A non-balanced survey-based indicator to track Industrial Production

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Abstract

This study considers the construction of synthetic indicators, based on monthly survey data from the European Union Program of Business and Consumer Surveys (BCS). More precisely, the paper explores alternatives to the commonly used balance statistics, with a specific application to the industry sector for the euro area.

Balances of opinion are interesting indicators in many respects, but theoretical foundations to the use of balance statistics appear to be valid under fairly restrictive assumptions. At aggregate level, balance statistics are an appropriate way of summarising survey data only when the proportion of respondents reporting or expecting "to stay the same" is fairly stable over the time. As a consequence, when this assumption does not hold the use of balance statistics could be controversial. This has been the case in the recent crisis juncture, where there is evidence that the observed collapse in the balances of opinion statistics was mainly due to the strong decline in the proportion of the "do not change" respondents throughout all the sectors of the economy. In such circumstances the use of balance statistics becomes questionable. This calls for a deeper investigation of the information conveyed by the percentage of positive, negative and stable respondents.

In this respect, the paper searches for a different way to summarise survey results, with a twofold objective: exploiting better the information content of the data and proposing a new synthetic survey-based indicator for the industry sector for the euro area.

Two different approaches have been followed: principal components analysis (as in Hild 2003; Etter *et al*., 2004) and regression analysis. The main finding of the study is that the percentage of negative answers is a good candidate to properly summarise the relevant information content of survey data and that indicators built on the percentage of negative

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answers tend to outperform balance statistics. This result is consistent with analogous findings in the literature on survey data (Entorf, 1993; Etter *et al*. 1994; Summer, 1997; Thomas, 1995).

On this basis, a new composite indicator – the average of the percentages of negative answers to questions concerning the past and the future production – is proposed for tracking and forecasting the industrial production growth in the euro area. The performance of this non-balanced synthetic indicator is assessed through in-sample and out-of-sample exercises, showing that it outperforms both the Industry Confidence Indicator and the Business Climate Indicator, which are currently published by the European Commission and have been chosen as benchmarks in this study.

Key Words: Composite Indicator, Industrial Confidence, Industrial Production, Principal Components, Predictive power

JEL Classification: C12, C53, E32

1. Introduction

Business survey data, either on their own or in conjunction with other (hard) data, play an important role for analysts to gauge the economic stance and to get a barometer of the economic activity. The main advantage of the survey (soft) data for short-term economic analysis is that they are timelier than official data: for example, in the euro area, survey data are released at the end of the reference month, whereas hard indicators – as the GDP and the industrial production – are published six weeks after the end of the reference quarter or month, respectively.

A key aspect of the business surveys is that the greatest part of questions asks for qualitative responses. For example, managers (respondents) are not asked to say by what percentage their output has changed over the past months (or they expect it will change in the next months), instead they are simply asked whether the output has fallen, stayed the same or risen (or whether they expect it will fall, stay the same or rise). Thus, a typical business survey question offers three alternative responses: "better" (or "increase"), "equal" (or "no change") and "worse" (or "decrease"), which are usually codified as "positive", "equal" and "negative" responses.

The consequence is that a key issue in the use of survey data is handling the link between qualitative data and the quantitative data they are supposed to track, as well as finding a suitable quantification conversion of the qualitative information they convey. A number of quantification procedures have been suggested in the literature (Pesaran and Weale, 2006). Most commonly, the quantification of survey data is obtained by means of a balance statistics (Theil, 1952; Anderson, 1952; Fansten, 1976) which is defined as the difference between the proportion of respondents reporting a positive answer and those reporting a negative one.

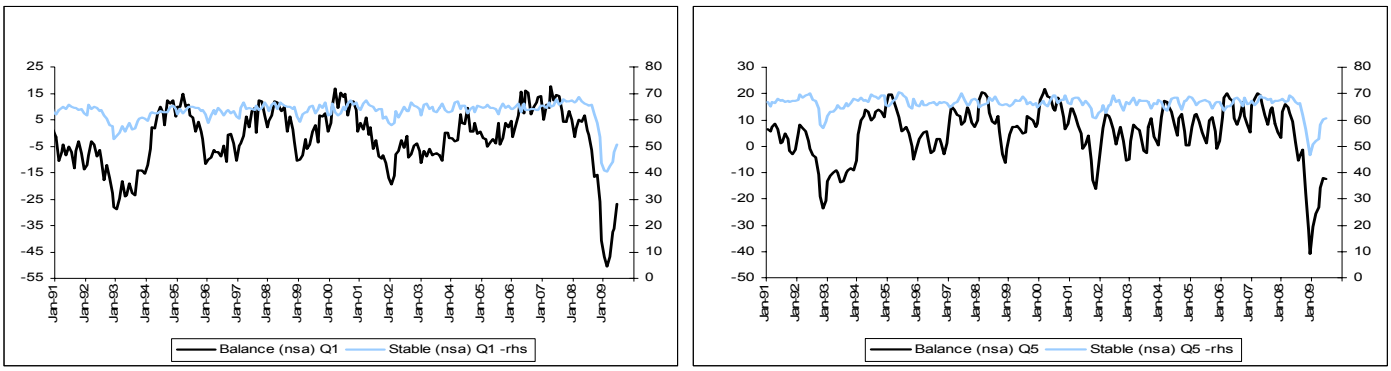
Balances of opinion are interesting indicators in many respects: they are easy to implement, to read and to follow over time. Moreover, they are subject to limited revisions across time and, in general, they exhibit a high correlation with the corresponding aggregates of interest, though being generally smoother. All these properties explain why the balances of opinion are the main (if not the exclusive) kind of survey-based indicators followed by short-term analysts.

However, theoretical foundations to the use of balance statistics appear to be valid under fairly restrictive assumptions on the individual responses behaviour, in particular concerning the stability of the indifference interval (e.g. the "do not change/stay the same" reply) over the time for each respondent. At aggregate level, it turns out to be that balance statistics are an appropriate way of summarising survey data only when the proportion of respondents reporting or expecting "to stay the same" is fairly stable over the time.

As a consequence, when this assumption does not hold the use of balance statistics could be controversial. This, for instance, has been the case in the recent crisis juncture, where there is evidence that the observed collapse in the balances of opinion statistics was mainly due to the strong decline in the proportion of the "do not change" respondents throughout all the sectors of the economy.

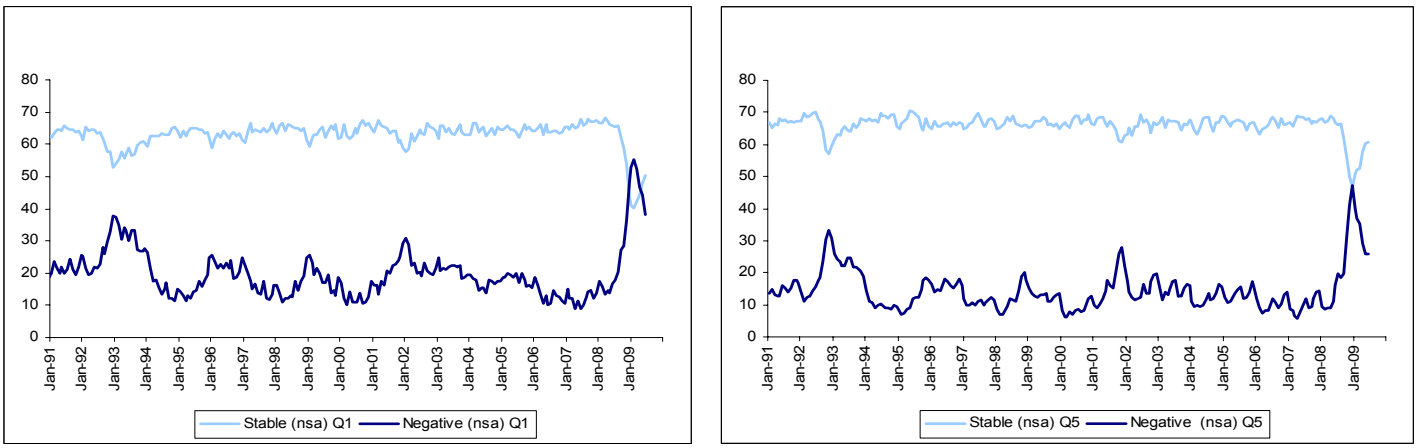
As an anecdotal example, the unprecedented fall – observed during the recent economic crisis – in the balance statistics of past and expected production (Industry survey) was due to a significant drop in the share of the "stay the same" respondents, accompanied by a shift towards "negative" responses, which eventually caused the balances' fall (Figure 1 and Figure 2 below).

Figure 1: Balance and Stable responses (not seasonally adjusted) – Euro area – Industry Questions 1 (past production) and 5 (expected production)



Source: European Commission

Figure 2: Negative and Stable responses (not seasonally adjusted) – Euro area – Industry Questions 1 (past production) and 5 (expected production)



Source: European Commission

In such circumstances the use of balance statistics becomes questionable. This calls for a deeper investigation of the information conveyed by the percentage of positive, negative and stable respondents. In this respect, the paper searches for a different way to summarise survey results, with a twofold objective: exploiting better the information content of the data and proposing a new synthetic survey-based indicator for the Industry sector.

The dataset used throughout the paper consists of time series from the euro area Industry Survey (within the BCS[1]), with a focus on the following monthly questions (as detailed in the Appendix): production trends in recent months (Q1), order books (Q2), export order books (Q3), stock of finished products (Q4) and production expectations (Q5). The reference hard data time series is the real-time euro-area monthly Industrial Production Index[2] (e.g. the Industrial Production Index data as they were available at any given point in the past). The sample covers the period January 1991 – June 2009 for survey data and January 1991 – April 2009 for the Industrial Production Index.

The paper is organised as follows. Section 2 presents two approaches (namely a Principal Components and a regression analysis) to summarise the information conveyed by survey data: the results from both approaches suggest the importance of taking into account the percentage of negative respondents. Then, in Section 3, different (composite) indicators (based on the percentage of negative respondents) are analysed in term of cross-correlation with the reference hard series (e.g. the euro area Industrial Production growth year on year), leading to the definition of a new confidence indicator. Its performance is assessed through both an in-sample (§3.1) and an out-of-sample analysis (§3.2), with respect to the benchmark of the Business Climate Indicator (BCI) and the Industrial Confidence Indicator (ICI), which are monthly published[3] by the European Commission. Section 4 concludes.

2. How much information is in detailed answers?

The BCS Industry questions are characterised by 3 different answer modalities (positive, stable, negative). The objective of this Section is to identify the best way to summarise their information content. This is pursued through two different approaches: a principal component analysis (§2.1) that has the aim of finding the linear combination of the 3 modalities which maximizes (best explains) the variance in the data, and a regression analysis (§2.2) to identify that combination with the highest explanatory power with respect to the variable of interest, e.g. the industrial production growth.

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[1] Joint Harmonised EU program of Business and Consumer Surveys (BCS): http://ec.europa.eu/economy_finance/db_indicators/surveys/method_guides/index_en.htm

[2] Industrial Production Index (2005=100): Total industry, excluding construction, working day and seasonally adjusted (source EABCN Real-time Database; see Giannone *et al*. (2010) for a description of the database).

[3] http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm

2.1 Principal Components analysis

The analysis of the correlation between the answer modalities shows that they are all highly correlated (Table 1). In particular, for all the considered questions in the Industry survey, there is a very strong (and negative) correlation between the percentages of firms giving a negative answer (assessment, expectation) and those reporting "do not change".

Table 1: Euro Area BCS Industry questions, sample 1991m1 – 2009m6 Correlation between answer modalities

Question 1	% +	% =	% –
% +	1.00	0.61	-0.90
% =	0.61	1.00	**-0.88**
% -	-0.90	**-0.88**	1.00
Question 2	**% +**	**% =**	**% –**
% +	1.00	0.76	-0.90
% =	0.76	1.00	**-0.97**
% -	-0.90	**-0.97**	1.00

The percentage time series have been seasonally adjusted (through TramoSeats).

(a) For Question 4, related to stocks, a negative assessment corresponds to a positive answer.

Source: Our calculation on European Commission data

Question 3	% +	% =	% –
% +	1.00	0.61	-0.84
% =	0.61	1.00	**-0.94**
% -	-0.84	**-0.94**	1.00
Question 4(a)	**% +**	**% =**	**% –**
% +	1.00	**-0.94**	-0.39
% =	**-0.94**	1.00	0.06
% -	-0.39	0.06	1.00
Question 5	**% +**	**% =**	**% –**
% +	1.00	0.57	-0.91
% =	0.57	1.00	**-0.83**
% -	-0.91	**-0.83**	1.00

The strong correlation between all the modalities suggests that a (new) meaningful indicator can be obtained by extracting the relevant information in the data through a Principal Components Analysis: the first principal component (PC1) will account for as much of the variability in the data as possible, while eliminating any residual redundancy.

In fact, even if principal components analysis is mostly used to analyse individual/panel data and to reduce dimension of data, this kind of approach has already been successfully proposed in the literature of time series analysis of survey data (e.g. Hild, 2003; Etter *et al*., 2004).

Table 2 shows the PC1 loadings of the 3 answer modalities for each of the five questions, as well as the percentage of variance explained by PC1. Hereafter, P, S, M will denote respectively the seasonally adjusted percentage series of positive, stable and negative answers.

Table 2: First Principal Component loadings

	PC1 Loadings			Explained variance
	L_1	L_2	L_3	
	% + (P)	% = (S)	% – (M)	
Q1	0.56	0.55	-0.62	87%
Q2	0.56	0.57	-0.60	92%
Q3	0.54	0.57	-0.62	87%
Q4	-0.70	0.64	0.30	68%
Q5	0.57	0.54	-0.62	85%

Source: Our calculation on European Commission data

The first principal component (PC1) explains for all the questions (with the exception of Q4) a proportion of the total variability equal or higher than 85%: it is, therefore, a good candidate to summarise the information content of the 3 answer modalities.

Moreover, the loadings for the 3 modalities are broadly constant over the questions (again with the exception of Q4[4]), and between P and S (e.g. $L_1 \cong L_2 \cong L$). This allows writing down the *PC1* as:

$$PC1 = L_1 * P + L_2 * S + L_3 * M = L * (P + S) + L_3 * M = L * (100 - M) + L_3 * M$$

or, in general terms, as: $PC1 = a + b * M$,

from which it appears that all the relevant information is contained in the percentage of respondents who give a negative answer (assessment or expectations).

2.2 Regression analysis

While the Principal Components approach does not take the variable to be predicted into account, the regression model approach does. Therefore, a regression analysis has been performed in order to identify the combination of answer modalities with the highest explanatory power with respect to the industrial production growth (IP). Indeed, the industrial production is the reference series which Industry surveys aim to track, being of utmost importance as a short-term indicator of the economic outlook.

For each question (j = 1, 2, …, 5) of the Industry survey, a linear regression model[5] has been specified as:

$$IP_t = c_1 * P_{jt} + c_2 * S_{jt} + c_3 * M_{jt} + u_{jt}, \qquad j = 1, 2, \ldots, 5,$$

[4] This is unsurprising as, in fact, Q4 -which asks for an assessment of the current level of stocks of finished products- has an intrinsic different nature when compared to the other questions of the industry surveys.

where t denotes the current month, and u_{jt} is assumed to be a Normal distributed white noise random variable.

The main results are the following (more details are shown in the Appendix).

- For all the questions, the M modality (e.g. negative answers[6]) is always the most significant in term of explanatory power of the industrial production index.
- The model with the best fit (as measured by adjusted R^2) is the one built on Q1 and Q5 data. This is unsurprising, as these two questions are those that refer explicitly to the (past and expected) production.
- For the model built on questions Q1 and Q5, the null hypothesis of equality between c_1 and c_2 cannot be rejected at 5% significance level (see Wald test in the Appendix), so that the linear model can be written down as:

$$IP_t = c^* (P_{jt} + S_{jt}) + c_3 * M_{jt} + u_{jt} = c^* (100 - M_{jt}) + c_3 * M_{jt} + u_{jt} = \alpha + \beta^* M_{jt} + u_{jt}, \qquad j = 1, 2, 5,$$

which confirms the results obtained through the Principal Components Analysis, e.g. that the relevant information, also in terms of explanatory power for the IP, is mainly contained in the percentage of respondents who give a negative answer (assessment or expectation).

Based on the results of both analyses (§ 2.1 and §2.2), it seems that a (new) meaningful indicator for tracking the industrial production growth can be obtained by using the percentage of negative answers. This finding is in line with analogous results in the literature on survey data (Entorf, 1993; Etter *et al*., 1994; Summer, 1997; Thomas, 1995).

In particular, based on the regression results, the share of negative responses to questions 1, 2 and 5 seem to be promising. Indeed, Q3 (export order books) and Q4 (stocks) cannot be expected to be good predictors of industrial production itself, while they are more meaningful to track trade and inventories dynamics

[5] The IP and the P, S, M series have preliminary passed the KPSS test of stationarity.

[6] Positive answer for Q4 (see note a in Table 1).

3. A new indicator to track industrial production

Out of the negative modality of answer to the three questions (Q1, Q2 and Q5), it is possible to construct 7 different indicators resulting from their combinations (averages). Thus, it is possible to search for the indicator that has the comparative highest correlation with industrial production growth.

In Table 3 the results in terms of correlation with the *IP* are shown. The indicators M12, M15, M25 and M125 are obtained as averages of the corresponding questions (for example, M12 is the average of the percentage of negative respondents to Q1 and Q2), where the series of negative answers have been preliminarily standardised to take into account different levels and variability.

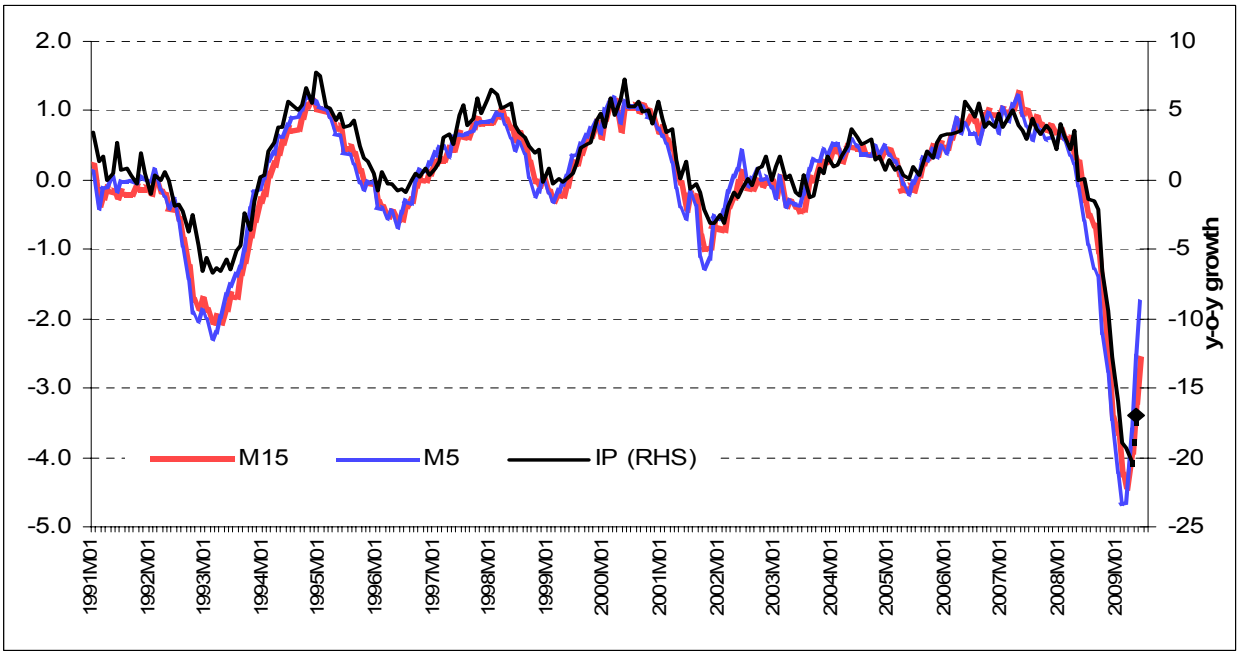
Table 3: Correlation with Industrial Production Index and ranking of indicators

Indicator	Coincident Correlation	Ranking	Lead 1	Lead 2	Lead 3
M1	-0.955	2	-0.888	-0.785	-0.688
M2	-0.823	7	-0.752	-0.659	-0.550
M5	-0.947	3	**-0.921**	**-0.868**	**-0.780**
M12	-0.908	6	-0.837	-0.742	-0.632
M15	**-0.964**	**1**	**-0.922**	**-0.844**	**-0.745**
M25	-0.931	5	-0.886	-0.804	-0.700
M125	-0.944	4	-0.891	-0.805	-0.670

Source: Our calculation on European Commission data

The indicator M15 (which is based on the negative answers to the questions concerning past and expected production) is the one that achieves the highest (in absolute value) coincident correlation with the Industrial Production growth (Figure 3), while the indicator M5 (percentage of negative responses on expected production) exhibits slightly better leading performance (lead 2 and 3, Table 3). However, M15 has the conceptual advantage of encompassing both managers' opinions on past production (which is likely to be more factual) and their expectations.

Figure 3: Indicator M5, M15 and Industrial Production growth – Euro area



M5 and M15 are plotted with inverted sign. The ◆ symbol represents the value of May 2009 IP (Eurostat release of July, 14th 2009). Source: Our calculation on European Commission data

3.1 A comparison with commonly used composite indicators

In this section we compare the selected M15 indicator (in terms of correlation with IP) to the Industrial Confidence Indicator (ICI)[7] and the Business Climate Indicator (BCI)[8], which are monthly published by the European Commission.

In Table 4, we present the results of the test of equality between two (coincident) correlation coefficients (Paul, 1989). The test- statistic is computed as:

$$T_n = \frac{\operatorname{arctanh}(corr_1) - \operatorname{arctanh}(corr_2)}{\sqrt{2/n-3}},$$

where arctanh(*corr*) is obtained through the Fisher's z' transformation:

[7] The ICI is the arithmetic average of the seasonally adjusted balances of the answers to questions Q2, Q4 (with inverted sign) and Q5.

[8] The BCI is obtained as a common factor from all the 5 seasonally adjusted balances of opinion; additional information on how the BCI is constructed can be found at: http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/studies/bci_presentation_paper.pdf

$\operatorname{arctanh}(corr) = \frac{1}{2}\ln\left(\frac{1+corr}{1-corr}\right)$, and n is the sample size (in our case, n=220). For n > 25, T_n converges to a Normal random variable; thus, the null hypothesis H_0: $corr_1 = corr_2$ is rejected when $|T_n| \geq 1.96$ at 5% significance level.

Table 4: Equality of correlation coefficients test

Indicator	Coincident Correlation with IP	T_n	Lead 1	Lead 2	Lead 3
M15	**-0.964**		**-0.922**	**-0.844**	**-0.745**
ICI	0.887	-4.93	0.838	0.758	0.661
BCI	0.879	-5.31	0.819	0.733	0.631

Source: Our calculation on European Commission data

The new indicator M15 clearly outperforms both the ICI and the BCI in term of correlation with the IP, as its correlation coefficient is significantly higher (in absolute value) than those of ICI and BCI.

This finding is confirmed through both an in-sample (§3.2) and an out-of-sample analysis (§3.3) of the performances of M15, ICI and BCI, in terms of explanatory/predictive power with respect to the Industrial Production growth.

3.2 In-sample analysis

In order to assess and to compare the explanatory power of the 3 different indicators, a linear regression model has been specified as follows:

$$IP_t = a_0 + a_1\, IP_{t-1} + a_2\, X_t + a_3\, X_{t-1} + u_t,$$

where the index t denotes the current month, X_t refers to the indicator[9] M15, ICI or BCI respectively, and u_t is assumed to be a Normal distributed white noise random variable.

The main results from the estimation of this model are shown in Table 5 (detailed results are presented in the Appendix). With respect to all the goodness of fit statistics (computed on the period January 1991 to April 2009), the indicator M15 outperforms both the ICI and the BCI.

[9] The M15, ICI and BCI series have preliminary passed the KPSS test of stationarity.

Table 5: In-sample analysis

Indicator	R^2	S.E. of regression	Durbin Watson	*h* modified * Durbin Watson	AIC
M15	0.95	0.93	2.06	-1.05	2.71
ICI	0.93	1.10	2.55	-5.47	3.04
BCI	0.93	1.09	2.63	-6.23	3.04

* The absolute value of *h* modified DW statistic, which is unbiased for models with autoregressive terms, is asymptotically normal distributed.

Source: Our calculation on European Commission data

In particular, the estimated model (Figure 4) with M15 turns out to be (standard errors in the brackets):

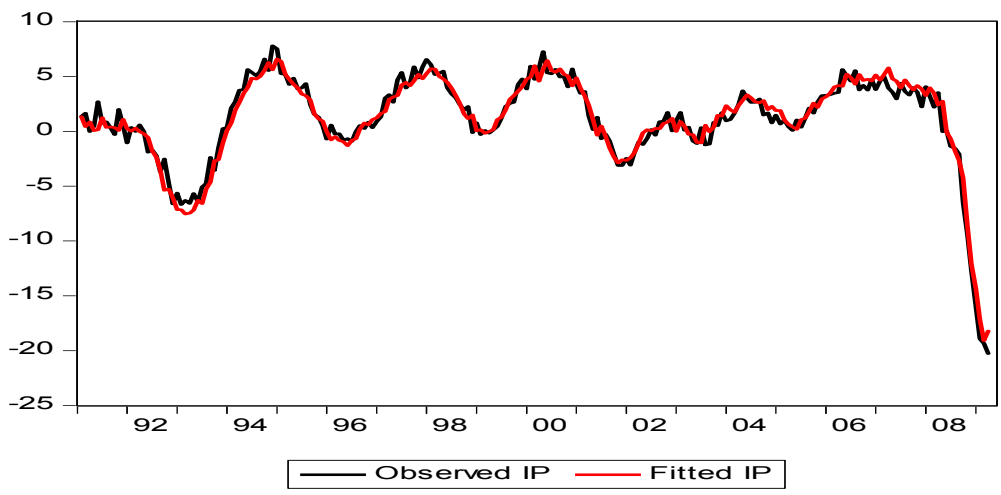
$$E(IP_t) = 0.50 + 0.45\ IP_{t-1} - 2.17\ M15_t - 0.34\ M15_{t-1}.$$

(0.09) (0.06) (0.31) (0.39)

where E() is the expectation operator.

It is worth noticing that this model correctly fitted the upturn for y-o-y IP growth (Figure 4) that has in fact been observed in May 2009.

Figure 4: Observed and fitted Industrial Production growth – Euro area



Source: Our calculation on European Commission data

3.3 Out-of-sample analysis

The results obtained by the in-sample analysis have been confirmed also through an out-of-sample analysis. This allows assessing the forecast ability of the chosen indicator with respect to the benchmark of both ICI and BCI.

For the out-of-sample exercise, the same dynamic forecasting model used for the in-sample analysis has been specified, where each indicator (namely M15, ICI and BCI) enters in turn as explanatory variable.

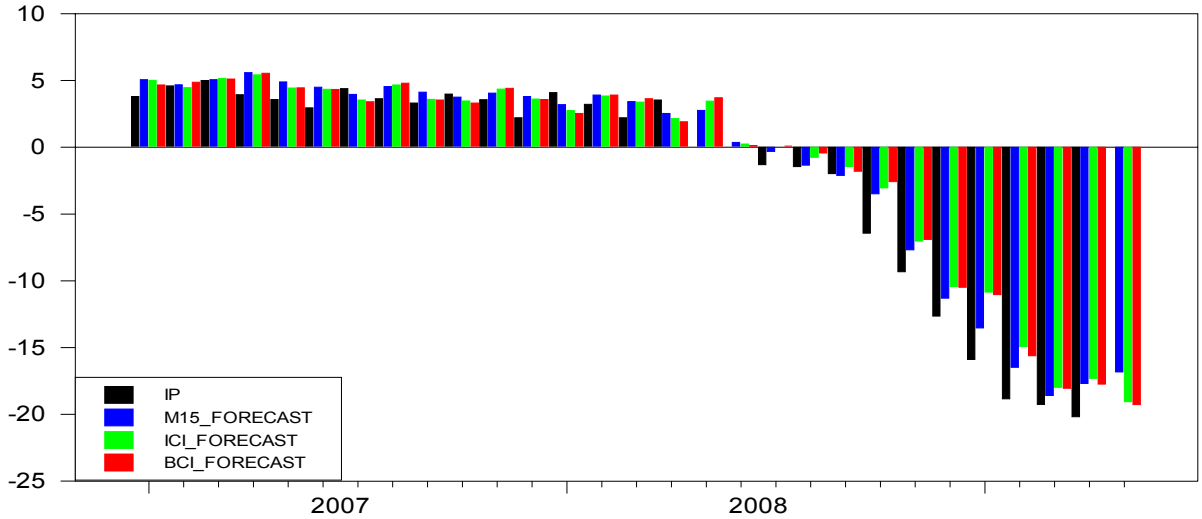
The out-of-sample analysis mimics the real-time forecasting exercise, and the forecast errors are constructed by a recursive forecasting scheme: from the model estimated on the period 1,…, t-1, and using the value of the indicators available up to month t, a forecast value IP^*_t is obtained. This yields a first forecast error: $e_t = IP_t - IP^*_t$. Then, observation IP^*_{t+1} is forecasted using all the observations up to period t+1, and again the forecast and the realized value are compared. This procedure continues until the end of the series, with the estimation sample expanding by one observation at a time.

Finally, the out-of-sample exercise yields three series (one for each explanatory indicator) of real time forecast at one-month horizon. For reasons of robustness, two sub-periods (January 2005 – April 2009; January 2007 – April 2009) have been used in the out-of-sample analysis.

It is worthy to notice (Figure 5) that the forecasts obtained by using the model with the M15 indicator have shown better tracking properties, especially during the collapse observed as from the second semester of 2008. The model built on M15 would also have been the first to signal a negative year-on-year growth of the industrial production in the euro area. Finally, by using the M15 indicator, the model would have correctly predicted an improvement in industrial production growth in May 2009[10].

[10] Eurostat release of July, 14th 2009: http://epp.eurostat.ec.europa.eu/cache/ITY_PUBLIC/4-14072009-AP/EN/4-14072009-AP-EN.PDF

Figure 5: Out-of-sample forecast of Industrial Production growth – (2007m1 – 2009m4)



Source: Our calculation on European Commission data

Indeed, the results from the out-of-sample analysis confirm the superiority of the model involving the new indicator M15 (Table 6a and 6b), both in terms of Mean Absolute Error (MAE) and of Mean Square Error (MSE).

Table 6a: Out-of-sample analysis – 2005m1 – 2009m4 (n=52)

Indicator	MAE	MSE	Harvey *et al* test *
M15	0.89	1.15	
ICI	1.10	1.52	-2.22
BCI	1.40	1.53	-2.58

Table 6b: Out-of-sample analysis – 2007m1 – 2009m4 (n=28)

Indicator	MAE	MSE	Harvey *et al* test *
M15	1.16	1.42	
ICI	1.50	1.93	-2.16
BCI	1.51	1.92	-2.34

* The Harvey *et al.* test is a modified version of the more known Diebold–Mariano test, used to check in small samples the null hypothesis of no difference between the MSEs of two different models. The absolute value of the test statistics is asymptotically distributed as a Student random variable with degree of freedom equal to *n*-1. The critical values, at 5% significance level, are therefore 1.68 (*n*=52) and 1.70 (*n*=28).

Source: Our calculation on European Commission data

The results from the Harvey *et al*. test of equal accuracy in forecast performance are robust over the 2 sub-periods under analysis, showing in both the cases that the model based on M15 has a significantly better forecast ability of the industrial production growth with respect to the ones based on the ICI or the BCI, respectively.

4. Conclusions and further developments

The analysis conducted in this study has highlighted that the negative modality of replies – in the industry survey – have the highest informative content with respect to the reference series of the industrial production growth. This is consistent with previous findings in the literature on the use of survey data for forecasting purposes. Moreover, analyses conducted on a restricted subsample (last observation June 2008, i.e. pre-crisis period) – which have not been shown for sake of shortness – yield the same conclusions.

Among all the questions and their possible combination, the indicator M15 (built as average of the standardised percentages of negative answers to Q1 – past production – and Q5 – expected production –) is the one with the better performance both in terms of explanatory power and as forecast tool for the IP. The M15 indicator, which *per se* can not be considered a global confidence/climate indicator as it disregards all the information not related to production, could therefore usefully complement the ones (ICI and BCI) currently in use.

In order to widen the results of the present study, two research directions have been identified.

Firstly, as the M15 indicator disregards the potential informative content of the questions Q2, Q3 and Q4 with respect to the general industrial cycle, a possible approach could be to build an indicator based on the series of negative answers to all the 5 questions in the industry survey. In this vein, a suitable synthetic indicator can be defined as the common factor over the negative answers to all the questions. This can be achieved by means of a factor analysis.

Secondly, the same kind of analysis/approach described in this study for the Industry sector, could be extended to other fields of the Joint Harmonised BCS (e.g. service, retail trade, building, and consumers) with the more general aim to define a new indicator to track and forecast euro area GDP.

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Appendix

Industry survey – Questionnaire (monthly questions, except Q6 and Q7)

Q1 How has your production developed over the past 3 months? It has...

+ increased
= remained unchanged
− decreased

Q2 Do you consider your current overall order books to be...?

+ more than sufficient (above normal)
= sufficient (normal for the season)
− not sufficient (below normal)

Q3 Do you consider your current export order books to be...?

+ more than sufficient (above normal)
= sufficient (normal for the season)
− not sufficient (below normal)

Q4 Do you consider your current stock of finished products to be...?

+ too large (above normal)
= adequate (normal for the season)
− too small (below normal)

Q5 How do you expect your production to develop over the next 3 months? It will...

+ increase
= remain unchanged
− decrease

Table A1: Q1: Regression model and Wald test

Dependent Variable: IP growth
Method: Least Squares
Sample (adjusted): 1991M01 2009M04
Included observations: 220 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	0.064045	0.033302	1.923159	0.0558
S	0.142470	0.012866	11.07336	0.0000
M	-0.459825	0.014714	-31.25115	0.0000

R-squared	0.915318	Mean dependent var	1.135327
Adjusted R-squared	0.914537	S.D. dependent var	4.186146
S.E. of regression	1.223777	Akaike info criterion	3.255303
Sum squared resid	324.9857	Schwarz criterion	3.301580
Log likelihood	-355.0834	Hannan-Quinn criter.	3.273991
Durbin-Watson stat	1.134495		

Wald Test - Equation: REGQ1

Test Statistic	Value	df	Probability
F-statistic	2.925229	(1, 217)	0.0886
Chi-square	2.925229	1	0.0872

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1) - C(2)	-0.078425	0.045854

Restrictions are linear in coefficients.

Table A2: Q2: Regression model and Wald test

Dependent Variable: IP growth
Method: Least Squares
Sample (adjusted): 1991M01 2009M04
Included observations: 220 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	0.240964	0.065694	3.667982	0.0003
S	0.064980	0.018997	3.420556	0.0007
M	-0.188166	0.016027	-11.74036	0.0000

R-squared	0.681074	Mean dependent var	1.135327
Adjusted R-squared	0.678134	S.D. dependent var	4.186146
S.E. of regression	2.374936	Akaike info criterion	4.581360
Sum squared resid	1223.949	Schwarz criterion	4.627637
Log likelihood	-500.9496	Hannan-Quinn criter.	4.600048
Durbin-Watson stat	0.204260		

Wald Test – Equation: REGQ2			
Test Statistic	Value	df	Probability
F-statistic	4.392789	(1, 217)	0.0373
Chi-square	4.392789	1	0.0361
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(1) - C(2)		0.175984	0.083966
Restrictions are linear in coefficients.			

Table A3: Q3: Regression model and Wald test

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M01 2009M04
Included observations: 220 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	0.376153	0.049874	7.542085	0.0000
S	0.029334	0.014877	1.971718	0.0499
M	-0.161249	0.013804	-11.68165	0.0000

R-squared	0.680215	Mean dependent var	1.135327
Adjusted R-squared	0.677267	S.D. dependent var	4.186146
S.E. of regression	2.378132	Akaike info criterion	4.584050
Sum squared resid	1227.246	Schwarz criterion	4.630327
Log likelihood	-501.2455	Hannan-Quinn criter.	4.602738
Durbin-Watson stat	0.211999		

Wald Test – Equation: REGQ3			
Test Statistic	Value	df	Probability
F-statistic	29.63117	(1, 217)	0.0000
Chi-square	29.63117	1	0.0000
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(1) - C(2)		0.346819	0.063713
Restrictions are linear in coefficients.			

Table A4: Q4: Regression model and Wald test

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M01 2009M04
Included observations: 220 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	-0.701656	0.034291	-20.46158	0.0000
S	0.120438	0.012752	9.444467	0.0000
M	0.532342	0.121515	4.380866	0.0000

R-squared	0.696859	Mean dependent var	1.135327
Adjusted R-squared	0.694065	S.D. dependent var	4.186146
S.E. of regression	2.315415	Akaike info criterion	4.530597
Sum squared resid	1163.368	Schwarz criterion	4.576874
Log likelihood	-495.3657	Hannan-Quinn criter.	4.549285
Durbin-Watson stat	0.307898		

Wald Test – Equation: REGQ4

Test Statistic	Value	df	Probability
F-statistic	9.705981	(1, 217)	0.0021
Chi-square	9.705981	1	0.0018

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(3) (*)	-0.411904	0.132214

Restrictions are linear in coefficients.
(*) For Q4, related to stocks, a negative assessment corresponds to a positive answer.

Table A5: Q5: Regression model and Wald test

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M01 2009M04
Included observations: 220 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
P	0.097463	0.044209	2.204608	0.0285
S	0.114674	0.017215	6.661302	0.0000
M	-0.580632	0.022879	-25.37862	0.0000

R-squared	0.898076	Mean dependent var	1.135327
Adjusted R-squared	0.897136	S.D. dependent var	4.186146
S.E. of regression	1.342597	Akaike info criterion	3.440631
Sum squared resid	391.1571	Schwarz criterion	3.486908
Log likelihood	-375.4695	Hannan-Quinn criter.	3.459319
Durbin-Watson stat	0.882318		

Wald Test – Equation REGQ5			
Test Statistic	Value	df	Probability
F-statistic	0.079130	(1, 217)	0.7787
Chi-square	0.079130	1	0.7785
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C(1) - C(2)		-0.017211	0.061184
Restrictions are linear in coefficients.			

IN-Sample results

Table A6: Regression model with M15

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M02 2009M04
Included observations: 219 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.499784	0.089164	5.605224	0.0000
IP(-1)	0.449329	0.059383	7.566627	0.0000
M15	-2.172281	0.311922	-6.964172	0.0000
M15(-1)	-0.342708	0.389772	-0.879255	0.3802

R-squared	0.951390	Mean dependent var	1.124878
Adjusted R-squared	0.950711	S.D. dependent var	4.192860
S.E. of regression	0.930858	Akaike info criterion	2.712676
Sum squared resid	186.2968	Schwarz criterion	2.774577
Log likelihood	-293.0380	Hannan-Quinn criter.	2.737676
F-statistic	1402.644	Durbin-Watson stat	2.067796
Prob(F-statistic)	0.000000		

Table A7: Regression model with ICI

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M02 2009M04
Included observations: 219 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.293702	0.205105	1.431957	0.1536
IP(-1)	0.922959	0.044727	20.63558	0.0000
ICI	0.292109	0.047091	6.203108	0.0000
ICI(-1)	-0.256515	0.044609	-5.750281	0.0000

R-squared	0.932573	Mean dependent var	1.124878
Adjusted R-squared	0.931632	S.D. dependent var	4.192860
S.E. of regression	1.096317	Akaike info criterion	3.039885
Sum squared resid	258.4107	Schwarz criterion	3.101786
Log likelihood	-328.8674	Hannan-Quinn criter.	3.064885
F-statistic	991.2127	Durbin-Watson stat	2.554536
Prob(F-statistic)	0.000000		

Table A8: Regression model with BCI

Dependent Variable: IP
Method: Least Squares
Sample (adjusted): 1991M02 2009M04
Included observations: 219 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.047932	0.102092	0.469497	0.6392
IP(-1)	0.925629	0.044448	20.82489	0.0000
BCI	2.791623	0.449288	6.213438	0.0000
BCI(-1)	-2.503544	0.412939	-6.062747	0.0000

R-squared	0.932777	Mean dependent var	1.124878
Adjusted R-squared	0.931839	S.D. dependent var	4.192860
S.E. of regression	1.094658	Akaike info criterion	3.036858
Sum squared resid	257.6296	Schwarz criterion	3.098759
Log likelihood	-328.5359	Hannan-Quinn criter.	3.061858
F-statistic	994.4355	Durbin-Watson stat	2.634458
Prob(F-statistic)	0.000000		