Temi di Discussione
(Working Papers)

Ita-coin: a new coincident indicator for the Italian economy

by Valentina Aprigliano and Lorenzo Bencivelli
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Editorial Assistants: Roberto Marano, Nicoletta Olivanti.

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy
Abstract

In this paper we present a coincident indicator for the Italian economy, Ita-coin. We construct a multivariate filter based on a broad information set, whose dimension is reduced by the Generalized Dynamic Factor Model (GDFM) approach proposed by Forni et al. (2002). A regression based on the least absolute shrinkage and selection operator (LASSO) is used to estimate Ita-coin. Most Italian macroeconomic indicators are characterized by high short-term volatility and the 2008-2009 crisis has affected the volatility of both the high- and low-frequency components and the relationships between the variables have become more unstable. LASSO regression allows us to select recursively the relevant information about the comovement of the variables over time. Our indicator displays a satisfactory performance in the pseudo real-time validation as a timely cyclical indicator.

JEL Classification: C5, E1.
Keywords: factor analysis, frequency-domain, LASSO regression, business cycle.
1 Introduction

Policy makers need a timely and reliable picture of the state of the economy. Unfortunately, GDP and other indicators of real activity are released with a considerable lag after the end of the reference period. Moreover, quantitative data are often affected by measurement errors and pronounced short-run volatility that make the observation of the underlying trend particularly challenging.

The methodological approach adopted in this paper, based on the use of a large dataset, allows us to tackle these problems efficiently.

In the last fifteen to twenty years, the research has developed methods to handle large datasets efficiently (see [12] and [13]). In particular, we rely on the Generalized Dynamic Factor models (GDFM), which collapses all the available information into a few common factors capturing the comovement among the variables (see [9]).

One relevant and successful application of GDFM to economic analysis is the €-coin indicator developed by Altissimo et al. (see [2] and [3]), which provides a real-time estimate of the medium- to long-run component of euro-area GDP growth rate (MLRG) at monthly frequency. This paper aims to build the Italian counterpart of that indicator, Ita-coin. However, as it will be argued more in more detail below, Ita-coin cannot be obtained by merely applying the same methodology used for €-coin to Italian data. Indeed, some specific features of the series involved must be taken into account. In particular, the Italian GDP quarterly growth (q-o-q GDP) displays a higher short-term volatility than that of the euro area. Furthermore, the recent economic crisis has induced major instability in the behavior of all indicators.

In the country-specific case, we handle a block-structure dataset, characterized by a fine breakdown of the main economic aggregates. This feature may increase the correlation between the idiosyncratic components representing, for instance, the specific dynamics of one block of indicators, loosening the weight of the commonality, which is important for estimating a business cycle indicator (see [10]). This issue was addressed by Boivin and Ng (see [5]), who suggest an a priori screening of the candidate regressors. We propose instead to retain as much information as possible and to implement the least absolute shrinkage and selection operator (LASSO) on a regression space estimated by the GDFM. LASSO selects the relevant information.

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1 Quarterly GDP flash estimates are published 45 to 50 days after the end of the reference period. The first estimate is published with a delay of 60 to 80 days, often embedding revisions.

2 The indicator, developed by the Bank of Italy with the contribution of CEPR is published monthly on the web sites [http://eurocoin.bancaditalia.it/](http://eurocoin.bancaditalia.it/) and [http://eurocoin.cepr.org/](http://eurocoin.cepr.org/)

3 For an extensive introduction of LASSO estimator see [14]. See also [8] for more details on threshold methods and their application to signal smoothing problems.
about the comovement of the variables based on their dynamic behavior in each period. Our indicator is meant to fit the medium- to long-run trend of GDP closely, as reflected by the bandpassed quarterly GDP obtained by a symmetric two-sided filter. However, Ita-coin is expected to provide stable estimates at the end of the sample. To assess its performance as a reliable real-time indicator, we compare it with the indicator estimated by the same methodology used for €-coin (traditional).

In Section 2 we present the dataset. Section 3 introduces the model. Section 4 assesses the performance of Ita-coin. Section 5 concludes.

2 Descriptive statistics of the data

The phenomenon of interest: Italian GDP. Figure (2) plots the spectra of Italian and euro area GDP. As mentioned, the high frequency fluctuations are actually much more important in explaining the variance of Italian GDP with respect to that of the euro area.

Explanatory variables. The dataset comprises 93 variables belonging to 11 different blocks. The sample starts in May 1996 (earliest period for retail sales and PMI). We also include some variables referred to economies whose business cycle is related to the Italian one.

The blocks of variables considered and their number are listed in Table (2). Since we consider a single country economy, our dataset shows a particularly fine breakdown of the main aggregates.

A large part of the dataset is composed of survey data, which are timely and seldom revised. The block named “Coincident and leading indicators” includes the OECD composite leading indicator for France, Germany and the euro area as well as €-coin, in order to account for the business cycle of the major trading partners of Italy. For the same reason, the dataset includes the manufacturing PMI series for Italy and the largest euro-area countries; these data are included in the block labelled “Industry surveys”.

All the series are normalized and cleaned of outliers. More specifically, we consider an outlier to be any point lying five or more standard deviations away from the series mean. Those points are substituted with a local mean centered on the outlier. In this way, possible outliers at the end of the sample weigh heavily on the local average but their importance vanishes as the series is updated.

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4In 1996 the Italian statistical institute ISTAT substantially changed the retail sales inquiry. The PMI series start around 1998; to be added to the dataset, whose first date is set in 1996, the series were back-casted using industrial productions and a number of surveys to achieve an explained variance of 90% for each PMI.

5The local mean is two-sided with a bandwidth of eleven values on each side of the outlier. The local mean is computed only on the available observations. When, instead, the most recent values are unavailable the local mean becomes asymmetric.
<table>
<thead>
<tr>
<th>Block</th>
<th>Number of series</th>
<th>Treatment</th>
</tr>
</thead>
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<tr>
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<td>(3)</td>
</tr>
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<td>Δ log</td>
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<td>Demand Indicators</td>
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<td>External trade</td>
<td>5</td>
<td>Δ log</td>
</tr>
<tr>
<td>Coinc/lead. indicators</td>
<td>4</td>
<td>none</td>
</tr>
</tbody>
</table>

Table 1: Variables used in the model. Third column reports the preliminary transformations of the series.

We transform all the variables to achieve a covariance stationarity. Finally, the seasonality is removed by means of seasonal dummies.

**The factors.** Figure [1] shows the share of variance in the data explained by the dynamic factors over frequencies in $[0, \pi]$, which are estimated by the generalized dynamic principal components. More precisely, the upper panel plots the variance explained by each of the first four factors, while the lower panel plots the cumulated variance. The information content of the dataset is well represented by the first two largest dynamic eigenvalues of the spectral density matrix. In particular, they explain about 70% of the total variance in the frequency band of interest $[0, \frac{\pi}{6}]$.

### 3 Estimation of Ita-coin

Our target is the MLRG, $c_t$, which is a latent component of the quarterly GDP growth rate, $y_t$, and could be estimated using an infinite two-sided band-pass filter:

$$c_t = \beta(L)y_t = \sum_{k=-\infty}^{\infty} \beta_k y_{t-k},$$  \hspace{1cm} (1)

where $\beta(L)$ represents the impulse response function of the filter, whose form is:

$$\beta_k = \begin{cases} \sin(k\pi/6) & k \neq 0 \\ \frac{1}{6} & k = 0 \end{cases}$$
Figure 1: Dynamic eigenvalues of the Spectrum of the dataset (the blue line represents the first eigenvalue, which explains most of the variance. The green, red and cyan lines represent the following eigenvalues in descending order of magnitude). The percentage of the variance explained by each factor is reported in the upper panel, while the lower panel plots the cumulated percentage explained variance.

Figure 2: Spectra of Italian and euro area GDP quarterly growth rates.
The main shortcoming of the two-sided symmetric filters is the high volatility of the estimates at the end of the sample; in order to obtain an efficient estimate of \( c_t \), we construct a one-sided filter by relying on the information embedded in our large dataset. The Baxter and King’s truncated version of (1) is the optimal finite approximation of the bandpass filter at the center of the sample and it will represent our target, \( c^*_t \) with \( 13 \leq t \leq T - 13 \).

The block-structure dataset and the high short-run volatility of the Italian macroeconomic indicators, furthermore worsened by the 2008 financial turmoil, means that the estimation of the medium- to long-run signal of the economy is now even more challenging. We estimate Ita-coin in real time, i.e. as new information becomes available. Hence, at each update of the estimates we select the relevant information by LASSO regression.

More specifically, we adopt a two steps estimation strategy: in step one we estimate the factor space via the GDFM while in step two we estimate the indicator via LASSO regression.

### 3.1 Step one: estimation of the factor space

The baseline assumption of the model is that any variable \( x_{it} \) in the dataset can be represented as the summation of the common \( (\chi_{it}) \) and idiosyncratic \( (\xi_{it}) \) components:

\[
x_{it} = \chi_{it} + \xi_{it} \tag{2}
\]

For the \( i \)-th variable, the common component, driven by \( q \) common shocks, may be represented as:

\[
\chi_{it} = b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \cdots + b_{iq}(L)u_{qt} \tag{3}
\]

where the \( b_{ij}(L) \) are polynomials of order \( s \) in the lag operator and the vector \( \mathbf{u}_t = [u_{1t}, \ldots, u_{qt}] \) is a \( q \)-dimensional orthonormal white-noise process, orthogonal to the idiosyncratic component \( \xi_{it} \). Equation (3) can be represented in static form:

\[
\chi_{it} = c_{i1}F_{1t} + c_{i2}F_{2t} + \cdots + c_{ir}F_{rt} \tag{4}
\]

where \( r = q(s + 1) \) and the \( F \)'s are the common static factors spanning the factor space \( \mathcal{G}_F \).

The common component can be further decomposed in the short-run \( (\chi^S) \) and in the long-run \( (\chi^L) \) component. We use the latter in order to obtain smoother estimates. Formally:

\[
x_{it} = \chi_{it} + \xi_{it} = \chi^L_{it} + \chi^S_{it} + \xi_{it}. \tag{5}
\]

\(^6\)For example, if \( q = 2 \) and \( s = 1 \), then \( r = 4 \) and \((F_{1t}, F_{2t}, F_{3t}, F_{4t}) = (u_{1t}, u_{1,t-1}, u_{2t}, u_{2,t-1})\).
According to Parceval’s theorem (see [6]) from the orthogonality of the elements in (5) follows:

\[ \Gamma_x(0) = \Gamma_{\chi L}(0) + \Gamma_{\chi S} + \Gamma_{\xi}(0), \]  

(6)

where \( \Gamma_x(0) \), \( \Gamma^L(0) \), \( \Gamma_S(0) \) and \( \Gamma_{\xi}(0) \) are the variance-covariance matrices of, respectively, the data, the long- and the short-run common components and the idiosyncratic part at lag 0.

The frequency domain equivalent of equation (6) is:

\[ \Sigma_x(\theta) = \begin{cases} 
\Sigma_{\chi L}(\theta) + \Sigma_{\xi}(\theta) & \text{if } 0 \leq \theta < \frac{\pi}{6} \\
\Sigma_{\chi S}(\theta) + \Sigma_{\xi}(\theta) & \text{otherwise}
\end{cases} \]

where \( \Sigma_s \) represent the spectral density matrices and \( \theta \)s are the frequencies in the interval \([0, 2\pi]\). Our intermediate goal is to estimate \( \Gamma_{\chi L} \) as the inverse Fourier transformation of the sample \( \hat{\Sigma}_{\chi L} \), which is obtained as

\[ \hat{\Sigma}_{\chi L}(\theta) = U(\theta)\Lambda(\theta)\tilde{U}(\theta) \]

where \( \theta \in [0, \bar{\theta}] \); \( \Lambda(\theta) \) is the diagonal matrices containing the first \( q \) eigenvalues of \( \hat{\Sigma}_x(\theta) \) and \( U(\theta) \) the corresponding eigenvectors; the tilde denotes complex conjugation.

Once we have \( \hat{\Gamma}_{\chi L} \), we construct the generalized principal components whose space represents a consistent estimate of \( G_F \).

Let \( V \) be, under standard normalizing conditions, the solution of the following generalized spectral decomposition problem:

\[ \hat{\Gamma}_{\chi L}(0)V = \hat{\Gamma}_x(0)V\mu. \]

The rationale behind this is that the generalized principal components of \( \hat{\Gamma}_x \) are the linear combination of the \( x_{it} \) with the largest ratio between the variance of the common component \( \chi^L \) and the total variance of \( x_{it} \).

One preliminary issue is the choice of the number \( r \) of static factors. We adapt to our case the Bai and Ng information criterion (see [4]) to select \( r \) on the basis of a value \( q \) corresponding to the number of the highest eigenvalues of \( \Sigma_{\chi L}(\theta) \).

According to these considerations together with the analysis on

\footnote{For the sake of simplicity, we get rid of the lag specification \( L = 0 \), being careful not to cause confusion.}

\footnote{Factors are identified up to a rotation matrix, therefore their sign is not determined during the estimation of the factor space. It turns out that the estimate of the factors, from one period to the next, may change the sign, the position (the \( n \)-th factor becomes the \( m \)-th) or both.}

\footnote{We adopt the \textit{generalized principal component method} that does not assume the idiosyncratic component to be non auto-correlated (i.e. we do not require the matrix \( \Gamma_{\xi}(0) \) to be diagonal).}

\footnote{The dynamic common factors are also defined \textit{primitive shocks} (see [4]), since they represent the core information conveyed by the available dataset. Therefore, the number of dynamic shocks is reasonably represented by the rank of the common components’ spectral matrix, estimated in the low frequency band.}
the dynamic eigenvalues provided in the previous section we decide to set the following parameters' values: $q = 2$, $r = 6$ and $s = 1$.

3.2 Step two: projecting the MLRG

The main aggregates of the Italian economy are characterized by high short-run volatility especially after the deep recession of 2008-2009. The relative importance of the factors is accordingly not constant over time. Therefore, we need to select the interesting information each time by smoothing the estimates accordingly. The LASSO regression provides an efficient solution, by solving a constrained minimization of the sum of squared residuals:

$$
\beta^{LASSO} = \arg \min_{\beta} \left\{ \sum_{i=1}^{T} \left( y_i - \sum_{j=1}^{r} \beta_j F_j \right)^2 \right\} \text{ s.t. } \sum_{j=1}^{q} |\beta_j| \leq \tau, \quad (7)
$$

where $\tau$ is a tuning parameter determining the amount of shrinkage required.

Since the factor space $G_F$ is by construction an orthonormal space, the LASSO estimator is equivalent to a soft threshold estimator as shown by Tibshirani [14]. In this case, the (7) boils down to the following:

$$
\hat{\beta}_j^{LASSO} = \text{sign}(\hat{\beta}_j^{OLS})(|\hat{\beta}_j^{OLS}| - \gamma)^+,
$$

where $\gamma$ represents a function of the tuning parameter $\tau$.

The OLS estimate of a parameter $\beta_j$ varies around the true value by some amount of noise:

$$
\hat{\beta}_j^{OLS} = \beta_j + \sigma z_j,
$$

where $z_j \sim \mathcal{N}(0,1)$. The LASSO estimator restricts toward zero all the coefficients which are smaller in absolute value than a certain threshold determined by the noise $\sigma$. The result is a reduction of the regressors’ space according to their relative information content. We will see later on how this reduction of the factor space leads to a more stable estimate of the indicator. Under optimality conditions, solving the (7) is equivalent to minimizing the following:

$$
\hat{\beta}_j^{LASSO} = \arg \min_{\beta} \left\{ \sum_{i=1}^{T} \left( y_i - \sum_{j=1}^{r} \beta_j F_j \right)^2 \right\} + \lambda \sum_{j=1}^{q} |\beta_j| \quad (8)
$$

where $\lambda$ represents an inverse function of $\tau$, the tuning parameter. We select $\lambda$ by a cross-validation procedure [12] whose optimum criterion is set to minimize the revisions of the estimates. Therefore, the shrinkage parameter is the best choice for obtaining the stability of Ita-coin. As a real-time indicator, Ita-coin is designed to provide a reliable signal.

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11 The solution is obtained numerically using the Gauss Seidel algorithm.
12 The training sample is selected to cover the period of the financial crisis.
Finally, the information content of the monthly regressors must be consistent with that on GDP, which is released quarterly\footnote{For computational purposes, we have linearly interpolated the quarterly growth rate in order to obtain a monthly series. This operation is neutral, since we filter out fluctuations whose frequency is even shorter than that of the fluctuations we are adding.}. Therefore, we apply the filter \((1 + L + L^2)^2\) that relates the two sampling frequencies.

4 Empirical results

In this section we present the empirical results. First, we show the characteristics of the common factors and of the common components; then we describe the indicator; finally, we assess the real-time behavior of Ita-coin.

4.1 Factors and the common component

One interpretation of the factors. We propose an heuristic strategy to identify the factors, by exploiting the block structure of our dataset. In practice, we split the dataset into real activity, survey, financial and price data and we estimate a single factor model for each subsample. The factors extracted in this way are then compared to the static factors estimated from the entire dataset in order to identify the ones that best capture the implicit dynamic of each data group. Figure (3) shows how the second factor, which is one of the smoothest of the six static factors, closely tracks the dynamics of the survey, of the real activity data and of the prices. As for the former, this result was expected since the variance of the survey data is chiefly explained by the low-frequency components. The remaining factors are designed to capture the residual dynamics in the dataset.

The common component. In Figure (4) we report the degree of correlation of each variable with its own common component, often referred to as commonality. Survey data are those showing the highest degree of commonality among all the series. Moreover, this degree is roughly homogeneous within the block of variables, while other blocks display more heterogeneity in this sense. This evidence can be explained by the peculiar dynamics of the surveys, which are characterized by smoother fluctuations than the quantitative data.

4.2 Descriptive statistics

Ita-coin estimated at time \(t\) conditional on the available information takes the following form:

\[
\hat{c}_{t|t} = \mu_{GDP|t} + \beta^{LASSO} F_t, \tag{9}
\]
Figure 3: Comparison between block-factors (blue solid line) relative to the real sector (first panel), financial sector (second panel), survey (third panel) and prices (fourth panel) and the static factors estimated on the whole dataset (red dashed dotted lines).

Figure 4: Degree of commonality (correlation of each variable with its common component) for the blocks of variables.
Figure 5: Ita-coin (blue solid line) versus the target (black dashed line) and GDP q-o-q growth (red spots).

Table 2: Descriptive statistics of Ita-coin versus the traditional computation method, the target and Italian GDP. In the left panel the statistics are computed on the whole sample (September 1996 to August 2012), in the right panel the sample ends in December 2006.

where $F_t$ are the estimated static factors and $\beta_{LASSO}$ are the coefficient estimates according to the LASSO algorithm; $\mu_{GDP|t}$ represents the mean of GDP conditional on the information available at time $t$.

Figure (5) shows the indicator (solid line) in comparison with its target $c_t^*$ (dashed line) and the Italian GDP quarterly growth (dots).\(^{14}\) The fit between Ita-coin and the target is fairly high (the contemporaneous unconditional correlation is 0.94).

Table (2) reports the descriptive statistics of Ita-coin together with the statistics of the traditional indicator, the target series and GDP. The left panel reports the statistics computed on the whole sample; the right panel

\(^{14}\)It is worth recalling that the target $c_t^*$ is defined for $13 \leq t \leq T - 13$ to ensure we do not distort the assessment of Ita-coin because of the low efficiency of the Baxter and King’s estimate at the extremes of the sample.
Table 3: Root mean squared error. In the upper panel the indicators are compared with the target series and the q-o-q GDP growth, while in the lower panel the comparison is with the yearly growth rates. Note: the whole sample covers the period from September 1996 to June 2012.

4.3 The real-time performance

The measure of the real-time performance is necessary for assessing the ability of the indicator to track the state of the economy. Indeed, the scope of this indicator is to provide a monthly figure of medium-run trends and turning points relying only on available information. The recent crisis appears to have modified the relationship between GDP and the main monthly indicators. Furthermore, the GDP dynamics displays a higher volatility in the aftermath of the crisis. In this environment, it is crucial to ensure that the indicator provides a stable signal month by month and does not convey misleading conclusions.

4.3.1 The stability of the estimates

We assess the stability of Ita-coin by performing a *pseudo* real-time exercise. Namely, we use the last available vintage of information cut month by month.

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We compared the quarterly series with the value of Ita-coin of the last month of the quarter.
Table 4: Real-time statistics of Ita-coin

<table>
<thead>
<tr>
<th></th>
<th>LASSO</th>
<th>Traditional</th>
<th>BK</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS revision error</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>MS nowcast error</td>
<td>0.75</td>
<td>0.73</td>
<td>0.71</td>
</tr>
<tr>
<td>Correct sign</td>
<td>0.61</td>
<td>0.59</td>
<td>0.59</td>
</tr>
</tbody>
</table>

(being careful to replicate the ragged-edge structure of the dataset in each period). Since we collected the vintages of the past 31 months, we are also able to look at the real-time behavior of Ita-coin for a suitable time interval.

Beyond the graphical analysis, the assessment of the indicator is pursued according to some statistics. We investigate the ability of Ita-coin in nowcasting the target, measured by the mean squared nowcast error (MSNe):

$$MSNe = \frac{1}{(T-12)\sigma_{c^*}} \sum_{t=T_0}^{T-12} [c_{t|t} - c_{t|T}]^2.$$  (10)

To assess the robustness of the estimates, we define the mean squared revision error (MSRe) as:

$$MSRe = \frac{1}{T\sigma_{c^*}} \sum_{t=T_0}^{T} [\hat{c}_{t|t+1} - \hat{c}_{t|t}]^2,$$  (11)

where $T_0$ and $T_1$ are respectively the starting and the end dates of the simulation, while $T$ is the sample size; $\sigma_{c^*}$ is the variance of the target. The MSRe measures the size of the revisions after one month. The variance of the estimates (i.e. variance row-wise) is given by:

$$\sigma(t) = \frac{1}{T - (t - 1)} \sum_{i=0}^{T} [\hat{c}_{t|i+1} - m(\hat{c}_t)]^2.$$  (12)

where $m(\hat{c}_t)$ is the unconditional mean of the estimates of the indicator at month $t$, with $t = 1, \ldots, T$.

Finally we take a look at the capacity of Ita-coin to predict the sign of the monthly change of economic growth’s trend (i.e., to grasp the sign of $\Delta c^*_{t|T} = c^*_{t|T} - c^*_{t-1|T}$).

Table 1 shows that Ita-coin, the traditional and the BK indicator are substantially in line as far as the sign prediction and the nowcasting ability are concerned, compared with the target $c^*_t$, while Ita-coin outperforms its competitors in terms of a tendency to revise the estimated signal. Ita-coin displays a low tendency to revise the series backward, as it reduces the mean squared revision error by 50 per cent with respect to the bandpassed GDP. Figure 6 plots the variance of the monthly estimates of Ita-coin. This statistics also provides some information on Ita-coin as a reliable real-time
indicator. We notice how the revisions worsen during the 2008 - 2009 period. Figure (7) shows the pseudo real-time estimates. The shape of Ita-coin looks smooth.

Since the official estimates of the Italian GDP are often revised, we find it interesting to show how the shape of Ita-coin looks in real time. We collected data vintages from January 2010 and plot the results in Figure (8). The real-time estimates of Ita-coin are quite stable. The dynamics of Ita-coin mirrors the sharp downturn of the economy in the last two years; furthermore, it smooths the exceptional events better than the traditional indicator, which shows more intense fluctuations. In mid-2011, Ita-coin predicted the Italian economy would enter a recession one quarter before it really happened and five months in advance compared with the preliminary release of GDP data for the third quarter (in which GDP growth first turned negative). At the beginning of 2012, the pattern of Ita-coin was influenced by the less severe evolution of qualitative indicators and sovereign debt markets.
Figure 7: Ita-coin computed in pseudo real time according to the traditional (red line) and the LASSO method (blue solid line). The figure also shows the GDP q-o-q growth rate series (black spots).

Figure 8: Ita-coin computed in real time according to the traditional (red line) and the LASSO method (blue line). The figure shows the GDP q-o-q growth rate series (black spots).
4.3.2 Behavior around turning points

In this section, we check whether Ita-coin tracks the turning points of the economic activity growth effectively. Here, we refer to growth rate cycle, which depicts cyclical upswings and downswings in the growth rate of the economy.

We define a downturn of the growth rate cycle as an outstanding and lasting decline of the growth rate of GDP (q-o-q GDP). Such a downturn may result in either recessions (when the growth rate $y_t$ becomes negative for some quarters) or soft landings. Therefore, turning points separate patterns of acceleration or deceleration of GDP. More formally, we observe a trough (peak) at time $t$ when $\Delta y_t = y_t - y_{t-1}$ is negative (positive) whereas $\Delta y_{t+1} = y_{t+1} - y_t$ is positive (negative).

The growth rate of GDP represents the reference cycle, whose turning points are identified by the Bry and Boschan (BB onward) algorithm (for more details see [7]). Someone may argue that targeting the series of the growth rates of GDP directly is not a proper choice because it embodies noisy components. However, the BB algorithm was conceived to be robust to short-term volatility.

Since Ita-coin depicts a smooth component of q-o-q GDP, its turning points can be identified by a simple procedure, which allows us to assess a change of the signal in real time. In practice, we use the pseudo real-time estimates of Ita-coin, available from June 2003, $T_0$, to August 2012, $T$.

First, we detect a potential turning point at $t - 1$, for $t = T_0, \ldots, T - 12$, if

$$\text{sign}(\Delta \hat{c}_{t-1|t}) \neq \text{sign}(\Delta \hat{c}_{t|t})$$

(C13)

Candidate turning points are further screened to eliminate the slope sign changes of Ita-coin caused by the variability of the pseudo real-time estimates, $\hat{c}_{t|t}$. Formally, the date $t - 1$ is accepted as a reliable turning point

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16 For a complete overview of the notions of the business cycle see [1]. See also the growth rate chronologies provided by The Economic Cycle Research Institute (ECRI) (http://www.businesscycle.com), for more than 20 countries, which uses the methodology introduced in Layton et al. (see [1]).

17 It is worth recalling that $y_t$ is the quarterly growth rate of GDP (q-o-q GDP); hence, $\Delta y_{t+1} = y_{t+1} - y_t$ represents the variation of q-o-q GDP.

18 In [11], the authors smooth the growth rates series used as reference cycle and then implement the BB (see [7]). However, at each step of the BB algorithm, the turning points are identified on progressively smoother series in order to get rid of those picked out during noisy periods. As a matter of fact, our chronology ultimately coincides with that provided by ECRi for Italy.

19 The pseudo real-time estimates are obtained by the iterative procedure introduced in Section 4.3.1.

20 At this stage of the analysis, we are interested in the comparison between the turning points of Ita-coin and those of q-o-q GDP, which are consistently detected by the BB algorithm only up to $T - 12$. 

---
Cyclical Phases of GDP q-o-q (Reference Cycle) | Leads (-)/Lags (+) of Turning Points in Ita-coin with respect to the Reference Cycle
--- | ---
Peaks | 06-Q4 | -2
10-Q1 | 1
Troughs | 05-Q4 | -2
09-Q1 | 0

Table 5: Lead and lags of Ita-coin with respect to q-o-q GDP.

Notes: (1) in the second column we report the turning points of GDP growth, detected by the Bry and Boschan algorithm. The series of GDP growth rates represents the reference cycle. The third column shows the leads (positive values) and lags (negative values) of Ita-coin expressed in quarters with respect to the reference cycle. Zero indicates that the turning point of both Ita-coin and GDP are located in the same quarter. We use the pseudo real-time estimates of Ita-coin; (2) the cyclical phases of q-o-q GDP are identified by the BB algorithm, which gets rid of the edges of the series (first and last 12 observations) for the sake of consistency.

only if the following conditions hold:

\[
\text{sign}(\Delta \hat{c}_{t-1} | t-1) = \text{sign}(\Delta \hat{c}_{t-1} | t) \quad (14)
\]
\[
\text{sign}(\Delta \hat{c}_{t-2} | t-1) = \text{sign}(\Delta \hat{c}_{t-1} | t-1) \quad (15)
\]

The turning points of Ita-coin are compared to those of the reference cycle (see table 5 and figure 9) to check whether the proposed indicator tracks well the cyclical fluctuations of the Italian GDP growth rate. In the sample considered here, the latter is characterized by two sharp declines culminating in the recessions caused by the financial crisis and the subsequent euro-area sovereign-debt crisis. Ita-coin tracks these phases well: it anticipates the downturn of activity in the last quarter of 2006, while its trough on the first quarter of 2009 coincides with that of q-o-q GDP; as for the downturn in the first quarter of 2010, Ita-coin shows its turning point in the first month of the following quarter.

To assess the consistency of the turning points of Ita-coin we follow the same argument of [3].

We identify only two false signals, i.e. two turning points of Ita-coin which correspond to any cyclical phase of the GDP q-o-q, between the last quarter of 2006 (thorough) and the first quarter of 2007 (peak); when the growth rate of GDP shows a deep swing.
Figure 9: *Pseudo* real-time estimate of Ita-coin (continuous line) compared with the phases of q-o-q GDP (black spots; shaded areas represent the negative phases of q-o-q GDP).
5 Conclusion

In this paper we have presented a new coincident indicator for the Italian economic cycle, reminiscent of €-coin. However, compared to the indicator for the euro area, we propose adjusting our procedure to tackle two important problems. Firstly, the single-country analysis entails a block structure dataset. The risk could be weighting the block-specific idiosyncratic components’ correlation too much. Secondly, the Italian GDP quarterly growth is more volatile at high frequencies compared with output in the euro area.

We have shown that Ita-coin tracks the target very closely. Our indicator fits the MLRG of GDP well, the prediction error with respect to GDP growth is mainly due to the short-run component in the latter variable, which we are intent on filtering out.

Ita-coin provides reliable estimates in real time. The signal is seldom subject to revisions even during periods characterized by large shocks like those that have been hitting the economy in the last five years.

Ita-coin effectively tracks the cyclical phases of the growth rate of GDP. In particular, it is coincident (although sometimes leading) with respect to the turning points of the growth rates of GDP.

Further investigation may be devoted to the role of the factors in shaping the indicator over time and to a time-varying method of selecting the shrinkage parameter $\tau$. 
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