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The Real Time Ability of Financial and Real Variables in Nowcasting

Antonio Frenda, Sergio Scippacercola and Luigi D'Ambra

Abstract In this paper we develop an approach to choose the variables useful for the nowcasting (short-term forecasting) of growth rate, that is based on the real time ability of financial and real variables to reproduce reference time series. We assess, for Germany and Italy, the impact of real and financial variables in estimating smoothed gross domestic product (GDP) from 2003 to 2012. In synthesis, the innovation of our work is the one to focus both on a limited number of series both on a large dataset of economic variables, by implementing the dynamic factor model.

***Keywords**:* Real and Financial Common Factors; Composite Indicator; Band-pass filters; Nowcasting; Medium to long run component of the growth

1 Introduction

Nowcasting GDP requires to focus on times series data that can provide information on the current state of the economy. At this stage, two main approaches exist in econometric literature to choose the variables useful for the nowcast of growth rate; the first focus on a limited number of series and it consists in selecting a reduced number of variables. The second approach, that is multivariate, is based on a large dataset of economic variables. The selection criteria are generally based on:

- the ex-post ability of the series to reproduce reference time series movements;
- a priori belief based on economic theory;
- the choice can almost be judged as subjective.

The main contribution of this paper is a selection criteria based on the real time ability of financial and real variables to reproduce reference time series by a generalized dynamic factor model. These procedures are focused on the Eurocoin methodology [1] in order to obtain smoothing of a stationary time series. In this work it is analyzed the MLRG, because we are interested in the performance of our indicators with respect to a measure of the "trend-cycle GDP growth" obtained in the middle of the sample by a band pass bilateral filter on GDP growth components. Removing erratic components can also be done by applying a two-sided band pass filter to the GDP growth series ([2],[6]). These filters perform well in the middle of the sample, but they work badly at the beginning and at the end of the sample, since they require knowledge of the future

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values of GDP, which of course we do not have. This is a technical reason why it is worthwhile to develop the indicators that we present in detail in the following sections.

2. The Generalized Dynamic Factor Model in Short Term Forecasting

In a classic dynamic factor model, considering the scalar time series variable Y_t to forecast and letting X_t be the N-dimensional time series of candidate predictors, it is assumed that (X_t, Y_{t+h}) admits a factor model with r common latent factors F_t :

$$X_t = \Lambda F_t + \varepsilon_t \quad Y_{t+h} = \beta_F^{'} F_t + \beta_\omega^{'} \omega_t + \varepsilon_{t+h} \tag{1}$$

where ε_t is an $N \times 1$ vector of idiosyncratic disturbances, h is the forecast horizon, $\beta_F^{'}$ and $\beta_\omega^{'}$ are the parameters, ω_t is an $m \times 1$ vector of observed variables (i.e. lags of Y_t) useful, with F_t, to estimate Y_{t+h} .The GDFM encompasses as a special case the model of Chamberlain and Rothschild [4], that allows for correlated idiosyncratic components but it is static. In this research we do the hypothesis that each national GDP in Euro Area is influenced by the same common factors; in fact, econometric literature shows a rising degree of integration and synchronization among European economies, while some differences in the cyclical behavior across countries still persist, see Altissimo et al. [2]. Furthermore Giannone and Reichlin [12] find that a large part of countries' business cycle is due to common (area wide) shocks while idiosyncratic fluctuations are limited. In [9,10,11], some procedures are shown to estimate the sectoral and national smoothed growths concerning Euro Area.

Differently from Eurocoin indicator, that has been recently created to estimate the whole smoothed Euro Area aggregate growth, we outline (for each country analyzed) two national estimates with two different groups of common factors: $R_i^{(k)}$ and $S_i^{(k)}$ $(i = 1,..., m)$ will be respectively the common factors relevant to the prediction of "real MLRG" and "financial MLRG", for each k country considered. National MLRG will be obtained by projecting each National GDP respectively on the same European real and financial common factors. The dynamic factor model is designed to extract common movements which represent the main sources of variation in the Thomson Financial Datastream, to estimate the smoothed components of European growth. Therefore the latent factors are "smooth factors", which are generalized principal components of current values of the variables in the dataset. Following [8], we use a two-step method, producing firstly an estimate of the spectral density matrix of the unobserved components F_t and ε_t , and then we use this estimate to obtain the factors by means of generalized principal components. We assume that, in our non-parametric approach, the covariance among the disturbances $\varepsilon^{'} s$ is weak, instead of no correlation at all: this is a reason for using "generalized" in the denomination of the model [7].
The methodology that we develop can be summarized in the following way:

$$X_t^S = \hat{\Lambda}_S S_t + \varepsilon_t^S \tag{2}$$

$$X_t^R = \hat{\Lambda}_R R_t + \varepsilon_t^R \tag{3}$$

The financial and real variables X_t^S and X_t^R that are used to construct the same factors for the two countries analyzed in this paper (Germany and Italy) are month-on-month rates of change. Therefore, Y^S is the estimate of the national MLRG, for each country, that is obtained only using some financial latent factors; while Y^R is the estimate of the national MLRG that is obtained by using real latent factors:

$$Y_{t+h}^S = \beta_S' S_t + \beta_{\omega S}' \omega_t^S + \varepsilon_{t+h}^S \tag{4}$$

$$Y_{t+h}^R = \beta_R' R_t + \beta_{\omega R}' \omega_t^R + \varepsilon_{t+h}^R \tag{5}$$

where the idiosyncratic disturbances are orthogonal to the factor, ω_t is an $m \times 1$ vector of observed lags of Y_t .The medium to long-run component of the growth can also be outlined at the end of the sample as a "composite indicator", that is a linear combination of the smooth factors with $t = T$ and the coefficients A_i $(i = 1,..., m)$:

$$\hat{c}_T = A_1 F_{1T} + A_2 F_{2T} + ... A_m F_{mT} \tag{6}$$

In equation (6) the common factors are linear combination both of real and financial variables.

3. Comparing real and financial indicators: Real time results

Our model is described by a set of regressors, that are the linear combination of the variables contained in the Thomson Financial Datastream (TFD). The regressors in (2-6) are constructed using techniques from large-dimensional dynamic factor models. We dispose of a dataset consisting of 157 monthly variables (Table 1) during the period between January 1987-December 2011. In our model X_t is a (157x300) matrix. The three indicators that we compare in real time to the bandpassed growth rate are:

- Composite (equation 6);
- Financial (equation 4);
- Real (equation 5).

In this section we divide the TFD in real and financial variables; the period 2003-2011 is analyzed in real time.

Our target, the medium to long run components c_t^k , for each country k , is the following infinite, two sided linear combination of the GDP growth series [3], [6]:

$$c_t^k = \beta(L) y_t^k = \sum_{k=-\infty}^{\infty} \beta_k y_{t-k}^k, \quad \beta_k = \begin{cases} \dfrac{\sin(k\pi/6)}{k\pi} & for \ k \neq 0 \\ 1/6 & for \ k = 0 \end{cases} \tag{7}$$

Since y_t, the growth rate, is observed only quarterly, while we are interested in a monthly indicator of economic activity, we use the techniques introduced in Chow and Lin [5]. According [1], a finite version of the target can be obtained by augmenting $y_t{}^k$ with its sample mean $\hat{\mu}$ in both infinite directions:

$$c_t^{*k} = \beta(L) y_t^{*k}, \quad \text{where } y_t^{*k} = \begin{cases} y_t & if \quad 1 \le t \le T \\ \hat{\mu} & if \quad t < 1 \;\; or \; t > T \end{cases} \tag{8}$$

Target value (7), which is not available at the end-of-sample time T, is available with good accuracy only at time T +h, for a suitable h.

Table 1. *Variables used in Estimation by Data Source*

Data Source	Variables	Type of data
Surveys	31	Real
Leading Indicators	6	Real
Demand Indicators	12	Real
Industrial Production	32	Real
Wages Indicators	2	Real
Employment Indicators	5	Real
Exchange rates	3	Real
Imports-Exports	8	Real
Money Supply	8	Financial
STANDARD &POOR'S INDEX	7	Financial
(Italy, Germany, USA, UK) SPREAD	10	Financial
Benchmark Bond	7	Financial
Producer Price Index	26	Financial
TOTAL	***157***	

3.1 Ability of indicators to approximate the target

In Tables 2 and 3 we analyze the performances in real time, where RMSFE is the root mean squared forecast error that is obtained by comparing each of the three indicators to the bandpassed target c_t^{*k} We observe that performance of the Composite Indicator (that considers the whole dataset of 157 variables) is better than the one concerning the others indicators since the economic crisis (2008), both for Germany and for Italy. Differently, from 2003 to 2007, we observe, for Germany, the better performance of the financial indicator to track underlying the whole GDP.

Table 2: *RMSFE in Real Time among Indicators and Bandpassed GDP: the German Case*

Indicators	2003-2007	2003-2011
Real	0.36	0.64
Financial	0.26	0.78
Composite	0.34	0.62

Table 3*: RMSFE in Real Time among Indicators and Bandpassed GDP: the Italian Case*

Indicators	2003-2007	2003-2011
Real	0.58	0.68
Financial	0.43	0.84
Composite	0.42	0.68

3.2: Analysis of regression coefficients

We are analyzing the following economic aggregates:

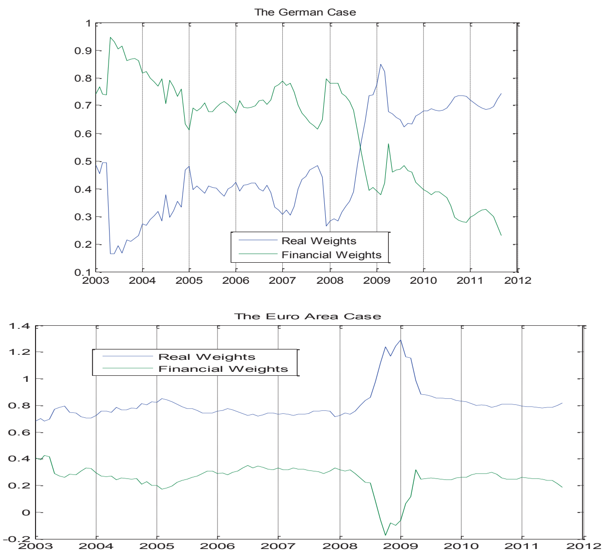
- Germany, Italy, Euro Area.

By a multiple linear regression analysis we estimate, for each aggregate, the National MLRG:

$$c_t = \alpha_t + \beta_{1t} c_t^R + \beta_{2t} c_t^S \qquad (9)$$

In (9) the weights α and β are shown updated monthly to underline our regression in real time estimation period (2003-2010) in which c_t indicates bandpassed GDP; c_t^R is the "Real Indicator" that we calculate only using European real variables; c_t^S is the "Financial Indicator" that we calculate using European financial variables only. The weights are updated every month on the basis of the newly available information. The values of β_{1t} and β_{2t} are respectively the regression coefficients concerning Real and Financial Indicator. In Figure 1 we show the weights calculated in the combination of real and financial indicators. We observe, for the three aggregates, that the relation between the two coefficients is quite stable till 2008; at the beginning of the last recession, we observe a strong change in the impact of real and financial data to estimate smoothed GDP. However, it seems interesting to observe that, from 2003 to 2009, while for Germany the impact of financial variables is stronger that the one concerning real variables, we show the opposite for Italy and Euro Area. This could mean that German GDP growth has been particularly influenced by financial Euro Area fluctuations until 2008. Since 2009, the Euro Area real effects of the crisis have an important weight on German growth.

Figure 1: *Combination of real and financial indicators: Regression coefficients*



4. Conclusions

In particular, in this paper we observe:
-for Germany, the better performance of financial common factors to track underlying the whole GDP from 2003 to 2007. Differently, we show the opposite for Euro Area and Italy.
-for all the three aggregates, we see a strong variation concerning the impact of real and financial variables in estimating smoothed GDP, during the structural break in 2008. Since the recession of 2008-2009, the role of real data becomes particularly relevant in relation to that concerning financial data: therefore, we find that a large part of countries' business cycle is due to real common shocks. In synthesis, we show an approach to choose the variables useful for the nowcasting of growth rate, that is based on the real time ability of financial and real variables to reproduce business cycle.

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