International Journal of Forecasting 37 (2021) 1376–1398

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Nowcasting GDP and its components in a data-rich environment: The merits of the indirect approach

Tommaso Proietti [a,*], Alessandro Giovannelli [b], Ottavio Ricchi [c], Ambra Citton [c], Christían Tegami [d], Cristina Tinti [c]

[a] Universita degli Studi di Roma Tor Vergata Dipartimento di Economia e Finanza, Italy
[b] Universitã dell'Aquila, Italy
[c] Ministero dell'Economia e delle Finanze, Italy
[d] SOGEI SPA, Italy

ARTICLE INFO

Keywords:
Mixed-frequency data
Dynamic factor models
Growth accounting
Model averaging
Ledoit–Wolf Shrinkage

ABSTRACT

The national accounts provide a coherent and exhaustive description of the current state of the economy, but are available at the quarterly frequency and are released with a nonignorable publication lag. The paper illustrates a method for nowcasting and forecasting the sixteen main components of Gross Domestic Product (GDP) by output and expenditure type at the monthly frequency, using a high-dimensional set of monthly economic indicators spanning the space of the common macroeconomic and financial factors. The projection on the common space is carried out by combining the individual nowcasts and forecasts arising from all possible bivariate models of the unobserved monthly GDP component and the observed monthly indicator. We discuss several pooling strategies and we select the one showing the best predictive performance according to a pseudo-real-time forecasting experiment. Monthly GDP can be indirectly estimated by the contemporaneous aggregation of the value added of the different industries and of the expenditure components. This enables the comparative assessment of the indirect nowcasts and forecasts vis-à-vis the direct approach and a growth accounting exercise. Our approach meets the challenges posed by the dimensionality, since it can handle a large number of time series with a complexity that increases linearly with the cross-sectional dimension, while retaining the essential heterogeneity of the information about the macroeconomy. An application to the Italian case leads to several interesting discoveries concerning the time-varying predictive content of the information carried by the monthly indicators.

1. Introduction

The national accounts offer a coherent and consistent set of macroeconomic aggregates for the analysis of economic structure and change. They are compiled quarterly according to the methods and definitions outlined in Eurostat (2013a, 2013b).

The most authoritative measure of aggregate economic activity is gross domestic product (GDP). From the output, or production, side of the economy it is defined as the sum of the value added of the productive sectors; when it is evaluated at market prices, taxes less subsides on products need to be added as well. If imports are added to the domestic supply of goods and services, then the total resources need to equal the total final uses for consumption, investment, and exports; hence, according to the expenditure approach, GDP results from the sum of final consumption expenditure, gross capital formation,

* Corresponding author.
E-mail address: tommaso.proietti@uniroma2.it (T. Proietti).

https://doi.org/10.1016/j.ijforecast.2021.04.003
0169-2070/

and net exports. As explained below, these definitions hold strictly when the aggregates are evaluated at current prices (and at the average prices of the previous year).

A key observation is that the compilation of the GDP accounts requires processing and combining a variety of sources of information on the supply and demand sides of the economy, both primary and secondary, based on quantitative surveys of firms and households. The amount of data and the complexity of the process of reconciling the information do not make it currently possible for statistical agencies to compile the national accounts in a more timely way and at an observation frequency faster than quarterly.

The objective of this paper is to apply the methodology proposed in Proietti and Giovannelli (2020) to the problem of nowcasting and forecasting the production and expenditure national accounts, using a large-dimensional set of economic indicators available at the monthly frequency. Though we focus on the Italian case, the methods and main issues can be extended to other countries of the European Union, and to the euro area itself, which produces a harmonized system of national accounts (the European System of National and Regional Accounts, known as ESA 2010) and monthly economic indicators, with the same timing and nomenclature.

There is ample literature on nowcasting GDP with mixed-frequency data: one approach directly targets GDP at the quarterly frequency of observation, as in bridge models, see Baffigi et al. (2004), the MIxed frequency DAta Sampling approach (Ghysels et al., 2004, 2006), as in Kuzin et al. (2011), and the density combination approach by Aastveit et al. (2014). Another strand of the literature focuses on monthly GDP as the target variable; see Aruoba et al. (2012), Camacho and Pérez–Quirós (2010), Foroni and Marcellino (2014), Mitchell et al. (2005), and Proietti et al. (2017), among others. consider the problem of nowcasting the quarterly growth of the output and expenditure components of the euro area GDP and find that aggregating the components forecasts can result in an improvement of the quality of the nowcasts of total GDP growth. Bańbura and Rünstler (2011) deal with nowcasting the euro area aggregate GDP quarterly growth using a large-dimensional mixed-frequency factor model and propose a method to assess the contribution of each individual indicator to the nowcasts. Koop et al. (2020) estimate quarterly output growth for 12 UK regions with the support of a mixed-frequency vector autoregressive model subject to temporal and cross-sectional aggregation restrictions. Arencibia et al. (2017) nowcast Spanish monthly GDP and its demand components via a mixed-frequency parametric dynamic factor model.

We contribute to the literature by applying and illustrating a method for nowcasting and forecasting the 16 main components of GDP by output and expenditure type at the monthly frequency, using a high-dimensional set of monthly economic indicators, spanning the space of the common economic factors. As an application of the model averaging methodology proposed by Proietti and Giovannelli (2020), the projection of the quarterly components on the monthly common space is carried out by combining the individual nowcasts and forecasts arising from all possible mixed-frequency bivariate models that jointly consider the quarterly national accounts component and the observed monthly indicator.

The components of GDP at market prices by output type that we consider are the value added of the 10 main branches of economic activity and taxes less subsidies:

Label	*Value added of branch*	
A–B	Agriculture, forestry, and fishing	+
C–D–E	Industry (except construction)	+
F	Construction	+
G–H–I	Wholesale and retail trade, transport, accommodation, and food service activities	+
J	Information and communication	+
K	Financial and insurance activities	+
L	Real estate activities	+
M-N	Professional, scientific, and technical activities; administrative and support service activities	+
O-Q	Public administration, defense, education, human health, and social work activities	+
R-U	Arts, entertainment, and recreation; other service activities; activities of household and extra-territorial organizations	=
	Total Gross Value Added (GDP at basic prices)	+
TlS	Taxes less subsidies on products	=
	GDP at market prices	

As for the breakdown of GDP by expenditure type, we consider the following components:

Label	*Component*	
FCE	Final consumption expenditure	
FCE_{gg}	Final consumption expenditure of general government	+
FCE_h	Household and NPISH final consumption expenditure	+
GCF	Gross capital formation	+
EXP	Exports of goods and services	−
IMP	Imports of goods and services	=
GDP	*GDP at market prices*	

The quarterly series are taken at chained volumes with the reference year 2015 from the Italian quarterly national accounts compiled by Istat (https://www.istat.it/en/national-accounts). The information set also includes a set of $N = 433$ monthly indicators that are selected on the basis of their coverage, representativeness, and timeliness, and are currently monitored by the Italian Ministry of Economy and Finance.

For each of the above 16 components and the GDP we estimate N bivariate dynamic factor models that provide monthly nowcasts, forecasts, and historical estimates of the components. These are then pooled according to different aggregation strategies. The optimal model averaging method requires estimating the nowcast (forecast) error covariance matrix. We argue that the Ledoit–Wolf shrinkage estimator (Ledoit & Wolf, 2004a, 2004b), with a compound symmetry shrinkage target, offers a solution that is both effective and feasible. Other weighting schemes, based on the goodness of fit of the indicator models within the training sample, and simple averaging are considered and compared.

Once consensus nowcasts and forecasts are obtained, they can be contemporaneously aggregated to form indirect GDP nowcasts and forecasts from the output and the expenditure side. This enables the comparison of the direct and indirect approaches to nowcasting and forecasting GDP.

The theoretical literature on the comparative merits of forecasting an aggregate by combining the components' forecasts is thoroughly reviewed in Lütkepohl (1986, 2011), for the case when the true model is vector ARMA. Poncela and García-Ferrer (2014) extended the results to the class of unobserved components models with shared and common trends that is used in this paper. Our contribution focuses on the comparison of direct and indirect predictions that use the same model averaging methodology, and thus it is in the same vein as Espasa et al. (2002), Heinisch and Scheufele (2018), Hendry and Hubrich (2011), and Hubrich (2005) .

A recursive nowcasting and forecasting experiment provides firm evidence that the indirect approach provides more accurate nowcasts and forecasts than the direct approach. The experiment generates a wealth of information leading to several interesting discoveries, enabling us, among other things, to identify the contribution of the monthly indicators to the nowcasts and forecasts of monthly GDP and its components, highlighting the role of business and consumer surveys when information on hard indicators has not yet accrued. This also allows us to carry out a growth accounting exercise, which is informative about the contribution to aggregate growth of sectorial value added, final consumption, and investment during the phases of the business cycle.

The plan of the paper is the following. Section 2 presents the bivariate model for the GDP components and the individual indicators at the basis of our methodology. In Section 3 we outline how consensus nowcasts and forecasts are obtained for the GDP components. Section 4 deals with the contemporaneous aggregation of the GDP components according to the output and the expenditure approaches, so as to form indirect GDP nowcasts. The empirical illustration starts with a description of the data available (Section 5). The results are presented in Section 6: the monthly indirect GDP estimates and growth accounting decomposition are discussed in 6.1; and 6.2 presents the results of a recursive pseudo-real-time nowcasting and forecasting experiment. Section 7 concludes the paper.

2. Bivariate dynamic factor model for the GDP component and the monthly indicator

Let y_{it} denote the ith monthly unobservable GDP component at time t, for $i = 0, 1, \ldots, M$, $t = 0, \ldots, n$, and let $Y_{it} = y_{it} + y_{i,t-1} + y_{i,t-2}$ be the observable quarterly total. In our application, $M = 16$ and $i = 0$ corresponds to GDP. The information set also consists of N monthly indicators, $\{x_{jt}, j = 1, \ldots, N, t = 0, \ldots, n\}$, which are available with a specific publication schedule. We shall denote by $\mathcal{Y}_{it} = \{Y_{i,3\tau}; \tau = 1, \ldots, \lfloor (t-\delta)/3 \rfloor\}$ the information available at time t on the ith component from the national statistical agency, where δ is the delay in the release of the quarterly national accounts. Also, the information available at time t for the jth monthly indicator will be denoted by $\mathcal{X}_{jt} = \{x_{j1}, \ldots, x_{j,t-\delta_j}\}$, where δ_j is the delay in their release with respect to the reference month.

Proietti and Giovannelli (2020) consider the problem of estimating the nowcasting or forecasting target $\mathrm{E}(y_{i,t+l}|\mathcal{Y}_{it}, \mathcal{X}_t)$, where $\mathcal{X}_t = \cup_{j=1}^N \mathcal{X}_{jt}$ is the complete information on the monthly indicators and $l \geq 0$ is the forecast horizon, by combining the estimates of the partial projections $\mathrm{E}(y_{i,t+l}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$, $j = 1, \ldots, N$, by means of the estimator

$$\hat{\mathrm{E}}(y_{i,t+l}|\mathcal{Y}_{it}, \mathcal{X}_t) = \sum_{j=1}^{N} w_{ij} \hat{y}_{i,t+l}^{(j)}, \tag{1}$$

where $\hat{y}_{i,t+l}^{(j)} = \hat{\mathrm{E}}(y_{i,t+l}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$. As the nowcasts or forecasts $\hat{y}_{i,t+l}^{(j)}$ can be easily obtained by a suitably specified bivariate model that can handle the mixed frequency and ragged-edge structure of the information set, the main issue lies with the choice of the weights w_{ij}, $j = 1, \ldots, N$. If $\hat{y}_{i,t+l}^{(j)}$ had a stationary distribution, and the monthly GDP component were observable, then the optimal weights could be estimated from the covariance matrix of the partial predictors $\hat{y}_{i,t+l}^{(j)}$ and their covariance with the target variable. However, neither of these two circumstances occur, and the optimal weights will depend on the covariance matrix of the prediction errors, estimated from a training or a test sample. This point will be followed up in Section 3. We now discuss the specification of the model leading to the partial estimates $\hat{y}_{i,t+l}^{(j)}$.

Our model assumes that the indicators are generated according to a nonstationary model, such that $\Delta x_{jt} = x_{jt} - x_{j,t-1}$ has an approximate factor structure, in the sense specified by Forni et al. (2000) and Forni and Lippi (2001):

$$x_{jt} = x_{j,t-1} + m_j + \chi_{jt} + \xi_{jt}, \quad j = 1, \ldots, N, \tag{2}$$

where $m_j = \mathrm{E}(\Delta x_{jt})$ is the constant drift; χ_{jt} represents the zero mean common component, which is a linear combination of q common dynamic factors driving the comovements among the series, whereas ξ_{jt} is the idiosyncratic component. The latter is specific to the jth series, or weakly correlated across a finite number of time series. As in Forni et al. (2000) and Forni and Lippi (2001), we write $\chi_{jt} = \mathbf{b}_j(L)'\mathbf{u}_t$, where $\mathbf{u}_t$ is a $q \times 1$ vector of common dynamic factors, $\mathbf{u}_t \sim \mathrm{WN}(\mathbf{0}, \mathbf{I}_q)$ and, denoting $b_{jr}(L) = \sum_{k\geq 0} b_{jr,k}L^k$, where L is the lag operator, $\mathbf{b}_j(L) = [b_{j1}(L), \ldots, b_{jr}(L), \ldots, b_{jq}(L)]'$. We assume that the common factors are pervasive and that ξ_{jt} and χ_{jt} are orthogonal at all leads and lags and across the series. Representation (2) has been at the core of applied macroeconomic analysis and forecasting; see, e.g., Forni et al. (2009) and Forni et al. (2018) and the references therein.

As far as the underlying monthly GDP component is concerned, we assume that it follows a similar structure,

$\Delta y_{it} = m_i + \mathbf{b}_i(L)'\mathbf{u}_t$, but with no idiosyncratic component. As a matter of fact, y_{it} results from the contemporaneous aggregation of many elementary component series, whose idiosyncratic components are averaged out. The projection of Δy_{it} on χ_{jt} is $\Delta y_{it} = m_i + \theta_{ij}\chi_{jt} + \xi_{it}$, where $\theta_{ij} = \sum_r \sum_k b_{irk} b_{jrk} / \sum_r \sum_k b_{jrk}^2$. The component ξ_{it} is orthogonal to χ_{jt} and to ξ_{jt}, by construction, since it measures the contribution of the common factors unaccounted for by χ_{jt}.

Under the additional assumption that χ_{jt} is generated by a parametric model, namely an ARMA(1,1) process, and that ξ_{it} is white noise, we consider the following bivariate model for the ith GDP component and the jth monthly indicator:

$$
\begin{aligned}
\begin{bmatrix} x_{jt} \\ y_{it} \end{bmatrix} &= \begin{bmatrix} x_{j,t-1} \\ y_{i,t-1} \end{bmatrix} + \begin{bmatrix} m_j \\ m_i \end{bmatrix} + \begin{bmatrix} 1 \\ \theta_{ij} \end{bmatrix} \chi_{jt} + \begin{bmatrix} \xi_{jt} \\ \xi_{it} \end{bmatrix}, \\
& t = 1, \ldots, n, \\
\chi_{jt} &= \phi_{ij}\chi_{j,t-1} + \eta_{jt} - \vartheta_{ij}\eta_{j,t-1}, \quad \eta_{jt} \sim \text{IID N}(0, \sigma^2_{\eta j}), \\
\begin{bmatrix} \xi_{jt} \\ \xi_{it} \end{bmatrix} &\sim \text{IID N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_j^2 & 0 \\ 0 & \sigma_i^2 \end{bmatrix} \right).
\end{aligned} \tag{3}
$$

In (3) we restrict the autoregressive coefficients ϕ_j to lie in the open interval $(0, 1)$ and ϑ_j in $[0, 1]$. The independence of ξ_{it} and ξ_{jt} follows from the structure of our model. On the contrary, serial independence is imposed for the identifiability of the model in the presence of temporal aggregation.

Model (3) provides a parsimonious representation capable of capturing the comovements between the GDP component and the monthly indicator. The ARMA(1,1) specification for the common component is sufficiently rich to capture its persistence. Obviously, it holds exactly if for the jth indicator $\mathbf{b}_j(L) = [0, \ldots, 0, (1 - \vartheta_j L)/(1 - \phi_j L), 0, \ldots, 0]$, and only approximately if χ_{jt} loads on multiple common shocks.

Summarizing, our bivariate model assumes that x_{jt} and y_{it} are difference stationary and conditionally independent, given the common component of the indicator variable, χ_{jt}, which is assumed to follow an ARMA(1,1) process. The common component of the jth indicator is a dynamic weighted combination of the common factors, whose number and nature, to our advantage, does not need to be specified.

3. Nowcasting and forecasting the monthly GDP components

The baseline model (3) is estimated for all pairs (i, j), $i = 0, \ldots, M$, and $j = 1, \ldots, N$, under the observational constraints posed by temporal aggregation, as only the quarterly totals, $Y_{it} = y_{it} + y_{i,t-1} + y_{i,t-2}$, are observable for times $t = 3\tau$, $\tau = 1, \ldots, \lfloor n/3 \rfloor$, where $\lfloor \cdot \rfloor$ denotes integer division, with a fixed publication delay with respect to the quarter τ and a revision schedule.

Maximum likelihood estimation of the unknown parameters $(m_i, m_j, \theta_{ij}, \phi_{ij}, \vartheta_{ij}, \sigma^2_{\eta j}, \sigma^2_i, \sigma^2_j)$ is performed by casting the model in state-space form and evaluating the likelihood by the associated Kalman filter. The technical details are given in Proietti and Giovannelli (2020).

Nowcasting and forecasting of the unobserved monthly GDP components, conditional on the maximum likelihood estimates of the parameters, is carried out with the support of the Kalman filter and updating equations, which compute the conditional means

$$\hat{y}^{(j)}_{i,t+l} = \hat{\text{E}}(y_{i,t+l} | \mathcal{Y}_{it}, \mathcal{X}_{jt}), \quad l = 0, 1, \ldots, L.$$

The N nowcasts and forecasts of the ith GDP component arising for $j = 1, \ldots, N$, can be pooled to produce the conditional mean averaging estimator

$$\hat{\text{E}}_t(y_{i,t+l}) = \sum_{j=1}^{N} w_{ij} \hat{y}^{(j)}_{i,t+l}, \quad \sum_{j=1}^{N} w_{ij} = 1. \tag{4}$$

The weights $\{w_{ij}, j = 1, \ldots, N\}$ should be chosen so as to minimize the mean square nowcast/forecast error; the latter can be estimated by performing a pseudo-real-time nowcasting/forecasting exercise. For instance, let $\nu_{ij,\tau} = Y_{i,3\tau} - \text{E}(Y_{i,3\tau} | \mathcal{Y}_{i,3\tau-1}, \mathcal{X}_{j,3\tau}), j = 1, \ldots, N, \tau = 1, \ldots, T$ denote the nowcasting error in predicting the quarterly value of the GDP component on the basis of the information available in real time, and let $\hat{\boldsymbol{\Sigma}}_i$ be a positive definite estimator of the covariance matrix of the nowcast errors $(\nu_{i1,\tau}, \ldots, \nu_{ij,\tau}, \ldots, \nu_{iN,\tau})'$. The optimal combination weights (Bates & Granger, 1969) are given by the elements of the vector

$$\hat{\mathbf{w}} = \frac{\hat{\boldsymbol{\Sigma}}_i^{-1} \mathbf{i}}{\mathbf{i}' \hat{\boldsymbol{\Sigma}}_i^{-1} \mathbf{i}}, \tag{5}$$

where $\mathbf{i}$ is an $N \times 1$ vector of ones.

The main difficulty with implementing (5) lies with the fact that the cross-sectional dimension N is large compared to the number of available quarterly forecast errors, T, so that the sample covariance matrix $\hat{\mathbf{S}}_i = \left\{\hat{s}_{i,hk}, (h, k) = 1, \ldots, N\right\}$, $\hat{s}_{i,hk} = \frac{1}{T}\sum_\tau (\nu_{ih,\tau} - \bar{\nu}_{ih})(\nu_{ik,\tau} - \bar{\nu}_{ik})$, is singular. Moreover, it is a highly inaccurate estimator of the true nowcasting error covariance matrix. The solution is offered by the optimal linear shrinkage estimator proposed by Ledoit and Wolf (2004a, 2004b), which achieves positive definiteness and estimation accuracy by setting the elements of the matrix $\hat{\boldsymbol{\Sigma}}_i$ as follows:

$$\hat{\boldsymbol{\Sigma}}_{i,hk} = \left\{(1 - \lambda_i)\hat{s}_{i,hk} + \lambda_i \tilde{\omega}_{i,hk}, \ (h, k) = 1, \ldots N\right\}. \tag{6}$$

This is a weighted linear combination of the sample covariance and a shrinkage target covariance, where $\lambda_i \in [0, 1]$ is the shrinkage intensity, and $\tilde{\omega}_{i,hk}$ is the covariance between the nowcast errors estimated by assuming a compound symmetry covariance structure. This assumes that the nowcast errors are equally correlated, due to the presence of a single common factor. The correlation can be estimated using the average sample correlation: $\bar{r}_i = \frac{2}{(N-1)N} \sum_{h=1}^{N-1} \sum_{k=h+1}^{N} \frac{\hat{s}_{i,hk}}{\sqrt{\hat{s}_{i,hh}}\sqrt{\hat{s}_{i,kk}}}$. Then, we set

$$\tilde{\omega}_{i,hk} = \begin{cases} \hat{s}_{i,hh}, & h = k, \\ \bar{r}_i \sqrt{\hat{s}_{i,hh}}\sqrt{\hat{s}_{i,kk}}, & h \neq k. \end{cases}$$

The shrinkage parameter λ_i is estimated by minimizing the mean square nowcast error, e.g., by performing a grid search over the unit interval or applying the closed-form estimator by Ledoit and Wolf (2004a).

An alternative weighting scheme is obtained from the estimation output. Since the series are processed sequentially, see Anderson and Moore (1979) and Koopman and Durbin (2000), we can obtain the deviance measure:

$$D_{ij} = -2\sum_{\tau=1}^{\lfloor n/3\rfloor} \ln f(Y_{i,3\tau}|\mathcal{Y}_{i,3\tau-1}, \mathcal{X}_{j,3\tau}), \quad j = 1,\dots,N, \quad (7)$$

where $f(Y_{i,3\tau}|\mathcal{Y}_{i,3\tau-1}, \mathcal{X}_{j,3\tau})$ is the Gaussian nowcast density of the quarterly ith component, conditional on its available past information, consisting of the quarterly values up to quarter $\tau-1$, and the monthly values of the ith indicator available up to the current time, $t = 3\tau$.

Then we can set

$$w_{ij} = \frac{\exp(-D_{ij})}{\sum_k \exp(-D_{ik})}. \quad (8)$$

As the number of parameters of the bivariate models remains constant across j, this weighting scheme is related to post-selection model averaging according to exponential AIC or BIC weights, see Claeskens and Hjort (2008) and the references therein.

4. The direct and indirect approach to GDP nowcasting and the issues posed by aggregation

When applied to aggregate GDP, our model averaging methodology delivers a direct nowcast/forecast of monthly GDP. An indirect nowcast/forecast can be obtained by the aggregation of the estimated monthly GDP components' nowcast/forecast.

As it is well known (Bloem et al., 2001), chain-linked volume measures are not consistent in cross-sectional aggregation. For example, the sum of the value added of the 10 branches plus taxes less subsidies would not deliver GDP at market prices.

The non-additivity is a consequence of the adoption of chain-linked methods in the construction of the national accounts. In particular, the annual overlap method is used, which calculates the chain-linked data with the annual data of the previous year as a point of reference. While the adoption is motivated by the need to remedy the problem of price structure obsolescence present in the old fixed-base approach, it has as a consequence the loss of additivity of volumes in all years except for the reference year and the year following the reference year.

Hence, in order to perform the aggregation of the estimates we need to restore the additivity by expressing the estimates at the average prices of the previous year. Subsequently, the GDP estimates can be chain-linked and expressed in chained volumes with the same reference year.

With a change of notation, let $y_{i,ms}^{(r)}$ denote the value of the ith GDP component in month m of year s evaluated at the average prices of year r. Let us assume that the initial year, $r = 0$, is taken as the reference year and that $i = 1,\dots,11$ indexes the value added of the 10 branches and taxes less subsidies, which are the GDP components in the output approach. The value of the chained volume component can be expressed recursively as

$$y_{i,ms}^{(0)} = \left(\sum_m y_{i,m,s-1}^{(0)}\right) \frac{y_{i,ms}^{(s-1)}}{\sum_m y_{i,m,s-1}^{(s-1)}}, \quad s \geq 1. \quad (9)$$

The denominator is the value of the component in year $s-1$ at current prices, so that the multiplicative factor is a Laspayres quantity index.

Our methodology provides estimates of $y_{i,ms}^{(0)}$ on the left-hand side of (9), and by inverting the above expression, we can obtain the component evaluated at the previous year average prices:

$$y_{i,ms}^{(s-1)} = y_{i,ms}^{(0)} \frac{\sum_m y_{i,m,s-1}^{(s-1)}}{\sum_m y_{i,m,s-1}^{(0)}}. \quad (10)$$

This operation can be referred to as *dechaining*. Notice that $\sum_m y_{i,m,s-1}^{(s-1)}$ is the annual total at current prices and this is available from the official national accounts.

At this point, the GDP components can be aggregated. Summing with respect to i we obtain the GDP at the previous year's prices:

$$y_{ms}^{(s-1)} = \sum_i y_{i,ms}^{(s-1)}. \quad (11)$$

As a final step we chain-link the GDP estimates to express them in chained volumes with reference year 0. This is achieved by computing recursively:

$$y_{ms}^{(0)} = \left(\sum_m y_{m,s-1}^{(0)}\right) \frac{y_{ms}^{(s-1)}}{\sum_m y_{m,s-1}^{(s-1)}}. \quad (12)$$

Note that, using (10) and (11), (12) can be written as follows:

$$y_{ms}^{(0)} = \sum_i y_{i,ms}^{(0)} \frac{P_{i,s-1}}{P_{s-1}}, \quad (13)$$

with

$$P_{i,s-1} = \frac{\sum_m y_{i,m,s-1}^{(s-1)}}{\sum_m y_{i,m,s-1}^{(0)}}, \; P_{s-1} = \frac{\sum_m y_{m,s-1}^{(s-1)}}{\sum_m y_{m,s-1}^{(0)}}.$$

Hence, we can express chained volumes GDP as a weighted linear combination of the components' chained volumes, where the weights are the ratio of the component Laspayres price index for the previous year with respect to the reference year and the price index of GDP for the same year.

The discussion in this section and expression (13) make it clear that GDP growth cannot be decomposed into a weighted average of the components' growth rates. Hence, the lack of additivity is an issue for any growth accounting exercise that is conducted with "real" aggregates, i.e., chained volumes.

With reference to the annual growth rates, after some manipulation of (13),

$$\frac{y_{ms}^{(0)} - y_{m,s-1}^{(0)}}{y_{m,s-1}^{(0)}} = \sum_i \left[\frac{y_{i,ms}^{(0)} - y_{i,m,s-1}^{(0)}}{y_{i,m,s-1}^{(0)}} W_{i,m,s-1}^{(0)} \frac{P_{i,s-1}}{P_{s-1}} + W_{i,m,s-1}^{(0)} \left(\frac{P_{i,s-1}}{P_{s-1}} - \frac{P_{i,s-2}}{P_{s-2}} \right) \right], \quad (14)$$

where

$$W_{i,m,s-1}^{(0)} = \frac{y_{i,m,s-1}^{(0)}}{y_{m,s-1}^{(0)}}.$$

As a result, the weighted sum of the yearly growth rates $\frac{y^{(0)}_{i,ms}-y^{(0)}_{i,m,s-1}}{y^{(0)}_{i,m,s-1}}$ does not add up to GDP growth and can only be seen as an approximation to the contribution of the ith component to aggregate growth.

5. Description of the dataset

Our dataset comprises the time series of GDP and its 16 components taken from the production and expenditure quarterly national accounts compiled by ISTAT (Istituto Nazionale di Statistica; see Bisio and Moauro (2018) for a thorough discussion of the methodology). The series are available for the period 1996.q1–2019.q3 at chained volumes. The corresponding series at current prices were used to compute the weights for contemporaneous aggregation according to expression (13).

A collection of $N = 433$ monthly time series currently in use at the Italian Ministry of Economics and Finance, collected from various sources and electronic databases, completes our dataset. The selection criteria were representativeness, coverage, timeliness, and availability: the set of monthly indicators need to provide ample coverage of economic and financial phenomena; indicators that are released with a publication delay longer than three months are unlikely to provide useful information for the objectives of this paper. The series cover the period 1996.m1–2019.m12 with a ragged-edge structure. A complete list is available in Appendix B, which also reports the publication delay with respect to the reference month.

The indicators can be grouped according to their main theme and geographical reference: Table 1 provides the distribution of the indicators according to the two characteristics. While one-fourth of the indicators refer to the Italian economy, the dataset also contains a number of indicators pertaining to the euro area, to account, e.g., for the developments of the German manufacturing sector, which are very important for the Italian one. More than one-third of the indicators relate to consumer and business surveys, which provide a timely and easily accessible assessment of the state of the economy.

Overall, the dataset is unbalanced towards the supply side of the economy: quantitative consumer surveys are much less timely and serve more the compilation of the national accounts (and microeconomic research). The qualitative surveys partially compensate for this. Reweighting the individual contribution of the indicators according to their ability to predict the national accounts target aims at readdressing the balance.

The preliminary transformations that are adopted for modeling the series according to (3) are the following: all the consumer and production price indices are transformed into monthly inflation rates; the survey series are cumulated: if z_{jt} denotes a survey series, then $x_{jt} = \sum_{r=0}^{t} z_{jr}$. All the other series are taken in levels.

6. Empirical results

6.1. Historical estimation and growth accounting

Historical estimation deals with the construction of monthly GDP estimates, by expenditure and output components, conditional on the full sample available. For this purpose the weights can be validly obtained by considering the in-sample predictive performance, as measured by the conditional deviance of the quarterly GDP estimation error.

Table 1
Breakdown of the 433 monthly indicators by theme and geographical reference.

Theme	Geographical reference			Total
	Euro area	Italy	Other	
Industry	3.2	8.1	1.2	*12.5*
Trade	-	7.9	0.2	*8.1*
Services	-	6.2	–	*6.2*
Finance	3.9	4.6	3.7	*12.2*
Labor	-	5.5	–	*5.5*
Prices	3.9	9.9	2.1	*15.9*
Survey	6.0	30.7	0.9	*37.6*
Other	–	1.8	–	*1.8*
Total	*17.1*	*75.1*	*8.1*	*100.0*

Using the batch of data described in the previous section, the N monthly estimates of the GDP components, $\tilde{y}^{(j)}_{it} = \hat{\mathrm{E}}(y_{it}|\mathcal{Y}_{in}, \mathcal{X}_{jn})$, have been computed and are later combined to produce the historical estimates $\tilde{y}_{it} = \sum_{j=1}^{N} w_{ij}\tilde{y}^{(j)}_{it}, \quad t = 1, \dots, n$. The weights used for aggregation are proportional to $\exp(-D_{ij})$, given in (7), and thus are an expression of the conditional likelihood of the observed quarterly GDP series.

The GDP components are then aggregated to form GDP monthly estimates according to the output and expenditure approach using the methodology outlined in Section 4. If we replace the time index with two indices (m, s), respectively labeling the month, $m = 1, \dots, 12$, and the year, $s = 1, \dots, \lfloor n/12 \rfloor$, so that $t = m + 12(s-1)$, and if i indexes the value added of the 10 branches and taxes less subsidies, GDP by output components is obtained as

$$\tilde{y}^{(o)}_{ms} = \sum_i \tilde{y}_{i,ms}\frac{P_{i,s-1}}{P_{s-1}},$$

where the cross-sectional aggregation weights are the ratio of the ith component deflator of year $s-1$ with respect to the reference year ($P_{i,s-1}$) to the GDP deflator for the same year (P_{s-1}). Both are obtained by the ratio of the annual value added or GDP at current prices to that at chained volumes, available from the national accounts. For the expenditure approach we apply the same aggregation rule, but imports have to be subtracted:

$$\tilde{y}^{(e)}_{ms} = \sum_i \tilde{y}_{i,ms}\frac{P_{i,s-1}}{P_{s-1}} - \tilde{y}_{IMP,ms}\frac{P_{IMP,s-1}}{P_{s-1}},$$

where $i = \{FCE_{gg}, FCE_h, GCF, EXP\}$.

The monthly GDP estimates are presented in Fig. 1 for the two approaches, along with the annual growth rate. The interval estimates refer to a nominal coverage probability set equal to 0.95. They are based on the assumptions that the estimates of the components are independent both within and between, i.e., across j and i, and that the conditional density of y_{it} is Gaussian. In particular, the variance of the monthly estimate for each component is computed as the average (with weights w_{ij}) of the

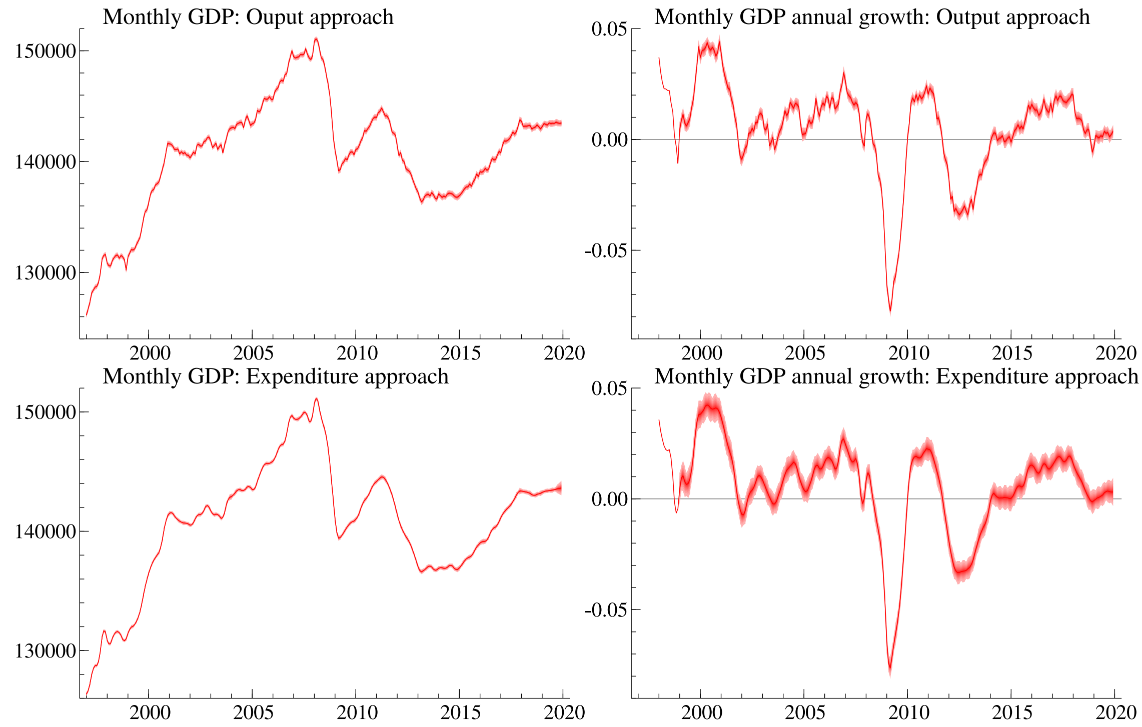

Fig. 1. Historical estimates of monthly GDP at market prices (chained volumes 2015) and its yearly relative changes, according to the output approach (top panels) and the expenditure approach (bottom panels).

variances $\widehat{\mathrm{Var}}(y_{it}|\mathcal{Y}_{in}, \mathcal{X}_{jn})$, provided by the Kalman filter and smoother (KFS), plus the variance of the monthly estimates of the same component. This second source of variability typically plays a minor role, except at the end of the sample, where the variability of the predictions is higher and can vary relevantly depending on the indicator used. The underlying idea is that the conditional distribution of y_{it} can be characterized as a mixture of N Gaussian distributions with mean $\tilde{y}_{it}$ and variance $\widehat{\mathrm{Var}}(y_{it}|\mathcal{Y}_{in}, \mathcal{X}_{jn})$, each one arising from selecting the jth indicator, with mixture probabilities $w_{ij}, j = 1, \ldots, N$.

The conditional variance of the growth rates is computed similarly, where $\widehat{\mathrm{Var}}(\Delta_{12}y_{it}/y_{i,t-12}|\mathcal{Y}_{in}, \mathcal{X}_{jn})$ is obtained by the delta method based on the output of the KFS. Hence, the confidence bands capture the so-called "filtering" uncertainty, which arises from the fact that only the quarterly sums are available for the components of GDP and the variability of the estimates that are obtained by conditioning on a different indicator.

In interpreting the plots, it must be brought in mind that neither parameter uncertainty nor model uncertainty is considered. A more complete assessment of these additional sources of uncertainty, along the lines of Corona et al. (2020) and Proietti et al. (2017), is left to future research.

Inspection of Fig. 1 induces the following considerations:

1. The filtering and indicator uncertainty is not large in historical estimation. The pseudo-real-time estimation experiment, not conditioning on the past and future history of the national accounts components, will bring to the surface the kind of uncertainty that is faced in real time. In Fig. 1 only the last three estimates, referring to October–December 2019 can be considered as a nowcast; in fact, the interval estimates widen.
2. Higher uncertainty characterizes the monthly estimates of GDP using the expenditure approach. This stylized fact, previously documented by Frale et al. (2011) and Proietti et al. (2017), is related to the availability of representative and relevant monthly indicators. A tentative explanation is that the statistical system is highly unbalanced towards the supply side of the economy.
3. The monthly estimates arising from the expenditure approach are generally smoother. This is a consequence of the higher volatility and idiosyncrasy of the shocks affecting industry and construction, which account for a large share of total value added in Italy.
4. For brevity, the estimates of monthly GDP arising from the direct approach are not presented. They are qualitatively similar and are a compromise between the two estimates from the expenditure and the output side. Also, the estimation error uncertainty lies in between the two approaches.

The availability of the estimates of the individual components opens the way to performing a growth accounting exercise. Figs. 2 and 3 present the contribution of the individual output components and expenditure components to the aggregate GDP annual growth rate.

The contribution is computed by multiplying the weight of the component as a fraction of total GDP, calculated on the annual value at current prices for the previous year, multiplied by the growth rate of the component, i.e., in the notation of (14), $\frac{y^{(0)}_{i,ms}-y^{(0)}_{i,m,s-1}}{y^{(0)}_{i,m,s-1}} W^{(0)}_{i,m,s-1}$. As a result, the decomposition of GDP growth is additive only up to an approximation that depends on the time pattern of the deflators of the components, relative to that of GDP.

This provides valuable information on the sources of growth in any particular month. For instance, during the Great Recession the strongest negative contribution was given by the industrial value added, followed with a lag by Sector G-H-I. These sectors also provide the largest positive contribution to GDP growth. The contribution of the construction sector has been negative thereafter until 2014. Export and household consumption are the components making the largest contribution to growth in 2016 from the expenditure side. The service sectors make a contribution that is relatively small; the most procyclical one is made by the value added of self-employed professionals in Sectors M–Z. The contribution of TLS is obviously strongly correlated to that of the industrial and trading sectors.

From the expenditure side, investments made the largest negative contribution during the Great Recession; interestingly, during the sovereign debt crisis (2011–2013) final household consumption made a sizable contribution, much larger than during the Great Recession. Net exports made a negative contribution to GDP growth during the Great Recession, and a positive one during the sovereign debt crisis, which compensated for the strong and negative growth in investment and private consumption.

6.2. A recursive pseudo-real-time nowcasting and forecasting experiment

6.2.1. Design of the experiment

We consider an econometrician using our methodology in real time to nowcast and forecast GDP and compare the predictions with the realized values. Her objectives would be multifold: (i) assess the predictive ability of the model for the components and aggregate GDP, both per se and comparatively; (ii) decide whether the aggregation of the components offers advantages over predicting GDP directly using the N indicators; (iii) evaluate the importance of the monthly indicators and their variability during business-cycle phases.

To address these issues she implements a recursive pseudo-real-time experiment, which at the end of each month produces a nowcast and a forecast of quarterly GDP by aggregating the monthly estimates. The design follows the flow of economic information available in three typical situations, positioned at the end of the three months making up each quarter.

Starting from January 2008, for every month m, $m = 1, 2, 3$, of reference quarter τ, she produces the nowcasts $\hat{\mathrm{E}}(y_{i,3\tau-k}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$, for $k = 0, 1, 2$, and $t = m + 3(\tau - 1)$, for all the GDP components and GDP itself, for all $i = 1, \dots, M$ and $j = 1, \dots, N$. Furthermore, she produces the forecasts for the three months making up quarter $\tau + 1$, $\hat{\mathrm{E}}(y_{i,3(\tau+1)-k}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$, $k = 0, 1, 2$.

Temporal aggregation across the index k will produce the nowcasts of the components and GDP for quarter τ, $\hat{Y}_{ij,\tau} = \sum_{k=0}^{2} \hat{\mathrm{E}}(y_{i,3\tau-k}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$, that she can compare with the quarterly published value, $Y_{i\tau}$. Let $\nu_{ij,\tau}$ denote the nowcast error $Y_{i\tau} - \hat{Y}_{ij,\tau}$. As for the next quarter forecast, she computes the prediction $\hat{Y}^{(f)}_{ij,\tau+1} = \sum_{k=0}^{2} \hat{\mathrm{E}}(y_{i,3(\tau+1)-k}|\mathcal{Y}_{it}, \mathcal{X}_{jt})$ and the corresponding forecast error $\nu^{(f)}_{ij,\tau+1} = Y_{i,\tau+1} - \hat{Y}^{(f)}_{ij,\tau+1}$.

At the end of the mth month she will have estimated N models for the ith component and she will combine the individual nowcasts with weights determined according to Section 3—either from the deviance of the estimated model or from the Ledoit–Wolf optimal shrinkage estimator, using $\nu_{ij,\tau}$ or $\nu^{(f)}_{ij,\tau+1}$, respectively—to construct a regularized estimator of the nowcast and forecast error covariance matrix. The model averaging nowcasts and forecasts are then $\hat{Y}_{i,\tau} = \sum_{j=1}^{N} w_{ij,t}\hat{Y}_{ij,\tau}$ and $\hat{Y}^{(f)}_{i,\tau+1} = \sum_{j=1}^{N} w^{(f)}_{ij,t}\hat{Y}^{(f)}_{ij,\tau+1}$. The aggregation weights $w_{ij,t}$ and $w^{(f)}_{ij,t}$ are indexed by t since they are re-estimated in each month.

Along with the direct nowcast of GDP she produces the indirect ones by performing the cross-sectional aggregation according to the method outlined in Section 4. Hence, three GDP nowcasts and forecasts will be made available: the direct one and two indirect ones from the output and the expenditure approaches. The nowcast and one-quarter-ahead forecast errors constitute the basis for the aggregation weights and for the assessment of the methodology.

It is assumed that the exercise is conducted at the end of each month m of quarter τ for all the months from January 2008 up to December 2018. While the nowcast and forecast target remain the same, the information set available to the econometrician varies with m. In particular, it increases as we progress towards the end of the reference quarter.

The first nowcast and forecast are made at the end of the first month of the reference quarter ($m = 1$, i.e., January, April, July, and October). The information available on GDP of the reference quarter and its components includes the soft indicators (business and consumer surveys), which are available up to the current month (all the indicators of Table B.1 with publication delay equal to 0 in the penultimate column), whereas the hard indicators are available according to a ragged-edge structure, such that, e.g., industrial production is available up to the last month of the previous quarter (all the indicators with publication delay equal to 1 in Table B.1). As far as the target series is concerned, the information set also includes the GDP series up to the previous quarter[1] ($\tau - 1$).

[1] The flash estimate of the GDP of quarter $\tau - 1$ would have been just published; since this is not available for a large part of the test sample (it becomes available only from April 2016), we replace it by the quarterly GDP figure published by Istat.

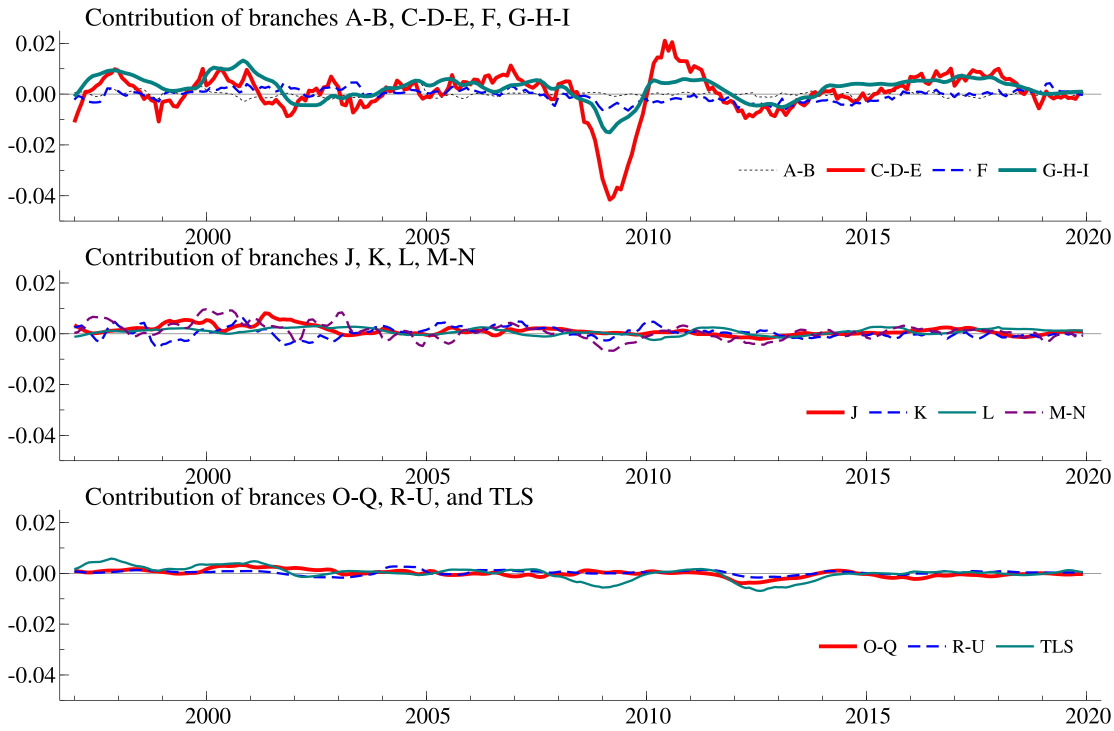

Fig. 2. Growth accounting: contribution of the 11 output components to yearly GDP growth.

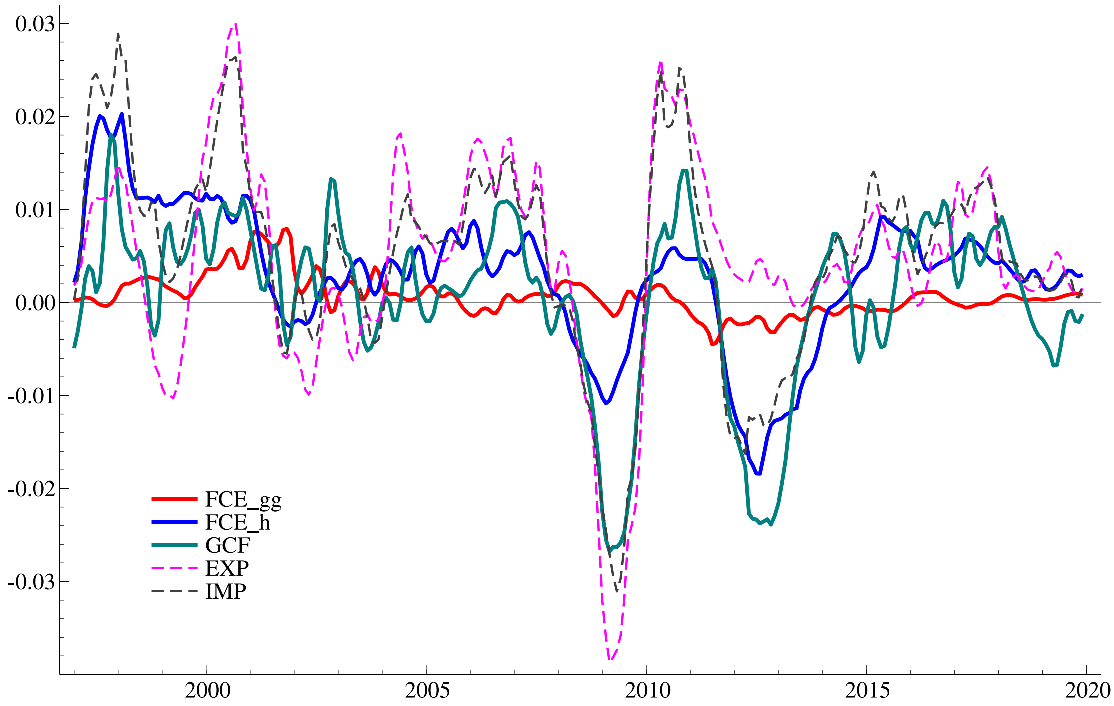

Fig. 3. Growth accounting: contribution of the five expenditure components (bottom panel) to yearly GDP growth. That of IMP has the sign reversed.

The second nowcast and forecast are made the last day of the second month of the reference quarter ($m = 2$, i.e., February, May, August, and November). The information set available includes the soft indicators up to the second month of the reference quarter, producer and consumer prices, and monetary and financial aggregates for the first month of the quarter become. Moreover, the monthly information concerning quarter $\tau - 1$ is complete, except for building permits and production in construction.

The third nowcast and forecast are made at the end of the reference quarter ($m = 3$, March, June, September, and December). The information set on the previous quarter is complete, but also that concerning the current quarter is relatively rich, featuring the index of industrial production and retail sales for the first month of the quarter.

6.2.2. Empirical assessment of predictive ability

The main results, referring to GDP, are presented in Tables 2 and 4. Detailed results for the individual GDP components are available in the Supplement. The tables report the root mean square errors (RMSEs), computed over $T = 44$ prediction errors, for the test sample 2008.q1 –2018.q4 (nowcasting) and 2008.q2–2019.q1 (forecasting) of the direct (Table 2) and indirect nowcast and forecast of the Italian GDP, by the output approach (Table 3), and the expenditure approach (Table 4).

Each table is divided into four panels: the first reports the RMSEs of four model averaging strategies using the deviance-based weights (8), with no selection (DEV_N), and selecting the 10, 30, and 50 best performing bivariate models in terms of their in-sample performance, as measured by the deviance within the training sample.

The second panel refers to the pooling scheme (5), using the Ledoit–Wolf (LW) estimator of the nowcast and forecast error covariance matrix. The latter is constructed according to (6), using the out-of-sample prediction errors for the last three years of data before time t. The shrinkage intensity is estimated according to Appendix A.

We also consider an equally weighted model averaging scheme (Panel C) and compare the predictive accuracy of our pooled nowcasts and forecasts with a univariate benchmark and a multivariate one based on a dynamic factor model (DFM, Panel D). The univariate benchmark latter is an ARIMA(p,1,0) model selected recursively according to the Bayesian information criterion (BIC) applied to quarterly GDP, for which we report the one-step-ahead RMSE under the nowcasting column and the two-step-ahead RMSE in the forecasting one. The benchmark should provide an upper bound to the nowcasting and forecasting RMSE in the absence of information concerning the monthly indicators.

A more informative benchmark arises from extracting from the monthly indicators r dynamic common factors, following Stock and Watson (2002a, 2002b). The forecasts of (the) quarterly GDP (components) are obtained from an autoregressive model augmented by the estimated common factors:

$$\widehat{Y}_{i,\tau+h} = \widehat{c} + \sum_{j=1}^{r} \widehat{\gamma}_j \widehat{F}_{j\tau} + \sum_{k=1}^{p} \widehat{\phi} Y_{i,\tau-j+1},$$

where Y denotes the GDP component, $h \geq 1$ is the forecast lead, and $\widehat{F}_{j\tau}$ is the jth estimated factor, obtained by averaging the monthly factor scores for the three months composing the quarter. The monthly factors are obtained by principal components analysis. The ragged-end structure of the dataset has been handled by applying the expectation–maximization-type algorithm proposed by Stock and Watson (2002a, 2002b). The parameters are estimated by least squares. Regarding the model specification, the number of factors is estimated through the information criterion proposed by Alessi et al. (2010, ABC), whereas the lag order p is estimated according to the BIC. We also tested the inclusion of lags for $\widehat{F}_{j\tau}$, and using the selection criteria by Bai and Ng (2002), but the results were not significantly better and are not reported here for brevity. Finally, the indirect predictions are obtained by means of the aggregating scheme according to Section 4. The best results were obtained with a number of factors selected a priori ($r = 4$). For the indirect approach, the forecasts were aggregated using the annual overlap method described in Section 6.1.

The main evidence arising from Table 2 can be summarized as follows.

- The monthly indicators carry information that is useful for nowcasting and forecasting GDP directly. Their use leads to a systematic and sizable reduction of the RMSE with respect to the univariate and DFM benchmarks. The RMSE reduction can be as large as 28% (19%) in nowcasting (forecasting) GDP at the end of the reference quarter ($m = 3$) with the LW predictor. The DFM approach using four factors shows superior performance only when forecasting GDP with the expenditure approach (see Table 4).
- As the monthly information on the GDP of the reference quarter increases, the nowcast and forecast accuracy improves: this is evidenced by the monotonic decrease in the RMSE as we move from $m = 1$ to $m = 3$.
- The best performing method for aggregating the individual GDP predictions is provided by the optimal weighting scheme in (5) using the Ledoit and Wolf (2004a) shrinkage estimator of the nowcast and forecast error covariance matrix.
- The second best strategy is to adopt deviance-based averaging. In general, it is beneficial to perform a preliminary screening, and restricting attention to the best 50 bivariate nowcasts and forecasts leads to the best performance in the subset.
- Simple averaging does not compare well with the other model averaging schemes.

The superior performance of the LW aggregate nowcasts and forecasts can be ascribed to the fact that the weights optimize the local out-of-sample predictive performance, based on the last two years of recursive prediction errors, as well as to the effectiveness of the shrinkage estimator (6).

The above findings are confirmed for both indirect nowcasting and forecasting methods. For comparison, Tables 3 and 4 report the RMSE of the indirect univariate and multivariate benchmarks. While there is no evidence that the indirect univariate predictor is superior to the direct one (the nowcast RMSE is smaller for the direct method, but the forecast RMSE is larger), there is decisive support for the indirect model averaging method, especially when the LW aggregation weights are adopted. In particular, the GDP nowcasts and forecasts by output,

Table 2
Nowcasting and forecasting results for Italy GDP (direct approach). The table reports the mean square prediction errors associated with the different methods. The predictand is quarterly GDP for the sample periods 2008.q1–2018.q4 (nowcasting) and 2008.q2-2019.q1 (forecasting).

	PANEL A: Deviance (In sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
DEV_N	2823.8	2753.0	2625.3	6098.9	5945.0	5699.3
DEV_{10}	2925.9	2803.9	2405.4	6154.7	6052.3	5554.6
DEV_{30}	2790.4	2659.0	2328.6	6087.3	5925.4	5489.2
DEV_{50}	2759.9	2609.6	2310.0	6002.0	5781.1	5369.9
	PANEL B: Ledoit – Wolf (Out of sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
$\text{OPT}_{LW}^{\lambda*}$	2659.6	2530.6	2294.7	5688.1	5376.9	4961.5
	PANEL C: Simple average					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
	2827.1	2765.6	2651.9	6106.9	5959.3	5732.6
	PANEL D: Benchmarks					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
$AR(BIC)^{Dir}$	2930.5			5918.3		
$DFM_{ABC,IC1}$	5467.6	5209.2	3976.7	8377.2	8757.5	5872.5
$DFM_{r=4}$	2788.1	3517.8	2686.2	6075.0	5919.2	6269.4

Table 3
Nowcasting and forecasting results for output-side GDP (chain-link method). The table reports the mean square prediction errors associated with the different methods. The predictand is quarterly GDP for the sample periods 2008.q1–2018.q4 (nowcasting) and 2008.q2-2019.q1 (forecasting).

	PANEL A: Deviance (In sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
DEV_N	2838.6	2756.5	2648.5	5946.3	5791.9	5614.9
DEV_{10}	2784.7	2628.0	2163.3	5817.4	5620.8	5133.6
DEV_{30}	2748.6	2574.1	2208.1	5873.9	5576.5	5117.8
DEV_{50}	2687.7	2521.6	2202.5	5741.0	5459.3	5038.0
	PANEL B: Ledoit – Wolf (Out of sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
$\text{OPT}_{LW}^{\lambda*}$	2219.9	2221.3	1829.2	4669.7	5149.3	4594.6
	PANEL C: Simple average					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m=1$	$m=2$	$m=3$	$m=1$	$m=2$	$m=3$
	2887.6	2780.4	2693.8	6006.3	5834.9	5680.1
	PANEL D: Benchmarks					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
$AR(BIC)^{Ind}$	2982.8			5909.5		
$DFM_{ABC,IC1}$	5488.6	5198.4	3767.9	8400.1	8565.2	5629.1
$DFM_{r=4}$	3155.5	3645.6	3076.7	5890.9	5797.0	6277.1

resulting from the contemporaneous aggregation of the value added of the branches, are the most accurate, despite a non-monotonic behavior with respect to m, with accuracy gains that reach 60% in nowcasting GDP at the end of the third month of the reference quarter. The expenditure approach offers a relative improvement only when starting from $m = 2$.

6.2.3. Inside the black box

When and how did the predictive accuracy gain of the LW pooling method accrue? What indicators contributed most to the outcome? What are the sources of the comparative advantages of the indirect approach?

To address these questions we set off by evaluating the local relative predictive performance of the LW model averaging method with respect to the univariate ARIMA(1,1,0) predictor by means of the fluctuation test

Table 4
Nowcasting and forecasting results for expenditure-side GDP (chain-link method). The table reports the mean square prediction errors associated with the different methods. The predictand is quarterly GDP for the sample periods 2008.q1–2018.q4 (nowcasting) and 2008.q2–2019.q1 (forecasting).

	PANEL A: Deviance (In sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
DEV_N	2941.4	2854.8	2748.6	6059.7	5912.1	5719.9
DEV_{10}	2943.3	2764.5	2205.7	5794.7	5658.0	5183.7
DEV_{30}	2779.8	2565.0	2181.2	5756.6	5478.2	5044.8
DEV_{50}	2764.6	2540.8	2245.1	5773.8	5489.4	5098.3
	PANEL B: Ledoit – Wolf (Out of sample)					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
$\mathrm{OPT}_{LW}^{\lambda *}$	3118.2	2230.0	2081.6	6203.3	4548.6	4667.1
	PANEL C: Simple average					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
	$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
	2948.9	2878.1	2788.7	6067.9	5950.7	5778.1
	PANEL D: Benchmarks					
	Nowcasting current quarter			Forecasting 1 quarter ahead		
$AR(BIC)^{Ind}$	3353.6			5588.9		
$DFM_{ABC,IC1}$	5054.5	4739.5	3678.7	7307.6	7810.8	5262.0
$DFM_{r=4}$	2542.7	3069.4	2792.0	5010.0	4728.9	5472.2

statistic proposed by Giacomini and Rossi (2010). The statistic is the standardized average squared loss differential of the univariate and LW prediction errors calculated over rolling windows of two years.

Fig. 4 displays the fluctuation tests for the direct LW case, according as to whether the nowcast (left panels) or nowcasts (right panels) are performed in months $m = 1, 2, 3$, of the reference quarter (nowcast) or of the quarter before (forecast). Values above zero signify that the LW method outperforms the benchmark, and vice versa. The dashed lines are drawn at the 5% critical values provided by Giacomini and Rossi (2010, Sec. 3.2) for the null hypothesis that the LW method and the univariate benchmark have equal out-of-sample performance at each point in time.

It should be noticed that the first point shown in each graph refers to the years 2008–2010, which include the Great Recession. Hence, it is evident that the direct LW predictor outperformed the benchmark significantly during the Great Recession, and that no significant accuracy gains are detectable thereafter. It was then that the monthly indicators carried relevant information in real time that was not contained in the GDP history.

It is remarkable that when it comes to comparing the indirect GDP predictors by output, see Fig. 5, the LW predictor shows a sizable and sometimes significantly greater increase in predictive accuracy during the downturn associated with the sovereign debt crisis. This characteristic can also be observed for $m = 2$ and $m = 3$ when GDP is predicted according to the expenditure approach (Fig. 6).

We performed an indicator-importance analysis by counting how many times each one belonged to the set of 50 indicators with largest weights w_{ijt} across the 44 recursive prediction exercises taking place in month $m = 1, 2, 3$, of quarter $\tau = 1, \dots, 44$. In the *balloon plots* 7–9 the top 50 indicators are listed on the left in increasing order of importance from top to bottom. The size and color of the balloons are proportional to the square of the nowcast and forecast error that arises from the bivariate models featuring a particular indicator. The latter reduce as we move from $m = 1$ to $m = 3$; the reduction is quite dramatic in nowcasting GDP indirectly using the output approach; see the panels on the left in Fig. 8.

The plots point out a very important fact: in nowcasting the current quarter GDP using the information accrued in the first month ($m = 1$), a prominent, if not exclusive, role is played by business-cycle indicators (BCIs), and economic sentiment indicators (ESIs) based on harmonized surveys of businesses and consumers. Thus, the main driver of the gains in nowcasting accuracy at the end of the first month of the quarter are the so-called soft indicators. If the output approach is used (Fig. 8), some hard indicators are also relevant, relating to the labor market (for the service sectors) or to economic activity (car registration and retail sales for Sector G-H-I, and motorway flow of trucks for industry). In other words, sector-specific indicators emerge now as drivers of the accuracy of the nowcast of a GDP component.

As we move to second and third month of the quarter ($m = 2, 3$) and more quantitative information on the current quarter accrues, hard indicators gain progressively more importance: in particular, industrial production indices, retail and industrial turnover, new orders, and import and export indices; see the second and third panels on the right in Figs. 7, 8, and 9. The motorway flow of trucks stands out as one of the most important coincident indicators. As a matter of fact, this is one of the indicators that is monitored by the authors in their

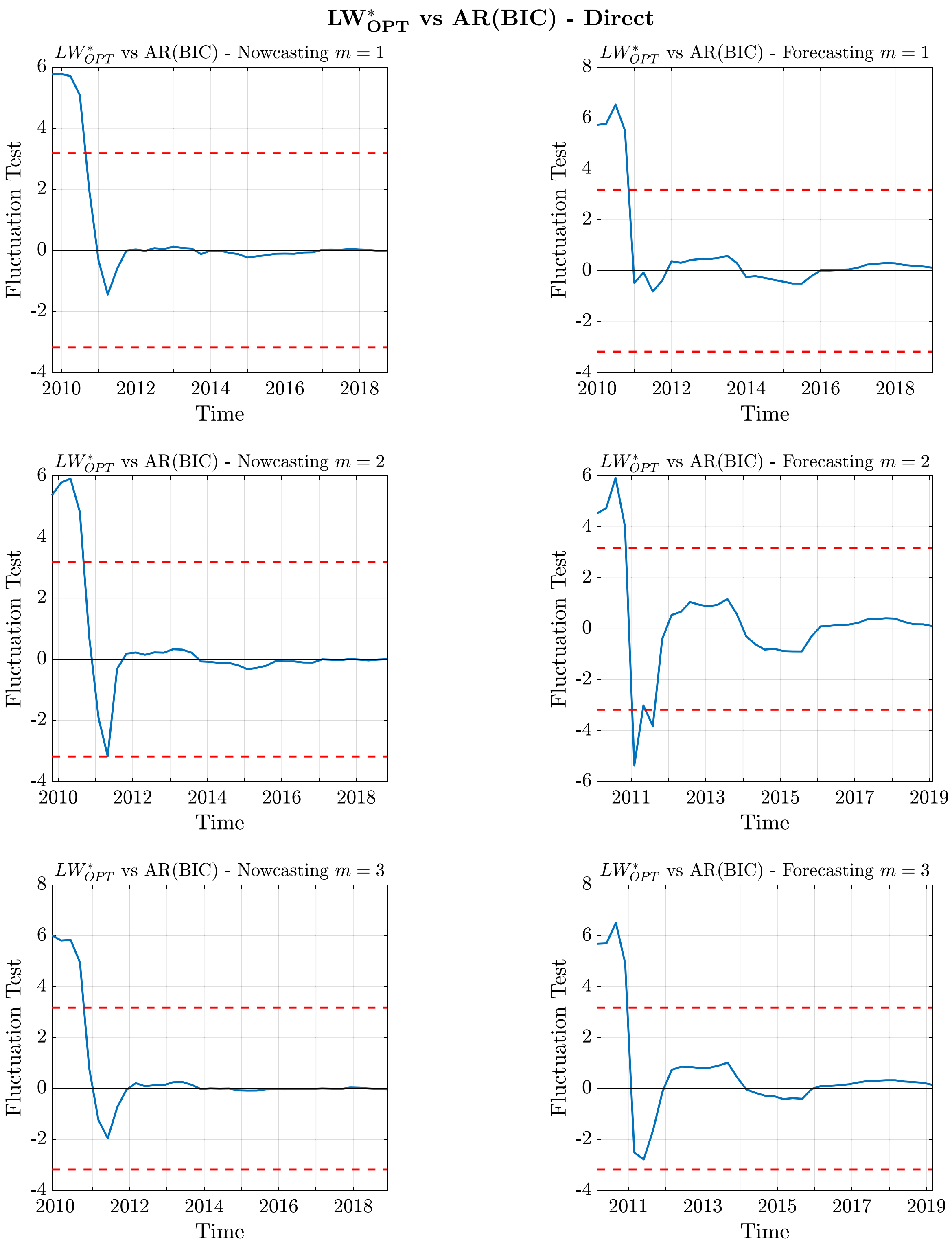

Fig. 4. Fluctuation test for the LW direct GDP predictor. The solid line in each figure is the average difference between the squared nowcast (forecast) errors of two LW methods and the univariate benchmark, normalized by its estimated standard deviation, computed over a rolling window of eight quarters. The zero horizontal line indicates equal performance, and the dotted lines indicate the 5% critical values. LW^*_{OPT} outperforms (underperforms) the AR(BIC) locally, at the 5% significance level, when the solid line is above (below) the upper (lower) dashed line.

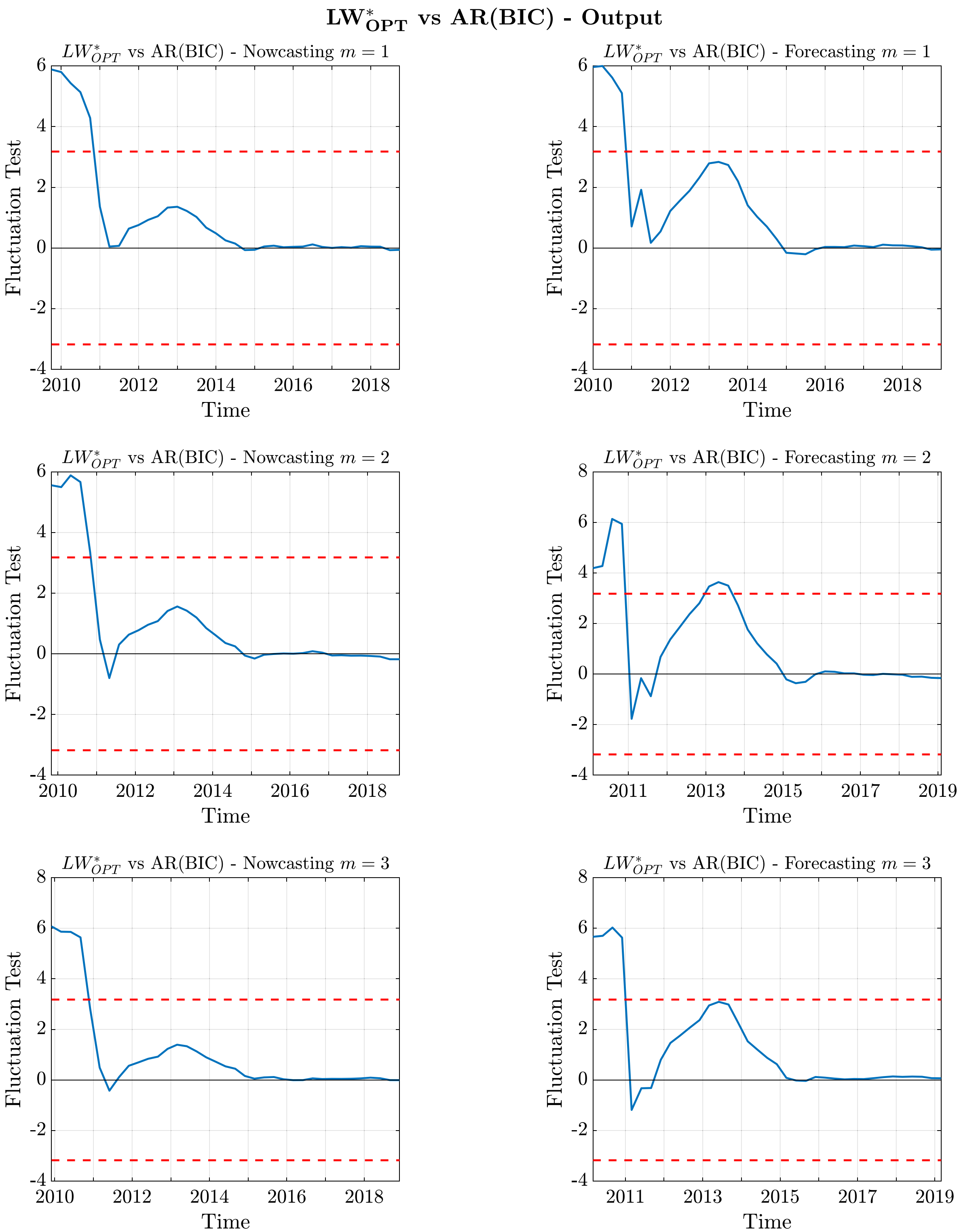

Fig. 5. Fluctuation test for the LW indirect predictor by the output approach. The solid line in each figure is the average difference between the squared nowcast (forecast) errors of two LW methods and the univariate benchmark, normalized by its estimated standard deviation, computed over a rolling window of eight quarters. The zero horizontal line indicates equal performance, and the dotted lines indicate the 5% critical values. LW^*_{OPT} outperforms (underperforms) the AR(BIC) locally, at the 5% significance level, when the solid line is above (below) the upper (lower) dashed line.

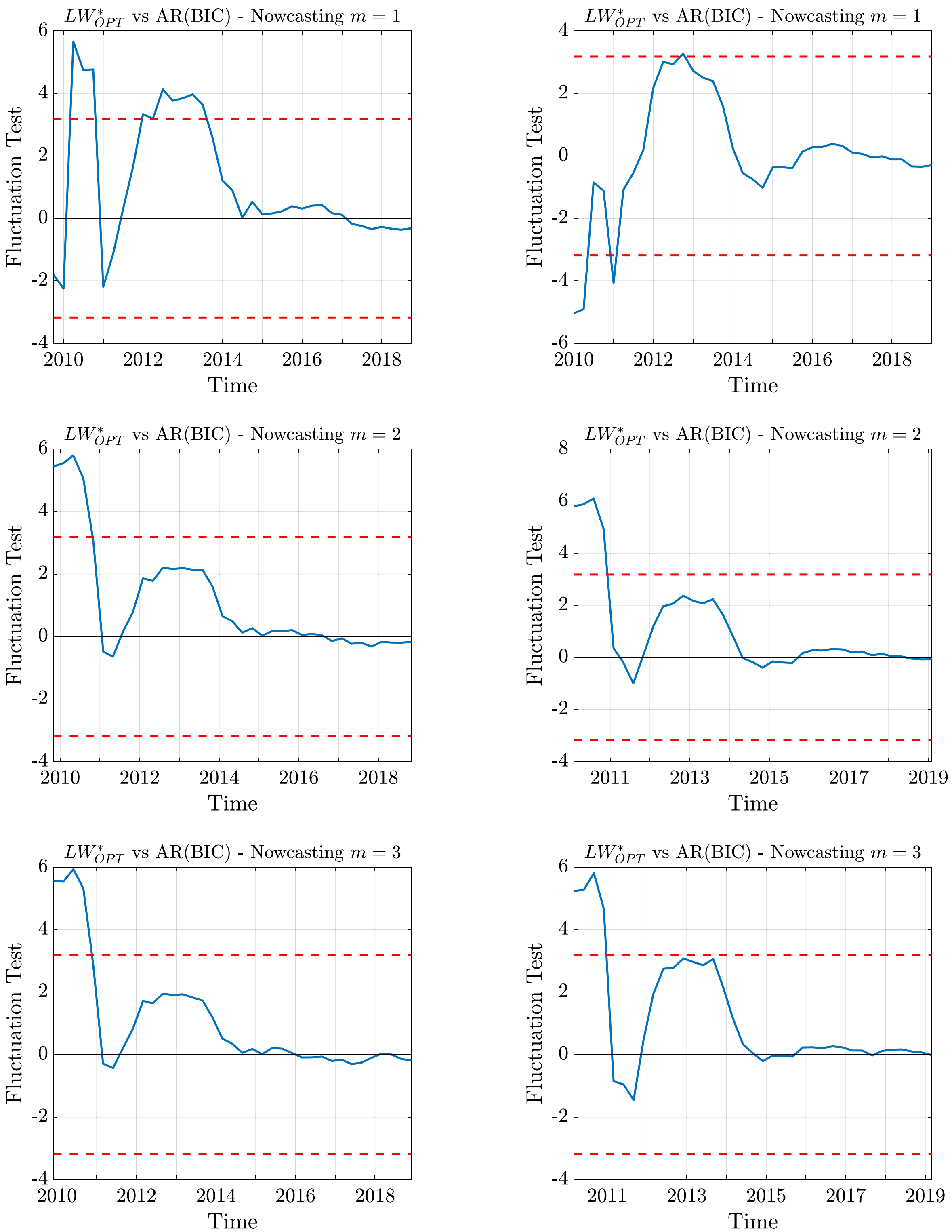

Fig. 6. Fluctuation test for the LW indirect GDP predictor by the expenditure approach. The solid line in each figure is the average difference between the squared nowcast (forecast) errors of two LW methods and the univariate benchmark, normalized by its estimated standard deviation, computed over a rolling window of eight quarters. The zero horizontal line indicates equal performance, and the dotted lines indicate the 5% critical values. LW^*_{OPT} outperforms (underperforms) the AR(BIC) locally, at the 5% significance level, when the solid line is above (below) the upper (lower) dashed line.

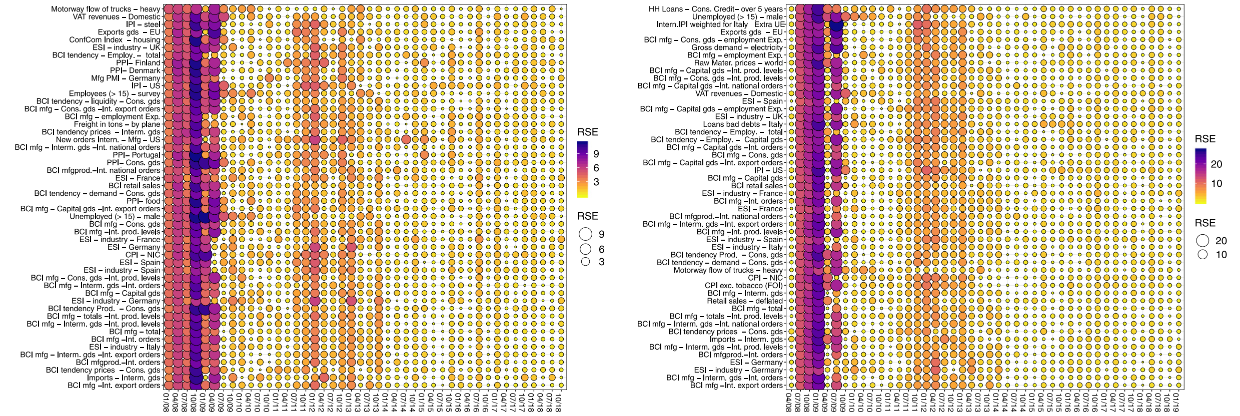

Fig. 7. LW^*_{OPT} balloon plot – direct approach, $m = 1$. Each figure, on the left, reports the evolution over time, measured in terms of the size of the nowcast (left column) and forecast (right column) errors (RSE), of the top 50 (most used) variables for the LW^*_{OPT} approach.

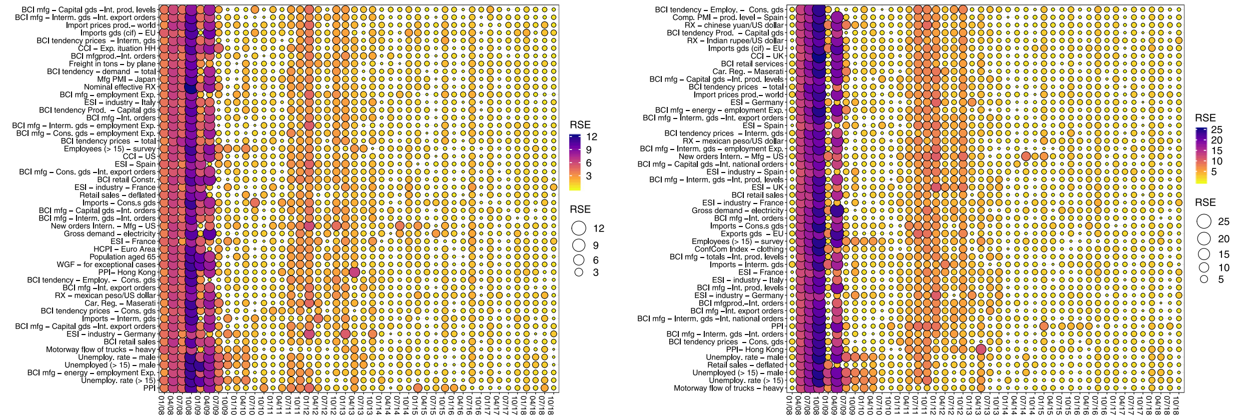

Fig. 8. LW^*_{OPT} balloon plot – chain-linking output side, $m = 1$. Each figure, on the left, reports the evolution over time, measured in terms of the size of the nowcast (left column) and forecast (right column) errors (RSE), of the top 50 (most used) variables for the LW^*_{OPT} approach.

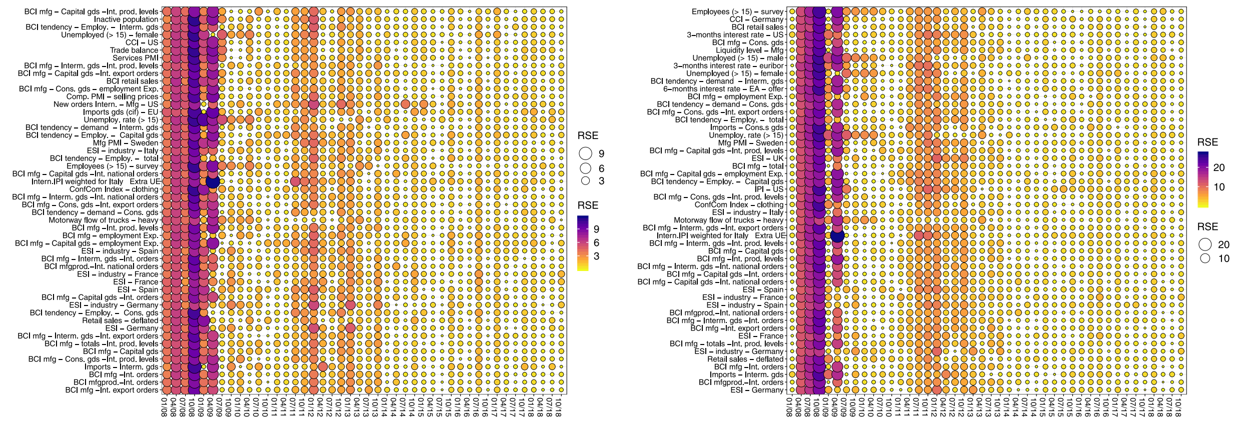

Fig. 9. LW^*_{OPT} balloon plot – chain-linking expenditure side, $m = 1$. Each figure, on the left, reports the evolution over time, measured in terms of the size of the nowcast (left column) and forecast (right column) errors (RSE), of the top 50 (most used) variables for the LW^*_{OPT} approach.

current nowcasting practice.

When it comes to forecasting, indicator importance becomes more sparse. The noteworthy tendency is that the hard indicators are used more in forecasting the next quarter than in nowcasting. That is, they better reflect the development of economic conditions at longer horizons.

Obviously, the nowcast and forecast errors are strongly procyclical, being larger during the Great Recession and the sovereign debt crisis. It was particularly hard to forecast the Great Recession since its inception, and in particular the three quarters from 2008.q4–2009.q2, which marked a deep trough of economic activity and the initial recovery.

The plots also show that in $m = 3$, the hard indicators relating to the freight of goods, including truck flow and industrial production, have the largest predictive accuracy for forecasting one quarter ahead.

7. Discussion and concluding remarks

The paper considered the problem of nowcasting and forecasting production and expenditure national accounts, using a large-dimensional set of economic indicators available at the monthly frequency.

Our methodology relies on estimating all the possible mixed-frequency bivariate models of the quarterly GDP component and each monthly indicator in turn, taking into account the temporal aggregation constraints and the ragged-edge structure of the data. The different nowcasts and forecasts are then combined with weights reflecting their local accuracy in out-of-sample predictions. A recursive pseudo-real-time exercise showed that the Ledoit–Wolf shrinkage approach, see Ledoit and Wolf (2004a, 2004b), provides a very effective solution to the estimation of the model averaging weights.

With reference to the Italian case, we illustrated that our approach can keep up with the challenges posed by the dimensionality, since it can handle a large number of time series with a complexity that increases linearly with the cross-sectional dimension, while retaining the essential heterogeneity of the information about the macroeconomy. The combination with aggregation weights that reflect the predictive ability of the indicators is quintessential to the efficiency of the methodology.

Along with nowcasting and forecasting aggregate GDP (synthesis), our approach can measure the contribution to GDP growth by the components by output and expenditure (by growth accounting) and assess the comparative merits of the indirect approach vis-à-vis the direct prediction of GDP (analysis). The estimation of all possible bivariate models generates a wealth of information, making it is possible to assess when and how each individual indicator contributes to the result (indicator importance). This analysis has led to several interesting discoveries, among other things, concerning the relative contribution of soft and hard indicators as they become available in real time, as well as their predictive performance during recessionary episodes.

The results on the relative importance of the indicators presented in Section 6.2 should not be interpreted as an expression of the *sparsity* of economic information, i.e. that only a few indicators matter for forecasting the level of aggregate economic activity.

A substantial amount of literature has challenged the comparative efficiency of large-scale versus small-scale forecasting approaches. Boivin and Ng (2006) show that substantial cross-correlation among the idiosyncratic components leads to the deterioration of the contribution of factors extracted from large macroeconomic panels to forecasting key variables such as GDP. Bai and Ng (2008) argue that supervising the factor extraction by a preliminary pre-selection of the indicators could lead to superior performance. Bańbura and Modugno (2012) find that for the euro area, using more disaggregated information does not improve the predictive accuracy. Poncela and Ruiz (2015) also point out that more information is not necessarily better, highlighting the loss in accuracy due to the increase in parameter uncertainty when higher-dimensional factor models are estimated. Alvarez et al. (2016) show that smaller-dimensional factor models using aggregate indicators, selected on the basis of their representativeness within economic categories, outperform larger-scale dynamic factor models for predicting the euro area GDP.

Against this background, we argue that the over-representation of categories of particular indicators (e.g., consumer and business surveys) and high levels of cross-sectional correlation in the idiosyncratic components are more likely to affect global approaches that use all the information at once, e.g., estimating a large dimensional factor model by principal components or the EM algorithm, than our approach. In our framework the individual indicators are entered one by one and thus the cross-correlation of the idiosyncratic effect does not play a role. Moreover, the supervision of the individual nowcasts and forecasts is guaranteed both by the estimation of the bivariate factor model, which is formulated such that the common component of the indicator under consideration is distilled, without having to specify the nature and number of the common dynamic factors, and by the model averaging methodology, which assigns weights to the nowcasts and forecasts according to the predictive accuracy manifested in the past.

Future research will be dedicated to introducing interventions to the model and the averaging method to account for the effects of the Covid-19 pandemic, and to evaluating the information content of the monthly indicators for nowcasting and forecasting GDP during the pandemic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research has been supported by a research grant by the Italian Ministry of Economics and Finance (MEF), Direction I (Department of Treasury), as part of the collaboration agreement "Short run forecasting of macroeconomic indicators" between MEF and the University of Tor Vergata.

Table B.1
List of monthly indicators.

Id	Variables name	Abbreviation	Sector	Timing	Country
1	Activity rate (15-64): Italy	Activity rate (15-64)	Labor	1	Italy
2	Freight in tons travelled by plane: Italy	Freight in tons - by plane	Services	1	Italy
3	Number of passengers travelled by plane : Italy	Passengers travelled by plane	Services	1	Italy
4	Arrivals in hotel, foreigners: Italy	Arrivals in hotel - foreigners	Services	3	Italy
5	Arrivals in hotel: Italy	Arrivals in hotel	Services	3	Italy
6	Attendance in hotel, foreigners: Italy	Attendance in hotel - foreigners	Services	3	Italy
7	Attendance in hotel: Italy	Attendance in hotel	Services	3	Italy
8	Loans to residents of Italy: bad debts	Loans bad debts - Italy	Finance	2	Italy
9	ESI - industry - Italy	ESI - industry - Italy	Survey	0	Italy
10	ESI - industry - France	ESI - industry - France	Survey	0	Europe
11	ESI - industry - Germany	ESI - industry - Germany	Survey	0	Europe
12	ESI - industry - Spain	ESI - industry - Spain	Survey	0	Europe
13	ESI - industry - UK	ESI - industry - UK	Survey	0	Europe
14	Current opportunity to purchase durable goods	Opport. purchase durable gds	Survey	0	Italy
15	Opinions on family budget	Opinions on family budget	Survey	0	Italy
16	Balance of payments - services - credits	BoP - services - credits	Trade	3	Italy
17	Balance of payments - services - debts	BoP - services - debts	Trade	3	Italy
18	Italy benchmark bond 10 years	Italy bond 10 years	Finance	0	Italy
19	BCI in construction	BCI retail Constr.	Survey	0	Italy
20	BCI Manufac. - Employ. expectations	BCI mfg - Employ. Exp.	Survey	0	Italy
21	BCI Manufac. - orders expectations	BCI mfg - orders Exp.	Survey	0	Italy
22	BCI Manufac. - selling prices expectations	BCI mfg - selling prices Exp.	Survey	0	Italy
23	BCI Manufac. - production expectations	BCI mfg - prod. Exp.	Survey	0	Italy
24	BCI Manufac. - goods - Employ. expectations	BCI mfg - Cons. gds - Employ. Exp.	Survey	0	Italy
25	BCI Manufac. - energy - Employ. expectations	BCI mfg - energy - Employ. Exp.	Survey	0	Italy
26	BCI Manufac. - intermediate goods - Employ. expectations	BCI mfg - Interm. gds - Employ. Exp.	Survey	0	Italy
27	BCI Manufac. - capital goods - Employ. expectations	BCI mfg - Capital gds - Employ. Exp.	Survey	0	Italy
28	BCI Manufac. - opinions on orders	BCI mfg -Int. orders	Survey	0	Italy
29	BCI Manufac. - opinions on production levels	BCI mfg -Int. prod. levels	Survey	0	Italy
30	BCI in the retail sales sector	BCI retail sales	Survey	0	Italy
31	BCI in the services sector	BCI retail services	Survey	0	Italy
32	BCI Manufac. - opinions on stocks of finished products	BCI mfg - finished products	Survey	0	Italy
33	Car Registration - Alfa Romeo	Car Reg. - Alfa Romeo	Industry	1	Italy
34	Car Registration - commercial vehicles - total	Car Reg. - total	Industry	1	Italy
35	Car Registration - Ferrari	Car Reg. - Ferrari	Industry	1	Italy
36	Car Registration - Fiat	Car Reg. - Fiat	Industry	1	Italy
37	Car Registration - heavy (over 16T)	Car Reg. - commercial - heavy	Industry	1	Italy
38	Car Registration - Lancia	Car Reg. - Lancia	Industry	1	Italy
39	Car Registration - light (up to 3.5T)	Car Reg. - commercial - light	Industry	1	Italy
40	Car Registration - Maserati	Car Reg. - Maserati	Industry	1	Italy
41	Car Registration - medium (over 3.5T)	Car Reg. - commercial - medium	Industry	1	Italy
42	Car Registration - Other brands	Car Reg. - Other brands	Industry	1	Italy
43	Car Registration	Car Reg.	Industry	1	Italy
44	Wage Guarantee Fund - for exceptional cases	WGF - for exceptional cases	Labor	1	Italy
45	Wage Guarantee Fund - ordinary	WGF - ordinary	Labor	1	Italy
46	Wage Guarantee Fund - extraordinary	WGF - extraordinary	Labor	1	Italy
47	Wage Guarantee Fund - total	WGF - total	Labor	1	Italy
48	BCI Manufac. - goods	BCI mfg - Cons. gds	Survey	0	Italy
49	BCI Manufac. - intermediate goods	BCI mfg - Interm. gds	Survey	0	Italy
50	BCI Manufac. - capital goods	BCI mfg - Capital gds	Survey	0	Italy
51	BCI Manufac. - total	BCI mfg - total	Survey	0	Italy
52	Compensation of employees (net of WGF) - total industry	Compensation (net of WGF) - Industry	Labor	2	Italy
53	Confcommercio index - clothing	ConfCom Index - clothing	Services	1	Italy
54	Confcommercio index - accomodation	ConfCom Index - accomodation	Services	1	Italy
55	Confcommercio index - food	ConfCom Index - food	Services	1	Italy
56	Confcommercio index - total goods	ConfCom Indexprod.gds	Services	1	Italy
57	Confcommercio index - housing	ConfCom Index - housing	Services	1	Italy
58	Confcommercio index - communication	ConfCom Index - communication	Services	1	Italy
59	Confcommercio index - person care	ConfCom Index - person care	Services	1	Italy
60	Confcommercio index - durable goods	ConfCom Index - durable gds	Services	1	Italy
61	Confcommercio index - mobility	ConfCom Index - mobility	Services	1	Italy
62	Confcommercio index - non-durable goods	ConfCom Index - non-durable	Services	1	Italy
63	Confcommercio index - recreational	ConfCom Index - recreational	Services	1	Italy
64	Confcommercio index - services	ConfCom Index - services	Services	1	Italy
65	Confcommercio index - total	ConfCom Index prod.	Services	1	Italy
66	Current savings opportunity	Current savings opportunity	Survey	0	Italy
67	BCI in the construction sector	BCI - Constr.	Survey	0	Italy
68	CCI	CCI	Survey	0	Italy
69	CCI - France	CCI - France	Survey	0	Europe
70	CCI - Germany	CCI - Germany	Survey	0	Europe
71	CCI - Spain	CCI - Spain	Survey	0	Europe
72	CCI - UK	CCI - UK	Survey	0	Europe
73	CCI - US	CCI - US	Survey	0	world
74	Gross demand of electricity	Gross demand - electricity	Industry	0	Italy
75	CCI - current climate	CCI - current climate	Survey	0	Italy
76	Cost of construction of a residential building	Cost residential building	Prices	2	Italy
77	BCI in the construction sector - prices expectations	BCI - Constr. - Prices Exp.	Survey	0	Italy
78	Consumer price index excluding tobacco (FOI)	CPI exc. tobacco (FOI)	Prices	1	Italy
79	Consumer price index - total - Germany	CPI - Germany	Prices	1	Europe
80	Consumer price index - core inflation	CPI - core inflation	Prices	1	Italy
81	Harmonized index of consumer prices - EA	HCPI - EA	Prices	1	Europe
82	Harmonized index of consumer prices	HCPI	Prices	1	Italy
83	Consumer price index - NIC	CPI - NIC	Prices	1	Italy
84	Consumer price index - NIC excluding tobacco	CPI - NIC exc. tobacco	Prices	1	Italy
85	Dummy for number of working days	n. Working Days	Working days	0	Italy
86	Dummy for number of working days (with bank holiday)	n. Working Days - bank holiday	Working days	0	Italy
87	Dummy for number of Mondays	Dummy for number of Mondays	Working days	0	Italy
88	Dow Jones stock market index	Dow Jones stock market index	Finance	0	world
89	CCI - economic climate	CCI - economic climate	Survey	0	Italy
90	BCI in the retail sector - expectations on the economy	BCI - retail - Exp. Economy	Survey	0	Italy
91	BCI in the retail sector - BCI current situation	BCI - retail - current situation	Survey	0	Italy
92	BCI in the retail sector	BCI - retail	Survey	0	Italy
93	BCI in the retail sector - Employ. expectations	BCI - retail - Empl. Exp.	Survey	0	Italy
94	BCI in the retail sector - orders	BCI - retail - orders	Survey	0	Italy
95	BCI in the retail sector - BCI stocks	BCI - retail - Int. the stocks	Survey	0	Italy
96	BCI in the services sector - BCI current situation	BCI - services -Int. the current situation	Survey	0	Italy
97	BCI in the services sector	BCI - services	Survey	0	Italy

(*continued on next page*)

Table B.1 (*continued*).

Id	Variables name	Abbreviation	Sector	Timing	Country
98	BCI in the services sector - BCI demand	BCI - services -Int. the demand	Survey	0	Italy
99	BCI in the services sector - expectations on the demand	BCI - services - Exp. on the demand	Survey	0	Italy
100	BCI in the services sector - BCI Employ.	BCI - services -Int. the Employ.	Survey	0	Italy
101	BCI in the services sector - Employ. expectations	BCI - services - Employ. Exp.	Survey	0	Italy
102	Employees (15 years and over) - survey of the Labor force	Employees (> 15) - survey	Labor	1	Italy
103	BCI Manufac. - Employ. expectations	BCI mfg - Employ. Exp.	Survey	0	Italy
104	ESI	ESI	Survey	0	Italy
105	ESI - France	ESI - France	Survey	0	Europe
106	ESI - Germany	ESI - Germany	Survey	0	Europe
107	ESI - Spain	ESI - Spain	Survey	0	Europe
108	ESI - UK	ESI - UK	Survey	0	Europe
109	Euro stoxx 50 stock market index	Euro stoxx 50	Finance	0	Europe
110	Export - goods	Export - Cons. gds	Trade	2	Italy
111	Export - energy	Export - energy	Trade	2	Italy
112	Current account BP - goods - credits	Current account BP - gds - credits	Trade	2	Italy
113	Export of goods - world	Export gds - world	Trade	2	Italy
114	Export of goods (fob) - extra EU	Export gds - extra EU	Trade	2	Italy
115	Export of goods (fob) - EU	Export gds - EU	Trade	2	Italy
116	Export - intermediate goods	Export - Interm. gds	Trade	2	Italy
117	Export - capital goods	Export - Capital gds	Trade	2	Italy
118	Current account BP - services - credits	BP - services - credits	Trade	2	Italy
119	CCI - future climate	CCI - future climate	Survey	0	Italy
120	Maastricht public debt: Italy	Maastricht public debt	Finance	2	Italy
121	Export of goods (fob) - world - volume	Export gds - world	Trade	2	Italy
122	Export of goods (fob) - extra EU - volume	Export gds - extra EU	Trade	2	Italy
123	Export of goods (fob) - EU - volume	Export gds - EU	Trade	2	Italy
124	Imports of goods (fob) - world - volume	Imports gds - world	Trade	2	Italy
125	Imports of goods (fob) - extra EU - volume	Imports gds - extra EU	Trade	2	Italy
126	Imports of goods (fob) - EU - volume	Imports gds - EU	Trade	2	Italy
127	Inactivity rate (15-64)	Inactivity rate (15-64)	Labor	1	Italy
128	Inactive population	Inactive population	Labor	1	Italy
129	IPI: Italy	IPI	Industry	2	Italy
130	IPI - Austria	IPI - Austria	Industry	2	Europe
131	IPI - Belgium	IPI - Belgium	Industry	2	Europe
132	IPI - Danmark	IPI - Danmark	Industry	2	Europe
133	IPI - energy	IPI - energy	Industry	2	Italy
134	IPI - Finland	IPI - Finland	Industry	2	Europe
135	IPI - France	IPI - France	Industry	2	Europe
136	IPI - Greece	IPI - Greece	Industry	2	Europe
137	IPI - Germany	IPI - Germany	Industry	2	Europe
138	IPI - Ireland	IPI - Ireland	Industry	2	Europe
139	IPI - Japan	IPI - Japan	Industry	2	world
140	IPI - Korea	IPI - Korea	Industry	2	world
141	IPI - Mexico	IPI - Mexico	Industry	2	world
142	IPI - excluding energy	IPI - exc. energy	Industry	2	Italy
143	IPI - The Netherlands	IPI - The Netherlands	Industry	2	Europe
144	IPI - Norway	IPI - Norway	Industry	2	Europe
145	IPI - Portugal	IPI - Portugal	Industry	2	Europe
146	IPI - Spain	IPI - Spain	Industry	2	Europe
147	IPI - Sweden	IPI - Sweden	Industry	2	Europe
148	IPI - UK	IPI - UK	Industry	2	Europe
149	IPI - US	IPI - US	Industry	2	world
150	IPI - manufacture of motor vehicles	IPI - manufacture of motor vehicles	Industry	2	Italy
151	IPI - manufacture of cement	IPI - manufacture of cement	Industry	2	Italy
152	IPI - goods	IPI - Cons. gds	Industry	2	Italy
153	IPI - durable goods	IPI - durable Cons. gds	Industry	2	Italy
154	IPI - non-durable goods	IPI - non-durable Cons. gds	Industry	2	Italy
155	IPI - construction	IPI - construction	Industry	2	Italy
156	IPI - energy	IPI - energy	Industry	2	Italy
157	IPI - intermediate goods	IPI - Interm. gds	Industry	2	Italy
158	IPI - capital goods	IPI - Capital gds	Industry	2	Italy
159	IPI - manufacturing	IPI - Mfg	Industry	2	Italy
160	IPI - steel	IPI - steel	Industry	2	Italy
161	CCI	CCI	Survey	0	Italy
162	VAT revenues - Imports	VAT revenues - Imports	Services	2	Italy
163	VAT revenues - Domestic	VAT revenues - Domestic	Services	2	Italy
164	World trade index: Italy	World trade index	International	2	Italy
165	International IPI weighted for Italy - world	Intern.IPI weighted for Italy - world	International	2	Italy
166	International IPI weighted for Italy - UE	Intern.IPI weighted for Italy - UE	International	2	Italy
167	International IPI weighted for Italy - Extra UE	Intern.IPI weighted for Italy - Extra UE	International	2	Italy
168	Unemployed (15 years and over) - female	Unemployed (> 15) - female	Labor	1	Italy
169	Unemployed (15 years and over) - male	Unemployed (> 15) - male	Labor	1	Italy
170	Dummy for a leap day	Dummy for a leap day	Working days	0	Italy
171	Motorway flow of trucks - light	Motorway flow of trucks - light	Industry	0	Italy
172	Labor force (15 years and over)	Labor force (> 15)	Labor	1	Italy
173	Loans to non-financial corporation - up to 1 year	Loans no financ. - up to 1 year	Finance	2	Italy
174	Loans to non-financial corporation - 1 to 5 years	Loans no financ. - 1 to 5 years	Finance	2	Italy
175	Loans to non-financial corporation - over 5 years	Loans no financ. - over 5 years	Finance	2	Italy
176	Loans to households - credit - up to 1 year	HH Loans - Cons. Credit- up to 1 year	Finance	2	Italy
177	Loans to households - credit - 1 to 5 years	HH Loans - Cons. Credit- 1 to 5 years	Finance	2	Italy
178	Loans to households - credit - over 5 years	HH Loans - Cons. Credit- over 5 years	Finance	2	Italy
179	Loans to households - home purchase - up to 1 year	HH Loans - home purchase - up to 1 year	Finance	2	Italy
180	Loans to households - home purchase - over 5 years	HH Loans - home purchase - over 5 years	Finance	2	Italy
181	BCI Manufac. - goods - opinions on orders	BCI mfg - Cons. gds -Int. orders	Survey	0	Italy
182	BCI Manufac. - goods - opinions on export orders	BCI mfg - Cons. gds -Int. export orders	Survey	0	Italy
183	BCI Manufac. - intermediate goods - opin. on export orders	BCI mfg - Interm. gds -Int. export orders	Survey	0	Italy
184	BCI Manufac. - capital goods - opinions on export orders	BCI mfg - Capital gds -Int. export orders	Survey	0	Italy
185	BCI Manufac. - total - opinions on export orders	BCI mfg -Int. export orders	Survey	0	Italy
186	BCI Manufac. - goods - opinions on national orders	BCI mfg - Cons. gds -Int. national orders	Survey	0	Italy
187	BCI Manufac. - intermediate goods - opinions on orders	BCI mfg - Interm. gds -Int. orders	Survey	0	Italy
188	BCI Manufac. - intermediate goods - opinions on nat. orders	BCI mfg - Interm. gds -Int. national orders	Survey	0	Italy
189	BCI Manufac. - capital goods - opinions on nat. orders	BCI mfg - Capital gds -Int. national orders	Survey	0	Italy
190	BCI Manufac. - total - opinions on national orders	BCI mfgprod.-Int. national orders	Survey	0	Italy
191	BCI Manufac. - capital goods - opinions on orders	BCI mfg - Capital gds -Int. orders	Survey	0	Italy
192	BCI Manufac. - total - opinions on orders	BCI mfgprod.-Int. orders	Survey	0	Italy
193	BCI Manufac. - goods - opinions on production levels	BCI mfg - Cons. gds -Int. prod. levels	Survey	0	Italy
194	BCI Manufac. - intermediate goods - opin. on prod. levels	BCI mfg - Interm. gds -Int. prod. levels	Survey	0	Italy
195	BCI Manufac. - capital goods - opinions on production levels	BCI mfg - Capital gds -Int. prod. levels	Survey	0	Italy

(*continued on next page*)

Table B.1 (*continued*).

Id	Variables name	Abbreviation	Sector	Timing	Country
196	BCI Manufac. - totals - opinions on production levels	BCI mfg - totals -Int. prod. levels	Survey	0	Italy
197	BCI Manufac. - goods - opinions on stocks	BCI mfg - Cons. gds -Int. stocks	Survey	0	Italy
198	BCI Manufac. - intermediate goods - opinions on stocks	BCI mfg - Interm. gds -Int. stocks	Survey	0	Italy
199	BCI Manufac. - capital goods - opinions on stocks	BCI mfg - Capital gds -Int. stocks	Survey	0	Italy
200	BCI Manufac. - total - opinions on stocks	BCI mfgprod.-Int. stocks	Survey	0	Italy
201	M1 monetary aggregate	M1 Mon. Agg.	Finance	2	Italy
202	M2 monetary aggregate	M2 Mon. Agg.	Finance	2	Italy
203	Liabilities of mfi & positions included in m1 : Italy	Liabilities of mfi & positions (M1)	Finance	2	Italy
204	M3 monetary aggregate	M3 Mon. Agg.	Finance	1	Italy
205	Imports - s goods	Imports - Cons.s gds	Trade	2	Italy
206	Imports - energy	Imports - energy	Trade	2	Italy
207	Current account - goods - debits	Current account - gds - debits	Trade	2	Italy
208	Imports - world	Imports - world	Trade	2	Italy
209	Imports of goods (cif) - extra EU	Imports gds (cif) - extra EU	Trade	1	Italy
210	Imports of goods (cif) - EU	Imports gds (cif) - EU	Trade	2	Italy
211	Stock market index	Stock market index	Finance	0	Italy
212	Imports - intermediate goods	Imports - Interm. gds	Trade	2	Italy
213	Imports - capital goods	Imports - Capital gds	Trade	2	Italy
214	Current account - services - debits	Current account - services - debits	Trade	2	Italy
215	Population aged 65: Italy	Population aged 65	Labor	0	Italy
216	Nominal effective exchange rate	Nominal effective RX	Finance	0	Italy
217	Nominal effective exchange rate ($)	Nominal effective RX ($)	Finance	0	Italy
218	Nominal effective exchange rate	Nominal effective RX	Finance	0	Italy
219	New orders - manufacturing - US	New orders - Mfg - US	Industry	2	world
220	New orders - vehicles	New orders - vehicles	Industry	2	Italy
221	New orders - total - industry	New orders - industry	Industry	2	Italy
222	New orders - total - internal market	New orders - internal	Industry	2	Italy
223	New orders - total - external market	New orders - external	Industry	2	Italy
224	CCI - personal climate	CCI - personal climate	Survey	0	Italy
225	Motorway flow of trucks - heavy	Motorway flow of trucks - heavy	Industry	0	Italy
226	Export prices - total - world	Export prices prod.- world	Prices	2	Italy
227	Export prices - total - extra EU	Export prices prod.- extra EU	Prices	2	Italy
228	Export prices - total - EU	Export prices prod.- EU	Prices	2	Italy
229	Export - unit values	Export - unit values	Trade	2	Italy
230	Raw materials price index - crude oil - world	Price Index - Crude Oil- World	Prices	0	world
231	Import prices - total - world	Import prices prod.- world	Prices	2	Italy
232	Import prices - total - extra EU	Import prices prod.- extra EU	Prices	2	Italy
233	Import prices - total - EU	Import prices prod.- EU	Prices	2	Italy
234	manufacturing PMI - work backlogs	Mfg PMI - work backlogs	Survey	1	Italy
235	Composite PMI - work backlogs	Comp. PMI - work backlogs	Survey	1	Italy
236	Composite PMI - production level	Comp. PMI - prod. level	Survey	1	Italy
237	Composite PMI - production level - EA	Comp. PMI - prod. level - EA	Survey	1	Europe
238	Composite PMI - production level - France	Comp. PMI - prod. level - France	Survey	1	Europe
239	Composite PMI - production level - Germany	Comp. PMI - prod. level - Germany	Survey	1	Europe
240	Composite PMI - production level - Spain	Comp. PMI - prod. level - Spain	Survey	1	Europe
241	Composite PMI - production level - UK	Comp. PMI - prod. level - UK	Survey	1	Europe
242	manufacturing PMI - quantity of purchases	Mfg PMI - quantity of purchases	Survey	1	Italy
243	Construction PMI - total	Constr. PMIprod.	Survey	1	Italy
244	Construction PMI - commercial	Constr. PMI - commercial	Survey	1	Italy
245	Construction PMI - Employ.	Constr. PMI - Employ.	Survey	1	Italy
246	Construction PMI - civil engineering	Constr. PMI - civil engineering	Survey	1	Italy
247	Construction PMI - residential	Constr. PMI - residential	Survey	1	Italy
248	Construction PMI - new orders	Constr. PMI - new orders	Survey	1	Italy
249	Construction PMI - input prices	Constr. PMI - input prices	Survey	1	Italy
250	Construction PMI - delivery time	Constr. PMI - delivery time	Survey	1	Italy
251	manufacturing PMI - Employ.	Mfg PMI - Employ.	Survey	1	Italy
252	Composite PMI - Employ.	Comp. PMI - Employ.	Survey	1	Italy
253	Services PMI - Employ.	Services PMI - Employ.	Survey	1	Italy
254	Manufacturing PMI - new export orders	Mfg PMI - new export orders	Survey	1	Italy
255	Manufacturing PMI - finished products	Mfg PMI - finished products	Survey	1	Italy
256	Manufacturing PMI - purchasing prices	Mfg PMI - purchasing prices	Survey	1	Italy
257	Services PMI - purchasing prices	Services PMI - purchasing prices	Survey	1	Italy
258	Manufacturing PMI	Mfg PMI	Survey	1	Italy
259	Manufacturing PMI - China	Mfg PMI - China	Survey	1	world
260	Manufacturing PMI - Denmark	Mfg PMI - Denmark	Survey	1	Europe
261	Manufacturing PMI - France	Mfg PMI - France	Survey	1	Europe
262	Manufacturing PMI - Germany	Mfg PMI - Germany	Survey	1	Europe
263	Manufacturing PMI - Ireland	Mfg PMI - Ireland	Survey	1	Europe
264	Manufacturing PMI - Japan	Mfg PMI - Japan	Survey	1	world
265	Manufacturing PMI - The Netherlands	Mfg PMI - The Netherlands	Survey	1	Europe
266	Manufacturing PMI - Spain	Mfg PMI - Spain	Survey	1	Europe
267	Manufacturing PMI - Sweden	Mfg PMI - Sweden	Survey	1	Europe
268	Manufacturing PMI - UK	Mfg PMI - UK	Survey	1	Europe
269	Composite PMI - new orders	Comp. PMI - new orders	Survey	1	Italy
270	Manufacturing PMI - new orders	Mfg PMI - new orders	Survey	1	Italy
271	manufacturing PMI - production levels	Mfg PMI - prod. levels	Survey	1	Italy
272	Composite PMI - selling prices	Comp. PMI - selling prices	Survey	1	Italy
273	Manufacturing PMI - selling prices	Mfg PMI - selling prices	Survey	1	Italy
274	Composite PMI - production levels	Comp. PMI - prod. levels	Survey	1	Italy
275	Manufacturing PMI - purchasing prices	Mfg PMI - purchasing prices	Survey	1	Italy
276	Composite PMI - purchasing prices	Comp. PMI - purchasing prices	Survey	1	Italy
277	Services PMI - purchasing prices	Services PMI - purchasing prices	Survey	1	Italy
278	Services PMI	Services PMI	Survey	1	Italy
279	Services PMI - new orders	Services PMI - new orders	Survey	1	Italy
280	Services PMI - expectations	Services PMI - Exp.	Survey	1	Italy
281	Services PMI - outstanding business	Services PMI - outstanding business	Survey	1	Italy
282	Services PMI - Germany	Services PMI - Germany	Survey	1	Europe
283	Manufacturing PMI - stocks	Mfg PMI - stocks	Survey	1	Italy
284	PMI Chicago Barometer	PMI Chicago	Survey	1	world
285	World price index non-fuel	World price index non-fuel	Prices	1	world
286	Raw materials prices - world - in euro	Raw Mater. prices - world	Prices	1	world
287	CCI - potential future savings	CCI - potential future savings	Survey	0	Italy
288	PPI	PPI	Prices	1	Italy
289	PPI - Austria	PPI- Austria	Prices	1	Europe
290	PPI - Belgium	PPI- Belgium	Prices	1	Europe
291	PPI - manufacturing	PPI- Mfg	Prices	1	Italy
292	PPI - goods	PPI- Cons. gds	Prices	1	Italy
293	PPI - Denmark	PPI- Denmark	Prices	1	Europe

(*continued on next page*)

Table B.1 (*continued*).

Id	Variables name	Abbreviation	Sector	Timing	Country
294	PPI - internal market	PPI- internal	Prices	1	Italy
295	PPI - durable goods	PPI- durable Cons. gds	Prices	1	Italy
296	PPI - energy	PPI- energy	Prices	1	Italy
297	PPI - external market - EA	PPI- external - EA	Prices	1	Italy
298	PPI - Finland	PPI- Finland	Prices	1	Europe
299	PPI - France	PPI- France	Prices	1	Europe
300	PPI - Greece	PPI- Greece	Prices	1	Europe
301	PPI - Germany	PPI- Germany	Prices	1	Europe
302	PPI - Hong Kong	PPI- Hong Kong	Prices	1	world
303	PPI - intermediate goods	PPI- Interm. gds	Prices	1	Italy
304	PPI - capital goods	PPI- Capital gds	Prices	1	Italy
305	PPI - Korea	PPI- Korea	Prices	1	world
306	PPI - Mexico	PPI- Mexico	Prices	1	world
307	PPI - The Netherlands	PPI- The Netherlands	Prices	1	Europe
308	PPI - external market	PPI- external market	Prices	1	Italy
309	PPI - non-durable goods	PPI- non-durable Cons. gds	Prices	1	Italy
310	PPI - external market - extra EU	PPI- external market - extra EU	Prices	1	Italy
311	PPI - Norway	PPI- Norway	Prices	1	Europe
312	PPI - Portugal	PPI- Portugal	Prices	1	Europe
313	International PPI weighted for Italy	Intern. PPI weighted for Italy	Prices	1	Italy
314	Competitiveness index - Italy	Competitiveness index - Italy	Prices	1	Italy
315	International PPI weighted for Italy - EA	Intern. PPI weighted for Italy -EA	Prices	1	Italy
316	International PPI weighted for Italy	Intern. PPI weighted for Italy	Prices	1	Italy
317	Euro zone PPI weighted for Italy	Euro zone PPI weighted for Italy	Prices	1	Italy
318	Extra euro PPI weighted for Italy	Extra euro PPI weighted for Italy	Prices	1	Italy
319	International PPI weighted for Italy - Extra EA	Intern. PPI weighted for Italy - ExtraEA	Prices	1	Italy
320	PPI - Spain	PPI- Spain	Prices	1	Europe
321	PPI - Sweden	PPI- Sweden	Prices	1	Europe
322	PPI - Switzerland	PPI- Switzerland	Prices	1	Europe
323	PPI - UK	PPI- UK	Prices	1	Europe
324	PPI - US	PPI- US	Prices	1	world
325	PPI - chemical products	PPI- chemical products	Prices	1	Italy
326	PPI - clothing	PPI- clothing	Prices	1	Italy
327	PPI - goods	PPI- Cons. gds	Prices	1	Italy
328	PPI - energy	PPI- energy	Prices	1	Italy
329	PPI - food	PPI- food	Prices	1	Italy
330	PPI - intermediate goods	PPI- Interm. gds	Prices	1	Italy
331	PPI - capital goods	PPI- Capital gds	Prices	1	Italy
332	PPI - manufacturing	PPI- Mfg	Prices	1	Italy
333	PPI - mining	PPI- mining	Prices	1	Italy
334	PPI - transports	PPI- transports	Prices	1	Italy
335	PPI - textile	PPI- textile	Prices	1	Italy
336	CCI - price expectations	CCI - price Exp.	Prices	1	Italy
339	CCI - expectations on the country current situation	CCI - Exp. situation of the country	Survey	0	Italy
340	Germany benchmark bond 10 years	Germany bond 10 years	Finance	0	Europe
341	6-month interest rate - Eurozone - offer	6-month interest rate - EA - offer	Finance	0	Europe
342	Real effective exchange rate	Real effective RX	Finance	1	Europe
343	Real effective exchange rate - EU	Real effective RX - EU	Finance	1	Europe
344	Real effective exchange rate - extra EU	Real effective RX - extra EU	Finance	1	Europe
345	Retail sales - food - volume	Retail sales - food	Services	2	Italy
346	Retail sales - food - value	Retail sales - food - value	Services	2	Italy
347	Main Refinancing Operations Fixed Rate - EA	Refinancing Operations Fixed Rate - EA	Finance	0	Europe
348	3-month interest rate - Euribor	3-month interest rate - Euribor	Finance	0	Europe
349	Nonfinancial corporations loans: new business	Nonfinan. loans: new business	Finance	0	Italy
350	3-month interest rate - US	3-month interest rate - US	Finance	0	world
351	Retail sales - deflated	Retail sales - deflated	Services	2	Italy
352	Exchange rate - Australian dollar/US dollar	RX - Australian dollar/US dollar	Finance	0	world
353	Exchange rate - Brazilian real/US dollar	RX - Brazilian real/US dollar	Finance	0	world
354	Exchange rate - Chinese yuan/US dollar	RX - Chinese yuan/US dollar	Finance	0	world
355	Exchange rate - Canadian dollar/US dollar	RX - Canadian dollar/US dollar	Finance	0	world
356	Exchange rate - Danish kroner/US dollar	RX - Danish kroner/US dollar	Finance	0	Europe
357	Exchange rate - Hong Kong dollar/US dollar	RX - Hong Kong dollar/US dollar	Finance	0	world
358	Exchange rate - Irish pound/US dollar	RX - Irish pound/US dollar	Finance	0	Europe
359	Exchange rate - Indian rupee/US dollar	RX - Indian rupee/US dollar	Finance	0	world
360	Exchange rate - Japanese yen/US dollar	RX - Japanese yen/US dollar	Finance	0	world
361	Exchange rate - Korean won/US dollar	RX - Korean won/US dollar	Finance	0	world
362	Exchange rate - Mexican peso/US dollar	RX - Mexican peso/US dollar	Finance	0	world
363	Exchange rate - Norwegian krone/US dollar	RX - Norwegian krone/US dollar	Finance	0	Europe
364	Exchange rate - New Zeland dollar/US dollar	RX - New Zeland dollar/US dollar	Finance	0	world
365	Exchange rate - Polish zloty/US dollar	RX - Polish zloty/US dollar	Finance	0	Europe
366	Exchange rate - Romanian leu/US dollar	RX - Romanian leu/US dollar	Finance	0	Europe
367	Exchange rate - Russian rouble/US dollar	RX - Russian rouble/US dollar	Finance	0	world
368	Exchange rate - Singapore dollar/US dollar	RX - Singapore dollar/US dollar	Finance	0	world
369	Exchange rate - Swedish krone/US dollar	RX - Swedish krone/US dollar	Finance	0	Europe
370	Exchange rate - Swiss franc/US dollar	RX - Swiss franc/US dollar	Finance	0	Europe
371	Exchange rate - Turkish lira/US dollar	RX - Turkish lira/US dollar	Finance	0	Europe
372	Exchange rate - pound sterling/US dollar	RX - pound sterling/US dollar	Finance	0	Europe
373	Exchange rate - US dollar/euro	RX - US dollar/euro	Finance	0	world
374	BCI in the services sector - Employ. expectations	BCI - services - Employ. Exp.	Survey	0	Italy
375	BCI economic situation of the households	HH BCI	Survey	0	Italy
376	BCI economic situation of the country	BCI economic situation of the country	Survey	0	Italy
377	S&P 500 stock market index	S&P 500 stock market index	Finance	0	world
378	BCI general tendency of the economy - goods	BCI tendency - Economy -Cons. gds	Survey	0	Italy
379	BCI general tendency of the economy - intermediate goods	BCI tendency - Economy -Interm. gds	Survey	0	Italy
380	BCI general tendency of the economy - capital goods	BCI tendency - Economy -Capital gds	Survey	0	Italy
381	BCI general tendency of the economy - total	BCI tendency - Economy -total	Survey	0	Italy
382	BCI tendency of the liquidity - goods	BCI tendency - demand - Cons. gds	Survey	0	Italy
383	BCI tendency of the liquidity - intermediate goods	BCI tendency - demand - Interm. gds	Survey	0	Italy
384	BCI tendency of the liquidity - capital goods	BCI tendency - demand - Capital gds	Survey	0	Italy
385	BCI tendency of the liquidity - total	BCI tendency - demand - total	Survey	0	Italy
386	BCI tendency of Employ. in 3 months - goods	BCI tendency - Employ. - Cons. gds	Survey	0	Italy
387	BCI tendency of Employ. in 3 months - interm. goods	BCI tendency - Employ. - Interm. gds	Survey	0	Italy
388	BCI tendency of Employ. in 3 months - capital goods	BCI tendency - Employ. - Capital gds	Survey	0	Italy
389	BCI tendency of Employ. in 3 months - total	BCI tendency - Employ. - total	Survey	0	Italy
390	BCI tendency orders and demand - goods	BCI tendency - liquidity - Cons. gds	Survey	0	Italy
391	BCI tendency orders and demand - intermediate goods	BCI tendency - liquidity - Interm. gds	Survey	0	Italy
392	BCI tendency orders and demand - capital goods	BCI tendency - liquidity - Capital gds	Survey	0	Italy
393	BCI tendency orders and demand - total	BCI tendency - liquidity - total	Survey	0	Italy
394	BCI tendency selling prices - goods	BCI tendency prices - Cons. gds	Survey	0	Italy

(*continued on next page*)

Table B.1 (*continued*).

Id	Variables name	Abbreviation	Sector	Timing	Country
395	BCI tendency selling prices - intermediate goods	BCI tendency prices - Interm. gds	Survey	0	Italy
396	BCI tendency selling prices - capital goods	BCI tendency prices - Capital gds	Survey	0	Italy
397	BCI tendency selling prices - total	BCI tendency prices - total	Survey	0	Italy
398	BCI tendency production - goods	BCI tendency Prod. - Cons. gds	Survey	0	Italy
399	BCI tendency production - intermediate goods	BCI tendency Prod. - intemediate gds	Survey	0	Italy
400	BCI tendency production - capital goods	BCI tendency Prod. - Capital gds	Survey	0	Italy
401	BCI tendency production - total	BCI tendency Prod. - total	Survey	0	Italy
402	Trade balance	Trade balance	Trade	2	Italy
403	Turnover - total - industry excluding construction	Turnover - industry exc. constr.	Trade	2	Italy
404	Turnover - internal market	Turnover - internal market	Industry	2	Italy
405	Turnover - external market	Turnover - external market	Industry	2	Italy
406	Unemployed (15 years and over) - survey of labor force	Unemployed (>15) - survey	Industry	1	Italy
407	CCI - Employ. expectations	CCI - Employ. Exp.	Labor	0	Italy
408	Unemploy. rate (15 years and over)	Unemploy. rate (> 15)	Labor	1	Italy
409	Unemploy. rate (15 - 24)	Unemploy. rate (15 - 24)	Labor	1	Italy
410	Unemploy. rate - female	Unemploy. rate - female	Labor	1	Italy
411	Unemploy. rate - male	Unemploy. rate - male	Labor	1	Italy
412	Consumer price index - US	CPI - US	Prices	1	world
413	Retail sales - food - value	Retail sales - food - value	Services	2	Italy
414	Retail sales - non-food - value	Retail sales - non-food - value	Services	2	Italy
415	Retail sales - total - value	Retail salesprod.- value	Services	2	Italy
416	Imports - unit values	Imports - unit values	Trade	2	Italy
417	Imports - goods - average unit values	Imports - Cons. gds -avg	Trade	2	Italy
418	Imports - energy - average unit values	Imports - energy -avg	Trade	2	Italy
419	Imports - intermediate goods - average unit values	Imports - Interm. gds -avg	Trade	2	Italy
420	Imports - capital goods - average unit values	Imports - Capital gds -avg	Trade	2	Italy
421	Liquidity level operative requirements - goods	Liquidity level - Cons. gds	Survey	0	Italy
422	Liquidity level operative requirements - intermediate goods	Liquidity level - Interm. gds	Survey	0	Italy
423	Liquidity level operative requirements - capital goods	Liquidity level - Capital gds	Survey	0	Italy
424	Liquidity level operative requirements - manufacturing	Liquidity level - Mfg	Survey	0	Italy
425	Compensation of employees - financial and insurance activity	Comp. of Employ. - financ. activity	Labor	2	Italy
426	Compensation of employees - wholesale and retail sales	Comp. of employ. - retail sales	Labor	2	Italy
427	Compensation of employees - construction	Comp. of employ. - constr.	Labor	2	Italy
428	Compensation of employees - energy	Comp. of employ. - energy	Labor	2	Italy
429	Compensation of employees - industry excluding construction	Comp. of Employ. - industry exc. Constr.	Labor	2	Italy
430	Compensation of employees - services	Comp. of employ. - services	Labor	2	Italy
431	Industries output price - retail: Ireland	Ind. output price - retail: Ireland	Prices	2	Europe
432	Manufacturing price index: Japan	Mfg price index: Japan	Prices	2	world
433	World trade index	World trade index	Trade	2	world

Appendix A. Ledoit–wolf estimator of the shrinkage intensity parameter

This appendix reviews the Ledoit and Wolf (2004a) optimal estimator of the shrinkage intensity parameter λ.

Suppressing reference to the generic ith GDP component and referring to the (h, k) pair of indicators, we let $q_{hk,\tau} = (\nu_{h\tau} - \bar{\nu}_h)(\nu_{k\tau} - \bar{\nu}_k) - \hat{s}_{hk}$, $\tau = 1, \ldots, T$, and define

$$\hat{\pi}_{hk} = \frac{1}{T}\sum_{\tau} q^2_{hk,\tau}, \quad \hat{t}_{hh,hk} = \frac{1}{T}\sum_{\tau} q_{hh,\tau} q_{hk,\tau}$$

$$(h, k) = 1, \ldots, N,$$

$$\hat{\pi} = \sum_{h=1}^{N}\sum_{k=1}^{N} \hat{\pi}_{hk},$$

$$\hat{\rho} = \sum_{h=1}^{N} \hat{\pi}_{hh} + \sum_{h=1}^{N}\sum_{k=1,k\neq h}^{N} \frac{\bar{r}}{2}\left(\sqrt{\frac{\hat{s}_{kk}}{\hat{s}_{hh}}}\hat{t}_{hh,hk} + \sqrt{\frac{\hat{s}_{hh}}{\hat{\sigma}_{kk}}}\hat{t}_{kk,hk}\right);$$

$\hat{\pi}$ estimates the sum of the variances of the elements of the sample covariance matrix, whereas $\hat{\rho}$ estimates the sum of the asymptotic covariances of the elements of the shrinkage target with those of the sample covariance matrix.

Finally,

$$\hat{\gamma} = \sum_{h=1}^{N}\sum_{k=1}^{N}(\hat{s}_{hk} - \tilde{\omega}_{hk})^2$$

estimates the deviation of the shrinkage target from the sample covariance matrix.

The Ledoit–Wolf estimator of λ is

$$\lambda^* = \max\left\{0, \min\left\{\frac{1}{T}\frac{\hat{\pi} - \hat{\rho}}{\hat{\gamma}}, 1\right\}\right\}.$$

Appendix B. List of monthly indicators

Here, we provide the complete list of the monthly indicators used for the estimation of monthly GDP and its components, with their group or sector in the fourth column, the publication delay in months with respect to the reference month, and their reference area in the last column.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2021.04.003.

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