ISTITUTO DI STUDI E ANALISI ECONOMICA

Factor based Composite Indicators for the Italian Economy

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Working paper n. 116
July 2009

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ABSTRACT

A factor based approach is often used to build Composite Indicators (CI) from qualitative data stemming from Business and Consumers Survey (BCS). Bruno and Malgarini (2002) and Gayer and Genet (2006) have used factor analysis to synthesize the information contained in the balances of the various surveys Harmonized by the EC (industry, consumers, retail, building and services). However, Marcellino (2006) pointed out that the use of aggregate balance series could imply missing relevant information contained in the surveys. For this reason, in this paper we consider additional information stemming from the percentage of equal answers; moreover, we also use more disaggregate data at the branch level (considering socio-economics characteristics of the respondents for the consumers survey). More specifically, we consider Main Industrial Groupings for the industry survey; small and large multiple shops for the retail survey; building and civil engineering for the construction survey; households and business services for the service survey.

Variables to be included in the analysis are preselected prior to factor extraction on the basis of their contemporaneous or leading/lagging correlation with sector-specific target series. Three methods are then used to extract Composite Indicators, namely Static Principal Component Analysis and Static and Dynamic Factor Analysis (Forni, Hallin, Lippi, Reichlin, 2000, 2001). The various Composite Indicators obtained from the factor based approach are then investigated against the traditional Confidence Indicators in terms of performance with respect to the reference series. As alternative evaluation criteria we use: a) the cross-correlation between the CI and the reference series; b) the directional coherence of movement with the targets; c) turning points analysis (determined applying the Bry-Boschan method).

Finally, from the whole set of data stemming from ISAE business and consumers survey we extract aggregate Composite Indicators for the whole Italian economy using the same methods and evaluation criteria outlined above. Indicators calculated with Static Factor Analysis on aggregate balances show the best performance in tracking the reference cycle, i.e. the rate of growth of Italian GDP.

Key Words: Business cycle, Confidence indicators, Factor models, Principal components

JEL Classification: C42, C43, E32

CONTENTS

1 INTRODUCTION[1]

A factor based approach is often used to construct Composite Indicators (Cis) from qualitative data stemming from Business and Consumers Survey (BCS). Bruno and Malgarini (2002) and Gayer and Genet (2006) have used factor analysis to synthesize the information contained in the balances of the various surveys Harmonized by the EC (industry, consumers, retail, construction and services); Marcellino (2006) has pointed out that various factor based methods can be used in order to construct cyclical indicators out of survey data, including Principal Component analysis and Static and Dynamic Factor models (Forni, Hallin, Lippi, Reichlin, 2000, 2001). Moreover, according to Marcellino (2006) a use of these factor based methods confined to aggregate balance series could imply missing relevant information contained in the surveys; in order to solve this problem, he suggested including in the analysis additional information stemming from the percentage of equal answers. Moreover, he recommended extending further the information set, considering also more disaggregated data at the branch level (taking into consideration socio-economics characteristics of the respondents for the consumers survey).

Following Marcellino approach, the aim of this paper is to select the "best" method to be applied to the more "efficient" dataset, in order to construct both survey-specific and aggregate indicators for the Italian economy. As "best" method, we intend a method allowing to build indicators that are particularly able to closely monitor the cyclical features of a chosen reference series; as reference, we select sector-specific variables for each survey. Accordingly, the most efficient dataset would be that containing all the relevant information needed to construct the "best" possible sector-specific indicator. In order to reach this goal, we first elaborate a large set of possible indicators, considering different alternative methods and datasets for each survey; then, we need to assess the performance of each indicator and eventually choose the best among them. In this respect, following Moore and Shiskin (1967) we consider that a cyclical indicator should be time consistent (i.e. should closely track the turning points) and show a large degree of conformity (in terms of its correlation function) with respect to the reference series. On the basis of these criteria, we are able to choose the best sector-specific indicator for each survey; as a final step, we can then derive synthetic indicators for the Italian economy using the

[1] The authors would like to thank Giancarlo Bruno for his precious help and valuable comments as well as Gennaro Zezza for useful discussions and suggestions on earlier versions of this paper. We also would like to thank Mauro Constantini and an anonymous referee for their valuable suggestions. The usual disclaimers apply.

data stemming from the five ISAE surveys. The performance of these indicators will be finally evaluated considering as reference series an aggregate measure of economic activity (the annual growth rate of GDP).

The paper is structured as follows: section 2 presents the three factor-based models; section 3 introduces the available datasets, while section 4 provides a detailed analysis of the performance of the various indicators extracted on the different datasets with various methods. Section 5 then proposes an aggregate Composite Indicator for the Italian economy using the same methods and evaluation criteria discussed above. Section 6 concludes.

2 METHODOLOGICAL APPROACH

Factor analysis is a broad family of statistical techniques used to uncover the latent structure present in a set of variables. It summarizes information stemming from large databases, reducing the original space from a large number of variables to a smaller number of factors. For this reason, factor models represent a proper option in deriving factor based indicators from survey data. Moreover, their particular features of revealing latent dimensions make them very appropriate to formalize Burns and Mitchell (1946) suggestion of an unobservable common force underlying the real economy, capturing co-movements in a set of economic time series.

Factor analysis can be carried out in a static or dynamic framework. The most common form of Static Factor Analysis searches for the least number of factors which can account for the common variance of a set of variables. The basic idea behind this method is that each variable results from the sum of two mutually orthogonal components: the common component, which is present in all variables, and an idiosyncratic component, particular of each individual variable. More specifically, if

- z_{it} represents a standardized value of the balance of opinion for the i^{th} question at date *t*, with *i* ranging from 1 to N (number of questions) and *t* from 1 to T;
- F_{jt} represents the value of the j^{th} common factor at date *t*, with *j* ranging from 1 to J (number of latent variables), and
- u_{it} represents the value of the specific component for question *i* at date *t*;

then the model can be expressed as follows:

$$\forall\ i \in [1;\ N],\ \forall\ t \in\ [1;\ T] \quad z_{it} = \lambda_{i1}F_{1t} + \lambda_{i2}F_{2t} + ... + \lambda_{ij}F_{jt} + u_{it} \quad (1)$$

$$\chi_{it} \equiv z_{it} - u_{it} = \lambda_{i1}F_{1t} + ... + \lambda_{ij}F_{jt}$$

The term χ_{it} is the common component of the i^{th} variable, driven by J common factors. Each factor loading λ_{ij} is the correlation coefficient between the i^{th} variable and j^{th} factor, and its squared value, λ_{ij}^2, represents the share of variance in that variable explained by the factor, since we have imposed that the factors are orthonormal. The overall sum of the squares of loadings for a given variable, $\sum_j^J \lambda_{ij}^2$, is called *commonality* and represents the share of variance of the specific variable explained by all factors.

Few basic assumptions are in order:

$E(u_{it})$ = 0, $\forall i \in [1; N]$ and $Var(u_{1t},...,u_{It}) = \sigma^2 I_N$ (1.1)

$E(u_{it}F_{js})$ = 0, $\forall\ i \neq j$ and $\forall\ t \neq s$ (1.2)

$E(F_{jt}F_{hs})$ = 0, $\forall\ j \neq h$ and $t \neq s$ and $Var(F_{1t},...,F_{jt}) = I_J$ (1.3)

All variables are assumed to have zero mean and unit variance. Moreover, the idiosyncratic components are uncorrelated with each other and with the common factors, i.e. they are said to be *mutually orthogonal*. It is also assumed that the common components are not correlated with each other at any time and have unit variance, where I_j represent the Identity matrix of dimension J.

When all factors and specific components are *identically and independently distributed* (i.i.d.) over time, the computation of the maximum likelihood estimates for all factors is straightforward. However, when variables are auto-correlated, as it is often the case with time series, a proper dynamic specification is required. One of the first attempts to account for dynamic dimension was proposed in Stock and Watson (1989, 1991), which introduced autoregressive processes for both common factors and specific components. In particular,

$$z_{it} = \lambda_i F_t + u_{it} \quad (2)$$

$$F_t = \varphi_1 F_{t-1} + \varphi_2 F_{t-2} + \varepsilon_t$$

$$u_{it} = \rho \cdot u_{it-1} + \varepsilon_{it}$$

with disturbances ε_{it} and ε_t following white noise processes. In this initial specification, the common factor followed an AR(2), while an AR(1) was assumed for the specific component. After that, the model was cast into state space form and, through the application of the Kalman filter, ML estimates of the factors were obtained. The model they proposed works quite well with a small number of series, but computational problems arise with large data sets. In addition, initial autoregressive structure needs to be cautiously specified for each series, but such a requirement cannot be met with the large dimension of our data sets.

However, Forni, Hallin, Lippi and Reichlin (2005, FHLR henceforth) proposed a Generalized Dynamic Factor Model, i.e. a dynamic approach based on frequency domain analysis. In particular, model (1) is extended as follow:

$$z_{it} = \chi_{it} + u_{it} = \lambda_i(L)F_t + u_{it} = \sum_{j=1}^{q} \lambda_{ij}(L)F_{jt} + u_{it} \tag{3}$$

where χ_{it} is the common component of the variable i at time t and u_{it} the corresponding idiosyncratic term. The common component is driven by a number q of factors or *shocks,* shared by all variables. In other words, $\boldsymbol{F}_t = (F_{1t},...,F_{qt})'$ is a q-dimensional vector of common factors, assumed to be orthonormal and with unit variance. It is also assumed that the impulse response function $\lambda_{ij}(L)$, $j = 1, \dots, q$, is a s-order polynomial in the lag operator, i.e. $\lambda_{ij}(L)F_{jt} = \lambda_{ij,0}F_{jt} + \lambda_{ij,1}F_{jt-1} + ... + \lambda_{ij,s}F_{jt-s}$ (meaning that a given factor j is loaded with s lags). Again, the idiosyncratic component u_{it} is orthogonal to $\boldsymbol{F}_{t-k}$, for any k and i, but differently from the traditional static framework, a limited amount of cross-correlation among the various idiosyncratic components is allowed. As a result, some other assumptions are required to achieve identification. More specifically, the largest eigenvalue of the variance-covariance matrix of the vector $\boldsymbol{u}_t = (u_{1t},...,u_{nt})'$ is bounded as $n \to \infty$, while the $q(s+1)$ largest eigenvalues of the variance-covariance matrix of the vector $\boldsymbol{\chi}_t = (\chi_{1t},...,\chi_{nt})'$ are unbounded.

The estimation procedure for this model is accomplished in different stages[2]. In the first stage, the estimated spectral density matrix for the vector of common components is derived and, through the inverse Fourier transform, its covariance matrices are identified at different leads and lags. The aim of the

[2] For a more detailed explanation of the theoretical basis of such procedure, see Altissimo et al. (2001) and FHLR (2005).

subsequent stage is achieving a consistent estimation of the unobservable space of common factors. An approximation of that space is obtained through a number of linear combinations of the initial variables, whose weights are the result of a generalized principal components problem requiring the contemporaneous variance-covariance matrices of the common and idiosyncratic terms estimated in the first stage. These estimates, maximizing the ratio between the variances of the common and idiosyncratic component, are considered to be the most efficient ones. At last, through a simple average of the estimated common components, $\hat{\chi}_i$, we are able to obtain the dynamic factor-based indicator[3].

Taking a step back to the multivariate static framework, Principal Component Analysis (PCA) offers an alternative statistical technique for summarizing information stemming from large database. It aims at finding the best linear combinations of the original variables, also known as principal components, in order to reproduce the maximum amount of the total variance of the observed data. This methodology finds as many components as the number of variables being analyzed, but only few of them, i.e. those who account for meaningful amounts of the total variability, are retained. In this view, the first principal component is supposed to account for a fairly large share of the total variance and each succeeding component will explain progressively smaller and smaller amounts of remaining variability. All principal components result from a constrained optimization problem of the original data covariance matrix, and their main characteristic is that they are orthogonal, i.e. not correlated, with each other.

In the following, we apply both the static factor models, i.e. common Factor Analysis and Principal Component Analysis, and the dynamic approach developed by FHLR, to the qualitative data stemming from the BCS. We will present results obtained considering just one factor for each method; in fact, first of all, taking in consideration more than one factor would have raised the problem of finding the best technique to combine them[4]. Moreover, the data we

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[3] Given the performance results of different specifications, we decided to consider one common factor ($q = 1$) with two lags ($s = 2$), when specifying the Generalized Dynamic Factor Model.

[4] In this respect, the literature has shown that it would be possible to explicitly include the reference series among the input data and use as best factor weights those resulting from the corresponding loadings (see Altissimo et al. 2001); however both this method and the one based on the use of "bridge equations" (i.e. regressions of the reference series on a set of extracted factors), provide indicators that are not independent of the reference series, whilst in our case we are interested in deriving a common signal from the survey data, regardless of the targeting series. An additional pitfall of these approaches is that their practical implementation requires the last observation of the reference series which is hardly published at the time of the analyses (the latter problem is solved in Altissimo et al. (2006); however also indicators of the kind of the "New Eurocoin" are not independent from the target series).

use are supposed to be rather homogenous, being derived with the same methodology and drawn from the same source; as a consequence, the first factors (calculated for each method) are generally able to account for a large proportion of the total variance (in our case, the first factor is able to explain, on average of all calculated indicators, more than 50% of the overall variance); indeed, considering more than one factor usually does not imply significant improvements in their explicative power (see Marcellino, 2006).

3 DATA DESCRIPTION

The different methodologies we apply in this work aim at deriving synthetic indexes which summarize the information obtained from monthly surveys among business and consumers, conducted by the Institution for Studies and Economic Analyses. Five sectors are covered, namely Industry (INDU), Consumers (CONS), Construction (CONSTR), Retail (RETA) and Business Services (SERV). Each survey covers a broad set of questions[5]: Table 1 in the Appendix briefly outlines the series drawn from each survey, while table 2 breaks down these series in the different branches or sub-sectors considered in the disaggregation process. We perform our analyses on several datasets, e.g. for the aggregated data, we consider balance series and the balances plus equals, while on a disaggregated or branch level we take into account only the balances.

The questionnaires are designed to collect some quantitative structural information along with qualitative data. The frame of qualitative questions follows the common methodological approach in which all the respondents can give a qualitative assessment by choosing among a fixed set of answers on the current and future economic situation. Typically, the answer scheme is based on a three-option ordinal scale, i.e. “the situation has improved” (+), “has remained the same” (=) or “has deteriorated” (-); in some cases, respondents have to choose among five or even more alternative options. The information on each question is then presented in the form of difference (hence the term

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[5] We drop some variables for not being highly related to the economic cycle. Previous studies, such as Forni et al. (2001), confirmed that price variables have less degree of communality with the real economy. Those variables are not considered in the consumers, retail, services and industry databases, and for this latter sector even employment expectations was dropped for its lagging behaviour with respect to the reference series. Due to the limited number of available series, the price variable is retained only in the construction sector.

“balance of opinion”) between the percentage of positive and negative responses. Each series therefore varies by construction between -100, when all respondents choose the negative option and +100, when all choose the positive option[6]. Sector-specific Confidence indicators are then obtained as simple arithmetic average of seasonally adjusted balances of opinions (see table 3 in the Appendix for more details).

The statistical models we adopt require variables to be stationary. As these opinion balances all occur in a fixed interval [+100;-100], it is natural to think that they are all drawn from stationary processes. However, previous works[7] have shown that the sample realizations for some series can be consistent with a unit root process. Indeed, the ADF test leads us, in the majority of cases, to consider the analyzed series to be generated by stationary processes (results of the tests are available upon request). Moreover, all series have been seasonally adjusted with Tramo-Seats when necessary and then standardized, so that they all have zero mean and standard deviation equal to one.

As shown in Marcellino (2006), using exclusively aggregate balances could imply missing relevant information contained in the surveys. Therefore, the initial dataset composed by aggregate balances was enlarged by adding the percentage of equal answers. Furthermore, an additional database was constructed by considering the balances on a more disaggregated level. As a consequence, for each sector we apply the three methods introduced in section 2 to the following selections of survey data:

Dataset 1: Aggregate balances of replies

Dataset 2: Aggregate balances plus equals replies

Dataset 3: Balances considered at the sub-sector level

As pointed out in Gayer and Genet (2006), however, the performance of factor analysis may also be enhanced considering sub-samples of input data selected according to some systematic pre-screening based on their relationship with the target series. In particular, we filter both Dataset 2 and 3 applying a selection criterion (Dataset 4 and 5) according to which we drop all variables with contemporaneous correlation with the target lower than a given threshold.

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[6] In the CONS survey, most of the questions have six possible answers, i.e. two positive, one neutral, two negative and the nil response; the balance is thus calculated assigning double weight to the extremes. As a consequences it is bounded in the [+200, -200] interval.

[7] Bruno, Malgarini (2002) and Brunello et al. (2000).

All in all, we have 15 possible Factor Indicators for each sector, calculated applying the 3 methods on each of the five datasets. The sample period starts in January 1991 and ends in December 2007 for almost all sectors. However, services sector data are available only since March 1992, and are referred exclusively to the business services sector[8]. All different indicators are then compared with corresponding sector specific reference series. In particular, for the industry sector we use the Industrial Production Index, for the consumers and retail survey Private Consumption, for the construction survey gross value added in the building sector and for the service survey total GDP. All these series are provided by National Accounts, are already seasonally adjusted and are filtered using the seasonal differences[9]. However, they have different frequencies: while the Industrial Production Index is monthly-based, all others are provided on a quarterly basis. In order to convert quarterly frequencies into monthly frequencies, we used different methods (cubic spline, linear, constant and quadratic match average methods), obtaining quite similar results. We choose the cubic spline interpolation, using a low degree polynomials in order to minimise the error[10].

4 SECTOR SPECIFIC FACTOR BASED INDICATORS

All the factors extracted from the above mentioned datasets are evaluated according to a number of criteria aiming at gauging their performances in tracking their sector-specific reference series; we also evaluate the performance of each factor with respect to that of the corresponding traditional Confidence Indicator (CI) monthly published by ISAE. More specifically, according to Moore

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[8] The services sector survey has been initially conducted on a quarterly basis, becoming monthly only in 2003, when it has also been enlarged to the consideration of the whole market services sector. However, the different scope of the survey after 2003 implies a structural break in the dataset. For this reason, we choose to use only information referred to the business service sector. To preserve the length of the series, quarterly (seasonal adjusted) data for the period 1992:1 to 2002:4 – have been converted into monthly frequencies applying a cubic spline interpolation. Because this frequency conversion method loses the first two months, all the series of this sector start on March 1992.

[9] Using the annual growth rate may alter the lead/lag structure, retaining also some of the erratic behaviour of the original series; however, we prefer to use annual growth rates with respect to other filters since our final goal is to evaluate the forecasting performance of each indicator with respect to the official figures published by ISTAT.

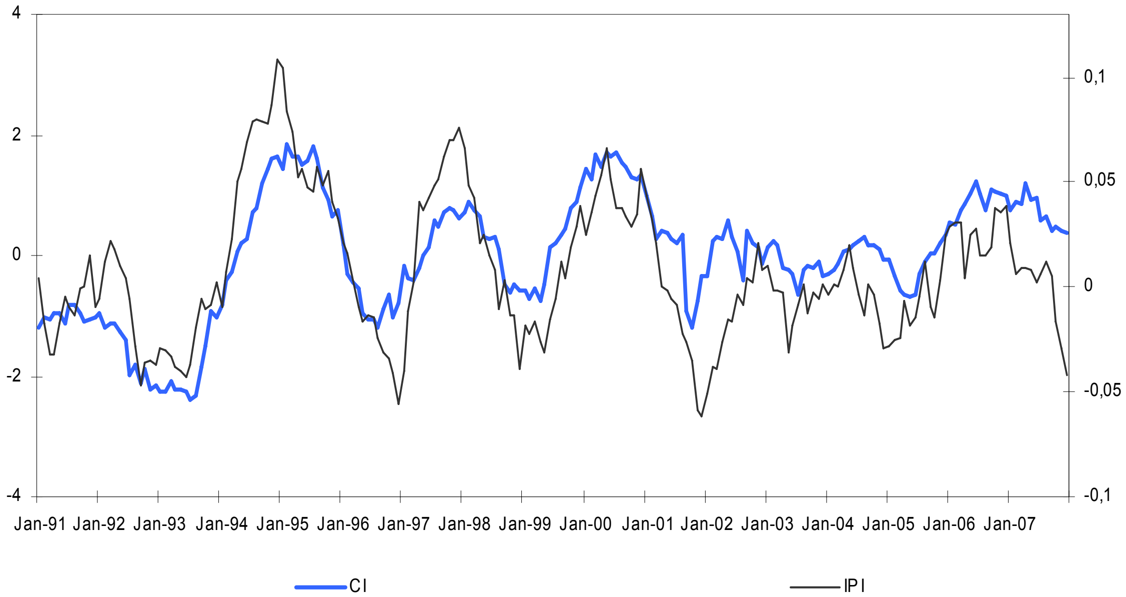
[10] Cubic spline yields a set of curves that are continuous and highly stable (i.e. aren't subject to oscillation effects).

and Shiskin (1967), a cyclical indicator should possess, among others, the following properties: 1) time consistency; 2) conformity and 3) economic significance. We measure time consistency evaluating the average lead/lag of the indicator at turning points, identified with the Bry-Boschan routine; as for conformity, we calculate an indicator of directional coherence consisting in the percentage of cases where the indicators show the same movement (plus or minus) as that of the reference series; we finally evaluate the economic significance of the indicators calculating their cross-correlation function with respect to the reference series.

4.1 Industry sector

Figure 1 plots the traditional ISAE Confidence Indicator (CI, calculated as the simple arithmetic average of balances concerning assessments on order

Fig. 1 **Confidence Indicator and Industrial Production Index**



books and inventories and production expectations) along with the annual rate of growth of industrial production, chosen as reference series. The CI is able to capture quite well and almost contemporaneously the cyclical movements of the reference series, even though some discrepancies emerge towards the end of the sample. In the following, performance of each indicator calculated on different datasets will be evaluated according to the criteria of time consistency, conformity and economic significance with respect to the reference series. No factor model clearly outperforms the others.

Time consistency and conformity at turning points. Table 1, column 1 shows the percentage of cases in which each indicator is able to correctly track

Table 1 **Indicators performance: industry sector**

INDUSTRY		Directional coherence	Correlation w/ ref series			Mean lead (-) / lag (+) at turning points
			ρ(0)	max ρ(l)	lag(+)/lead (-)	TOTAL
CONFIDENCE		0,560	0,711	0,711	(0)	-1,09
SECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset1)						
	DFA	0,547	0,711	0,711	(0)	-1,82
	SFA	0,562	0,671	0,679	(+1)	-0,71
	SPCA	0,562	0,709	0,710	(+1)	-1,55
BALANCES + EQUALS (dataset2)						
	DFA	0,606	0,625	0,630	(+1)	-0,10
	SFA	0,581	0,640	0,644	(+1)	-0,11
	SPCA	0,567	0,625	0,628	(+1)	-0,90
SELECTION 1 (B + E) (dataset4)	DFA	0,616	0,79	0,82	(-2)	-0,727
	SFA	0,567	0,79	0,82	(-2)	-0,125
	SPCA	0,567	0,78	0,82	(-2)	-0,200
SUBSECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset3)						
	DFA	0,576	0,704	0,705	(+1)	-1,20
	SFA	0,576	0,704	0,706	(+1)	-1,20
	SPCA	0,581	0,703	0,706	(+1)	-1,20
SELECTION 1 BALANCES (dataset5)						
	DFA	0,576	0,78	0,82	(-2)	-0,900
	SFA	0,557	0,78	0,82	(-2)	-0,600
	SPCA	0,557	0,78	0,82	(-2)	-0,600

DFA = Dynamic Factor Analysis; SFA = Static Factor Analysis ; SPCA = Static Principal Component Analysis.

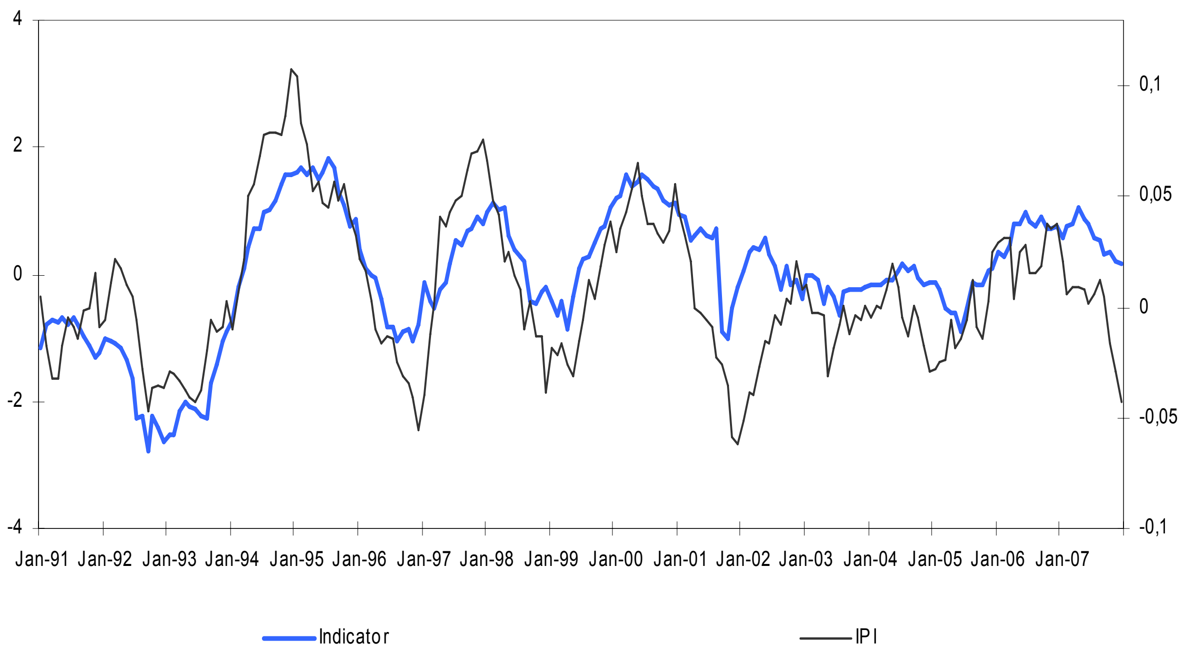
* DFA: one dynamic factor

the rate of change of the reference series; significant improvements over the standard Confidence Indicator are obtained adding equal answers to the initial aggregate set of balances and extending it to branch level. As for the methodologies, we obtain the highest measures of coherence using Dynamic Factor Analysis on the dataset containing balances and equal answers (both pre-screened and not): the indicators correctly predict the sign of the rate of change of the reference variable in over 60% of the cases. Table 1 also presents turning points analysis, evaluating the average lead/lag with respect to the reference series. Both the traditional CI and factor-based indicators generally lead industrial production growth. However, best performances are obtained using indicators extracted from aggregated datasets comprising only balance series and applying Dynamic Factor methods.

Economic significance: cross correlation analysis. In the rest of table 1 we present results concerning cross-correlation of the indicators with the reference variable. The confidence indicator is included in the analysis as a benchmark; best results, both in terms of correlation magnitude and average lead, are obtained with indicators extracted from the pre screened datasets, using both the aggregated balance plus equals dataset and branch level data, regardless of the methodlogy applied (with a maximimum reached with a lead of one month and equal to 0.82).

All in all, enlarging the dataset and using factor methods allow to calculate indicators that marginally outperform the standard ISAE Confidence in terms of time consistency, conformity at turning points and economic significance. Even if it is not easy to establish the “best” indicator according to the aforementioned criteria, the one calculated on disaggregated, preselected data using Dynamic Factor Model shows desirable leading properties both on average and at turning points along with high directional coherence (Fig. 2).

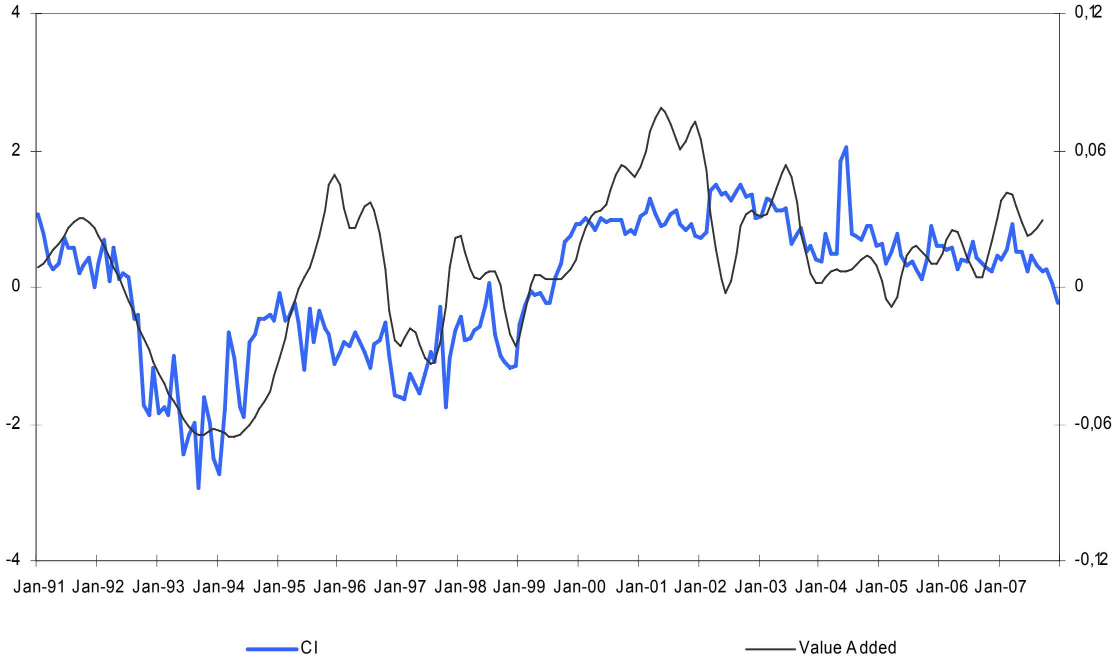
Fig. 2 Selected “best” indicator and Industrial Production Index



4.2 CONSTRUCTION

Figure 3 plots the traditional ISAE Confidence Indicator for the construction sector, calculated as the simple arithmetic average of balances concerning assessments on order books and production plans and employment expectations; the annual rate of growth of sector-specific value added is chosen as reference series[11]. The CI is able to capture quite well the cyclical movements of the reference series. As described in section 3, datasets 4 and 5 were obtained filtering the initial variables according to their relationship with the target series. Also in this case, to evaluate the performance of each indicator we present results relative to their time consistency, conformity and economic significance with respect to the reference series. Results seem to suggest that it is difficult to propose a single factor-based index that systematically outperforms the confidence indicator. However, factor based indicators obtained using equal answers seem to work slightly better.

Fig. 3 **Confidence Indicator and value added**



[11] We started from the consideration of three possible target series, namely value added and investments of the sector and aggregate GDP; we didn't consider the construction production index because it is available only from 1995. Moreover, as highlighted in previous analyses (Crosilla, Leproux, 2007) ISAE data have not leading features with respect to this reference series. We finally choose value added as the reference series because it resulted more closely correlated with survey data.

Time consistency and conformity at turning points. Factor based indicators often outperform the standard ISAE confidence indicator in terms of directional coherence (Table 2); the best performance is found in this case for the indicator based on dataset including branch level data and using Static Principal Component Analysis. All indicators considered are indeed leading at turning points; best results are obtained on average for indicators calculated with Static Principal Component Analysis on aggregated pre selected data comprising equal answers. However, standard CI outperform all the other indicators at turning points.

Tab. 2 Indicators performance: construction sector

BUILDING		Directional coherence	Correlation w / ref series			Mean lead (-) / lag (+) at turning points
			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
CONFIDENCE		0,51	0,707	0,730	(-3)	-5,20
SECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset1)						
	DFA	0,54	0,714	0,737	(-4)	-4,14
	SFA	0,54	0,713	0,739	(-4)	-4,14
	SPCA	0,53	0,712	0,736	(-4)	-4,14
BALANCES + EQUALS (dataset2)						
	DFA	0,525	0,734	0,764	(-3)	-2,80
	SFA	0,50	0,720	0,749	(-4)	-3,00
	SPCA	0,51	0,713	0,740	(-3)	-4,50
SELECTION 1 (B + E) (dataset4)						
	DFA	0,51	0,721	0,746	(-3)	-2,80
	SFA	0,51	0,734	0,762	(-3)	-2,80
	SPCA	0,50	0,731	0,756	(-3)	-4,86
SUBSECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset3)						
	DFA	0,55	0,696	0,729	(-4)	-4,00
	SFA	0,56	0,694	0,723	(-4)	-3,86
	SPCA	0,57	0,693	0,720	(-4)	-3,71
SELECTION 1 BALANCES (dataset5)						
	DFA	0,545	0,694	0,730	(-4)	-1,90
	SFA	0,56	0,701	0,735	(-4)	-3,86
	SPCA	0,57	0,700	0,733	(-4)	-3,71

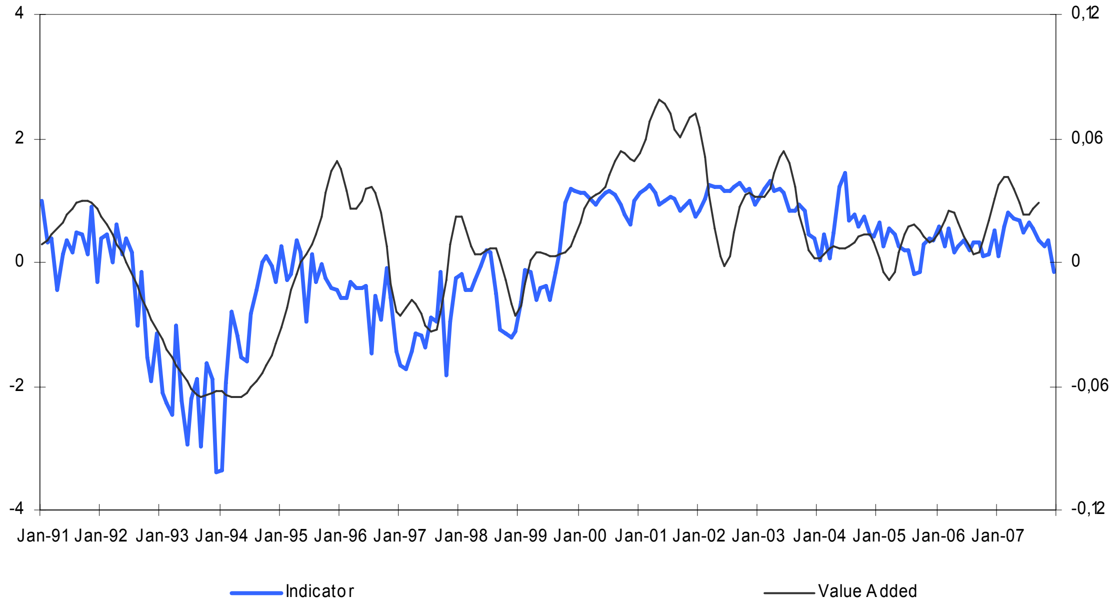
DFA = Dynamic Factor Analysis; SFA = Static Factor Analysis ; SPCA = Static Principal Component Analysis

* DFA: one dynamic factor

Economic significance: cross-correlation analysis. The other columns of table 2 provides cross correlation analysis of factor-based indicators with the reference series. Correlation is maximised using aggregated data including equal answers, with a lead being at most equal to almost 3 months when Dynamic Factor models are used.

Also in this case, there is no single indicator clearly outperforming the others; however, the one calculated with Dynamic Factor Analysis on the dataset including equal answers (with no preselection) shows a good correlation at turning points reached with a lead of almost 3 months, a significant degree of directional coherence and the highest max correlation, overall showing a better performance with respect to the traditional indicator published by ISAE (Fig. 4).

Fig. 4 **Selected "best" indicator and Value Added**



4.3 Retail trade sector

Figure 5 plots the traditional ISAE Confidence Indicator for the retail sector, calculated as the simple arithmetic average of balances concerning assessments and expectations on the business situation and assessment on inventories; the annual rate of growth of private consumption is chosen as reference series[12]. Overall, the CI is able to capture quite well the cyclical movements of the reference series, especially in recent years. As usual the

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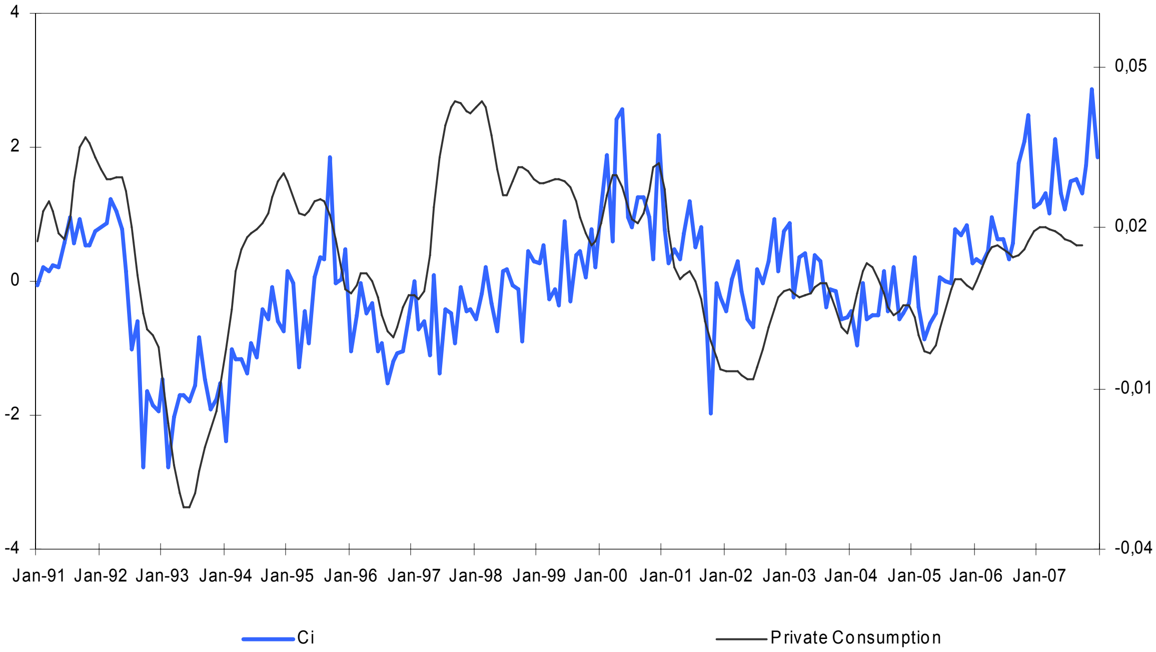
[12] As in Gayer, Genet (2006) and in Crosilla, Leproux (2007).

performance of each indicator is evaluated in terms of time consistency, conformity and economic significance with respect to the reference series.

Fig. 5 **Confidence Indicator and Consumption Expenditures**



Time consistency and conformity at turning points. Factor based indicators are generally more able to correctly predict the direction of change of reference series with respect to the CI (Table 3); the best result is obtained considering aggregate data and applying Dynamic Factor Analysis on dataset 4. Moreover, survey data are generally leading at turning points, with factor based indicators usually able to anticipate the reference earlier than the CI; looking at aggregate data, best results are provided from indicators extracted from dataset 2 using Dynamic Factor Analysis. The use of disaggregated data does not significantly improve the performance, with results obtained with static methods generally better than the others.

Economic significance: cross-correlation analysis. In the rest of table 3 we provide cross correlation among the various indicators and the reference series. Traditional CI clearly outperforms the indicators calculated on aggregate databases (including or not equal answers); however, best results are achieved using the pre-selected sub-sector dataset. Indeed, the use of more disaggregated data actually allow to select an indicator clearly outperforming the standard ISAE confidence indicator; more specifically, best results seem to be obtained using Static Factors analysis on dataset 5[13].

Tab. 3 Indicators performance: retail sector

RETAIL		Directional coherence	Correlation w/ ref series			Mean lead (-) / lag (+) at turning points
			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
CONFIDENCE		0,525	0,461	0,461	(0)	-1,14
SECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset1)						
	DFA	0,53	0,311	0,311	(0)	-1,13
	SFA	0,55	0,287	0,287	(0)	-2,00
	SPCA	0,555	0,277	0,277	(0)	-2,11
BALANCES + EQUALS (dataset2)						
	DFA	0,51	0,230	0,275	(-12)	-3,38
	SFA	0,56	0,262	0,262	(0)	-3,13
	SPCA	0,535	0,243	0,251	(-12)	-3,25
SELECTION 1 (B + E) (dataset4)	DFA	0,57	0,402	0,402	(0)	-1,63
	SFA	0,535	0,400	0,400	(0)	-1,50
	SPCA	0,565	0,400	0,400	(0)	-1,63
SUBSECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset3)						
	DFA	0,535	0,481	0,481	(0)	-3,00
	SFA	0,545	0,461	0,461	(0)	-3,33
	SPCA	0,54	0,446	0,446	(0)	-2,25
SELECTION 1 BALANCES (dataset5)						
	DFA	0,545	0,546	0,546	(0)	-1,86
	SFA	0,525	0,549	0,549	(0)	-3,25
	SPCA	0,535	0,545	0,545	(0)	-3,38

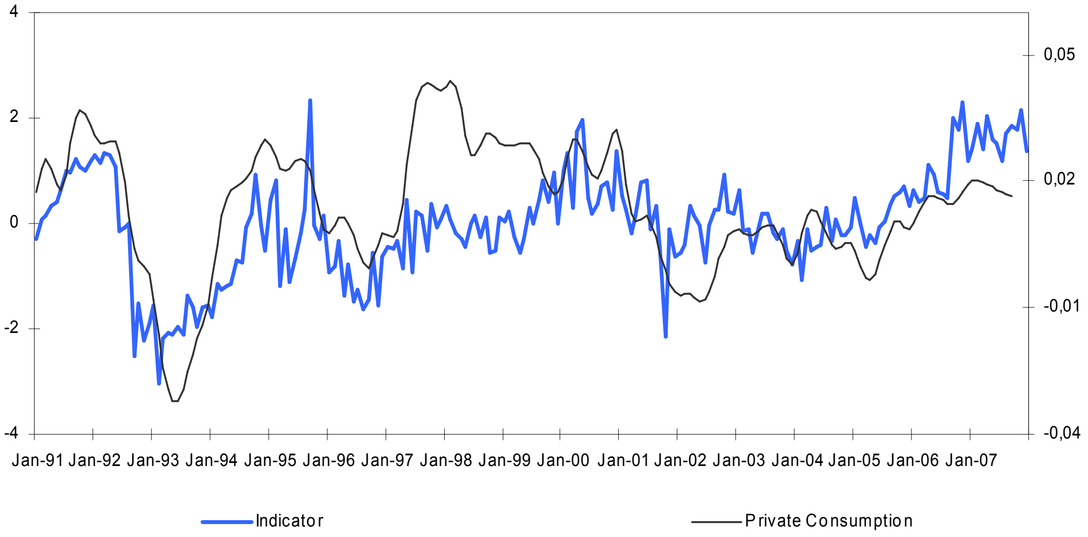
DFA = Dynamic Factor Analysis; SFA = Static Factor Analysis ; SPCA = Static Principal Component Analysis.

* DFA: one dynamic factor.

13 Two indicators extracted from the "balances plus equals" dataset show a 12-month statistical lead with respect to the reference series, hardly significant from an economic standpoint.

All in all, best results seem to be obtained using disaggregated data, pre selected according to the level of correlation with the reference series; as for the methodology, the indicator calculated with Static Principal Components analysis seems to be preferred, showing an higher lead at turning points, a good directional coherence and one of the highest contemporaneous correlation coefficient with respect to the reference series (Fig. 6).

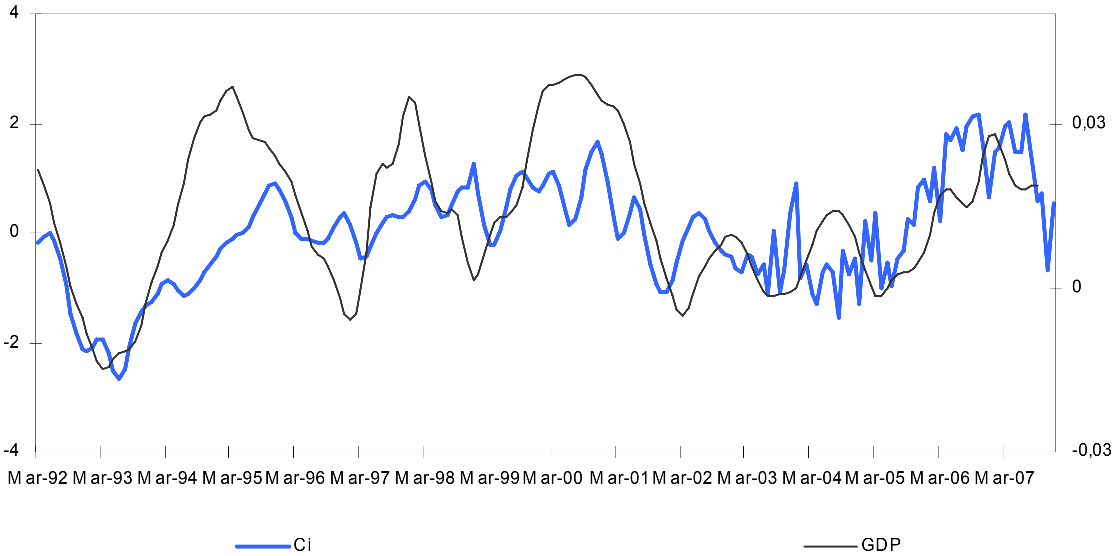
Fig. 6 **Selected "best" indicator and Private Consumption**



4.4 Business services

The ISAE confidence indicator for the business services sector is able to closely monitor the cyclical evolution of the reference series (Fig. 7), in this case

Fig. 7 **Confidence Indicator and GDP**



a measure of aggregate economic activity as the annual rate of growth of GDP[14]. Table 4 reports the usual results for cross-correlation, directional coherence and turning points analysis. In this case we consider only a sub-set of the data sets that have been considered for other sectors; in particular, we do not disaggregate by sub-sector. As a result, the analysis is performed on 3 distinct data sets (Dataset1, 2 and 4 according to the taxonomy adopted above).

Tab. 4 Indicators performance: business services sector

BUSINESS SERVICES		Directional coherence	Correlation w/ ref series			Mean lead (-) / lag (+) at turning points
			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
CONFIDENCE		0,53	0,562	0,569	(-1)	0,33
SECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset1)						
	DFA	0,527	0,538	0,548	(-2)	-1,13
	SFA	0,532	0,512	0,524	(-2)	-2,13
	SPCA	0,548	0,523	0,533	(-2)	-1,13
BALANCES + EQUALS (dataset2)						
	DFA	0,543	0,327	0,329	(-1)	-1,20
	SFA	0,527	0,510	0,523	(-2)	-2,40
	SPCA	0,554	0,565	0,579	(-2)	0,00
SELECTION 1 (B + E) (dataset4)						
	DFA	0,532	0,539	0,549	(-2)	-0,67
	SFA	0,522	0,522	0,532	(-2)	-2,30
	SPCA	0,543	0,534	0,541	(-2)	-1,75

DFA = Dynamic Factor Analysis; SFA = Static Factor Analysis ; SPCA = Static Principal Component Analysis.

* DFA: one dynamic factor.

Time consistency and conformity at turning points. All factor based indicators present a directional coherence similar to that calculated on the basis of the traditional ISAE indicator; however, the indicators calculated using Static Principal Component Analysis are better in correctly gauging the sign (of the rate of growth) of the reference series, especially if calculted on the dataset including equal answers. Table 4 also presents turning points analysis; factor based indicators are usually leading, in this sense significantly improving on the performance of the standard confidence index (which is basically a coincident

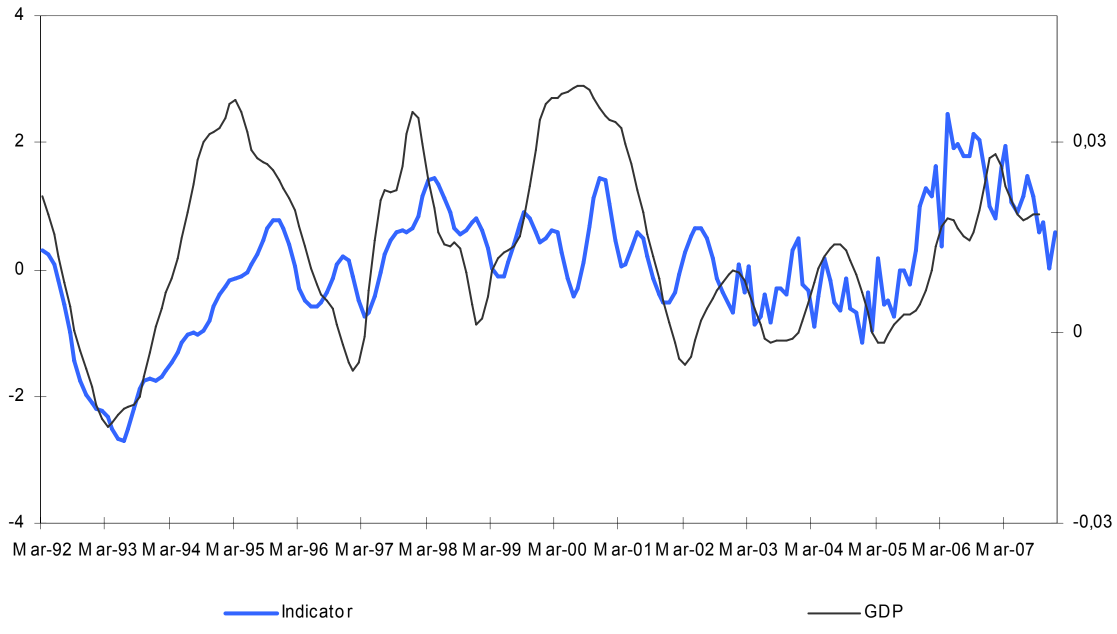
[14] According to preliminary analysis, business service survey data show a closer relationship with aggregate activity rather than with value added for the whole service sector.

indicator of GDP growth). Best results are obtained in this case using Static Factor Models, with a lead of over two months on average, particularly if the dataset considered is that containing also all equal answers, without pre selection based on correlation analysis.

Economic significance: cross-correlation analysis. Looking at the correlation with the reference series, first of all, the coefficient calculated for the standard Confidence index peaks at lead 1 (i.e. the indicator leads the reference series by one month) with a value of 0.57; the new indicators have generally a longer lead (2 months) and a correlation coefficient similar to that of the CI. Adding equal answers and using Static Principal Component Analysis maximise the cross-correlation function, confirming results already obtained in terms of directional coherence.

However, the indicator calculated with SPCA on the balance + equals dataset does not show leading properties at turning points; for this reason, all in all best results are probably those obtained using Static Factor Analysis on dataset 4, with the indicator showing high correlation with a two months lead, leading properties at turning points and good directional coherence with respect to the reference series (Fig. 8).

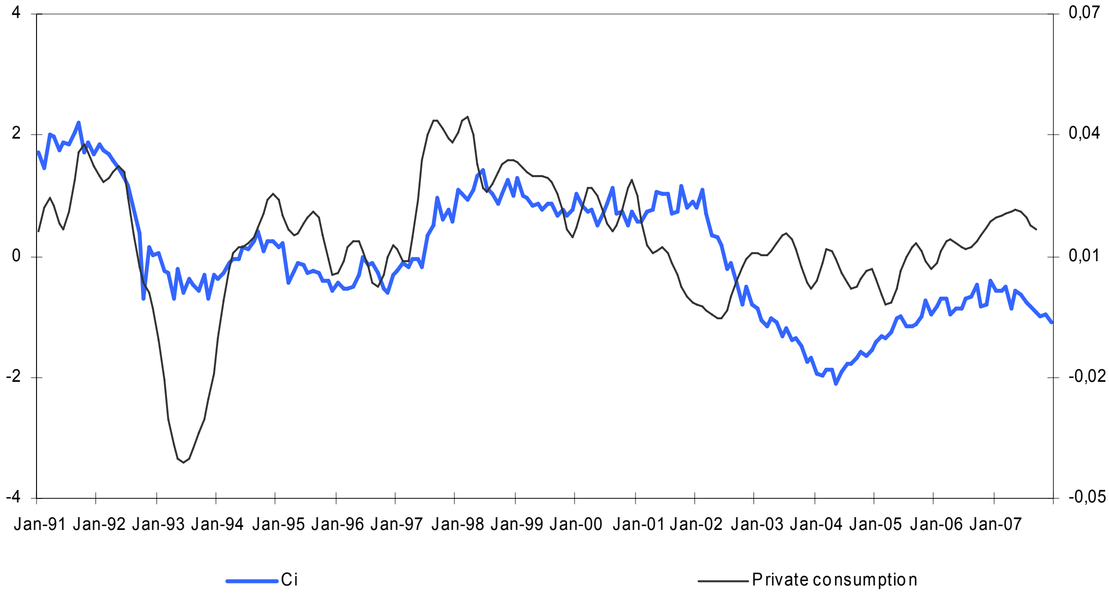
Fig. 8 **Selected "best" indicator and GDP**



4.5 Consumers

We finally analyse the performance of indicators elaborated on the basis of the consumers survey. This is the only survey that targets the demand side of the economy; in the literature survey findings have been alternatively related to GDP or some (more or less aggregate) measure of private consumption (see for instance Golinelli, Parigi (2004) and Malgarini, Margani (2007). In the following we chose as reference series the (annual rate of growth of) private consumption. Figure 9 plots the traditional confidence indicator along with the reference series. Correlation of the CI with private consumption is among the lowest obtained over all surveys; this is mainly due to last part of the sample, when the slow down of actual consumption expenditures was followed by that of the CI only one year later. After this discrepancy the two series seem to be slightly mismatched in the peak/trough structure.

Fig. 9 **Confidence climate indicator and Private Consumption Expenditures**



Time consistency and conformity at turning points. Table 5 shows directional and turning points analyses; best results are obtained using static methods on database 4, for which the indicators are able to capture the sign of the reference series movements in almost 57% of the cases (53% for the CI). The failure of the indicators in closely matching the behaviour of private consumption in the recent past is apparent from the results of turning point analysis: both the CI and the various factor based indicators on average usually lag private consumption at turning points; however, indicators extracted from database 5 show a lower average lag.

Tab. 5 **Indicators performance: consumers survey**

CONSUMERS		Directional coherence	Correlation w/ ref series			Mean lead (-) / lag (+) at turning points
			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
CONFIDENCE		0,53	0.471	0.482	(-2)	5.75
SECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset1)						
	DFA	0.48	0.546	0.573	(-2)	5.60
	SFA	0.495	0.495	0.530	(-3)	7.22
	SPCA	0.515	0.553	0.580	(-2)	6.63
BALANCES + EQUALS (dataset2)						
	DFA	0.535	0.522	0.550	(-2)	7.57
	SFA	0.53	0.415	0.462	(-3)	8.00
	SPCA	0.505	0.250	0.321	(-8)	9.57
SELECTION 1 (B + E) (dataset4)						
	DFA	0.535	0.62	0.63	(-1)	10.14
	SFA	0.565	0.58	0.59	(-1)	11.60
	SPCA	0.57	0.59	0.60	(-1)	9.50
SUBSECTOR DATA*			ρ(0)	max ρ(l)	lag(+)/lead(-)	TOTAL
BALANCES (dataset3)						
	DFA	0.53	0.496	0.522	(-2)	5.75
	SFA	0.545	0.473	0.502	(-2)	5.70
	SPCA	0.545	0.548	0.569	(-2)	5.70
SELECTION 1 BALANCES (dataset5)						
	DFA	0.55	0.61	0.62	(-1)	4.33
	SFA	0.54	0.60	0.61	(-1)	4.25
	SPCA	0.545	0.60	0.61	(-1)	4.25

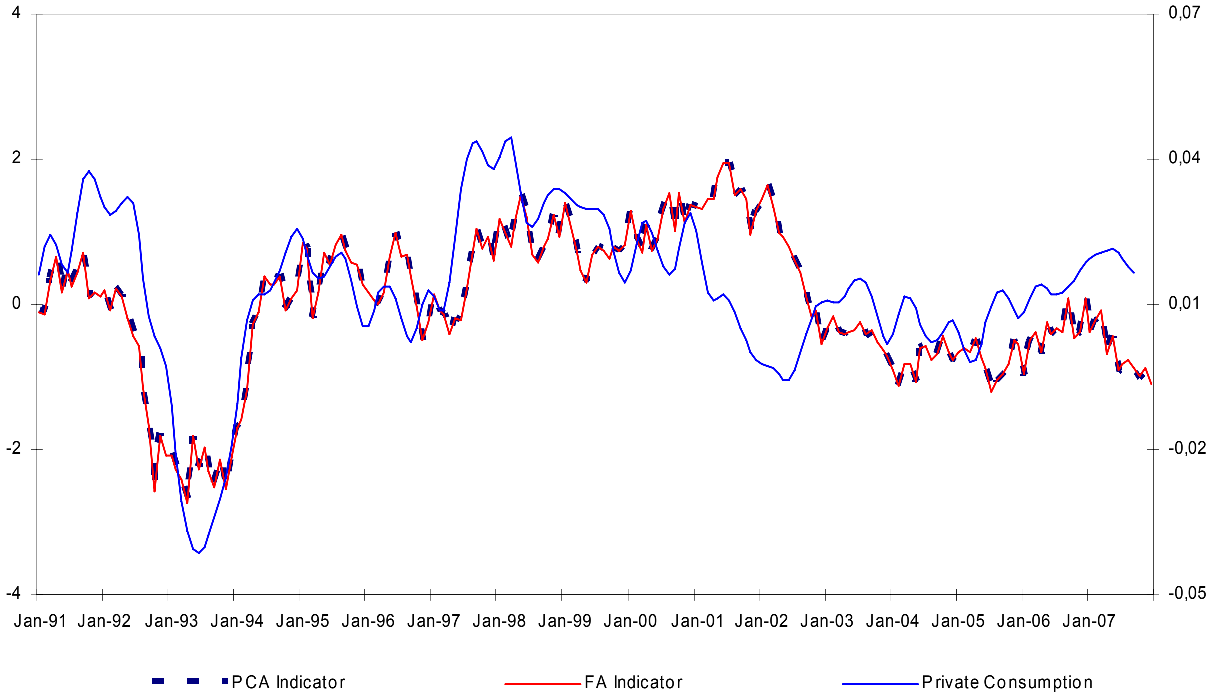
DFA = Dynamic Factor Analysis; SFA = Static Factor Analysis ; SPCA = Static Principal Component Analysis.

* DFA: one dynamic factor.

Economic significance: cross-correlation analysis. Table 5 also shows cross-correlation results; looking first at aggregated data, highest correlation is obtained applying dynamic factor analysis on database 4 , with the resulting indicator leading by 1 month the reference series. Higher lead are obtained using static factor analysis on both balance and balance + equals databases, but with a lower correlation. Considering the data disaggregated by income, higher correlation is again obtained using preselected data with a 1-month lead. Overall, almost all of the indicators outperform the traditional confidence indicator in terms of cross-correlation analysis.

All in all, on the basis of the chosen criteria, there is no a specific indicator clearly outperforming the others; however, the indicators calculated on the more disaggregated database (i.e considering the data for different income groups) show high correlation with an average lead of 1 month and they also show a lower lag at turning points. More specifically, the indicators calculated with static techniques on dataset 5 seem to provide the best results (Fig. 10).

Fig. 10 Selected "best" indicator and Private Consumption



5 CHOOSING THE BEST INDICATORS AND BUILDING SENTIMENT INDICATORS FOR THE ITALIAN ECONOMY

The final goal of the paper is the computation of an aggregate cyclical indicator for the Italian economy using survey data. In the previous sections, performance analysis has shown that neither a specific method nor a specific dataset should be generally preferred for all sectors: usually, a method applied on a given dataset performs better than the others according to one or more but not all criteria. To reach our goal we therefore choose to derive 9 different composite indicators applying the three different multivariate techniques on the three available datasets comprising data stemming from all the five survey monthly realised by ISAE. Table 6 evaluates their performance with respect to a reference series that describes the whole economy, using the (annual growth rate of the) Italian GDP. In this case, the benchmark counterpart is the Economic Sentiment Indicator (ESI), i.e. the weighted average of the sector-specific confidence indicators, whose weights are those suggested by the European Commission[15].

Tab. 6 Indicators performance: aggregate Composite Indicators

		CROSS - CORRELATION			DIR. COHER	TP ANALYSIS
		ρ(0)	max ρ(l)	lag(+)/lead(-)		mean lead/lag
	ESI	0.77	0.78	(-1)	0.43	0.29
SECTOR DATA BALANCES (dataset1)	PCA.Ba	0.72	0.72	(0)	0.58	-0.80
	FA.Ba	0.75	0.75	(-1)	0.57	-0.50
	DFA_Ba	0.71	0.71	(0)	0.57	1.13
SELECTION 1 B+E (dataset4)	PCA.D4	0.72	0.72	(0)	0.66	0.00
	FA.D4	0.75	0.75	(0)	0.64	-1.00
	DFA_D4	0.70	0.71	(+1)	0.58	2.63
SELECTION 1 SUBSECTOR DATA BALANCES (dataset5)	PCA.D5	0.77	0.77	(0)	0.59	1.75
	FA.D5	0.78	0.78	(-1)	0.62	2.00
	DFA_D5	0.75	0.75	(0)	0.61	2.75

Time consistency and conformity at turning points. All the factor based indicators are capable of improving the performance of the standard ESI

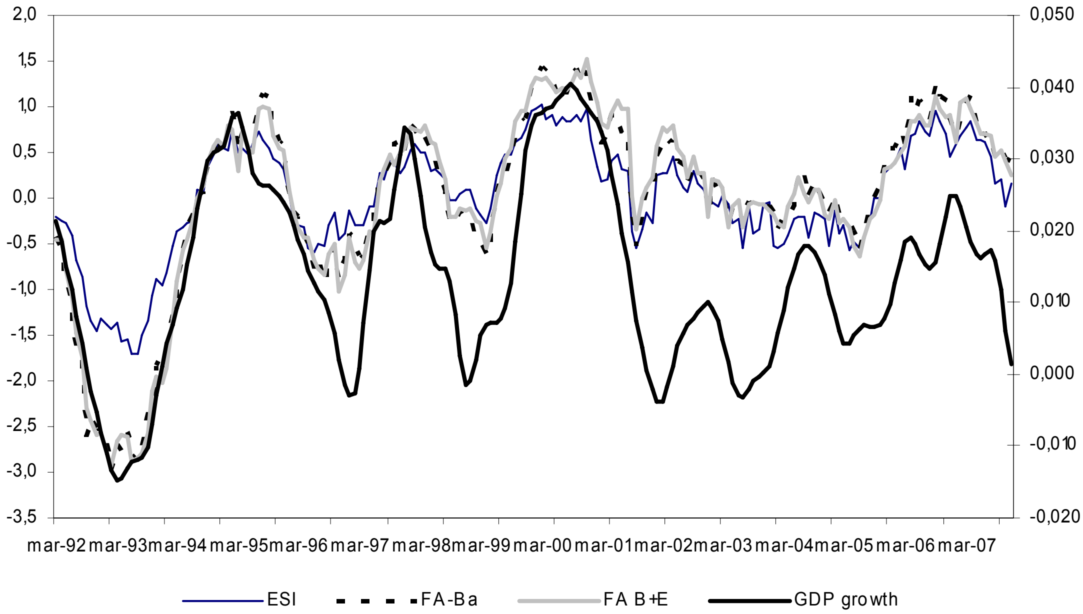
[15] For a more detailed explanation on the computation of the ESI see the European Commission Guide (2002) at http://ec.europa.eu/economy_finance/db_indicators/db_indicators8650_en.htm.

calculated on the basis of the EC methodology in terms of directional coherence; more specifically, the indicator calculated on preselected disaggregated balances and aggregate balances and equal answers using Static Factor analysis is able to correctly gauge the direction of movement of the reference series in over the 60% of the cases, as opposed to only 43% for the standard ESI. However, indicators calculated on disaggregated balances usually lag at turning points; in this sense, on the other hand, the best performance is achieved by indicators calculated with static factor analysis on both aggregated balances and the dataset composed of both balances and equal answers: indeed, these indicators are able to anticipate on average GDP growth at turning points by half a month and 1 month respectively, being also able to correctly gauge the direction of movement of the reference series in the 57 and 64% of cases, much more than the traditional ESI.

Economic significance: cross-correlation analysis. None of the aggregated indices gains over the ESI in contemporaneous or maximum correlation with GDP; yet, Static Factor Analysis applied on the datasets comprising disaggregated balances provides an indicator that is leading by one month with respect to the annual rate of growth of GDP.

All in all, looking at the different criteria used to evaluate indicators performance, best results are obtained by the two indicators calculated using Static Factor Analysis on both aggregate balances and the dataset comprising both balances and equal answers at the aggregate level (see Fig. 11): they are

Fig. 11 Aggregate Composite indicators and GDP growth



able to anticipate the reference series at turning points by half a month and a full month on average, and they also correctly gauge the direction of GDP growth respectively in the 57 and 64% of cases; moreover, the indicator calculated on aggregate balances shows a cross-correlation with the reference series peaking at lead 1 and being equal to .75, i.e. very close to that achieved by the standard ESI, that is however lagging at turning points and show a poor directional coherence with respect to the reference series. Hence, this indicator may be considered as the "best" emerging from the application of different factor methods on various datasets derived from the data monthly elaborated on the framework of the European project of Business and Consumers surveys.

6 CONCLUSIONS

The main result of our study is that using factor models and better exploiting the informative content of survey data does not easily allow building indicators that systematically outperform the traditional Confidence indicators monthly published by ISAE. In this sense, results are in line with previous findings at the European level (Marcellino, 2006). However, for all the surveys – the only exception being that on the business service sector - a careful selection of the most efficient data-set and of the best method improves the performance with respect to the traditional ISAE Confidence Indicator in terms of time consistency, conformity and economic significance.

More specifically, applying a number of statistical criteria we have been able to select for each survey the more efficient data set and the best method in order to track the cyclical behaviour of the reference series. In this respect, the use of data disaggregated at the branch level improves the performance in the industry, retail trade and consumers survey; the consideration of equal answers is on the other hand the best option to obtain more reliable information from the construction and business service sector surveys. With respect to the method to be used to extract cyclical information, Dynamic Factor Analysis perform better for all the surveys, the only exception being the retail survey for which better results are obtained using Static Principal Component Analysis.

Finally, we have tried to use the full dataset stemming from all the five ISAE surveys in order to build with each of the three methods considered in the analysis an aggregate Composite Indicator for the Italian economy; we have then evaluated the results in terms of time consistency, conformity and economic significance with respect to those obtained using the standard Economic Sentiment Indicator calculated using the EC methodology. The indicators calculated using Static Factor Analysis on aggregated balances and also including equal answers are those providing the best results.

However, further research is needed in order to have a more thorough evaluation of the indicators' performance in view of their eventual publication. In particular, the possibility of extracting more than just one factor should be explored, together with the issue of finding the most appropriate method to obtain a synthetic information from them. Moreover, at the moment for evaluating indicators' performance we have used only the final estimates of the reference series; however, official series are often updated as soon as more information become available, and the performance of the indicators may indeed differ if considered in "real time". Similarly, whilst the standard ISAE Confidence indicators are not revised (with the only exception of their seasonal components), factors estimations may vary over time, as soon as new information become available; in this sense, also the performance of the indicators should be validated using "real time" data on the indicators themselves and not only on the reference series[16].

[16] We thank an anonymous referee for having raised this point.

APPENDIX

Tab. 1 **Survey questions**

Number	Acronym	Variable description
INDUSTRY		
1	PRD	Production trends over last 3 months
2	ORDT	Assessment of order-book levels
3	ORDEXP	Assessment of export order-book levels
4	INVENT	Assessment of stocks of finished products
5	LIQ	Assessment of Liquidity
6	EXPRD	Production expectations over next 3 months
7	EXORDT	Order books expectations over next 3 months
8	EXEC	Economic situation expectations
9	EXPLIQ	Liquidity expectations
CONSUMERS		
1	ECSITH	Economic situation of households over last 12 months
2	EXECSITH	Economic situation of households over next 12 months
3	FINSITH	Statement on financial situation of household over past 12 months
4	ECSITIT	General economic situation over last 12 months
5	EXECSITIT	General economic situation over next 12 months
6	EXEMPL	Unemployment expectations over next 12 months
7	DUR	Major purchases at present
8	EXDUR	Major purchases over next 12 months
9	SAVING	Saving at present
10	EXSAVING	Saving over next 12 months
CONSTRUCTION		
1	ORDLEV	Evolution of current order books over last 3 months
2	COSACT	Building activity development over the past 3 months
3	EXORD	Order books expectation over next 3 months
4	EXPRICE	Prices expectations over next 3 months
5	EXEMPL	Employment expectations over next 3 months
RETAIL		
1	BACT	Business activity (sales) development over past 3 months
2	EXBACT	Business activity expectations over next 3 months
3	INVENT	Volume of stock currently hold
4	EXORD	Orders placed with suppliers, expectations over next 3 months
5	EXEMPL	Employment expectations over next 3 months
SERVICES		
1	ORD	Evolution of the demand over past 3 months
2	EXORD	Expectation of the demand over next 3 months
3	TURN	Business situation (turnover) development over past 3 months
4	EXTURN	Business situation development over next 3 months
5	EXEMPL	Expectations of the employment over next 3 months

The exact wording of the questions can be found in the User Guide available on the European Commission web page: http://ec.europa.eu/economy_finance/db_indicators/surveys11283_en.htm

Tab. 2 **Disaggregation level of each sector**

INDUSTRY	CONSUMER	CONSTRUCTION	RETAIL	SERVICES
Main Industrial Groupings	Income of Households	Main Sectors	Types of distribution	Market services.
Consumer Goods:	1st quartile	Building:	Small shops	None
Durable Cons. Goods	2nd quartile	Residential	Large multiple shops	
Non durable Cons. Goods	3rd quartile	Non Residential		
Investment Goods	4th quartile	Civil Engineering		
Intermediate Goods				

Tab. 3 **Confidence Indicators**

Survey	Confidence Indicator construction
Industry	The industrial confidence indicator is the arithmetic average of the seasonal adjusted balances (in percentage points) of the answers to the questions on production expectations, order books and stocks of finished products (with inverted sign).
Construction	The construction confidence indicator is the arithmetic average of the s.adj. balances on order book assessments and employment expectations.
Retail	The retail trade confidence indicator is the arithmetic average of the s.adj. balances on the present and future business situation, and on stocks (with inverted sign).
Services	The services confidence indicator is the arithmetic average of the s.adj. balances (in percentagepoints) of the answers to the questions on business climate and on recent and expected evolution of demand.
Consumers	The consumer confidence indicator is the arithmetic average of seasonal unadjusted balances of 9 survey questions reporting the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings and major purchases of durable goods, both assessments and expectations. The indicator thus obtained is then adjusted correcting for seasonal components.

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