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EVALUATION OF DIFFERENT TEMPORAL DISAGGREGATION TECHNIQUES AND AN APPLICATION TO ITALIAN GDP

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ABSTRACT

In this paper, temporally disaggregation is conducted through regression-based models, namely by Chow-Lin (1971) and Fernandez (1981). The disaggregation is carried out using four GDP series of Italy, collecting data from ISTAT (Statistical office of Italy). We evaluated disaggregating capacity as well as forecasting ability about the future series by different simulation techniques. The analysis shows that Chow-Lin maximum likelihood estimation disaggregates the GDP better than Fernandez although, for the case of seasonal adjusted data the performance of both procedures are very close. In contrast, the prediction quality of Fernandez seems to outperform Chow-Lin (MaxLog). This a scholastic work, but the results may be a guideline to temporally disaggregate the annual GDP series into quarterly series by Chow-Lin and Fernandez approaches, which will be beneficial for the countries where high frequency (quarterly) GDP are not available. It is noted that the paper was written during a two months research training under EMMA program (20/08/2009-20/10/2009) at the Department of Statistical Sciences, University of Padua, Italy.

Key words: GDP, Temporal disaggregation, Related series, Estimates, Forecast.

I. INTRODUCTION

Quantitative economic analysis relies on statistical data, which is normally generated through continuous sample survey. As it requires enormous resources in collecting statistical information, most of the countries conducted large sample survey only annually and obtained different estimates of national accounts on annual basis (low frequency). For the efficient statistical and economic analysis and timely decision-making, it is very essential to obtain national accounts in quarterly or monthly (high frequency). Thus, the process of deriving high frequency (quarterly, monthly) data from low frequency (yearly, quarterly) data is known as temporal disaggregation. In contrast, some economic series are available at high frequency (quarterly or monthly) can be used as indicator (related series) in temporal disaggregation to obtain quarterly or monthly national accounts. Therefore, some different approaches for disaggregating low frequency data to high frequency data have been developed in the past years, which can be broadly generalized as two alternative approaches:

i) models developed without indicator (related) series but which rely upon purely mathematical criteria or time series models to derive a smooth path for the unobserved series;
ii) models based on indicator (related) series observed at the desired higher frequency.

The former approach deals with the problems where the only available information is the aggregated series. It comprises purely mathematical methods proposed by Boot et al. (1967) and Jacobs (1994), and more theoretically founded model-based methods (Wei and Stram, 1990) relying on the ARIMA representation of the series to be disaggregated.

On the other hand, in the second case it is assumed that a logically correlated high frequency series is available. The approach includes the procedure proposed by Denton (1971) and the related one by Ginsburgh's (1973), which are adjustment methods; the method proposed by Chow and Lin (1971) and further developed by Bournay and Laroque (1979), Fernández (1981) and Litterman (1983) are optimal procedures. In addition, Al-Osh (1989), Wei and

Strram (1990), Guerrero (1990) and Guerrero and Martinez (1995) combine an ARIMA model-based techniques with the use of high frequency related series in a regression model to overcome some arbitrariness in the choice of the stochastic structure of the high frequency disturbances.

In this paper, disaggregation is performed according to the regression-based temporal disaggregation procedures of Chow-Lin (1971) and Fernandez (1981), and we compared the performance of the methods with an application to the GDP of Italy. Also the capability of forecasting of the two methods is analyzed.

It is also mentioned that disaggregation from low frequency (annually) series to high frequency (quarterly) series is conducted with the help of a software tool ECOTRIM, developed by Eurostat, the European Statistical Office (Di Fonzo, Roberrto Bercellen).

II. BRIEF DESCRIPTION OF THE REGRESSION MODEL-BASED TEMPORAL DISAGGREGATION APPROACH

A. Chow and Lin procedure:

This procedure is known as the best linear unbiased estimator (BLUE) approach, which was developed by Chow and Lin (1971, 1976). In this method, a regression model relates the unknown disaggregated series and a set of known high frequency indicators.

Suppose that annual series of N years are available which is to be disaggregated into quarterly series, which is related to the k indicator (related) series, then relationship between the disaggregated series (to be estimated) and indicators series is

$$y = X\beta + u \qquad (1)$$

where y is (n×1) vector (n=4N) of the quarterly series to be estimated, X is the matrix (n×k) of the k indicator variables which are observed quarterly, β is a (k×1) vector of coefficients, and u is the (n×1) vector of stochastic disturbances with mean, $E(u) = 0$ and variance, $E(uu') = V$, where V is a (n×n). matrix.

It has to be mentioned that the disaggregated model (1), at the high frequency level (here quarterly) is not directly observable and thus cannot be estimated. In Chow-Lin approach model (1) is transformed into a low frequency (here yearly) model, which is observable. This transformation is accomplished by pre-multiplying the model (1) by the (N×n) aggregation matrix $D = c' \otimes \mathrm{I}_N$, converting high frequency data into low frequency and where $c = (1,1,1,1)'$ and $\otimes$ denotes the Kronecker product.

After pre-multiplying the model (1) by *D*, the aggregated regression model is

$$y_0 = X_0\beta + u_0 \qquad (2)$$

where $y_0 = Dy$ is a (N×1) observed vector, and $X_0 = DX$ is a (N×k) matrix. The (N×1) aggregated disturbance vector, $u_0 = Du$ has mean $E(u_0) = E(Du) = DE(u) = 0$ and (N×N) covariance matrix, $E(u_0 u_0') = E(Duu'D') = DVD' = V_0$.

Now the aggregated model (2) at annual level is observable provided that y_0, X_0 and u_0 are known. The aggregation only affects the error process, while the parameters characterizing the linear relationship between the dependent and independent variables is completely described by β.

Estimation:
Chow and Lin (1971) derive the unbiased estimator $\hat{y}$ of y subject to the aggregation constraint (2). Assuming that V_0 is known (which means V is known), for the unbiased estimator of $\hat{y}$, it is required that the weighted sum of squared residuals (SSR) $= (\hat{y} - y)'V^{-1}(\hat{y} - y)$ is minimum and provided that

$$D\hat{y} = y_0 . \qquad (3)$$

Suppose that a linear unbiased estimator $\hat{y}$ of y satisfies for some matrix *A*, then according to the condition (3),

$$\hat{y} = Ay_0 = A(X_0\beta + u_0) \qquad (4)$$

So the expected estimation error

$$\begin{aligned} E(\hat{y} - y) &= E[A(X_0\beta + u_0) - (X\beta + u)] \\ &= (ADX - X)\beta \qquad (5) \\ &= (Ay_0 - X)\beta \end{aligned}$$

For an unbiased estimation, the expected error must be minimum, that is

$$E(\hat{y}-y)=0$$

To fulfill the condition the following must be satisfied:

$$Ay_0 - X = 0 \tag{6}$$

then, $\hat{y}-y = Au_0 - u$ (7)

with the covariance matrix

$$Cov(\hat{y}-y) = E[(\hat{y}-y)(\hat{y}-y)']$$
$$= E[(Au_0-u)(Au_0-u)']$$
$$= AV_0A' - AVD' - VD'A' + V \tag{8}$$

since $E(uu_0') = E[(y-X\beta)(y_0 - X_0\beta)']$

$$= E[(y-X\beta)(Dy-DX\beta)'] = VD'$$

By minimizing this equation (8) with respect to *A*, subject to (6), the solution for *A*, will be as

$$A = X(X_0'V_0^{-1}X_0)^{-1}X_0V_0^{-1} + (VD'V_0^{-1})$$
$$[\mathrm{I} - X_0(X_0'V_0^{-1}X_0)^{-1}X_0'V_0^{-1}]$$

Then the unbiased minimum variance estimator $\hat{y}$ is

$$\hat{y} = Ay_0 = X\hat{\beta} + (VD'V_0^{-1})\hat{u}_0 \tag{9}$$

where $\hat{\beta} = (X_0'V_0^{-1}X_0)^{-1}X_0'V_0^{-1}y_0$ (10)

$\hat{\beta}$ is the generalized least square estimator of the aggregated model, and the corresponding residual vector

$$\hat{u}_0 = [\mathrm{I} - X_0(X_0'V_0^{-1}X_0)^{-1}X_0'V_0^{-1}]$$

Again, $D\hat{y} = DX\hat{\beta} + D(VD'V_0^{-1})\hat{u}_0$

$$= X_0\hat{\beta} + u_0 = y_0$$

which fulfills the requirement set in (3). We have the estimator $\hat{y}$ of y as

$$\hat{y} = X\hat{\beta} + (VD'V_0^{-1})\hat{u}_0 \tag{11}$$

The first term on the RHS of equation (11) gives the predicted quarterly y based on observed quarterly X and estimated $\hat{\beta}$ from annual totals, equation (10), whereas the second term allocates annual residuals $\hat{u}_0$ to the four quarters of the year such that the annual sum of the interpolated values equal the observed value y_0 .

A major drawback of the Chow and Lin (1971) procedure is that covariance matrix V is unknown. Chow and Lin (1971) have proposed two assumptions to estimate the covariance matrix *V*, which are

i. the disturbances are not serially correlated, each with variance σ^2 ,then $V=\sigma^2\mathrm{I}$, and
ii. the disturbances u follow the autoregressive model of first order, AR(1) as

$$u_t = \rho u_{t-1} + \varepsilon_t$$
$$|\rho| < 1 \ \forall \text{ t}$$

ε ~i.i.d $(0, \sigma_\varepsilon^{\ 2})$, and $E(\varepsilon_i\varepsilon_j) = 0$, i≠j

Under assumption (a), $\hat{\beta}$ reduces to the OLS estimator, $\hat{\beta} = (X_0'X_0)^{-1}X_0'y_0$, and the second term on the RHS of equation (12) amounts to allocating one quarter of the annual residual to each quarter of the year. Under assumption (b), V takes the form

$$V = \frac{\sigma_\varepsilon^{\ 2}}{(1-\rho^2)}\begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{n-1} \\ \rho & 1 & \rho^2 & \cdots & \rho^{n-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{n-3} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho^{n-1} & \rho^{n-2} & \cdots & \cdots & 1 \end{bmatrix}$$

ρ is unknown and has to be estimated. Unfortunately there may not be a convenient way of estimating *ρ*. If a sufficient length of quarterly data is available then one may estimate *ρ* from the OLS residuals of equation (1). Chow and Lin(1971) suggested a procedure to estimate *ρ*. The following polynomial need to solve

$$\hat{\rho}_a = \frac{\rho(\rho+1)(\rho^2+1)^2}{2(\rho^2+\rho+2)} \tag{12}$$

where $\hat{\rho}_a$ is the estimated first order autocorrelation coefficient from the OLS residuals of the annual-data regression (4). The equation (5) is derived by using the relationship that ρ_a is equal to the ratio of the off diagonal element to the diagonal element of the matrix $V_0 = DVD'$. Under the assumption that both ρ_a and ρ are positive, the equation (12) has only one positive real root which is an estimate of *ρ*.

If it is assumed that the aggregated disturbances term *u* follow the normal distribution as, *u* ~N (0, *V)*, then *ρ*, β and $\sigma_\varepsilon^{\ 2}$ can be estimated through maximization of the log likelihood function.

In our study of temporal disaggregating, with the help of ECOTRIM, where a scanning procedure is adopted to estimate *ρ*. In this process first of all a set of values between -1 to 1 is assigned to *ρ* and then *V*, $\hat{\beta}, \sigma_\varepsilon^{\ 2}$ are determined by choosing the value which maximizes the log likelihood function (Di Fonzo,1987).

B. Fernandez Random walk Model:

The assumption of no serial correlation in the disturbances (residuals) of the disaggregated estimates is not generally supported by empirical evidence. There are two static variants to overcome the limitation of serial correlation in the disaggregated estimates of Chow and Lin approach. One is the random walk model developed by Fernandez (1981), and the other is the random walk-Markov model derived by Litterman (1983). In this study, the Fernandez technique will be considered.

Fernandez argues that economic time series data are often composed of a trend and a cyclical component, and he suggests to transform the series first to eliminate the trend before estimation. He proposes the usual regression model of Chow-Lin; and estimates $\hat{\beta}$ and $\hat{y}$ but assuming that the disturbances (residuals) in the disaggregated model follow a random walk process as:

$$u_t = u_{t-1} + \varepsilon_t \quad t=1,2,\ldots..n, \qquad (13)$$

where the white noise $\varepsilon_t \sim N(0, \sigma^2)$ given that $u_0 = 0$. This approach allows to simplify the computation, the covariance matrices are:

$$Cov(\varepsilon_t \varepsilon_l) = \sigma^2 \min(t,l) \quad t \neq l \; t,l = 1,2,\ldots\ldots n$$

which means $E(uu') = V = \sigma^2 (\Delta'_{1.n}\Delta_{1,n})^{-1}$

and $V_0 = DVD' = \sigma^2 D(\Delta'_{1,n}\Delta_{1,n})^{-1} D'$ (14)

where $\Delta_{1,n}$ is the (n×n) matrix performing (approximate) first differences as

$$\Delta_{1,n} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix}$$

Putting the value of (14) and as defined early, $V_0 = DVD'$ in (9) and (10) follows:

$$\hat{y} = X\hat{\beta} + (\Delta'_{1,n}\Delta_{1,n})^{-1} D' \left[D(\Delta'_{1,n}\Delta_{1,n})^{-1} D'\right] \hat{u}_0$$

and

$$\hat{\beta} = \left\langle X'_0 \left[D(\Delta'_{1,n}\Delta_{1,n})^{-1}\right] X_0 \right\rangle^{-1} X'_0 \left[D(\Delta'_{1,n}\Delta_{1,n})^{-1} D'\right]^{-1} y_0$$

III. TEMPORAL DISAGGREGATION: AN APPLICATION TO ITALIAN GDP

In this section we will apply Chow-Lin and Fernandez temporal disaggregation techniques to disaggregate annual GDP of Italy into quarterly series using quarterly industrial production index(IPI) as indicator series, and will make comparison between the two methods. In addition, the forecasting capacity of each technique will be tested by a simple rolling extrapolating experiment.

The estimation is carried out using the entire data span from the year 1990 to 2009/2 (up to second quarter of 2009). It has to be mentioned that quarterly GDP of Italy is already available in the estimation period. However, we aggregate the quarterly GDP series from 1990 to 2008 to make it annual series, in order to assess the disaggregating quality and forecasting ability of two methods from different points of view. Industrial production index is available in monthly and we averaged to make the series into quarterly.

The aggregated annual series, which have to be disaggregated into quarterly, are:

1. GDP at current prices-raw data
2. GDP at current prices-seasonally adjusted
3. GDP at previous year's prices-raw data, and
4. GDP at previous year's prices -seasonally adjusted.

The quarterly indicator series are:

1. Industrial Production Index-raw data, and
2. Industrial Production Index-seasonally adjusted.

To find out the procedure, which delivers an estimation closest to the true (original) series, it is necessary to carry out some simulations for comparing the different methods. We performed several simulations with different time series, which are discussed in succession. True quarterly GDP up to the second quarter of 2009, which is already published, is also considered in this process.

A. Disaggregation of Italian GDP (Current prices-Raw data):

With the quarterly indicator series Industrial Production Index (IPI)-raw data, the annual GDP at current prices (raw data) is disaggregated into quarterly series by applying Chow-Lin and Fernandez procedure, and the analytical results are summarized in the following Table.1:

Table 1: Results of the disaggregation of Italian GDP at current prices (raw data, 1990-2009/2)

	Chow-Lin (MinSSR)	Chow-Lin (MaxLog)	Fernandez
Valid Cases (years):	19	19	19
The value of the parameter (ρ) :	0.854056	0.975888	-
i. Constant (value)	-457963	50843	31469
(Std Error)	(172498.45)	(125198.91)	(83829.42)
(t-Stat)	(-2.65)	(0.41)	(0.38)
ii. IPI-q(raw)(value)	7585.6	2401.02	1550.69
(Std Error)	(1756.08)	(1255.12)	(920.78)
(t-Stat)	(4.32	(1.91)	(1.68)
RMSE(%) between the growth rates of Indicator & Disaggregated GDP			
i. T-1 growth (lag 1)	25.287005	2.339137	4.481945
ii. T-4 growth(lag 4)	7.533462	4.772488	5.153360

where the root mean square errors (RMSE) between the quarterly growth rates of the indicator series IPI (raw) and the estimated quarterly disaggregated GDP at current prices (raw) can be expressed as:

RMSE: T-1 growth (lag of one quarter)

$$= \sqrt{\sum \frac{(x_t - \hat{y}_t)^2}{n-1}} \times 100, \text{ and}$$

RMSE: T-4 growth (lag of four quarters)

$$= \sqrt{\sum \frac{(u_t - \hat{v}_t)^2}{n-4}} \times 100$$

x_t and $\hat{y}_t$ denote the quarterly T-1 growth rates; and u_t and $\hat{v}_t$ denote quarterly T-4 growth rates of the indicator series and estimated (disaggregated) series respectively; and n=(4×19+2)=78.

As RMSE evaluates the precision of the estimates, from the Table.1, it is evident that min sum of Squares estimates by Chow-Lin (MinSSR) is far worse than the maximum log likelihood estimates of Chow-Lin (MaxLog) as well as the estimates by Fernandez. In addition, it is evident from Figure1 and Figure 2 that there are huge discrepancies between the true series and disaggregated series by Chow-Lin min sum of Squares estimates. So for farther analysis this estimate of Chow-Lin will not be considered

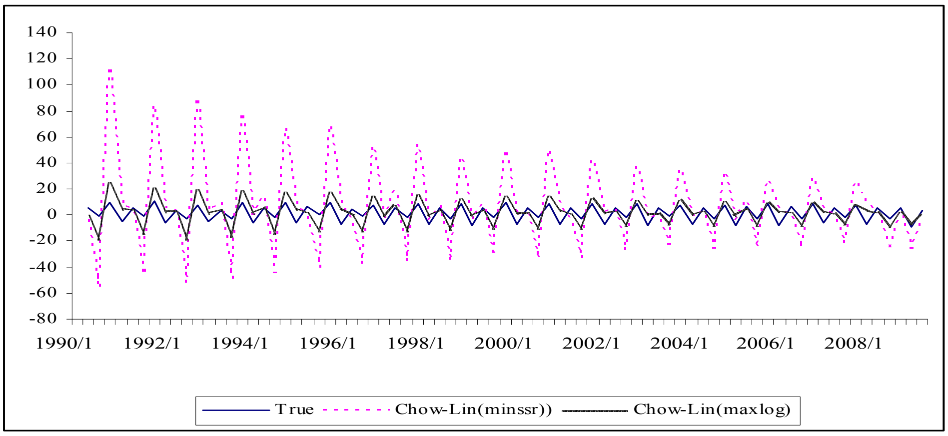

Figure 1: T-1 growth rates (quarterly) of GDP disaggregated by Chow-Lin and actual GDP (1990-2009/2)

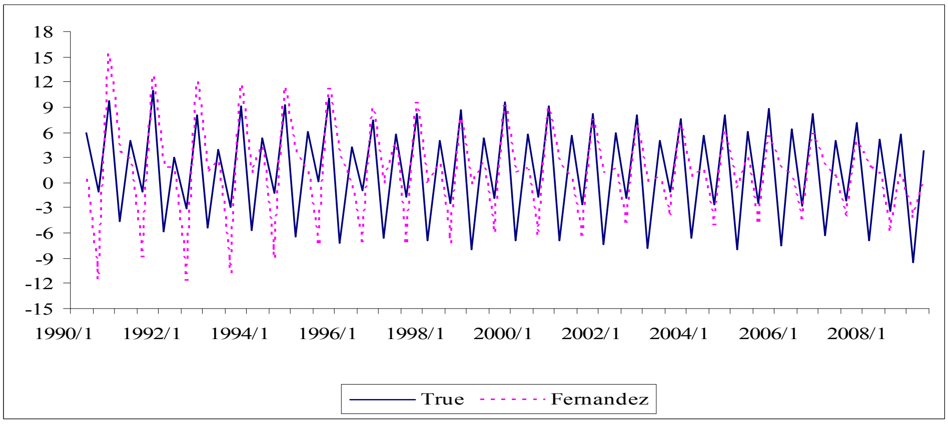

Figure 2: T-1 growth rates (quarterly) of GDP disaggregated by Fernandez and actual GDP (1990-2009/2).

In the case of RMSE for T-1 grow rates (Table.1), it can be said that disaggregation by Chow-Lin (MaxLog) procedure yields better results than Fernandez, which is furthermore visualized from Figure 3 and Figure 4 as follows

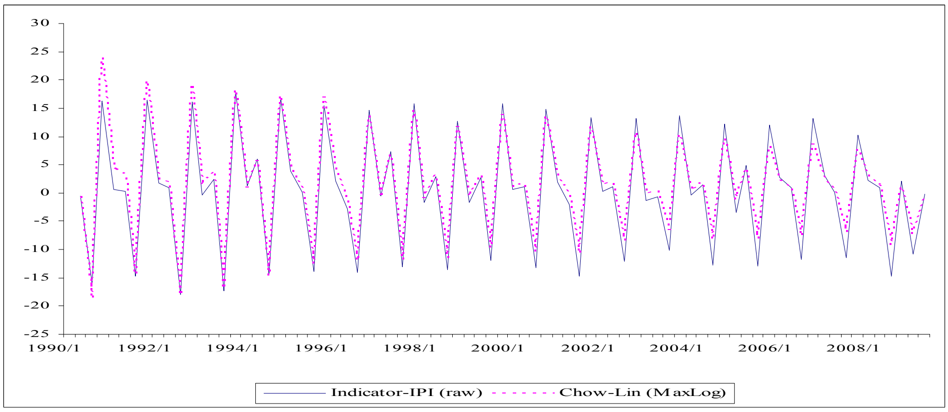

Figure 3: T-1 growth rates (quarterly) of GDP disaggregated by Chow-Lin and indicator, IPI (1990-2009/2)

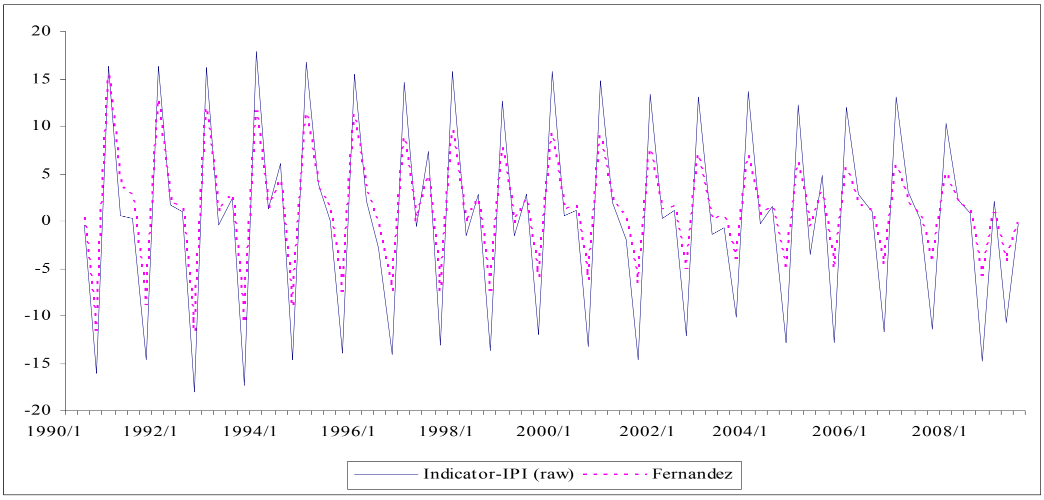

Figure 4: T-1 growth rates (quarterly) of GDP disaggregated by Fernandez and indicator, IPI (1990-2009/2)

It is interested to note (Figure 3 and Figure 4) that at the beginning Chow-Lin (MaxLog) estimates departure highly from the indicator series but in the long run it become smoother, whereas inverse situation is happen for Fernandez.

Although, from the point of T-4 growth rates (Figure 5) Fernandez leads to a slightly better result than the Chow-Lin (MaxLog), two approaches displayed the almost same (fairly higher) departure from the indicator series.

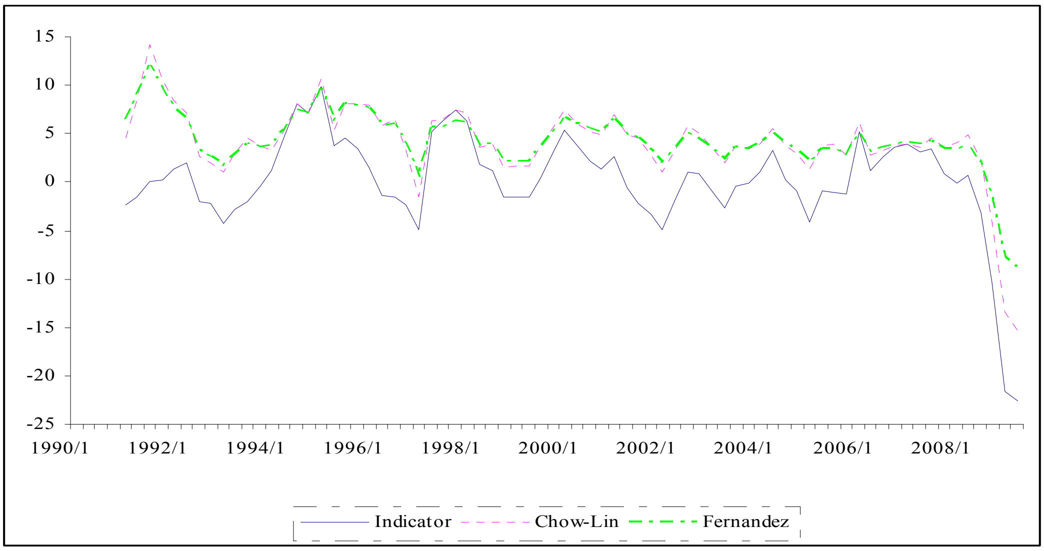

Figure 5: T-1 Growth rates (quarterly) of GDP disaggregated by Chow-Lin (Maxlog) and Fernandez and over the indicator, IPI (1990-2009/2)

Forecasting:

The quality of a model not only depends on the estimation ability but also on the capacity of forecasting about the future movement of the series. By forecasting it can be displayed the consistency of the disaggregated series obtained from the aggregated regression model by different procedures.

The series are extrapolated quarterly year by year (rolling extrapolated exercise) from 2000 to 2008, on the basis of disaggreagation procedure using data from 1990 to 1999 for the year 2000, from

1990 to 2000 for the year 2001, and so on. The same process is followed to disaggregate the annual series into quarterly. The results of forecasting by Chow-Lin (MaxLog) and Fernandez are summarized below in Table 2:

It is clearly evident (Table.2) that in the case of forecasting Fernandez procedure totally outperforms Chow-Lin (MaxLog), which also displays by the Figure 6.

From the point of view of relative differences (in %) between the annual extrapolated and disaggregated GDP, Fernandez explicit more smooth and less fluctuated values (Figure 6).

Therefore, it can be said that Fernandez approach produces forecasts which in line with the temporally disaggregated estimates, which would be an important characteristic for a National Statistical Institute (NSI). For this means that Fernandez procedure requires less revision (or correction or adjustment) than the Chow-Lin (MaxLog) for prediction of the economic series.

Table.2 Forecasting results of GDP at current prices (raw data, 2000-2008)

	Chow-Lin (MaxLog)	Fernandez
RMSE(%) between the growth rates of Extrapolated & disaggregated GDP		
i. T-1 growth(lag one)	5.200102	1.353491
ii. T-4 growth(lag fours)	8.660717	3.304290

It has to be mentioned that in the forecasting analysis (graphical) for the case of T-4 growth rates, both Chow-Lin (MaxLog) significantly underestimate the disaggregated series although both approaches follow almost the same pattern of change in accordance with disaggregated series.

So, we conclude that for disaggregating the GDP (raw data) Chow-Lin (MaxLog) method estimates the disaggregated series more accurately than the Fernandez method, whereas the extrapolating capacity of Fernandez is superior to Chow-Lin (Maxlog)

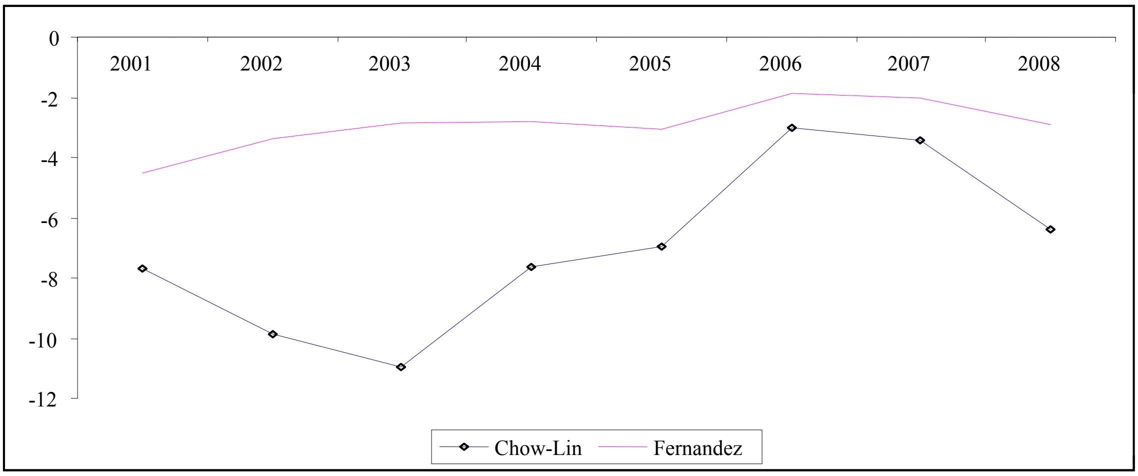

Figure 6: Relative differences (in %) between the annual extrapolated and disaggregated GDP (2001-2008)

B. Disaggregating GDP (previous year's prices-Seasonally adjusted)**:**
From the economic point of view, GDP at constant prices with seasonally adjusted is regarded as the most important and useful series. Let disaggregate this GDP at previous year's prices with seasonally adjusted data relate to the indicator series, quarterly Industrial Production Index (IPI) also seasonally adjusted, the results are shown briefly in Table.3.

Although Chow-Lin (MaxLog) disaggregates the series more accurately than the Fernandez but the estimation performance between the procedures (Table.3) differs not so significantly (direction of departures is almost similar), which is supported by the following Figure 7.

Similar situation is observed for the case T-4 growth rates.

Table.3 Results of the disaggregation of Italian GDP at previous year's prices (seasonally adjusted, 1990-2009/2)

	Chow-Lin(MinSSR)	Chow-Lin(MaxLog)	Fernandez
The value of the parameter(ρ) :	0.85671018	0.97660355	-
i .Constant (value)	-409767	73684	36845
(Std Error)	(170561.65)	(117319.3)	(78056.47)
(t-Stat)	(-2.4)	(0.63)	(0.47)
ii .IPI-q(raw)(value)	6997.6	2056.52	1343.59
(Std Error)	(1735.62)	(1169.21)	(856.21)
(t-Stat)	(4.03)	(1.76)	(1.57)
RMSE(%) between the growth rates of Indicator & Disaggregated GDP			
i. T-1 growth (lag one)	3.033000	1.456928	1.702806
ii. T-4 growth (lag fours)	6.881218	5.365140	5.718113

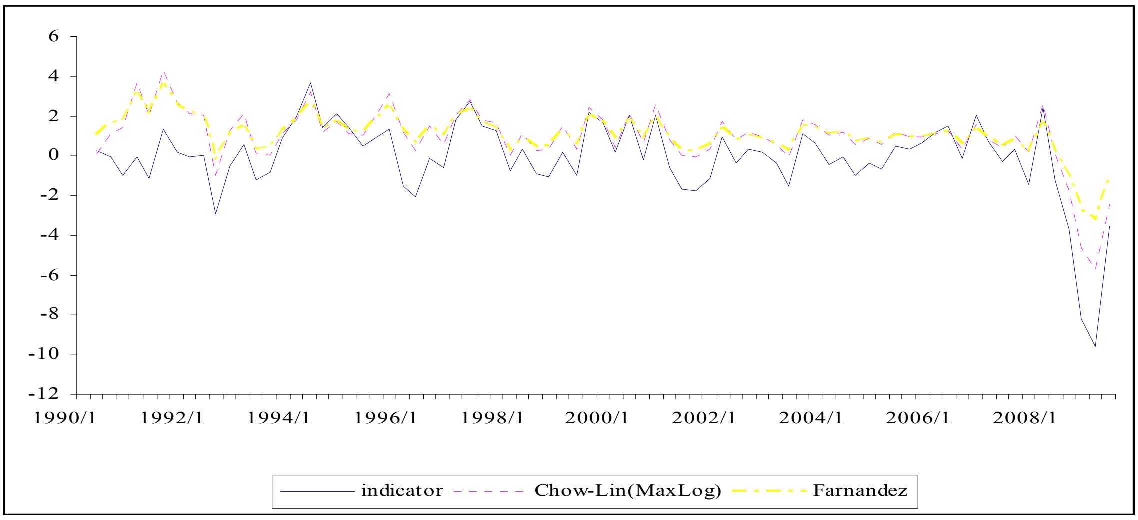

Figure 7: T-1 Growth rates (quarterly) of GDP disaggregated by Chow-Lin (Maxlog) and Fernandez over the indicator, IPI (1990-2009/2, previous year's prices-seasonally adjusted)

Forecasting:
GDP at previous year's prices with seasonally adjusted data is forecasted by Chow-Lin (MaxLog) and Fernandez as same manner as for the GDP at current prices (raw data). The results are as follows in Table.4:

Table.4 exhibits that Fernandez technique forecasts the aggregated series far better than Chow-Lin (MaxLog) as it did for the GDP at current prices (raw data). It is important to mention that both procedures underestimate the aggregated series for T-1 as well as T-4 growth rates (Figure 8, Figure 9).

Table.4. Forecasting results of GDP at previous year's prices (seasonally adj., 2000-2008)

	Chow-Lin (MaxLog)	Fernandez
RMSE(%) between the growth rates of Extrapolated & disaggregated GDP		
i. T-1 growth(lag one)	5.200102	1.353491
ii. T-4 growth(lag fours)	8.660717	3.304290

Figure 8: T-1 growth rates of disaggregated and extrapolated GDP by Chow-Lin (2000-08).

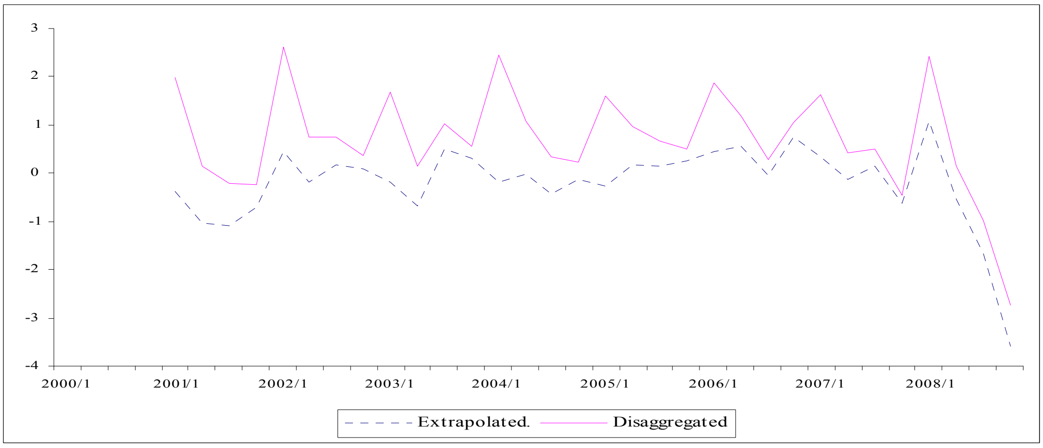

Figure 9: T-1 growth rates of disaggregated and extrapolated GDP by Fernandez (2000-08).

Therefore, the remaking point for disaggregating the series at constant prices with seasonally adjusted data, Chow-Lin (MaxLog) procedure is slightly ahead but for the case of forecasting Fernandez is superior.

It is noticed that for the case of GDP at previous year's prices-seasonally adjusted series, Chow-Lin (MaxLog) as well as Fernandez, underestimate the disaggregated series for both types of growth (T-1 and T-4).

Similar analyses are conducted for the other series of the GDP (current prices-seasonally adjusted, precious year's prices-raw data) and the results are shown in Table 5, where the parenthesized values are the RMSEs between the extrapolated and disaggregated growth rates.

Finally, it is ended with the conclusion that for disaggregating the annual series, Chow-Lin (MaxLog) technique is reliable whereas for making prediction about the future, Fernandez approach recommended

Table 5: Results of the disaggregation of Italian GDP

	Chow-Lin (MaxLog)	Fernandez
RMSE (%) (GDP at current prices-seasonally adjusted		
i. T-1 growth(lag 1)	1.408391 (3.027270)	1.668112 (1.160856)
ii. T-4 growth(lag 4)	4.990734 (7.523554)	5.383890 (3.197003)
RMSE (%) (GDP at previous year's prices-raw		
i. T-1 growth(lag 1)	2.506902 (5.395209)	4.222282 (1.705397)
ii. T-4 growth(lag 4)	5.170581 (8.706803)	5.483667 (4.037387)

IV. CONCLUSION

This study helped us to familiarize with the basis temporal disaggregation procedures based on the regression model. We have acquired a good knowledge and understanding how each method works for different series.

We have disaggregated four different series of Italian GDP by the regression method of Chow-Lin and Fernandez and carried out different simulation experiments to evaluate and find out which procedure closely estimates the disaggregated series as well forecasts more precisely.

The core findings of our analysis is that Chow-Lin (MaxLog) technique estimates more correctly than Fernandez although for the seasonally adjusted series the estimates from both procedures are very close. On the other hand, the prediction abilities of Fernandez, seem better than Chow-Lin for any disaggregated series of our experiment.

It has to be mentioned that our experiment is totally a scholastic process and that both methods are based on some strong assumptions about the econometric link between the series of interest and its related indicator. In addition, the indicator series, industrial index only a part (around 35% of Italian GDP) of total economy whereas GDP, total economy of a country, which is very broad, diverts and depends on many factors. Therefore, it is not easy to find out a procedure, which reveals the true picture of the economy.

This result will help to us to find out the feasibility of applying the appropriate procedure to disaggregate the annual series for the countries where quarterly national accounts (QNA) are not available.

The ending word is that, the study provides us a preliminary basis in this area, which will benefit in future research.

REFERENCES

[1] Barcellan, R., "Ecotrim: A program for temporal disaggregation of time series", Workshop on Quarterly National Accounts, Eurostat, Theme 2 Economy and finance, 79-95, 2002 edition.

[2] Chen, B., "An Empirical Comparison of Methods for Temporal disaggregation at the National Accounts" Office of Directors Bureau of Economic Analysis, Washington, DC, August 30, 2007

[3] Chow, G. C. and Lin, A., "Best linear unbiased interpolation, distribution and extrapolation of time series by related series", Review of Economics and Statistics, 53 (1971), 372-375.

[5] Di Fonzo, T. and M. Marini, "Simultaneous and Two-step Reconciliation of Systems of Time Series", Working Paper Series, N. 9, May 2009.

[6] Di Fonzo, T., "Introduction to the priceless of benchmarking and Temporal disaggregation for economic series", Talk n. 1, Santiago, Central Bank of Chile,July 2008.

[7] Di Fonzo, T., "Extension of the classical Chow and Lon's temporal disaggregating method", [2] Talk n. 2, Santiago, Central Bank of Chile, July 2008.

[8] Di Fonzo, T., Benchmarking a system of time series: Denton's movement preservation principle vs. a data based procedure", Eurostat, Working Paper 2006 No KS-DT-05-008-EN.

[9] Di Fonzo, T., "Temporal disaggregation of economic time series: towards a dynamic extension", Working papers and studies, Eurostat, Theme 1 General statistics, 2003 edition.

[10] Di Fonzo, T., "Temporal disaggregation using related series: log-transformation and dynamic extensions"," *Rivista Internazionale di Scienze Economiche e Commerciali*, 50, 371-400, 2003.

[11] Di Fonzo, T., "Temporal disaggregation of a system of time series when the aggregate is known. Optimal vs. adjustment methods", Workshop on Quarterly National Accounts, Eurostat, Theme 2 Economy and finance, 63-77, 2002 edition.

[12] Di Fonzo, T., "The estimation of *M* disaggregated time series when contemporaneous and temporal aggregates are known," *The Review of Economics and Statistics*, 72, 178 -182, 1990.

[13] Fernandez, R. B., "A methodological note on the estimation of time series", Review of Economics and Statistics, 63 (1981), 471-478.

[14] Kemal, A. R. and Arby, M. F., "Quarterization of Annual GDP of Pakistan", Pakistan Institute of Development Economics, Statistical paper series, No. 5, 2004.

[15] Lupi, C. and Parigi, G., "Temporal of time disaggregation series: Some econometrisues", Workshop on Quarterly National Accounts, Eurostat, Theme 2 Economy and finance: 111-140, 2002 edition.

[16] Muller, C., "Testing temporal disaggrega tion", Swiss institute of Business Cycle Research, Zurich, No. 134, April 2006.

[17] Tilak, A. and Lee, C.(1998), "Best Linear Unbiased Disaggregation of Annual GDP to Quarterly Figures: The Case of Malaysia", Institute of South East Asian Studies, Singapore, Journal of Forecasting J. Forecast. 17, 527-53 537 (1998).