Review of Income and Wealth
Series 45, Number 4, December 1999

THE CHOICE OF THE AGGREGATION LEVEL IN THE ESTIMATION OF QUARTERLY NATIONAL ACCOUNTS

BY GIULIO CAINELLI
IDSE-CNR, Milano, Italy and University of Bologna

AND

CLAUDIO LUPI
ISAE, Roma, Italy

Many central statistical offices use indirect time series disaggregation methods to produce quarterly national accounts estimates or other high frequency variables. This paper investigates the relation existing between the statistical properties of indirectly estimated time series and the contemporaneous aggregation level at which estimation is carried out, when a version of the Chow–Lin (1971, 1976) method is used to evaluate quarterly time series. It is shown that estimation at the lowest possible level of contemporaneous aggregation is not always optimal. In order to choose the level of contemporaneous aggregation at which time series disaggregation should be carried out, the use of formal econometric tests is suggested.

1. INTRODUCTION

The implications for applied economic analysis of the sources and methods used to estimate National Accounts (NA) aggregates have been recently strongly emphasized. In fact, some recent contributions highlight the possible consequences deriving from the presence of sampling errors (Bell and Wilcox, 1993; Wilcox, 1992), from the use of seasonal adjustment methods (Ghysels and Perron, 1993; Maravall, 1997), and from the adoption of untested hypotheses such as specific aggregation schemes (Richter, 1994). In this paper we investigate the discrepancies arising in indirectly estimated NA quarterly time series, when estimation is carried out at different levels of contemporaneous aggregation. The interest in this case derives from a common presumption that the best estimate is carried out at the lowest possible level of contemporaneous aggregation. We show that this is not necessarily the case when indirect estimation methods are used.

Indeed, many central statistical offices use indirect time series disaggregation methods in the estimation of quarterly and/or monthly time series (see e.g. Bruno *et al.*, 1994; Eurostat, 1997). When directly observable quarterly (or monthly) measures are not available, time series disaggregation techniques allow the statistician to disaggregate annual time series into higher frequency ones

Note: This paper stems largely as the result of the joint work the authors have carried out together in 1996 when they were both working at revising the quarterly national accounts estimates (1970q1–1996q4) at ISTAT (the Italian Central Statistical Office). Our thanks go to Gianluca Cubadda, Patrizia Ordine, and to an anonymous referee for comments and criticisms. A special thank also to Gilberto Antonelli for his continuous support to the present research. However, the usual disclaimer applies. Though ISTAT has largely accepted the results of this research, any responsibility for the opinions expressed in this paper rests on the authors only. The views of the authors also do not imply any responsibility of ISAE or IDSE-CNR.

using the information embodied in related series. The Chow–Lin method (Chow and Lin, 1971, 1976) and its successive developments (see e.g. Stram and Wei, 1986) have gained a predominant role in practical applications of these techniques. The idea underlying many of these methods is simple: let $\{Y_j\}_1^T$ be a time series observed with frequency 1 and $\{\mathbf{X}_j\}_1^T$ a vector of k series which can be observed also with frequency $m > 1$ and are related to $\{Y_j\}_1^T$. For the typical case of interest we have frequency 1 corresponding to annual data and $m = 4$ for quarterly data. Further, small letters denote the variables with frequency $m > 1$. The basic intuition is that of estimating the quarterly unknown values $\{y_t\}_1^{mT}$ using the indicators $\{\mathbf{x}_t\}_1^{mT}$ in the model

$$\tilde{\mathbf{y}} = \mathbf{x}\tilde{\beta} + \tilde{\varepsilon} \tag{1}$$

where $\tilde{\beta}$ is estimated over an analogous regression among the observable annual values $\{Y_j\}_1^T$ and $\{\mathbf{X}_j\}_1^T$. $\tilde{\varepsilon}$ is a function of the annual fitted residuals that ensures that the quarterly figures are consistent with the annual ones.[1]

In this paper we investigate the relation existing between the statistical properties of the indirectly estimated time series and the contemporaneous aggregation level at which estimation is carried out, when a version of the Chow–Lin method is used to estimate (seasonally and non-seasonally adjusted) quarterly time series. We show that estimation at the lowest possible level of contemporaneous aggregation is not necessarily the "best" choice. Therefore, we suggest the use of contemporaneous aggregation tests when estimating NA quarterly series by indirect methods. We also provide empirical evidence of the practical relevance of the arguments raised in this paper.

The remainder of the paper is organized as follows: Section 2 is devoted to the comparison of the statistical properties of two series which have been (indirectly) estimated at different levels of contemporaneous aggregation. In particular, the first series results from the sum of ten elementary series which have been individually estimated; the second has been estimated directly on the contemporaneous total. In Section 3 we briefly describe and suggest the use of a test for contemporaneous aggregation due to Pesaran *et al.* (1989). We show how this approach naturally fits within the problem at hand. Section 4 points out the implications of these aggregation problems in NA practice. Finally, in the last section some interpretations are sketched and some tentative conclusions relevant for both data producers and users are proposed.

2. The Relevance of Contemporaneous Aggregation: Empirical Evidence

In this section we provide empirical evidence about the practical relevance of estimated time series discrepancies arising when different contemporaneous

[1] In particular, the Chow–Lin estimator is given by

$$\tilde{\mathbf{y}} = \mathbf{x}\tilde{\beta} + \mathbf{S}\tilde{\mathbf{U}},$$

where $\tilde{\beta}$ and $\tilde{\mathbf{U}}$ are the GLS parameters estimates and the GLS fitted residuals from the regression on the annual values, respectively. $\mathbf{S}$ is a smoothing matrix whose form generally depends on the covariance matrix assumed for the $\mathbf{U}$'s. Further details on this and other time disaggregation methods can be found in the relevant literature which includes Al-Osh (1989), Bournay and Laroque (1979), Chow and Lin (1971, 1976), Di Fonzo (1990), Guerrero (1990), Harvey and Pierse (1984), Lupi and Parigi (1994), Marcellino (1996), Rossi (1982), Stram and Wei (1986), Wei and Stram (1990).

aggregation levels are used in time series disaggregation procedures. In order to do so, we analyze ten quarterly series of constant prices households' food consumption. These series are part of the households' final consumption quarterly NA aggregate. These ten quarterly elementary time series are: bread and cereals; meat; fish; milk, cheese and eggs; oils and fats; fruits and vegetables; potatoes; sugar; coffee, tea and cocoa; other food, including preserves. The indicator series used to estimate these ten quarterly NA series are constituted by the corresponding items taken from the Households' Budget Survey (HBS). These indicators are at constant prices.

Let $\bar{f}_t$ ($t = 1970q1, \ldots, 1994q4$) be the quarterly estimate of households' food consumption obtained by aggregation of ten quarterly elementary series (each indirectly estimated from its own annual value and using its own indicator(s) series), and f_t the quarterly estimate of food consumption deriving from time series disaggregation of the cross-aggregated figures (the contemporaneous totals).

A first comparison between the two different versions of the estimated series can be carried out by estimating the model

$$f_t^i = c + \gamma \bar{f}_t^i + e_t^i \tag{2}$$

with $i \in \{sa, nsa\}$ according to whether the series are seasonally adjusted or non-seasonally adjusted. Indeed, using (2) we can check interesting null hypotheses such as the absence of cointegration between $\bar{f}_t^i$ and f_t^i, and unbiasedness. The results of these tests are reported in Table 1.[2]

TABLE 1

RESIDUALS AUTOCORRELATION UP TO ORDER 2 (AR(1–2)), COINTEGRATION (COINT), AND UNBIASEDNESS (H_0) TESTS

	AR(1–2)	Coint	$H_0: (c=0, \gamma=1)$
sa	12.467	−9.767	0.007
	[0.000]	[<0.010]	[0.993]
nsa	60.093	−5.975	0.696
	[0.000]	[<0.010]	[0.501]

The null of no-cointegration is decidedly rejected for both seasonally adjusted and non-seasonally adjusted series. This result could have been anticipated, since the annual totals of the two series $\bar{f}_t^i$ and f_t^i are the same. The null of unbiasedness cannot be rejected, apparently confirming the absence of systematic differences between the two series, also reflecting the fact that the annual totals are the same for both series. However, the presence of residuals autocorrelation for both the *sa* and *nsa* versions indicates that more subtle departures between the two series are present. Since this can indeed be a crucial point for data users, we carry out a more sophisticated investigation of this issue.

Let us define $d_t^i \equiv f_t^i - \bar{f}_t^i$. In order for $\bar{f}_t^i$ and f_t^i to be essentially equivalent (possibly apart a zero-mean white noise measurement error), not only one series

[2]An ADF test of the I(1) hypothesis could not reject the unit root null for both $\bar{f}_t^i$ and f_t^i. The null of no cointegration is tested using the approach described in Banerjee and Hendry (1992).

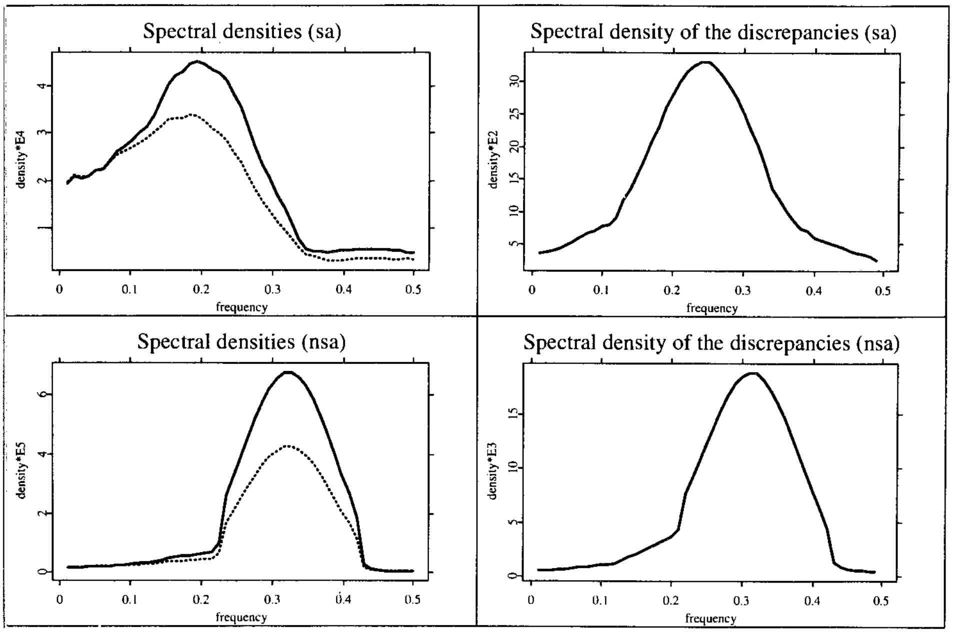

Figure 1. Spectra of Δf_t^i (Solid Line), $\Delta \bar{f}_t^i$ (Dotted Line), and $d_t^i = f_t^i - \bar{f}_t^i$ (Discrepancies)

must be an unconditionally unbiased version of the other one, but also the discrepancies $\{d_t^i\}$ between the two series must behave as martingale difference sequences.

First of all it is instructive to look at the spectral densities of the (first differences of the) estimated series and of (the levels of) the discrepancies. From Figure 1 it is fairly clear that the series estimated using different aggregation schemes have also different dynamic properties. It is interesting to note that the estimated spectrum of the series of the discrepancies for the seasonally adjusted data has a clear peak at seasonal frequencies. The peak is shifted towards higher frequencies in the case of raw data. According to this piece of evidence, the $\{d_t^i\}$ series do not seem to be martingale difference sequences. However, we check formally this hypothesis by using two tests originally developed by Durlauf (1991).[3] The advantage of these tests is that they are robust under fairly general conditions and,

[3]Durlauf (1991) shows that if $\{z_t\}$ is a martingale difference sequence, then under some fairly general regularity conditions when the sample size $T \to \infty$,

$$\mathsf{U}_T(k) = \sqrt{2T} \int_0^{k\pi} \left(I_z(\lambda) - \frac{1}{2\pi} \right) d\lambda \Rightarrow \mathsf{B}(k)$$

where $k \in [0, 1]$, $I_z(\lambda)$ is the periodogram of $\{z_t\}$ at frequency λ, and $\mathsf{B}(\cdot)$ is the Brownian bridge on $[0, 1]$."$\Rightarrow$" means convergence in probability measure. Various tests based on $\mathsf{U}_T(k)$ are possible. We use the following ones: $\mathrm{CvM} = \int_0^1 \mathsf{U}_T^2(k)\, dk$ (Cramér–von Mises), and $\mathrm{FB} = \mathsf{U}_T(k_1) - \mathsf{U}_T(k_2) \sim \mathrm{N}[0, (k_1 - k_2) - (k_1 - k_2)^2]$ (frequency band). The first one checks the significance of deviations from the (difference) martingale hypothesis over all the frequencies $\lambda \in [0, \pi]$, while the second focuses only on the frequency band $\lambda \in [k_1\pi, k_2\pi]$, with $0 \le k_1 < k_2 \le 1$. For more details see Durlauf (1991).

TABLE 2

CRAMÉR–VON MISES TESTS FOR (DIFFERENCE) MARTINGALITY

	CvM	Marginal Signif.
sa	2.429	< 0.010
nsa	2.062	< 0.010

since they do not refer to any specific alternative hypothesis, they are consistent with respect to a wide range of alternatives.[4]

We apply first the CvM (Cramér–von Mises) test, which checks the overall "whiteness" of $\{d_t^i\}$. The results are reported in Table 2 (the test rejects for "high" values of the statistic).

The null of (difference) martingality is strongly rejected, irrespective of seasonal adjustment. In other words, the dynamic properties of $\bar{f}_t^i$ and f_t^i appear to be significantly different. At this point it is interesting to investigate these differences more deeply. In order to do so we apply the second version of the spectral test that checks for the significance of departures from the null of (difference) martingality over specific frequency bands. In this way it is possible to verify if rejection of the CvM test has been caused by high- or low-frequency components of the series.

The results listed in Table 3 confirm the presence of statistically significant deviations from the hypothesis of (difference) martingality at frequencies close to the seasonal ones for both the seasonally adjusted and the raw versions of the data. In our opinion these findings should be explained in terms of the indicator significance in determining the dynamics of the final series.

TABLE 3

FREQUENCY-BAND TESTS FOR (DIFFERENCE) MARTINGALITY

Period (quarters)	Seasonally Adjusted		Non-seasonally Adjusted	
	Value	Significance	Value	Significance
32.00–16.00	−0.416	0.085	−0.431	0.074
16.00–10.67	−0.204	0.398	−0.378	0.118
10.67–8.00	−0.033	0.891	−0.336	0.164
8.00–6.40	−0.164	0.498	−0.375	0.121
6.40–5.33	−0.054	0.822	−0.347	0.151
5.33–4.57	1.496	0.000	−0.043	0.859
4.57–4.00	1.368	0.000	−0.027	0.910
4.00–3.56	0.183	0.477	1.744	0.000
3.56–3.20	−0.241	0.317	1.540	0.000
3.20–2.91	−0.008	0.973	−0.315	0.192
2.91–2.67	−0.310	0.199	−0.399	0.098
2.67–2.46	−0.319	0.187	−0.405	0.093
2.46–2.29	−0.359	0.137	−0.411	0.089
2.29–2.13	−0.310	0.199	−0.399	0.098
2.13–2.0	−0.347	0.150	−0.342	0.157

[4]An extensive Monte Carlo analysis of this issue can be found in Lupi (1996).

Overall, the evidence strongly suggests that the problem of the choice of the contemporaneous aggregation level at which the NA aggregates should be estimated is not just a matter of academic curiosity. On the contrary, this choice can affect the dynamic properties of the final estimates.

3. Choosing Among Different Levels of Contemporaneous Aggregation

We have shown that the choice of contemporaneous aggregation level at which the quarterly time series are estimated can significantly affect the statistical properties of the published series. Therefore, it is necessary to use a firm statistical criterion in order to select the best aggregation level for each specific case.

Given that many time series disaggregation procedures are based on regressions of the kind of (1) or some other closely related model, the obvious framework to look at in order to find a solution to the contemporaneous aggregation level choice problem should be model selection criteria.[5] In particular, the problem of deciding whether to disaggregate each elementary series or the contemporaneous total series can be restated to selecting between the r-equation disaggregate linear model

$$\text{(3)} \qquad \mathrm{H_d}: \mathbf{Y}_i = \mathbf{X}_i \beta_i + \mathbf{U}_i$$

with $(i = 1, 2, \ldots, r)$ and the aggregate one

$$\text{(4)} \qquad H_\mathrm{a}: \mathbf{Y}_a = \mathbf{X}_a \beta_a + \mathbf{U}_a$$

where $\mathbf{Y}_a = \sum_{i=1}^r \mathbf{Y}_i$ and $\mathbf{X}_a = \sum_{i=1}^r \mathbf{X}_i$. Note that it is possible to allow each $\mathbf{X}_i$ and $\mathbf{X}_a$ to be composed respectively by k_i and k_a regressors with $k_{i_1} \neq k_{i_2}$ for $i_1 \neq i_2$ and also $k_i \neq k_a$. Selection among $\mathrm{H_d}$ and $\mathrm{H_a}$ can be accomplished by using a generalized goodness-of-fit criterion based on the comparison of the variance of the residuals from the aggregate model with that of the error deriving from predicting $\mathbf{Y}_a$ from the disaggregate model, $\mathrm{V}(\sum_{i=1}^r \mathrm{U}_i)$. That is, the disaggregate model is chosen if and only if it performs better than the aggregate one in terms of variance of the residuals with respect to the aggregate variable. Following Pesaran *et al.* (1989), the disaggregate model is therefore chosen when $S^2 < S_a^2$, with

$$S^2 = \sum_{i_1, i_2 = 1}^{r} \hat{\sigma}_{i_1 i_2}$$

$$\text{(5)} \qquad S_a^2 = \frac{\hat{\mathbf{U}}_a' \hat{\mathbf{U}}_a}{T - k_a}$$

where S^2 is an unbiased and consistent estimate of $\mathrm{V}(\sum_{i=1}^r \mathrm{U}_i)$, $\hat{\sigma}_{i_1 i_2} = [T - k_{i_1} - k_{i_2} + \mathrm{tr}\,(\mathbf{M}_{i_2}' \mathbf{M}_{i_2})]^{-1} \hat{\mathrm{U}}_{i_1}' \mathrm{U}_{i_2}$ with $\mathbf{M}_i = \mathbf{X}_i (\mathbf{X}_i' \mathbf{X}_i)^{-1} \mathbf{X}_i'$. $\hat{\mathbf{U}}_a$ and $\hat{\mathbf{U}}_i$ are the fitted residuals from (4) and (3), respectively.[6]

[5]Useful references include Grunfeld and Griliches (1960) and Pesaran *et al.* (1989).

In our application, $\mathbf{X}_a$ and $\mathbf{Y}_a$ correspond to the annual households' food consumption as measured by the (yearly) Households' Budget Survey (HBS) figure (used as the indicator variable) and the NA estimate, respectively. $\mathbf{X}_i$ and $\mathbf{Y}_i$ (with $i = 1, 2, \ldots, 10$) are the corresponding consumption measures relative to the ten elementary consumption items. Applying (5) to our annual households' food consumption models we obtain $S^2 = 2.460 \times 10^6$ and $S_a^2 = 1.056 \times 10^6$, that make us conclude that in this case the aggregate model outperforms the disaggregated one.[7]

When the final goal is a reliable estimate of the aggregate time series for total households' food consumption, the evidence we provide suggests a clear superiority of the aggregate model over the disaggregate one. If this viewpoint is accepted, disaggregate figures should then be derived in such a way that they are consistent with the quarterly (contemporaneously) aggregate ones. Various techniques are conceivable, possibly related to Champernowne *et al.* (1942), Stone (1990), Di Fonzo (1990), and Rossi (1982).

The fact that the aggregate model can perform better than the disaggregate one should not come as a surprise. A possible interpretation of this finding is that the annual NA households' final consumption estimate and the HBS data (the indicators series) take into account different definitions of households' consumption. The main differences concern the definition of consumers' population, where the survey grossing coefficients are based on *resident* households while the NA final consumption definition is related to the *present* population, but there are also important differences as far as definitions of specific consumption items are concerned. Very often, the finer is the disaggregation level, the more relevant are these differences. This problem is not related to consumption only and appears to be a very diffuse problem regarding many other important macrovariables in many countries.

4. The Relevance of Contemporaneous Aggregation in National Accounts Estimates: Some General Considerations

The aggregation problem debate is not new in economics and in NA theory. In economics this debate traces back to Theil (1954), who investigated the aggregation problem of a set of linear equations. By assuming perfect specification and non-stochastic nature of the equations, Theil found an aggregation loss result, that is a general superiority of the disaggregate model over the aggregate one. The econometric criteria developed by Pesaran *et al.* (1989) is largely an extension of these seminal contributions. The aggregation issue has a long tradition in NA as well. Two main research lines can be identified. The first concerns the problems

[6] An early contribution to the literature is Grunfeld and Griliches (1960) that simply compares $\sum_{i=1}^{r} \hat{\mathbf{U}}_i'\hat{\mathbf{U}}_i$ and $\hat{\mathbf{U}}_a'\hat{\mathbf{U}}_a$. However, this test has two main shortcomings. First, it does not allow for contemporaneous covariance between the errors of the disaggregate model. Second, the "explanatory" variables are assumed to be the same for all equations. Therefore, we strongly prefer the version of the test proposed by Pesaran *et al.* (1989), since it overcomes both these limits.

[7] Using the simpler criterion suggested by Grunfeld and Griliches (1960) on the same data set we obtain $\sum_{i=1}^{r} \hat{\mathbf{U}}_i'\hat{\mathbf{U}}_i = 3.207 \times 10^7$ and $\hat{\mathbf{U}}_a'\hat{\mathbf{U}}_a = 2.006 \times 10^6$. Though this test is far less general than the one developed by Pesaran *et al.* (1989), in the present case the main conclusion remains the same with the aggregate model being the preferred one.

of aggregation over individuals (Arkhipoff, 1990); the second deals with the choice of the appropriate level at which NA estimates should be carried out. However, this latter aspect seems not to have been completely settled. Indeed, Richter (1994, p.103) points out that

> "*although the aggregation problem always was considered among the tricky ones in economic research, NA usually provides one prefabricate solution*",

the solution being that of estimating the NA variables at the finest possible level of contemporaneous aggregation. In our opinion, the aggregation problem in NA estimation has two fundamental implications. First of all, the use of untested aggregation schemes in NA estimation introduces theoretical hypotheses which may or may be not supported by data into the data production itself. In this way, the statistical data generation process can take the form of a data modeling process based on a definite set of *ex ante* hypotheses with obvious consequences on the presumed "neutrality" of the produced statistics. For this reason, some authors have introduced the concept of "hypotheses-generated data" that can result, from the viewpoint of data users, in "modeling on the basis of the results of modeling" (Richter, 1994; Holub and Tappeiner, 1994). Secondly, the use of untested hypotheses such as those concerning the level of aggregation at which NA estimates are carried out can alter the statistical properties of the data by introducing "sources of errors which, due to their systematic bias, differ fundamentally from the usual sources of errors in empirical statistics" (Holub and Tappeiner, 1994). Similarly, errors induced from the adoption of untested aggregation schemes can have consequences on the dynamic properties of the estimated time series essentially in the same way as the presence of serial correlation in surveys sampling errors or the use of seasonal adjustment methods. In Section 2 we have shown the empirical relevance of this problem. Our suggestion is to condition each choice in NA aggregates estimation process on firmly based statistical criteria whenever possible. This, of course, has much to do with the growing interest about the reliability of official statistics since errors

> "*might be reduced, perhaps through better interpretation and more effective use of the available information set*" (York and Atkinson, 1997).

5. Conclusions

A quite common presumption in NA estimation current practice is that the most reliable estimates of NA aggregates are obtained at the lowest (finest) possible level of contemporaneous aggregation. However, it is worth noting that neither the UN System of National Accounts (SNA) nor the last edition of Eurostat's SEC (SEC 95) deal with this particular issue. The only explicit reference to contemporaneous aggregation problems in SEC 95 is related to regional accounts.

In this paper we show that the practice of estimating the NA aggregates at the lowest possible level of aggregation is not necessarily the best route to obtain reliable aggregate estimates. Furthermore, the choice of different levels of aggregation can significantly affect the statistical properties of aggregate NA quarterly time series, when indirect estimation methods are used. This seems to us an important issue, given that indirect methods are used in many European countries. Using real data and building on the actual experience faced by the Department of National Accounts of ISTAT (the Italian Central Statistical Office) during the last quarterly NA revision (October 1996), we examine the relation between the statistical properties of quarterly time series estimated at different levels of contemporaneous aggregation. We find that the choice of the aggregation level is important in shaping the dynamic properties of the estimated series. Moreover, the analysis shows clearly that the best choice is not always related to the maximum level of disaggregation. For this reason we suggest the extensive use of contemporaneous aggregation tests before using time series disaggregation procedures to estimate quarterly NA aggregates. In particular, we suggest implementing formal econometric tests, such as those proposed by Pesaran *et al.* (1989), in current quarterly NA estimation practice.

The results of our analysis also have important implications for data users. Our evidence suggests that since the aggregation choice may affect data properties, particular care has to be taken with respect to the economic interpretation of some "stylized facts" derived solely on the basis of univariate time series analysis. For example, autocorrelation properties which should in theory have economic interpretations can instead be largely the result of the choices made during the data production stage. In this sense, it is very important that the users know in some detail the statistical sources and the methods used by the statistical agencies for estimating data.

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