 (12)	1.00000	0.99997	1.00010	0.00012	0.00002	0.00	-0.01	0.01	0.02	0.00

* Provinces are ordered by range of levels' correction; ranking by mean is indicated in parentheses.

Table 9 and Figure 4 present in turn the benchmarking results for the PR system while preserving the growth rates, as proposed in section 7. It clearly appears that the peaks in the corrections are somewhat smoothed with respect to the results obtained using Denton's PFD variant, but now almost all the series are touched by corrections.

Table 9: Proportional corrections (levels) and additive corrections (growth rates) made by benchmarking PR system while preserving the growth rates and with binding constraint - Descriptive statistics

Variable*	Levels					Growth rates (%)				
	Median	Min	Max	Range	St. dev	Med.	Min	Max	Range	St. dev
PR300321 (1)	0.99962	0.98369	1.02294	0.03924	0.00474	-0.06	-1.97	2.51	4.48	0.63
PR300221 (2)	0.99979	0.98710	1.01775	0.03066	0.00355	-0.04	-1.30	1.75	3.05	0.46
PR300521 (3)	0.99980	0.99144	1.01297	0.02153	0.00257	-0.03	-1.09	1.28	2.37	0.34
PR300481 (4)	0.99980	0.99248	1.01186	0.01938	0.00234	-0.02	-1.02	1.18	2.20	0.31
PR300421 (5)	0.99983	0.99462	1.00849	0.01387	0.00167	-0.02	-0.70	0.83	1.53	0.22
PR300121 (6)	0.99983	0.99485	1.00827	0.01342	0.00164	-0.02	-0.68	0.83	1.51	0.21
PR300471 (7)	0.99982	0.99490	1.00830	0.01340	0.00163	-0.01	-0.70	0.82	1.53	0.21
PR300131 (8)	0.99984	0.99500	1.00796	0.01296	0.00158	-0.02	-0.65	0.79	1.44	0.21
PR300101 (9)	0.99985	0.99516	1.00764	0.01248	0.00151	-0.02	-0.62	0.76	1.38	0.20
PR300111 (10)	0.99985	0.99566	1.00713	0.01147	0.00140	-0.01	-0.57	0.72	1.29	0.18
PR300641 (11)	0.99986	0.99576	1.00704	0.01127	0.00138	-0.01	-0.56	0.69	1.26	0.18
PR300601 (12)	0.99985	0.99582	1.00699	0.01117	0.00137	-0.01	-0.56	0.71	1.27	0.18

* The provinces are ordered by range of levels' correction; ranking by mean is indicated in parentheses.

10.2. Simultaneous benchmarking of series by province and trade groups

Let us now move on to the simultaneous adjustment of provincial and trade groups systems of series (cases 3 and 4).

In case 3 the component series for both systems are adjusted without taking into account Canada total aggregate neither as an unbinding constraint nor as a preliminary series (see section 6.2 for details). The variables are treated as if they belong to a single system, consequently the proportional nature of the method adjust the series according with the total ranking of the 30 variables (see Table 10). The growth rates of the two largest series, PR300321 and TG100001, show the biggest corrections (ranging between [-1.39%, 1.87%] and [-1.38%, 0.96%], respectively).

Table 10: Proportional corrections (levels) and additive corrections (growth rates) made by benchmarking PR and TG component series without binding constraint - Descriptive statistics

Variable*	Levels					Growth rates (%)				
	Median	Min	Max	Range	St. dev	Med.	Min	Max	Range	St. dev
PR300321 (1)	0.99963	0.98767	1.01571	0.02804	0.00346	-0.04	-1.39	1.87	3.27	0.46
TG100001 (2)	1.00017	0.98506	1.00663	0.02157	0.00248	0.03	-1.38	0.96	2.34	0.31
PR300221 (3)	0.99992	0.99116	1.01051	0.01935	0.00224	-0.02	-0.78	1.14	1.92	0.29
TG010001 (4)	1.00018	0.99121	1.00788	0.01667	0.00211	0.02	-1.20	0.84	2.04	0.28
PR300521 (5)	0.99991	0.99554	1.00588	0.01034	0.00125	-0.01	-0.53	0.65	1.17	0.17
PR300481 (6)	0.99990	0.99662	1.00483	0.00821	0.00101	-0.01	-0.45	0.53	0.98	0.14
TG110001 (7)	1.00008	0.99729	1.00248	0.00519	0.00069	0.01	-0.40	0.26	0.66	0.09
TG131001 (8)	1.00005	0.99737	1.00235	0.00498	0.00060	0.01	-0.32	0.25	0.56	0.08
TG120001 (9)	1.00004	0.99766	1.00209	0.00444	0.00053	0.00	-0.28	0.23	0.51	0.07
TG030001 (10)	1.00003	0.99790	1.00183	0.00393	0.00050	0.01	-0.27	0.20	0.47	0.07
TG132001 (11)	1.00005	0.99822	1.00155	0.00333	0.00043	0.00	-0.23	0.18	0.41	0.06
PR300421 (13)	0.99997	0.99882	1.00152	0.00270	0.00032	0.00	-0.14	0.17	0.31	0.04
TG080001 (12)	1.00003	0.99835	1.00099	0.00264	0.00038	0.01	-0.22	0.15	0.37	0.05
TG140001 (14)	1.00002	0.99852	1.00098	0.00246	0.00031	0.00	-0.17	0.13	0.30	0.04
TG150001 (18)	1.00002	0.99880	1.00109	0.00228	0.00026	0.00	-0.12	0.09	0.22	0.03
PR300121 (15)	0.99997	0.99903	1.00129	0.00226	0.00030	0.00	-0.12	0.17	0.29	0.04
PR300471 (16)	0.99998	0.99909	1.00133	0.00225	0.00028	0.00	-0.13	0.15	0.27	0.04
TG161001 (17)	1.00002	0.99893	1.00092	0.00199	0.00027	0.00	-0.16	0.10	0.27	0.04
PR300131 (19)	0.99998	0.99920	1.00102	0.00182	0.00023	0.00	-0.09	0.13	0.22	0.03
TG070001 (20)	1.00002	0.99889	1.00066	0.00177	0.00022	0.00	-0.11	0.09	0.20	0.03
TG020001 (23)	1.00001	0.99930	1.00085	0.00155	0.00018	0.00	-0.08	0.07	0.15	0.02
TG162001 (21)	1.00002	0.99919	1.00073	0.00154	0.00020	0.00	-0.12	0.08	0.19	0.03
TG060001 (22)	1.00002	0.99927	1.00066	0.00139	0.00018	0.00	-0.10	0.07	0.17	0.02
PR300101 (24)	0.99999	0.99938	1.00068	0.00130	0.00016	0.00	-0.06	0.09	0.15	0.02
TG090001 (25)	1.00001	0.99949	1.00027	0.00078	0.00010	0.00	-0.06	0.04	0.10	0.01
TG040001 (26)	1.00001	0.99973	1.00041	0.00068	0.00008	0.00	-0.04	0.03	0.07	0.01
TG050001 (27)	1.00001	0.99974	1.00025	0.00051	0.00007	0.00	-0.05	0.03	0.07	0.01
PR300111 (28)	1.00000	0.99986	1.00018	0.00033	0.00004	0.00	-0.02	0.02	0.04	0.01
PR300641 (29)	1.00000	0.99994	1.00009	0.00016	0.00002	0.00	-0.01	0.01	0.02	0.00
PR300601 (30)	1.00000	0.99998	1.00005	0.00007	0.00001	0.00	0.00	0.01	0.01	0.00
Canada	1.00005	0.99297	1.00411	0.01114	0.00130	0.01	-0.67	0.56	1.23	0.17

* Provinces and trade groups are ordered by range of levels' correction; ranking by mean in the whole system is indicated in parentheses.

As far as TG system is concerned, significant corrections are found only for TG010001, whereas the remaining trade groups remain quite unchanged (see Figure 5). The provincial data show instead greater corrections with respect to the benchmarked figures in case 1 (see Figures 2 and 6²²). On the contrary, the growth rates of the benchmarked Canada total aggregate are closer to those shown by the preliminary series.

Figure 5 here

Figure 6 here

In case (4) we wish to evaluate whether introducing the Canada preliminary series can induce significant improvements on the benchmarked estimates (Table 11). In fact, the range of corrections is slightly shrunk (from 1.23 to 1.06 for month-to-month rates of change). Furthermore, the whole benchmarked system gets benefit from it (21 out of 30 variables show lower variability of the additive corrections to growth rates, see Figures 7 and 8).

Figure 7 here

Figure 8 here

We display the proportional corrections to the levels (Figure 9) of the unbenchmarking Total Canada series made by the sums of the benchmarked component series in cases (1), (3) and (4), and the additive corrections to month-to-month rates of change (Figure 10) in cases (1) and (3)²³. From both graphs it clearly emerges that simultaneous benchmarking of both systems (either with or without a preliminary estimate of the contemporaneous constraint) reduces half of the correction induced by benchmarking system PR only.

Figure 9 here

Figure 10 here

²² It should be noted that the ranges of y-axes in figures 2 and 5 are different.

²³ The additive corrections registered in case (4) are practically indistinguishable from those of case (3).

Table 11: Proportional corrections (levels) and additive corrections (growth rates) made by simultaneously benchmarking Total Canada, PR and TG component series - Descriptive statistics

Variable*	Levels					Growth rates (%)				
	Median	Min	Max	Range	St. dev	Med.	Min	Max	Range	St. dev
PR300321 (1)	0.99961	0.98718	1.01666	0.02948	0.00362	-0.04	-1.47	1.95	3.42	0.48
PR300221 (3)	0.99991	0.99080	1.01114	0.02034	0.00234	-0.03	-0.82	1.19	2.01	0.30
TG100001 (2)	1.00016	0.98629	1.00612	0.01983	0.00229	0.03	-1.27	0.88	2.14	0.28
TG010001 (4)	1.00017	0.99194	1.00727	0.01534	0.00195	0.02	-1.11	0.77	1.88	0.26
PR300521 (5)	0.99990	0.99536	1.00623	0.01087	0.00130	-0.02	-0.56	0.67	1.23	0.17
PR300481 (6)	0.99990	0.99648	1.00512	0.00863	0.00106	-0.01	-0.47	0.55	1.03	0.14
TG110001 (7)	1.00007	0.99752	1.00229	0.00477	0.00064	0.01	-0.37	0.24	0.61	0.09
TG131001 (8)	1.00005	0.99759	1.00217	0.00458	0.00056	0.00	-0.30	0.23	0.52	0.07
TG120001 (9)	1.00004	0.99785	1.00193	0.00408	0.00049	0.00	-0.25	0.21	0.47	0.07
TG030001 (10)	1.00003	0.99808	1.00169	0.00361	0.00046	0.01	-0.25	0.18	0.43	0.06
TG132001 (11)	1.00005	0.99837	1.00143	0.00306	0.00039	0.00	-0.22	0.16	0.38	0.05
PR300421 (13)	0.99997	0.99877	1.00161	0.00284	0.00034	0.00	-0.15	0.18	0.32	0.05
TG080001 (12)	1.00003	0.99849	1.00091	0.00243	0.00035	0.01	-0.20	0.14	0.34	0.05
PR300121 (15)	0.99997	0.99899	1.00137	0.00238	0.00031	0.00	-0.13	0.18	0.30	0.04
PR300471 (16)	0.99998	0.99905	1.00141	0.00236	0.00029	0.00	-0.14	0.15	0.29	0.04
TG140001 (14)	1.00001	0.99864	1.00090	0.00226	0.00029	0.00	-0.16	0.12	0.28	0.04
TG150001 (18)	1.00002	0.99890	1.00100	0.00210	0.00024	0.00	-0.11	0.09	0.20	0.03
PR300131 (19)	0.99998	0.99916	1.00108	0.00191	0.00024	0.00	-0.10	0.13	0.23	0.03
TG161001 (17)	1.00002	0.99901	1.00085	0.00183	0.00025	0.00	-0.15	0.10	0.24	0.03
TG070001 (20)	1.00001	0.99898	1.00061	0.00162	0.00020	0.00	-0.10	0.08	0.19	0.03
TG162001 (21)	0.99998	0.99922	1.00066	0.00145	0.00018	0.00	-0.11	0.07	0.18	0.02
TG020001 (23)	1.00001	0.99936	1.00079	0.00143	0.00017	0.00	-0.08	0.06	0.14	0.02
PR300101 (24)	0.99999	0.99935	1.00072	0.00137	0.00017	0.00	-0.06	0.10	0.16	0.02
TG060001 (22)	1.00002	0.99933	1.00061	0.00128	0.00016	0.00	-0.09	0.06	0.15	0.02
TG090001 (25)	1.00001	0.99953	1.00025	0.00072	0.00009	0.00	-0.06	0.03	0.09	0.01
TG040001 (26)	1.00001	0.99975	1.00038	0.00063	0.00007	0.00	-0.04	0.03	0.06	0.01
PR300641 (29)	0.99965	0.99947	1.00002	0.00055	0.00013	0.00	-0.01	0.01	0.02	0.00
TG050001 (27)	1.00001	0.99976	1.00023	0.00047	0.00007	0.00	-0.04	0.02	0.07	0.01
PR300111 (28)	1.00000	0.99985	1.00019	0.00034	0.00004	0.00	-0.02	0.02	0.04	0.01
PR300601 (30)	1.00000	0.99998	1.00006	0.00008	0.00001	0.00	-0.01	0.01	0.01	0.00
Canada	1.00004	0.99355	1.00380	0.01025	0.00119	0.01	-0.61	0.52	1.13	0.16

* Provinces and trade groups are ordered by range of levels' correction; ranking by mean in the whole system is indicated in parentheses.

Appendix: Derivation of the Moore-Penrose generalized inverse of $\Omega_a = \mathbf{H}\Omega\mathbf{H}'$

Denote by $\mathbf{e}_a = \mathbf{H}\mathbf{e}$ the stochastic disturbances vector obtained by pre-multiplying model (16) by the aggregation matrix \mathbf{H} . This vector is characterized by N linear constraints, that is

$$\mathbf{e}_a = \begin{bmatrix} \mathbf{H}_w \\ \mathbf{H}_M \end{bmatrix} \mathbf{e} = \begin{bmatrix} \mathbf{H}_w \mathbf{e} \\ \mathbf{W}\mathbf{H}_w \mathbf{e} \end{bmatrix}, \quad (\text{A.1})$$

thus its covariance matrix, $E(\mathbf{e}_a \mathbf{e}_a') = \mathbf{H}\Omega\mathbf{H}' = \Omega_a$, is singular. More precisely, it is:

$$\Omega_a = \begin{bmatrix} \Omega_w & \Omega_w \mathbf{W}' \\ \mathbf{W}\Omega_w & \mathbf{W}\Omega_w \mathbf{W}' \end{bmatrix} = \mathbf{R}\Omega_w \mathbf{R}', \quad (\text{A.2})$$

where $\Omega_w = E(\mathbf{H}_w \mathbf{e} \mathbf{e}' \mathbf{H}_w') = \mathbf{H}_w \Omega \mathbf{H}_w'$ is the non-singular covariance matrix of the disturbances

$$\mathbf{H}_w \mathbf{e} = \begin{bmatrix} \mathbf{J}\mathbf{e}_1 \\ \vdots \\ \mathbf{J}\mathbf{e}_i \\ \vdots \\ \mathbf{J}\mathbf{e}_M \end{bmatrix}.$$

The Moore-Penrose generalized inverse of Ω_a can be built as follows (Powell, 1969, pp. 917-918):

- select a sub-matrix $((r+N) \times r)$ of Ω_a , say \mathbf{S} , of full column rank r ;
- find a $(r \times (r+N))$ matrix, say \mathbf{T} , such that $\Omega_a = \mathbf{S}\mathbf{T}$;
- the Moore-Penrose generalized inverse, which is unique, is given by:

$$\Omega_a^- = \mathbf{T}'(\mathbf{T}\mathbf{T}')^{-1}(\mathbf{S}'\mathbf{S})^{-1}\mathbf{S}'. \quad (\text{A.3})$$

The choice of \mathbf{S} and \mathbf{T} follows immediately from (A.2):

$$\mathbf{S} = \begin{bmatrix} \Omega_w \\ \Omega_w \mathbf{W}' \end{bmatrix} = \mathbf{R}\Omega_w \quad \text{and} \quad \mathbf{T} = [\mathbf{I}_r \quad \mathbf{W}'] = \mathbf{R}'.$$

Substitution into (A.3) gives

$$\Omega_a^- = \mathbf{R}(\mathbf{R}'\mathbf{R})^{-1}(\Omega_w \mathbf{R}'\mathbf{R}\Omega_w)^{-1}\Omega_w \mathbf{R}',$$

from which expression (22) can be easily derived:

$$\Omega_a^- = \mathbf{R}(\mathbf{R}'\mathbf{R})^{-1}\Omega_w^{-1}(\mathbf{R}'\mathbf{R})^{-1}\Omega_w^{-1}\Omega_w \mathbf{R}' = \mathbf{R}(\mathbf{R}'\mathbf{R})^{-1}\Omega_w^{-1}(\mathbf{R}'\mathbf{R})^{-1}\mathbf{R}'.$$

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Figure 1: Monthly discrepancies of PR system

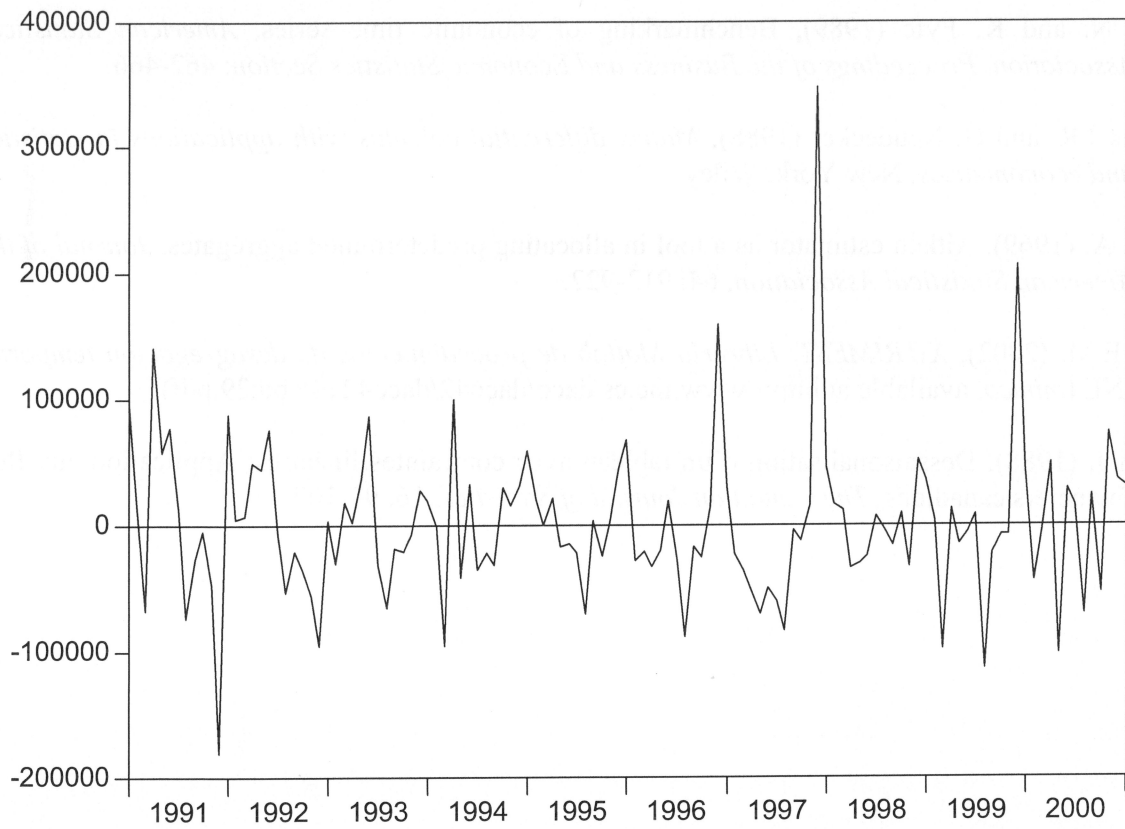


Figure 2: Additive corrections to growth rates made by benchmarking PR component series and Total Canada without binding constraint

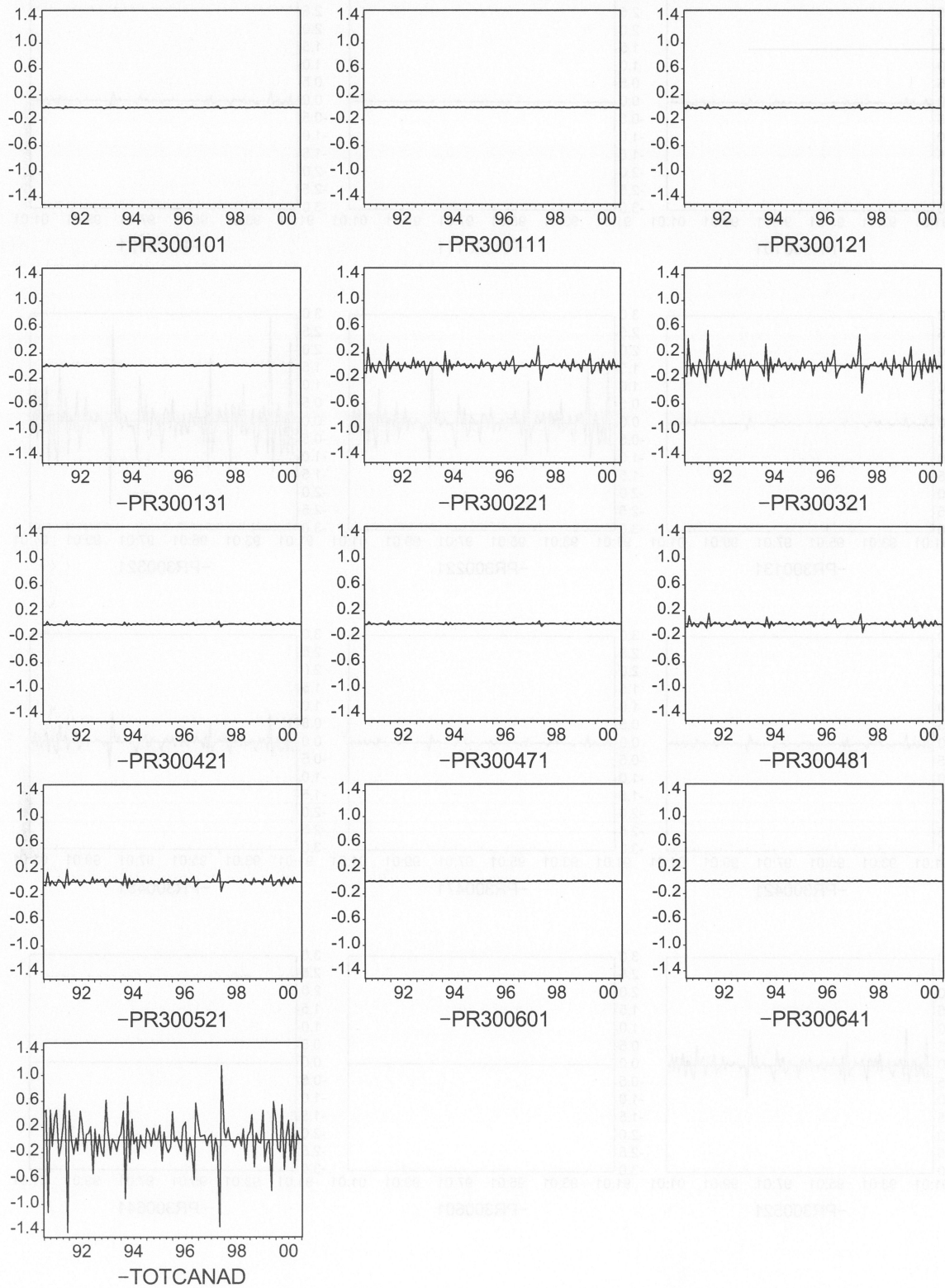


Figure 3: Additive corrections to growth rates made by benchmarking PR component series with a binding constraint

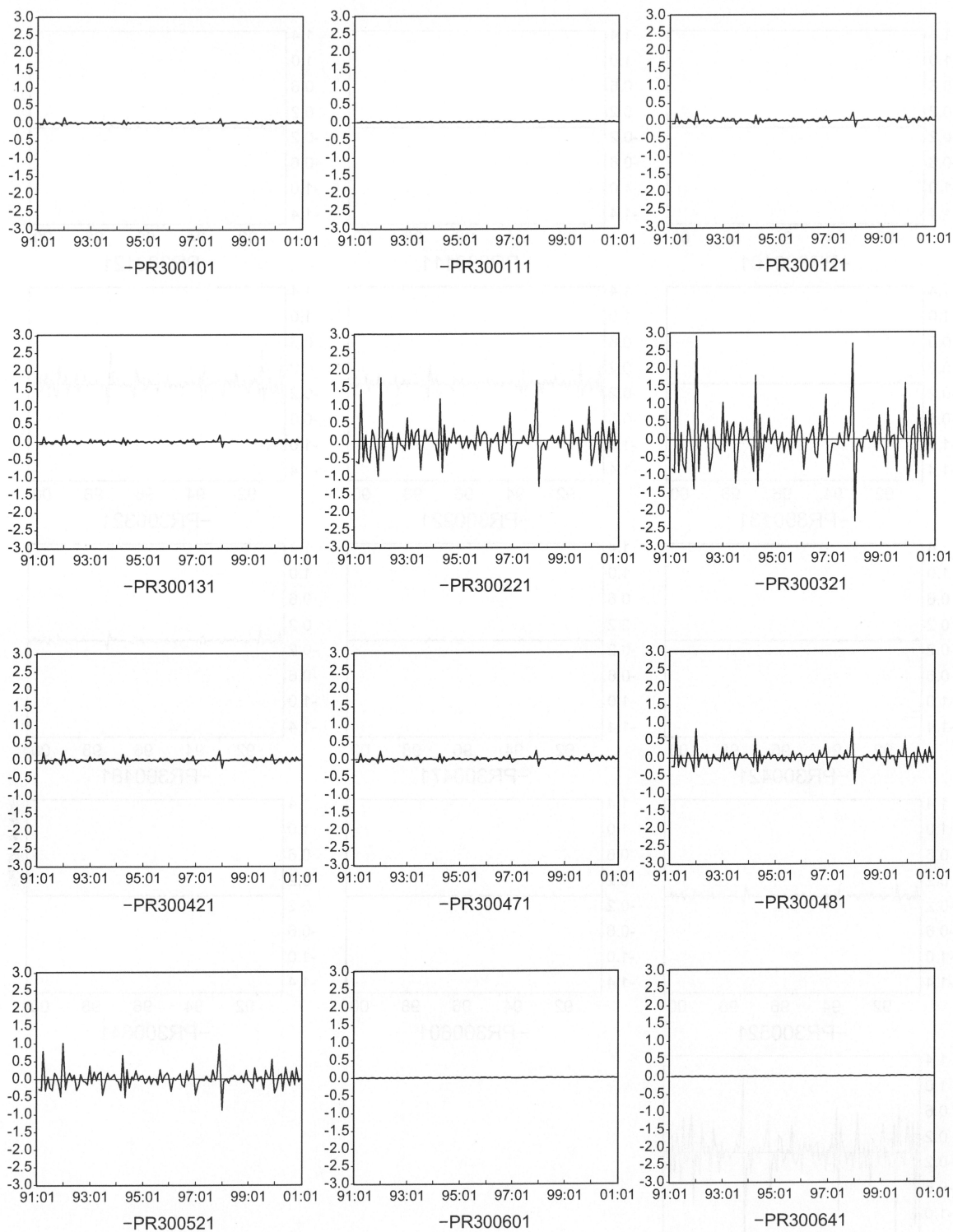


Figure 4: Additive corrections to growth rates made by benchmarking PR component series while preserving the growth rates and with binding constraint

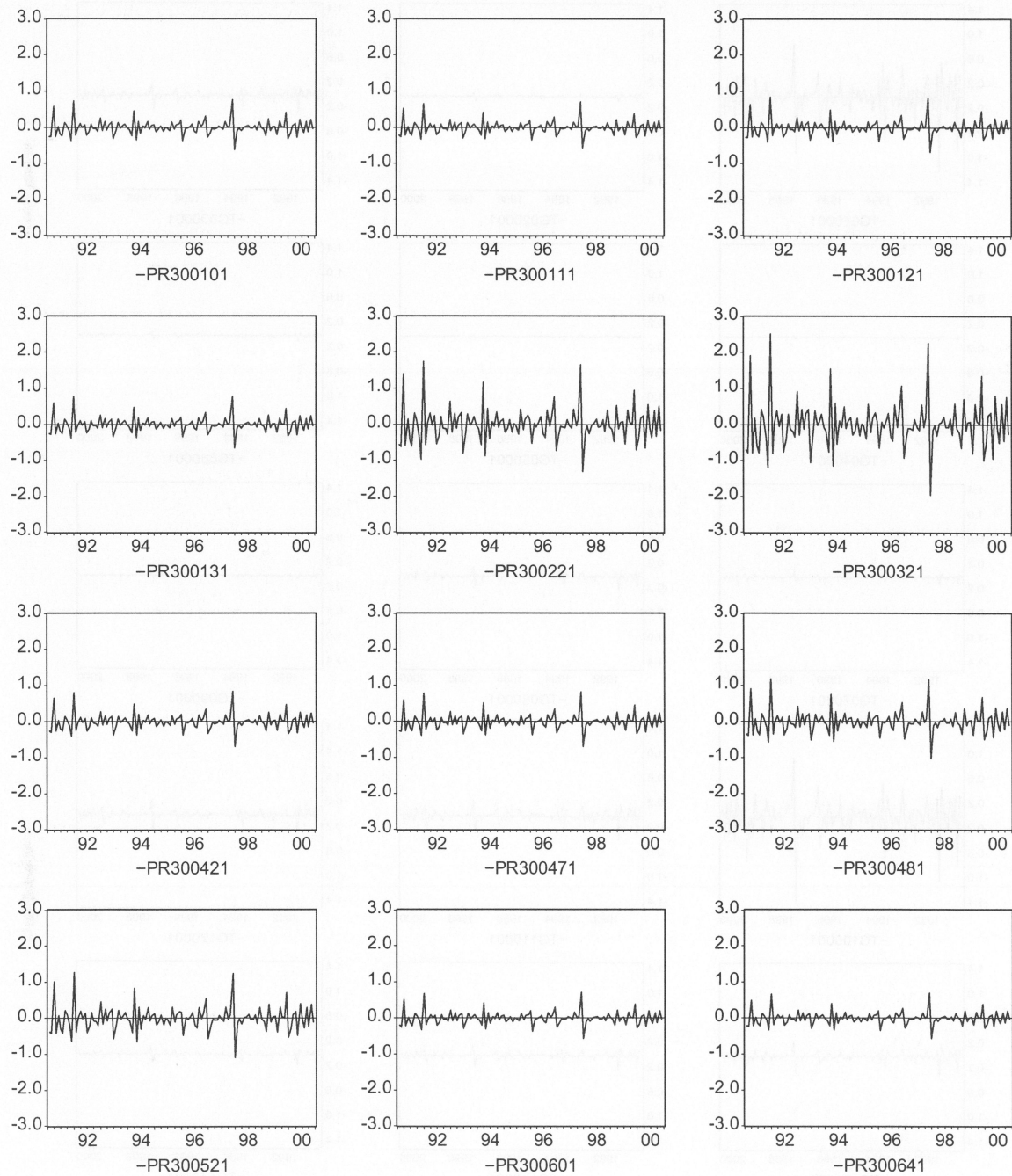


Figure 5: Additive corrections to growth rates made by benchmarking PR and TG component series without a binding constraint – Series by trade groups

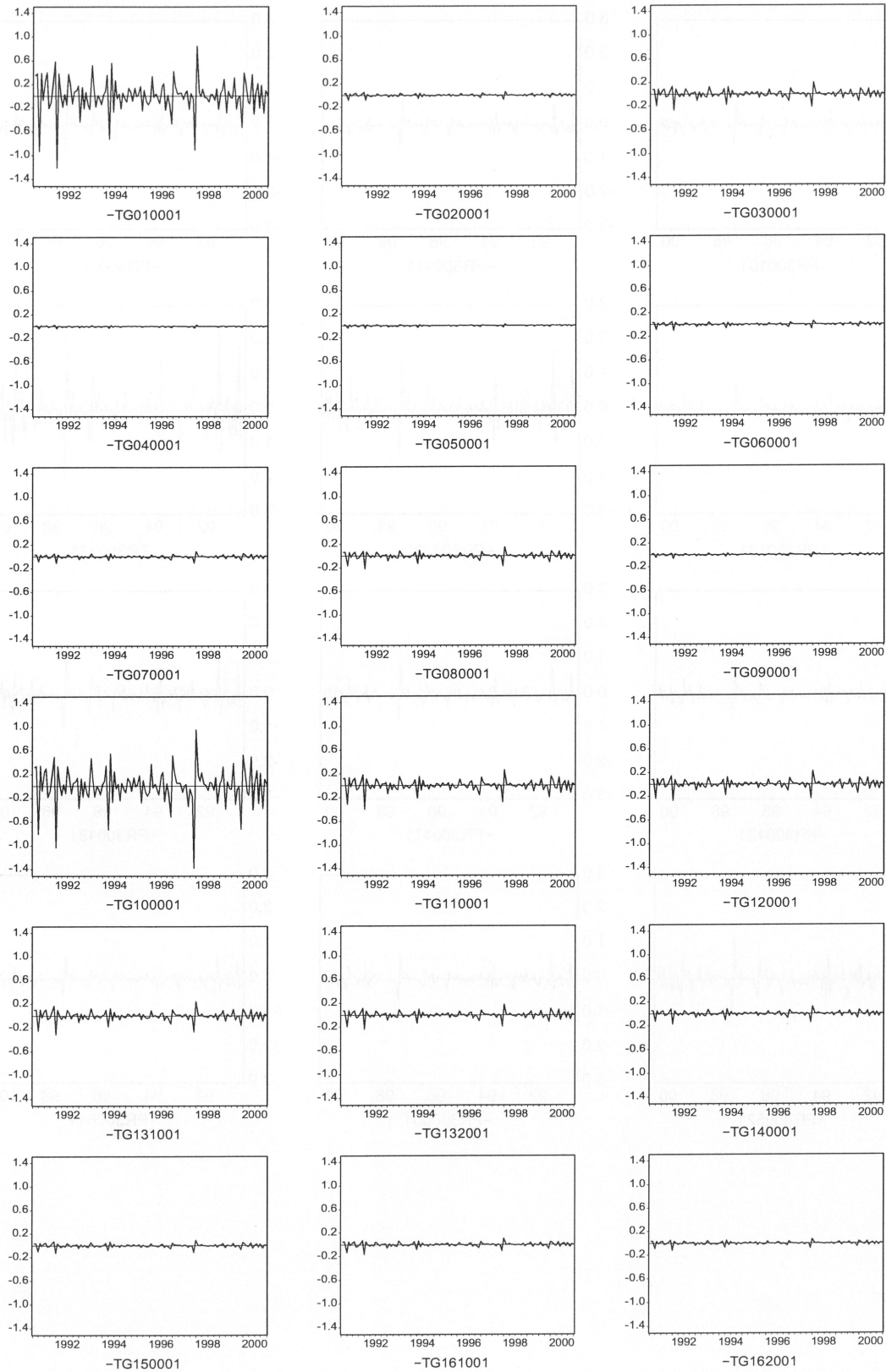


Figure 6: Additive corrections to growth rates made by benchmarking PR and TG component series without a binding constraint – Series by province and Total Canada

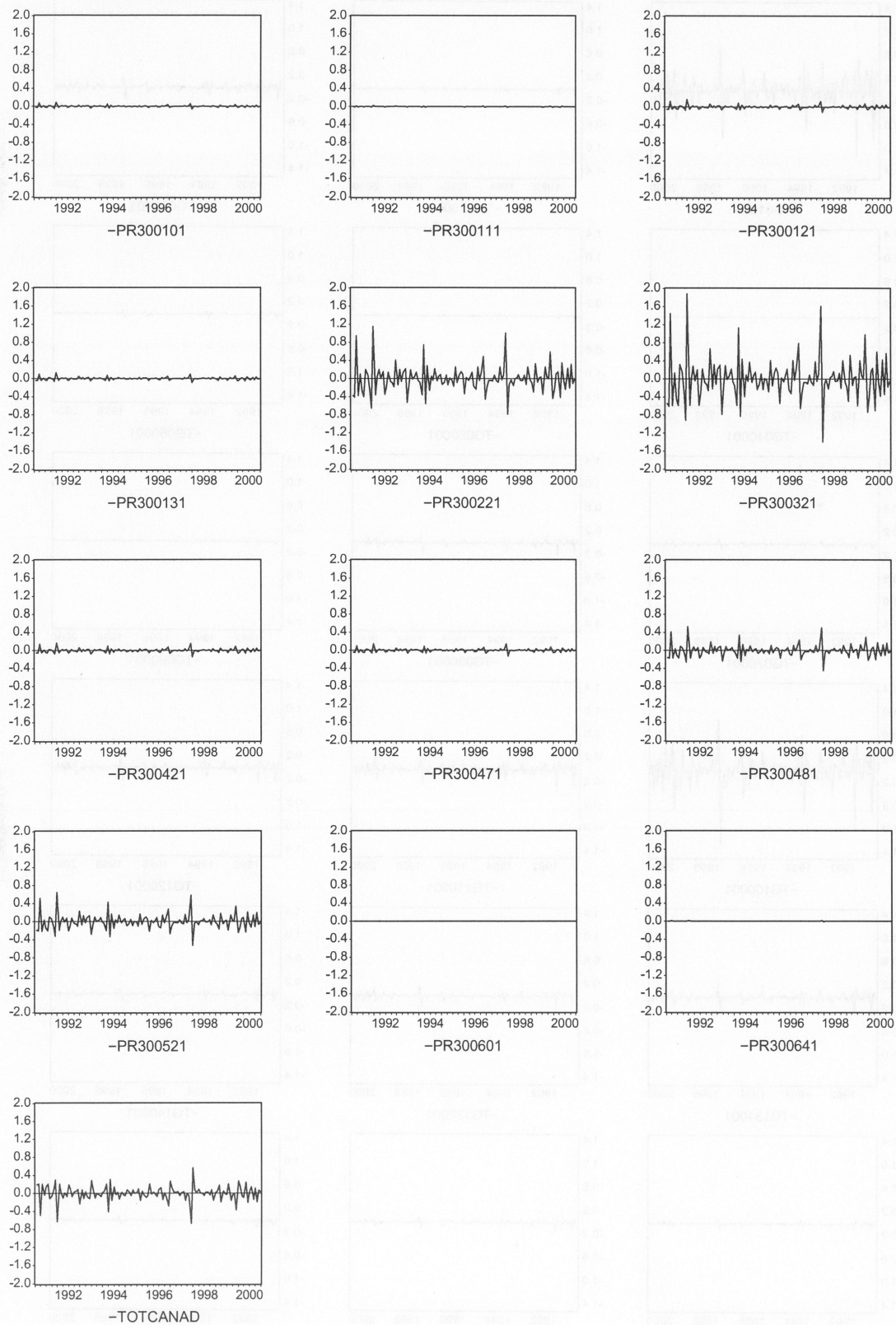


Figure 7: Additive corrections to growth rates made by benchmarking Total Canada, PR and TG component series - Series by trade groups

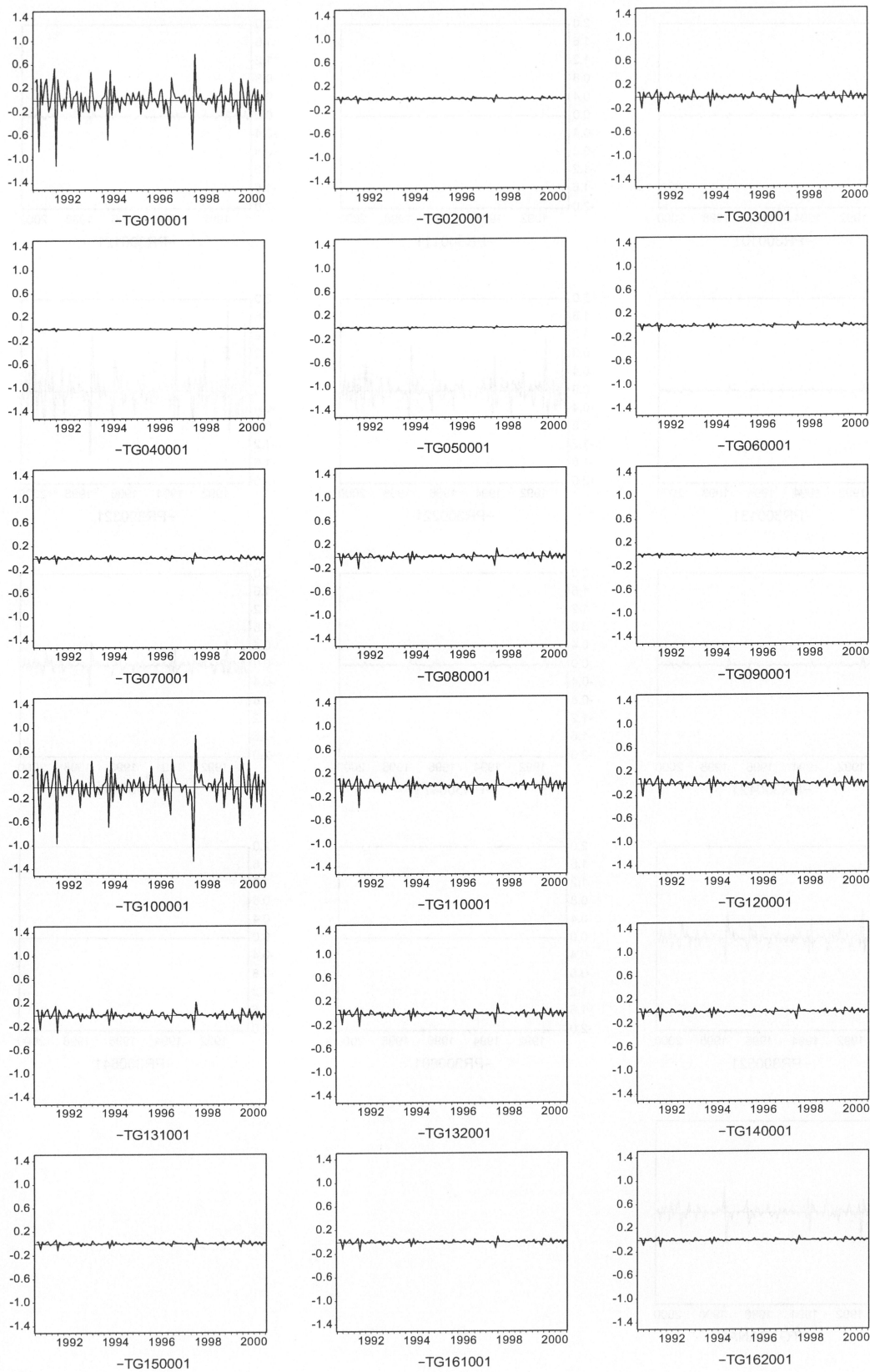


Figure 8: Additive corrections to growth rates made by benchmarking Total Canada, PR and TG component series - Series by province and Total Canada

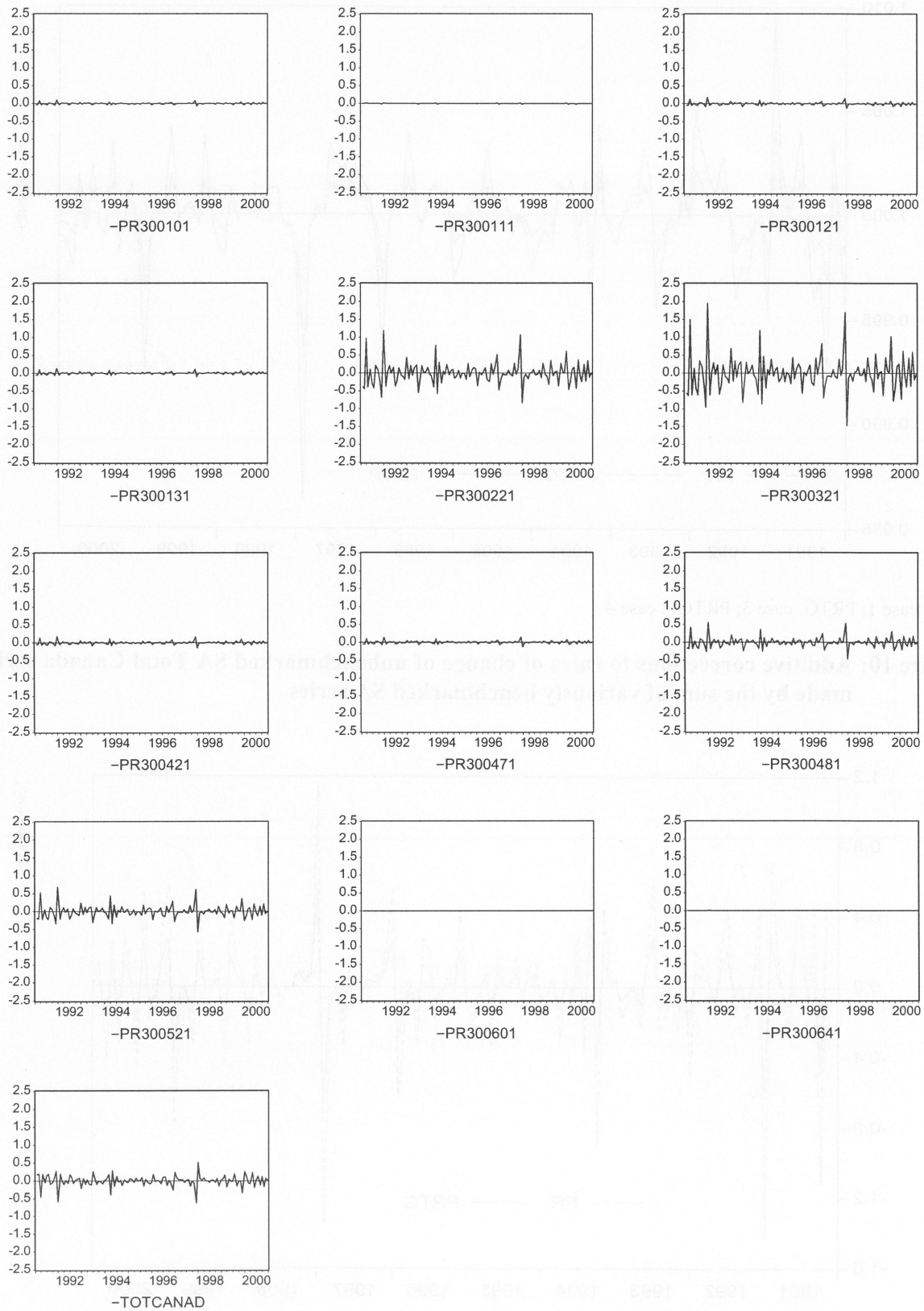
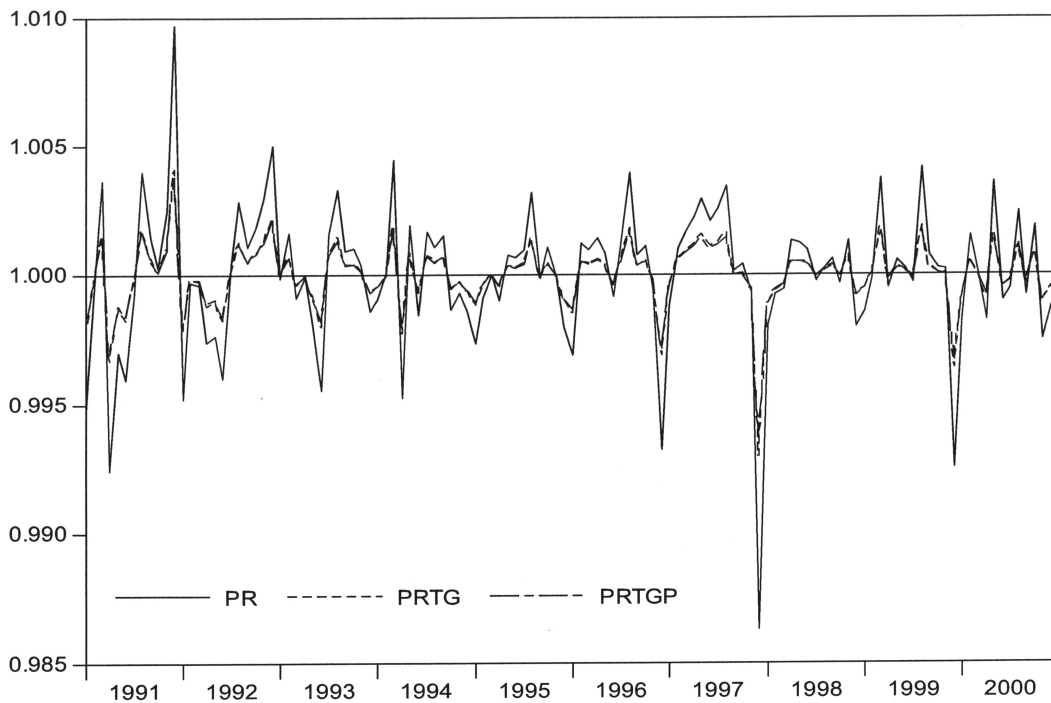
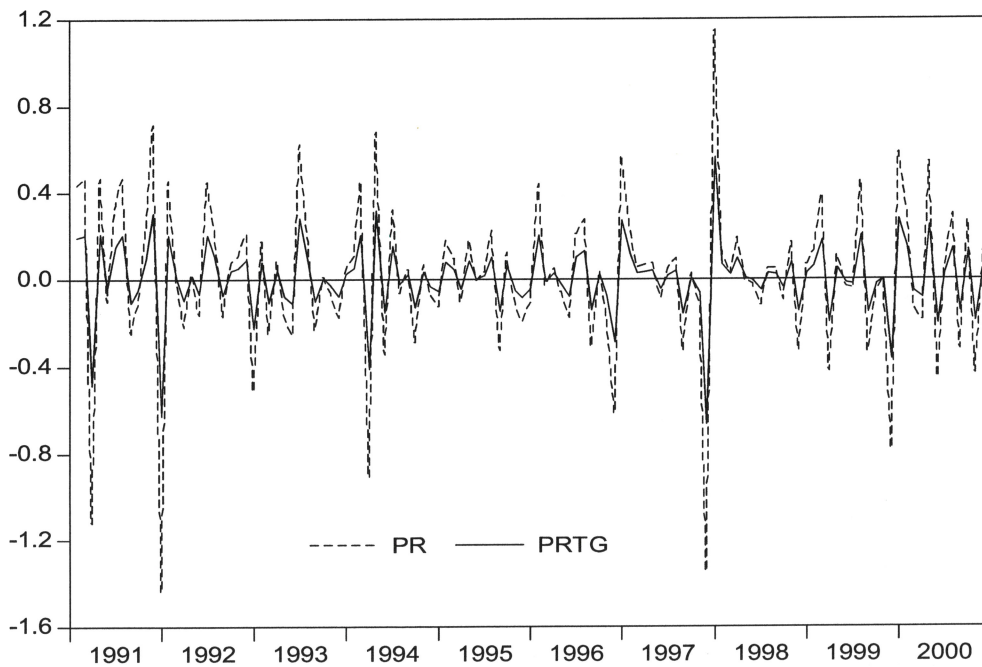


Figure 9: Proportional corrections to the unbenchmarked SA Total Canada made by the sum of variously benchmarked SA series



* PR: case 1; PRTG: case 3; PRTGP: case 4.

Figure 10: Additive corrections to rates of change of unbenchmarked SA Total Canada series made by the sum of variously benchmarked SA series



* PR: case 1; PRTG: case 3.