ITER: A QUARTERLY INDICATOR OF REGIONAL ECONOMIC ACTIVITY IN ITALY

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Abstract

This work documents the construction of the new quarterly indicator of regional economic activity (*Indicatore Trimestrale dell'Economia Regionale* – ITER), which uses a parsimonious set of regional variables and combines them by means of temporal disaggregation techniques to obtain a quarterly index that is consistent with the official data on national and regional GDP and marked by a small lag compared with the reference period. The methodology was implemented to produce quarterly indicators for the economies of Italy's four macro-areas in the period 1995-2017. With a view to assessing the performance of the quarterly indicator, a forecasting exercise was conducted regarding annual GDP growth in the four macro-areas for the period 2014-17. The forecasting performance of ITER is in line with that of the indicators developed by other national research institutions.

JEL Classification: C22, C61, C82.
Keywords: temporal disaggregation by related series, regional economies benchmarking and extrapolation, real time estimates.

Contents

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1. Introduction

The availability of regional data is of the utmost importance for medium and large economies characterized by territorial dualism or decentralized fiscal systems. The case of Italy is paradigmatic. The industrialized North is open to world trade, while the Southern regions are less exposed to international competition and are lagging behind in terms of growth. Moreover, Italy has been moving toward fiscal federalism, for more than a decade, which in principle should require a full set of regional statistics suitable for supporting policy decisions.

Notwithstanding these needs, economic cycle analysis is difficult for the Italian regions, given the lack of reliable and timely data. Official statistics on annual GDP and its components are released with a long delay and only a few business cycle indicators cover all the twenty primary administrative regions.

In this paper we propose a quarterly Indicator of Territorial Economic Activity (ITER),[1] able to trace in real time the GDP of Italy's four main macro-areas (North-West, North-East, Centre and South). ITER combines the small number of available local indicators and the official information on regional and national GDP released by the Italian National Institute of Statistics (Istat). These data are characterized by different frequencies, different publication lags and different geographical coverage. In more detail, the model uses three sources of information: a) the regional annual GDP, released by Istat after a delay of about one year; b) quarterly regional indicators, provided with a short delay by public or private organizations; and c) a quarterly series of Italian GDP, published one month after the reference period.[2]

The methodology adopted by the ITER is based on the literature on temporal disaggregation, extended to take into account the additive cross-sectional units. The model provides a quarterly time series disaggregation of the annual GDP of the four macro-areas, subject to the constraint that the sum of the quarterly regional values is equal to the Italian GDP. Piselli and Pappalardo (2002) provide an earlier implementation of temporal disaggregation techniques in order to evaluate territorial business cycles in Italy, while Cuevas, Quilis and Espasa (2015) have recently adopted a similar model in order to produce estimates of the quarterly GDP for Spanish regions.

The timing of the data releases needed to estimate ITER is such that the indicator is able to provide an estimate of the regional dynamics with a lag of about one quarter, therefore well in advance with respect to the official series. Moreover, a byproduct of the model is a quarterly time series for territorial economic activity, starting from the mid-nineties, that may be of interest per se, for a variety of regional empirical studies.

Although ITER is based on GDP data and maintains an accounting consistency between regional and national series, the resulting index should not be considered as an official regional GDP. The time series used to estimate ITER may be provided by private entities and in some cases are produced ad hoc by us; moreover we do not apply chain-linking to the additivity constraints across regions, as is done in the official statistics.

[1] In Italian the ITER acronym stands for "*Indicatore Trimestrale dell'Economia Regionale*".
[2] Note that before May 2018, flash estimates of Italy's GDP were only released after 45 days.

With these caveats, ITER can be considered useful to provide timely information on the quarterly territorial developments. For instance, in late winter a preliminary estimate of the economic growth for the previous year may be provided, in advance with respect to those released by private organizations (Prometeia and SVIMEZ, which usually publish in late spring). In addition, a preliminary assessment of the GDP for the current year may be obtained in autumn, starting from the carryover effect of the quarterly series.

This paper describes the statistical model adopted to estimate ITER and briefly discusses its out-of-sample forecasts. At present, a comprehensive forecasting analysis is not performed, due to the lack of long enough time series. Still, a preliminary exercise seems to show that the forecasts on GDP produced by ITER are in line with those published by other private analysts.

The paper is organized as follows: Section 2 introduces the econometric model and Section 3 deals with temporal and regional aggregation constraints. Section 4 briefly describes the data set and the statistical treatment of the data. Section 5 presents recent estimates and an out of sample exercise and Section 6 compares the empirical properties with alternative approaches. Section 7 concludes.

2. The temporal disaggregation and forecasting methodology

The temporal disaggregation method proposed by Chow and Lin (1971), subsequently extended and implemented for Italy's national accounts by Barbone, Bodo and Visco (1981), is our starting point. The Chow-Lin approach derives high-frequency estimates of a given series by exploiting the information conveyed by a set of indicators observed at the desired frequency (or even higher) and that are significantly correlated with the variable of interest.

More specifically, the disaggregation method assumes the existence of the following linear relationship between the dependent variable and a set of *K* indicators, at the desired infra-annual frequency

(1) $$y_i = X_i\beta + \varepsilon_i$$

where, in the case considered here, $y_i = \{y_{i1}, \ldots, y_{it}, \ldots, y_{iN}\}'$ refers to the (unobserved) quarterly regional GDP time series, with $i=1,\ldots,M,$ and t respectively indexing regions and quarters, and where X_i is an NxK matrix and ε_i is a random disturbance term with a covariance matrix $E(\varepsilon_i \varepsilon_i') = \sigma^2 \Omega$.

In order to allow for serial correlation in model residuals, it is assumed that the stochastic error term evolves over time according to the following first-order autoregressive model

(2) $$\varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it},$$

where u_{it} is a white-noise process with zero mean and a variance equal to σ^2.

By applying a proper aggregation operator, which in the case of the quarterly disaggregation of a yearly time series is given by a C matrix of dimensions Tx$(4T)$, where T is the length of the annual series, the higher frequency model (1) can be aggregated at an annual frequency as follows:

(3) $$\bar{y}_i = \bar{X}_i\beta + \bar{\varepsilon}_i$$

where $\bar{y}_i = Cy_i$ now coincides with the observed annual regional GDP series and where $\bar{X}_i = CX_i$, $\bar{\varepsilon}_i = C\varepsilon_i$, $C = (I \otimes c)$ and $c = [1\ 1\ 1\ 1]$, in the case of the production of quarterly GDP estimates.

When recast at an annual frequency, the model only uses observed variables and hence its parameters can be estimated by the usual methods, such as maximum likelihood. Once the model's parameter estimates have been obtained, quarterly estimates of the regional GDP series can be computed by the following formula:

(4) $$\hat{y}_i = X_i\hat{\beta} + \hat{\Omega}C'\left(C\,\hat{\Omega}C'\right)^{-1}(\bar{y}_i - \bar{X}_i\hat{\beta}).$$

Hence, equation (4) provides the basis for the ex-post interpolation or distribution of a given yearly time series according to the Chow-Lin methodology. The temporal disaggregation approach can, however, be extended to yield forecasts too, or ex-ante estimates, of the quarterly series, prior to the release of the corresponding annual series. By exploiting the information on high-frequency indicators that becomes available during the year, it is possible to extrapolate the data for the quarterly GDP series beyond the end of the corresponding annual series.

Ex-ante estimates for t=N+1, N+2,…,N+F can be computed through the following recursion:

(5) $$\hat{\hat{y}}_{i,N+f} = X_{i,N+f}\hat{\beta} + \hat{\varepsilon}_{i,N+f}$$

where

(6) $$\hat{\varepsilon}_{i,N+f} = \hat{\rho}\hat{\varepsilon}_{i,N+f-1}, \quad f=1,2,\ldots,F.$$

Differently from ex-post estimates, the ex-ante quarterly estimates are not anchored to the corresponding annual value. Therefore, according to their nature, they are updated after the release of regional annual accounts, when they are replaced by ex-post estimates computed by equation (4).

Once forecasts for all four quarters of the year have been obtained according to the described procedure, by cumulating the quarterly figures it is possible to get a prediction for the annual regional GDP series. In order to make allowances for the long delay in publishing the annual regional GDP series, forecasts can be produced with a time horizon of more than one year. As an example, by letting T denote the last year for which the official annual regional GDP estimates are available, it is possible to extend the forecast horizon up to the first two quarters of the year T+2 and therefore well in advance of the release of the official figures. Table 1 displays the time span of the quarterly estimates that can be obtained by using the ITER's temporal disaggregation procedure; three consecutive years are presented, from T to T+2.

Table 1. Available information and corresponding ITER estimates

ITER Region 1												
…	Ex-post estimates				Ex-ante estimates							
ITER Region *M*												
National quarterly GDP												
Annual GDP Region 1												
…												
Annual GDP Region *M*												
Quarter	1	2	3	4	1	2	3	4	1	2	3	4
Year	*T*				*T+1*				*T+2*			

Note: The table considers real-time estimates that could be produced in October of the year *T+2*. The table refers to the releases of the regional data (NUTS 2 level territorial units), as the indicator is designed for regions; in the empirical application presented below the indicator is produced for macro-regions (NUTS 1 level territorial units), for which a preliminary estimate of GDP is provided by Istat in summer of the year *T+1*.

3. Aggregation constraints in the temporal and spatial dimensions

The temporal disaggregation methods are designed in order to ensure consistency between high frequency estimated values and the corresponding low frequency series. In the case of our GDP series, this means placing the ex-post consistency between the yearly and the quarterly regional estimates, over the four quarters of each year,

(7) $$\sum_{q=1}^{4} y_{iaq} = \bar{y}_{ia}, \quad (a=1,\ldots,T)$$

where y_{iaq} denotes the quarterly GDP series in region i, year a and quarter q and $\bar{y}_{ia}$ is the corresponding annual series.

Quarterly regional GDP estimates, as well as the corresponding yearly series, also have to satisfy a constraint specific to the cross-sectional structure: in each quarter, the sum of the regional GDP estimates over all regions must be equal to the national quarterly GDP value, as in:

(8) $$\sum_{i=1}^{M} y_{iaq} = \bar{\bar{y}}_{aq}$$

where $\bar{\bar{y}}_{aq}$ denotes the quarterly national GDP series.

Methods for addressing the joint temporal disaggregation of multiple time series under cross-sectional constraints have been proposed in the literature, e.g. by Rossi (1982) and Di Fonzo (1990). More recently, Cuevas, Quilis and Espasa (2015), have developed a new two-stage approach; they estimate quarterly individual time series which are then balanced in the second stage (through a constrained quadratic optimization algorithm), in order to impose both the temporal and the transversal constraints. In this work a slightly simpler version of this two-stage approach is considered by implementing, in the second stage, the bi-proportional adjustment method initially proposed by Bacharach (1965).

When producing ex-ante estimates, the information on the annual figures for regional GDP is unavailable, hence only the cross-sectional constraints apply. A straightforward way of imposing consistency between regional and national quarterly estimates, in analogy with Proietti (2002) is

based on a proportional adjustment. According to this procedure, letting $\hat{\hat{y}}_{i,N+f}$, i=1,…, M, thus denoting as above the ex-ante quarterly regional GDP estimates, the second stage balanced estimates are computed as:

$$\hat{\hat{y}}^{*}_{i,N+f} = \hat{\hat{y}}_{i,N+f} + w_{i,N+f} D_{N+f} \quad (9)$$

where $D_{N+f} = \bar{\bar{y}}_{N+f} - \sum_{i=1}^{M} \hat{\hat{y}}_{i,N+f}$ denotes the discrepancy between the national GDP figure in quarter $N+f$ and the corresponding sum of the ex-ante regional estimates and where $w_{i,T+f}$ is a weight proportional to the economic size of the region, which is normalized so as to sum to 1 over the M regions, i.e. $\sum_{i=1}^{M} w_{i,N+f} = 1$.

4. The pool of quarterly territorial indicators

In order to get reliable estimates of the unobserved quarterly regional GDP series using the Chow-Lin approach, the selection of the high frequency indicators is crucial; they should be highly correlated with the macro-regional GDP and the relationship should be sufficiently stable over time.

We collected indicators representing different features of the regional business cycle. They refer to the demand and supply sides of the economy and range from goods and services markets to labour and credit markets. The list of selected variables is provided below, together with a short description of each indicator.[3]

Number of employed workers (quarterly series; availability: about two and half months delay. Sources: Istat and INPS). – The total number of both independent and payroll employees resident in the region. The measurement of payroll workers is net of the full-time equivalent number of workers receiving benefits under the *Cassa integrazione guadagni* (wage supplementation) program.

Export of goods (quarterly series; availability: about three months delay. Source: Istat). – Volume of exports.

Electricity consumption (monthly series; availability: about 1 month delay. Source: Terna). – Total amount of electric energy dispatched quarterly (in GWh).

Regional Index of Industrial Production (monthly series; availability: about 1 month delay. Source: our calculations based on Istat data). – See the Appendix for a detailed description.

Business demographics (monthly series; availability: about 1 month delay. Source: our calculations based on Infocamere data). – The number of new firms recorded in the public registry in each quarter, net of transfers.

[3] At first, we also considered car registrations as an explanatory variable. Later, this variable was excluded, due to its low significance in preliminary regressions. In a future extension, a data set including payments will be available and will provide more timely information.

Bank loans to the private sector (monthly series; availability: about 1 month delay. Source: Banca d'Italia). – End-of-quarter outstanding amounts of bank loans to firms and households, deflated by the consumer price index.

Residential transactions (quarterly series; availability: about 2 months delay. Source: *Agenzia delle Entrate – Osservatorio sul mercato immobiliare* - Tax revenue Agency). – The number of residential transactions concluded in each quarter in the real estate market.

Foreign Tourism (monthly series; availability: about 1 month delay. Source: Banca d'Italia). – Quarterly expenditure of foreign tourists.

Google Trends (monthly series; availability: about 1 month delay. Source: Google). –Google measures searches with the keyword 'disoccupazione' (unemployment) for people dwelling within the region in each quarter.

The series, when needed according to pre-testing results, were seasonally adjusted using TRAMO-SEATS. All individual variables are available at regional level.

The selected indicators are plotted separately for the four macro-regions in Figure 1. While some degree of common cyclical comovement can be detected from the inspection of the four plots, there are also idiosyncratic components as well, conveying additional information that may be useful for nowcasting.

5. Modelling and forecasting: an empirical application for Italy's macro-regions

As a first empirical application of the methodology outlined in the previous sections, we apply the methodology described in the previous Sections to Italy's four macro-areas (North West, North East, Centre and South). This coarser spatial scale shows a lower level of volatility, compared with the twenty administrative regions (especially for the smaller regions), therefore regressions yield to more precise estimates.

Given the limited time span of the regional series, the estimation period considered goes from 1995 to 2016. The predictive ability of the high-frequency indicators (our explanatory variables) is evaluated by selecting the best performing econometric model; with reference to the in-sample goodness-of-fit and the out-of-sample forecasting accuracy.

We implement the following empirical modelling strategy.[4] The initial specification includes the whole set of high-frequency variables, taken for the current quarter. Subsequently, alternative model specifications are obtained by considering lagged values of the indicators, in order to capture potential leading features of the variables. Estimation results for the baseline specification are displayed in each column (1) of Table 3. Only a few indicators are statistically significant in all areas, namely the proxy of the industrial production index at the regional level, bank loans and business demographics indicators. The number of transactions in the residential real estate market is significant in the North East and in the Centre. The export of goods is significant in the North East

[4] All computations were performed utilizing the Matlab TD Toolbox by Enrique M. Quilis (2013).

model while electricity consumption features in the North West model. In the remaining cases the explanatory variables lack statistical significance. Note that, when they are significant, all the estimated coefficients also have the expected signs.

The in-sample goodness-of-fit, as measured by the correlation at quarterly frequency between the ex-post quarterly GDP level estimates and the predicted values yielded by the linear regression on the set of explanatory variables ($X\beta$), is high in all areas, both in levels and percentage changes. Residual serial correlation, gauged by the ρ coefficient, is absent for two of the four areas and has moderate values for the remaining two areas.

In order to achieve a more parsimonious specification, the non-significant variables were ruled out from the regressions in a second round. Estimation results for these more parsimonious specifications are given in column (2) of Table 3, showing that the in-sample fit is largely preserved after eliminating the non-significant regressors.

As a final step the specifications were slightly revised, aiming at properly balancing the ex-post and the ex-ante predictive ability of the regional models; the resulting models are shown in column (3) of Table 3. The above modelling exercise was conducted separately for each area, and therefore the cross-sectional constraints were not enforced (the additional information for the national quarterly GDP was not exploited). Only once the best performing individual regional models had been selected the quarterly ITER estimates are balanced to the national value, by means of the procedures outlined in Section 3. Figure 2 displays the balanced ITER series together with corresponding annual GDP series separately for the four geographical partitions, where the latter are assumed to be uniformly distributed across the four quarters of each year. The ex-post ITER estimates are plotted for the 2007-2016 period, while for the year 2017 the ex-ante estimates are displayed.

Although ITER is computed on a quarterly basis, the forecasting accuracy was necessarily assessed with reference to the annual GDP series, because the latter are the only official statistics available.

A forecasting exercise was hence carried out according to the following three-stage procedure:

- First, the temporal disaggregation is estimated for each area, considering a time series of a length up to year T^*;
- Secondly, the annual growth rate of the ITER indicator for the year T^*+1 is computed based on the ex-ante estimates for the four quarters of the year;
- Third, the growth rate of the ITER computed in the previous step is compared with the actual regional annual GDP growth as gathered from the officially published Istat data.[5]

The procedure outlined above was recursively iterated considering as the final year T^* the years from 2013 to 2016; Table 4 shows the forecasts (ex-ante estimates) of the yearly GDP growth rates based on the final specifications (reported in column 3 of Table 3). The ITER forecasts are reported for both the unbalanced and the balanced estimates of Italian quarterly GDP. The national

[5] In this regard, the first release of the official regional accounts was considered; it was issued by Istat with a delay of about 11 months with respect to the end of the year.

anchor seems to improve the model's predictive ability, as it lowers the forecast errors in three of the four areas considered. The average absolute forecasting errors are small in the case of the North East and of the Centre (0.2 per cent in both cases) and slightly higher the North West and South.

The forecasts produced by ITER are in line with those made by Prometeia and Svimez. Taking as a reference the average absolute forecast error over the forecasting period and over the four areas, the error incurred by ITER amounts to 0.3 percentage points, as in the Svimez estimates; a slightly larger forecasting error is recorded for the projections made by Prometeia. The forecasting comparison has been conducted for a short sample and hence the conclusions cannot be easily generalized.

6. A comparison of alternative dynamic specifications for the temporal disaggregation model

While the seminal Chow-Lin approach has been used extensively in many empirical applications, other temporal disaggregation models have been introduced later. In a recent contribution, Cuevas, Quilis and Espasa (2015) show that the dynamic specification of many interpolating models can be nested in the following generalized model specification:

(10) $$y_{it} = \phi y_{it-1} + \beta_0 x_{it} + \beta_1 x_{it-1} + \varepsilon_{it}$$

(11) $$\varepsilon_{it} = \rho \varepsilon_{it-1} + u_{it}$$

(12) $$u_{it} \sim iid\ N(0, \sigma_u^2).$$

In particular, the model specifications à la Chow and Lin (1971), Fernández (1981), Santos-Silva and Cardoso (2001) and Proietti (2006) may be obtained by imposing the parameter constraints reported in Table 2.

Table 2. Dynamic specifications of temporal disaggregation models

Method	Parameter		
	ϕ	β_1	ρ
Chow Lin	0	0	(0,1)
Fernández	0	0	1
Santos-Silva Cardoso	(0,1)	0	0
Proietti	(0,1)	≠0	0

In order to check the robustness of the dynamic model specification implied by the Chow-Lin methodology, we implemented the Fernández and the Santos-Silva Cardoso (SSC from now on) models into the GDP series for the four macro-regions,[6] using the same indicators as the final specification for ITER.

[6] The estimations were carried out by means of the Fernandez and SSC functions included in the Quilis (2013) Matlab Temporal Disaggregation Toolbox. At present, the Proietti model has not yet been implemented, as the corresponding Matlab function in the Toolbox only covers the case of a single short term indicator.

In Table 5 we report a few summary statistics for in- and out-of-sample predictive accuracy. The out-of-sample forecasting exercise is performed following the procedure presented in the previous Section; we are interested in assessing the model's performance without imposing the cross-sectional aggregation constraints, in order to get a direct term of comparison with the alternative approaches, and therefore only the unbalanced forecasts were considered.

We consider three performance statistics for each of the four macro-regions; in six out of twelve cases the Chow-Lin method yields the most accurate estimates and obtains results very close to those of the best performing method in most of the remaining cases. The Chow-Lin approach therefore looks appropriate for our empirical application.

7. Conclusions

In this paper we present ITER, a quarterly index of the territorial economic activity for Italy. ITER may be promptly updated, thus representing a useful tool for nowcasting the dynamics of territorial GDP.

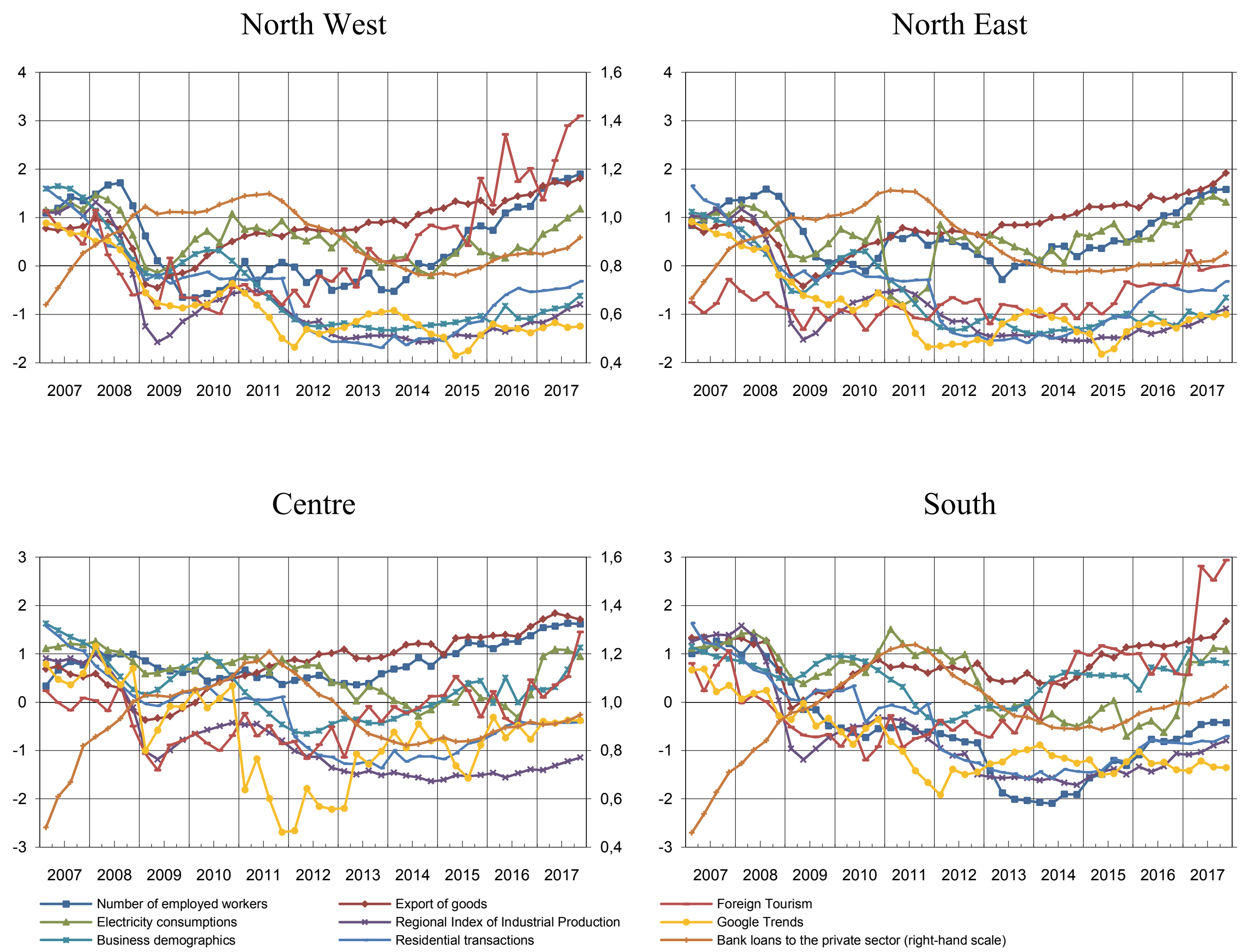
The methodology is easy to implement and uses most of the available regional business cycle indicators in Italy. The econometric approach extends and adapts the temporal disaggregation methods, which were originally developed for univariate time series, in order to satisfy the additivity constraints due to the cross-sectional nature of the data.

We illustrate the model's estimates for Italy's macro-regions and the resulting historical quarterly time series, which may be of interest for a variety of economic regional studies. Looking at the forecasts, we find that the ITER's predictions are in line with those of Italy's major forecasters of regional economic activity. As a robustness checking exercise, a comparison of the ITER's predictive performance, based on the Chow and Lin approach, with other competing methods was also carried out; the results support our approach.

This work is a first attempt to provide up-to-date territorial indicators for Italy. Many extensions may be explored. First, ITER is currently estimated for Italy's macro-regions, but the same approach may be directly extended at regional level and second, the set of indicators may be expanded to eventually explore new big data sources.

Figure 1. Quarterly business cycle indicators in Italy’s four macro areas

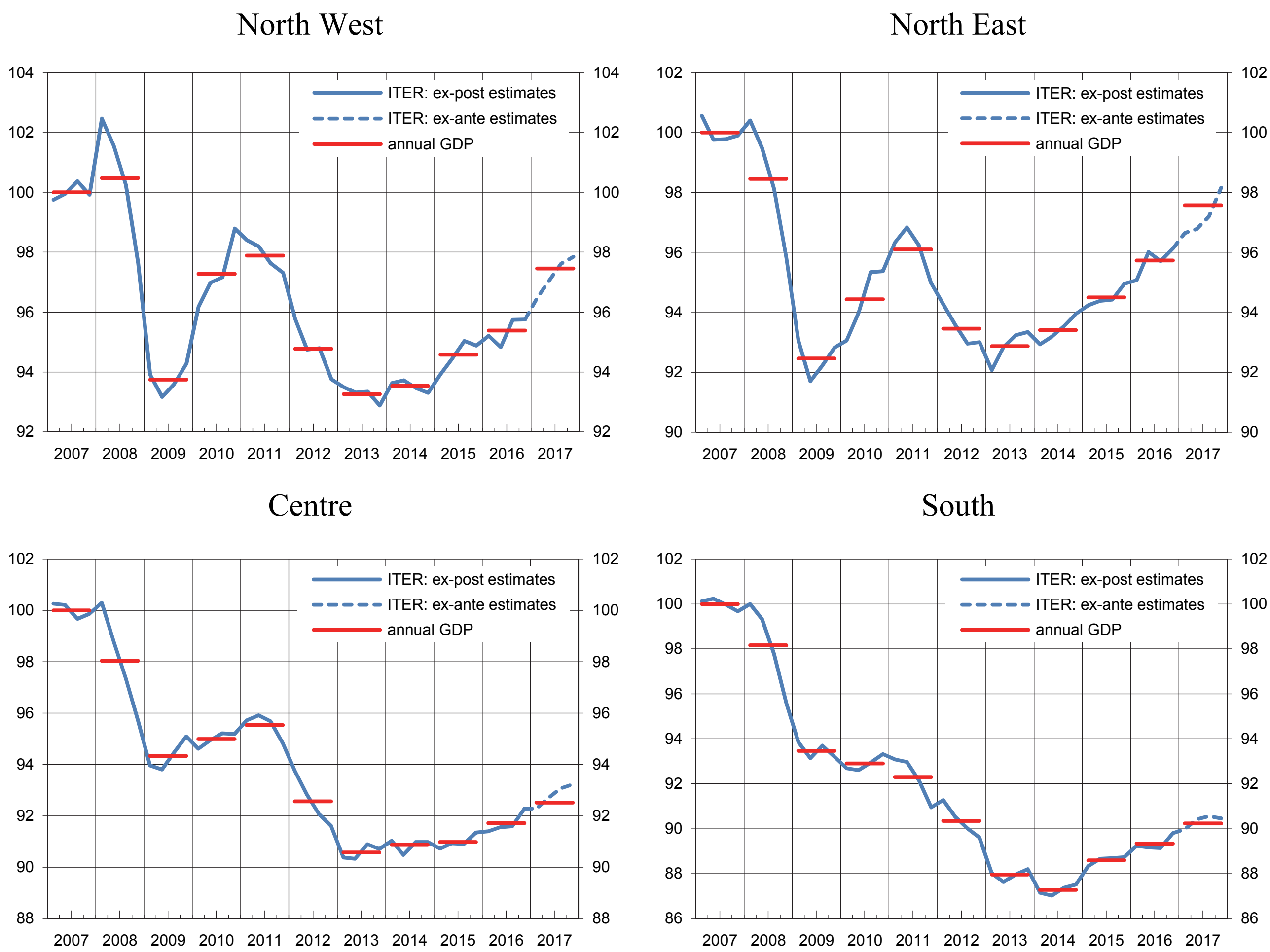
(standardized values)



Sources are detailed in Section 4.

Figure 2. ITER indicator and annual GDP dynamics in Italy's four macro-areas

(indices: 2007 =100) (1)



(1) For the years 1995-2016 the GDP data come from Istat's regional accounts database, released in December 2016, which formed the basis for the model estimation procedure. The 2017 GDP figures were obtained by applying the annual growth rate computed from the regional accounts database released in December 2018 to the 2016 levels.

Table 3A. Estimation results: North West

Indicator variables	Estimated coefficients (p-values)		
	(1)	(2)	(3)
Number of employed workers	3.885 (0.232)		1.968 (0.405)
Exports of goods	0.159 (0.361)		
Electric power consumption	1.627 (0.033)	2.349 (0.000)	2.153 (0.000)
Regional index of industrial production	167.333 (0.02)	122.487 (0.01)	96.362 (0.048)
Business demographics	0.719 (0.055)	0.553 (0.076)	
Business demographics, lagged 1 quarter			0.683 (0.040)
Bank loans to the private sector	40.26 (0.037)	39.842 (0.004)	36.828 (0.006)
Residential transactions	-0.008 (0.879)		
Foreign tourism	-4.67 (0.117)		
Google trends: unemployment	24.768 (0.498)		
Number of variables (excluding the intercept)	9	4	5
Estimation period	1995-2016	1995-2016	1995-2016
Innovation parameter (ρ)	0.6830	0.0500	0.0500
High-freq. corr. (y, Xb): levels	0.9947	0.9946	0.9952
High-freq. corr. (y, Xb): year-on-year rates	0.9707	0.9564	0.9615
Adjusted R-squared[(a)]	0.9865	0.9221	0.9764
Durbin-Watson[(a)]	2.6953	0.9969	1.6585

[(a)] It refers to the regression of the annual GDP on the annual series of indicators and not produced by the Chow-Lin procedure.

Table 3B. Estimation results: North East

Indicator variables	Estimated coefficients (p-values)		
	(1)	(2)	(3)
Number of employed workers	6.16 (0.01)	10.23 (0.00)	
Exports of goods	0.41 (0.00)	0.51 (0.00)	0.49 (0.00)
Electric power consumption	-0.14 (0.36)		
Regional index of industrial production	95.69 (0.00)	0.29 (0.99)	
Regional index of industrial production, lagged 1 quarter			90.50 (0.00)
Business demographics	0.98 (0.00)	0.81 (0.03)	1.05 (0.00)
Bank loans to the private sector	17.15 (0.26)		41.87 (0.00)
Residential transactions	0.07 (0.02)	10.23 (0.00)	0.09 (0.00)
Foreign tourism	-2.55 (0.20)		
Google trends: unemployment	11.04 (0.30)		
Number of variables (excluding the intercept)	9	5	5
Estimation period	1995-2016	1995-2016	1995-2016
Innovation parameter (ρ)	0.0500	0.0500	0.0500
High-freq. corr. (y, Xb): levels	0.9987	0.9977	0.9982
High-freq. corr. (y, Xb): year on year rates	0.9840	0.9732	0.9813
Adjusted R-squared[(a)]	0.9897	0.9841	0.9851
Durbin-Watson[(a)]	2.1102	1.8827	1.6710

[(a)] It refers to the regression of the annual GDP on the annual series of indicators and not produced by the Chow-Lin procedure.

Table 3C. Estimation results: Centre

Indicator variables	Estimated coefficients (p-values)		
	(1)	(2)	(3)
Number of employed workers	3.383 (0.153)	3.996 (0.106)	
Exports of goods	0.12 (0.262)		
Electric power consumption	0.83 (0.219)		
Regional index of industrial production	168.0 (0.00)	151.63 (0.00)	139.90 (0.00)
Business demographics	0.47 (0.22)	0.34 (0.253)	0.49 (0.10)
Bank loans to the private sector	43.15 (0.00)	62.41 (0.00)	74.85 (0.00)
Residential transactions	0.156 (0.010)	0.23 (0.00)	0.24 (0.00)
Foreign tourism	-0.62 (0.351)		
Google trends: unemployment	82.16 (0.587)		
Number of variables (excluding the intercept)	9	5	4
Estimation period	1995-2016	1995-2016	1995-2016
Innovation parameter (ρ)	0.0500	0.4377	0.5979
High-freq. corr. (y, Xb): levels	0.9983	0.9966	0.9956
High-freq. corr. (y, Xb): year on year rates	0.9686	0.9599	0.9555
Adjusted R-squared[(a)]	0.9876	0.9507	0.9138
Durbin-Watson[(a)]	2.1926	1.1400	1.1941

[(a)] It refers to the regression of the annual GDP on the annual series of indicators and produced by the Chow-Lin procedure.

Table 3D. Estimation results: South

Indicator variables	Estimated coefficients (p-values)		
	(1)	(2)	(3)
Number of employed workers	6.32 (0.04)	6.95 (0.00)	6.96 (0.01)
Exports of goods	0.04 (0.93)		0.33 (0.25)
Electric power consumption	0.80 (0.33)		
Regional index of industrial production	204.99 (0.01)	183.11 (0.00)	138.80 (0.05)
Business demographics	0.98 (0.01)	0.50 (0.04)	
Bank loans to the private sector	3.24 (0.82)		
Residential transactions	-0.03 (0.78)		
Foreign tourism	-2.53 (0.33)		
Google trends: unemployment	-73.60 (0.39)		
Number of variables (excluding the intercept)	9	3	3
Estimation period	1995-2016	1995-2016	1995-2016
Innovation parameter (ρ)	0.0500	0.9806	0.9853
High-freq. corr. (y, Xb): levels	0.9947	0.9363	0.9281
High-freq. corr. (y, Xb): year on year rates	0.9500	0.9284	0.8975
Adjusted R-squared[(a)]	0.9817	0.7709	0.9179
Durbin-Watson[(a)]	2.3944	1.5879	1.3193

[(a)] It refers to the regression of the annual GDP on the annual series of indicators and not produced by the Chow-Lin procedure.

Table 4. Forecasts of the yearly GDP growth rate

	Unbalanced forecasts				Cross-sectionally balanced forecasts			
	2014	2015	2016	2017	2014	2015	2016	2017
					North West			
Forecast	-0.66	0.61	0.60	2.00	-0.23	0.45	0.42	1.95
Istat estimates[(a)]	0.27	0.81	0.86	2.17	0.27	0.81	0.86	2.17
Forecast error	-0.93	-0.20	-0.26	-0.17	-0.50	-0.36	-0.44	-0.21
Forecast error Prometeia[(b)]					-0.20	0.15	0.13	-0.52
Forecast error Svimez[(b)]					-0.76	0.00	0.15	-0.17
					North East			
Forecast	0.27	1.01	1.41	1.56	0.70	0.85	1.23	1.53
Istat estimates[(a)]	0.69	0.67	1.30	1.92	0.69	0.67	1.30	1.92
Forecast error	-0.42	0.34	0.11	-0.36	0.01	0.18	-0.07	-0.39
Forecast error Prometeia[(b)]					-0.68	0.27	-0.13	-0.25
Forecast error Svimez[(b)]					-0.30	-0.11	-0.10	-0.42
					Centre			
Forecast	-0.38	0.42	1.25	1.26	0.05	0.26	1.07	1.21
Istat estimates[(a)]	0.20	0.32	0.80	0.87	0.20	0.32	0.80	0.87
Forecast error	-0.58	0.10	0.45	0.39	-0.15	-0.05	0.27	0.33
Forecast error Prometeia[(b)]					-0.32	0.47	-0.06	0.49
Forecast error Svimez[(b)]					-0.51	0.37	-0.62	0.13
					Mezzogiorno			
Forecast	-0.44	1.62	1.28	1.19	-0.01	1.46	1.10	1.14
Istat estimates[(a)]	-0.85	1.06	0.83	1.01	-0.85	1.06	0.83	1.01
Forecast error	0.41	0.55	0.45	0.18	0.84	0.40	0.27	0.13
Forecast error Prometeia[(b)]					-1.02	-0.80	-0.26	0.10
Forecast error Svimez[(b)]					-0.42	-0.09	0.22	0.39

[(a)] Estimates taken from Istat's release of regional accounts for the years 2014 and 2015 in December 2016, from Istat's release of regional accounts for the year 2016 in December 2017 and from Istat's release of regional accounts for the year 2017 in December 2018.

[(b)] The first estimates released are considered, i.e. the ones produced in the year *T+1* for year T. The Svimez estimates are produced few months later than those released by Prometeia and ITER, thus benefiting of an informative advantage.

Table 5. Accuracy statistics for alternative dynamic model specifications

	North West			*North-East*		
	Chow-Lin	Santos-Silva Cardoso	Fernández	Chow-Lin	Santos-Silva Cardoso	Fernández
High-freq. corr. (y, Xb):						
Levels	0.9952	0.9943	0.9780	0.9982	0.9959	0.9933
Year-on-year rates	0.9615	0.9563	0.9651	0.9813	0.9685	0.9816
Yearly GDP forecast error [(a)]	0.44	0.49	0.72	0.33	0.33	0.28
	Centre			*Mezzogiorno*		
	Chow-Lin	Santos-Silva Cardoso	Fernández	Chow-Lin	Santos-Silva Cardoso	Fernández
High-freq. corr. (y, Xb):						
Levels	0.9956	0.9938	0.9886	0.9281	0.9452	0.9133
Year-on-year rates	0.9555	0.9332	0.9552	0.8975	0.8340	0.8989
Yearly GDP forecast error [(a)]	0.41	0.63	0.39	0.45	0.53	0.46

[(a)] Absolute mean percentage error computed on the basis of unbalanced yearly forecasts for the years 2014-2016.

APPENDIX

The Regional Index of Industrial Production[1]

In this Appendix we present the methodology that we use to construct the regional series for industrial production, which hinges on a procedure of extrapolation and re-aggregation of national series for the industrial production at the sectoral level. The seasonally adjusted national series are available from 1990 onwards on a monthly basis for the 15 sectors of the ATECO 2007 two-digit classification of economic activities. To approximate the contribution of the industrial sectors of each region to the corresponding national index, we use data on sectoral value added at current prices taken from the territorial economic accounts. To begin with, we calculate the industrial production index for sector s in region R (i.e. IP_s^R) as:

$$IP_s^R = \frac{VA_s^R}{\sum_R VA_s^R} IP_s^{ITA}$$

where VA_s^R denotes the regional sectoral value added and IP_s^{ITA} the Italian industrial production aggregate. The regional index is subsequently obtained by re-aggregating the individual sectoral regional indices, weighed by the share of each sector on the total industrial value added of each region, that is:

$$IP^R = \sum_s \frac{VA_s^R}{\sum_s VA_s^R} IP_s^R \ .$$

The IP^R index may be deemed able to capture the common cyclical component underlying regional dynamics in manufacturing activity, obtained by properly weighting the national sectoral trends.

[1] We follow the approach developed in Petrella and Piselli (2012).

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