Estimating potential output using business survey data in a SVAR framework

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Abstract

Potential output and the related concept of output gap play a central role in the macroeconomic policy interventions and evaluations. In particular, the output gap, defined as the difference between actual and potential output, conveys useful information on the cyclical position of a given economy. The aim of this paper is to propose estimates of the Italian potential GDP based on structural VAR models. With respect to other techniques, like the univariate filters (i.e. the Hodrick-Prescott filter), the estimates obtained through the SVAR methodology are free from end-of-sample problems, thus resulting particularly useful for short-term analysis.

In order to provide information on the economic fluctuations, data coming from business surveys are considered in the model. This kind of data, given their cyclical profile, are particularly useful for detrending purposes, as they allow to include information concerning the business cycle activity.

To assess the estimate reliability, an end-of-sample revision evaluation is performed. The ability of the cyclical GDP component to detect business cycle turning points is then performed by comparing the estimated output gaps, extracted with different detrending methods, over the expansion and recession phases of the Italian business cycle chronology.

Key Words: potential output, business survey data, structural VAR models, end-of-sample revisions.

JEL Classification: C32, E32

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1 Introduction

Potential output and output gap are considered important indicators of the economic activity evolution. More in detail, the output gap, i.e. the difference between the actual output level and its potential, provides information concerning the cyclical position of the economy. In this sense it represents a benchmark to achieve non inflationary growth since if the output gap is positive (negative) the inflationary pressures raise (fall) and the policy makers are expected to tighten (ease) monetary policies. This indicator it is also used by central banks to fix interest rates according to the so-called Taylor rules (Taylor, 1993).

However, in spite of the attention received, the estimates of those aggregates are still surrounded by a huge amount of uncertainty (cfr. Orphanides and van Norden, 1999 and 2001). This is mainly due to the fact that the output decomposition into its trend and cyclical components are not unique depending on the method used.

In the literature different methods have been used to estimate potential GDP. The most known univariate statistical techniques are based on the use of univariate filters (i.e. Hodrick and Prescott, 1997 and Baxter and King, 1995). Other univariate approaches include unobserved components models (see for details, Harvey, 1985 and Clark, 1987) and the Beveridge and Nelson (1981) decomposition. In addition, multivariate decompositions based on those techniques (i.e. multivariate filters or multivariate unobserved components models) have also been developed. Recently, considerable attention has been focused on the use of VAR models. To this end St-Amant and van Norden (1997) use a VAR model with long run restrictions including output, inflation, unemployment and real interest rate to estimate the Canadian output gap. Similarly Claus (2003) employs a SVAR model with long run restrictions to estimate New Zealand output gap for the period 1970-99.

The aim of this paper is to estimate Italian potential output using a multivariate decomposition based on the use of structural VAR models. Compared to other standard techniques, this kind of models show several advantages. Firstly, the estimates are free from end-of-sample problems, thus proving particularly useful for short-term analysis. In fact, compared to other methods using both past and future information to estimate the current data (i.e. moving averages), the end-of-sample VAR estimates are obtained by using only backward information. Secondly, the use of a multivariate decomposition model allows to include information coming from more then one variable. In this sense, if compared to univariate decomposition methods, which only incorporate information coming from the decomposed variable, the multivariate method takes into account the external dynamics coming from other data. Moreover, as against other decomposition methods based on univariate filtering, the detrended series obtained with the SVAR methodology satisfies the Cogley and Nason (1995) critique, inasmuch the decomposition introduces no spurious cyclicality in the data.

Thirdly, compared to other multivariate techniques (i.e. multivariate filters) the framework allows for an economic interpretation of each variable's shocks. Fourthly, given its ability to act as a prediction model, the SVAR can be applied for forecast purposes.

Furthermore, to incorporate information on the economic fluctuations, data coming from business tendency surveys are considered in the model. Such data, given their cyclical behaviours are particularly useful for detrending purposes, since allow to incorporate information on the cyclical economic activity. To assess the estimate reliability, an end-of-sample revision evaluation is performed. The results show that, compared with others standard methods, the output gap estimates obtained through the SVAR model seems to have a negligible impact on the end-of-sample data revisions. This result makes this methodology particularly suitable for short-term analysis.

Finally, the ability of the output gap indicators (obtained through different methods) to detect the business cycle turning points is performed by comparing their peaks and troughs over expansion and recession periods of the Italian business cycle chronology.

The paper is organized as follows. Section 2 introduces the SVAR model and the identifying restrictions. Section 3 reports the empirical output gap estimates for Italy. Section 4 contains an evaluation of the impact of data revisions on SVAR estimates and a comparison with other univariate detrending methods. Section 5 includes an assessment of the ability of the estimated GDP cyclical components to detect turning points of the Italian official chronology. Section 6 concludes the work.

2 The model

To provide output gap estimates for Italy, we apply a SVAR model based on Blanchard and Quah (1989) identifying restrictions. The MA representation of the bivariate structural VAR model is given by:

$$
\begin{bmatrix} \Delta y_t \\ bs_t \end{bmatrix} = \begin{bmatrix} K_1 \\ K_2 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} v_{st} \\ v_{dt} \end{bmatrix}
\tag{1}
$$

where Δy_t is the growth rate of output, bs_t is a cyclical stationary variable coming from business tendency surveys, v_{st} and v_{dt} represent structural incorrelated supply and demand shocks and $A(L)$ is a 2x2 dimension polinomial matrix in the lag operator L. Alternatively, the model can be written in a compact form:

$$
x_t = k + A(L)v_t
\tag{2}
$$

where $x_t = \begin{bmatrix} \Delta y_t & bs_t \end{bmatrix}$ represents the vector of endogenous variables and $v_t = \begin{bmatrix} v_{st} & v_{dt} \end{bmatrix}$ is the vector of aggregate shocks. Moreover, the shocks are normalized in order to have unit variance ($E(v_t v'_t) = I$).

The identifying restrictions are provided by assuming that demand-side shocks (i.e.to the cyclical indicator) only have a short-run impact on output, whereas supply-side shocks (i.e. productivity shocks) can produce long-run effects on output. More in detail, the identification is ruled out, imposing long-run restrictions on the coefficients of the MA representation of the structural VAR model.

Since the structural shocks are not observed, to evaluate the effects on the economy we need to derive them from the estimated residuals of the reduced-form model. The standard matrix representation of the bivariate reduced VAR form is given by:

$$
\begin{bmatrix} \Delta y_t \\ bs_t \end{bmatrix} = \begin{bmatrix} \Phi_{10} \\ \Phi_{20} \end{bmatrix} + \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ bs_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{dt} \end{bmatrix}
\tag{3}
$$

or in a more compact formula:

$$
x_t = \Phi_0 + \Phi_1(L)x_{t-1} + \varepsilon_t
\tag{4}
$$

where $\varepsilon_t = \begin{bmatrix} \varepsilon_{st}, \varepsilon_{dt} \end{bmatrix}$ indicates the residual vector of the estimated model and $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon'_t)$ indicates the variance and covariance residual matrix, which generally are not diagonal. If the process is invertible (the polinomial matrix $\Phi(L)$ has unit root out of the unit circle), its moving average representation is given by:

$$
x_t = K + C(L)\varepsilon_t
\tag{5}
$$

3

where $K = (I - \Phi_1)^{-1}\Phi_0$ e $C(L) = (I - \Phi_1(L)L)^{-1}$

Under the hypothesis that innovations are a linear combination of structural shocks, by equating (2) and (5) we obtain:

$$K + A(L)v_t = K + C(L)\varepsilon_t \qquad (6)$$

For $L=0$, since $C(0) = I$ we have:

$$A(0)v_t = \varepsilon_t \qquad (7)$$

where $E(\varepsilon_t \varepsilon_t{}') = A(0)E(v_t v_t{}')A(0)' = \Sigma_\varepsilon$

The sigma matrix is given by:

$$\Sigma_\varepsilon = \begin{bmatrix} A_{11}(0)^2 + A_{12}(0)^2 & A_{11}(0)A_{21}(0) + A_{12}(0)A_{22}(0) \\ A_{11}(0)A_{21}(0) + A_{12}(0)A_{22}(0) & A_{21}(0)^2 + A_{22}(0)^2 \end{bmatrix} \qquad (8)$$

Structural shocks v_t are determined from equation (7):

$$v_t = A(0)^{-1}\varepsilon_t \qquad (9)$$

or in a matrix form:

$$\begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix} = \begin{bmatrix} A_{11}(0) & A_{12}(0) \\ A_{21}(0) & A_{22}(0) \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{gt} \end{bmatrix} \qquad (10)$$

To recover the structural form shocks, it is necessary to know the coefficients of the $A(0)$ matrix. This latter expresses the contemporary effects of structural shock*s* on the variables considered. To identify the four coefficients of matrix *A(0)*, the following restrictions are applied:

$$Var(\varepsilon_{yt}) = A_{11}(0)^2 + A_{12}(0)^2 \qquad (11)$$

$$Var(\varepsilon_{gt}) = A_{21}(0)^2 + A_{22}(0)^2 \qquad (12)$$

$$Cov(\varepsilon_{yt}\varepsilon_{gt}) = A_{11}(0)A_{21}(0) + A_{12}(0)A_{22}(0) \qquad (13)$$

$$C_{11}(L)A_{12}(0) + C_{12}(L)A_{22}(0) = 0 \qquad (14)$$

The first three restrictions stem from (8), the last restriction is obtained by assuming that cumulated demand shocks have no permanent effects on output.

For the GDP to be decomposed into cycle/trend components, the output gap Δy_t^{gap} is obtained by cumulating the demand shocks to output. Similarly, the potential output component Δy_t^p is determined by cumulating supply-side shocks. Starting from (2) and given that $C(L)A(0) = A(L)$, we have:

$$x_t = K + A(L)v_t = K + C(L)A(0)v_t = K + \sum_{i=0}^{\infty} \Phi_1^i L^i A(0)v_t = K + \sum_{i=0}^{\infty} \Phi_1^i A(0)v_{t-i} \qquad (15)$$

Considering only the first variable, we obtain:

$$\Delta y_t = K_1 + A_{11}(L)v_{st} + A_{12}(L)v_{dt}$$
$$= K_1 + A_{11}(0)v_{st} + A_{12}(0)v_{dt} + A_{11}(1)v_{st} + A_{12}(1)v_{dt} + A_{11}(2)v_{st} + A_{12}(2)v_{dt} + A_{11}(3)v_{st} + A_{12}(3)v_{dt} + \ldots\ldots$$

4

The potential GDP growth rate is given by:

$$\Delta y_t^{pot} = K_1 + A_{11}(L)v_{st} = K_1 + A_{11}(0)v_{st} + A_{11}(1)v_{st} + A_{11}(2)v_{st} + A_{11}(3)v_{st} + ...$$
$$= K_1 + \sum_{i=0}^{\infty} \Phi^i_{11} L^i A_{11}(0)v_{st} = K_1 + A_{11}(0)\sum_{i=0}^{\infty} \Phi^i_{11} v_{st-i}$$

(16)

the output gap is given by:

$$\Delta y_t^{gap} = A_{12}(L)v_{dt} = A_{12}(0)v_{dt} + A_{12}(1)v_{dt} + A_{12}(2)v_{dt} + A_{12}(3)v_{dt} + ...$$
$$= \sum_{i=0}^{\infty} \Phi^i_{12} L^i A_{12}(0)v_{dt} = A_{12}(0)\sum_{i=0}^{\infty} \Phi^i_{12} v_{dt-i}$$

(17)

By using this kind of decomposition is thus possible to obtain an estimate of potential growth and cyclical output component based on economic hypothesis of the structural shocks effects.

3 Empirical results

In this Section, the results of the SVAR model specification are showed. As a preliminary analysis, we estimated different bivariate models by using output and various survey data indicators. Output is defined as the Italian Gross Domestic Product (expressed in euros at constant 1995 prices, seasonally adjusted source ISTAT). The business survey data come from Italian Manufacturing Business Surveys carried out by ISAE. In particular we used data on the degree of plant utilization, on inventories, on the production level and on the confidence climate index[1] etc. These data,(except the degree of plant utilization) are qualitative data and are quantified through the balances[2]. The selection of business survey data to be included in the model was based on their degree of contemporary correlation with the GDP cyclical component obtained with an Hodrick-Prescott filter and on the basis of their stationarity in the sample.
Although we tried different specifications in what follows we show the results of the bivariate model including the degree of plant utilization. This variable is able capture the whole economy cyclical dynamics[3] with great precision and to match business cycle evolution without introducing phase shifts.
The structural model specification, called SVAR, thus includes GDP in log differences and the degree of plant utilization. The lag structure of the reduced form was selected by using the Schwartz and Akaike criteria. The results of the Portmanteau test for the residual autocorrelation do not allow to reject the null hypothesis of autocorrelation absence. The usual heteroscedasticity test indicates omoscedastic residuals.
Figure 1 shows the estimated cyclical and trend components alongside with the actual GDP series. The output gap determined through the SVAR specification is positive from the second half of the Eighties till the Nineties and from 1994 to 1996.
The end-of-sample cycle becomes more erratic. These findings reflect the stagnation experienced by the Italian manufacturing sector in the past five years.

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[1] The confidence climate index is obtained combing data on orders level, inventories and production expectations.
[2] Balances are built as the difference between positive and negative answers provided by firms.
[3] Although the survey data refer to the manufacturing sector, they are able to thoroughly capture the whole economy dynamics (on this point see Hearn and Woitek, 2001 and Cesaroni, 2007).

Figure 1 Trend/Cycle decomposition SVAR Model
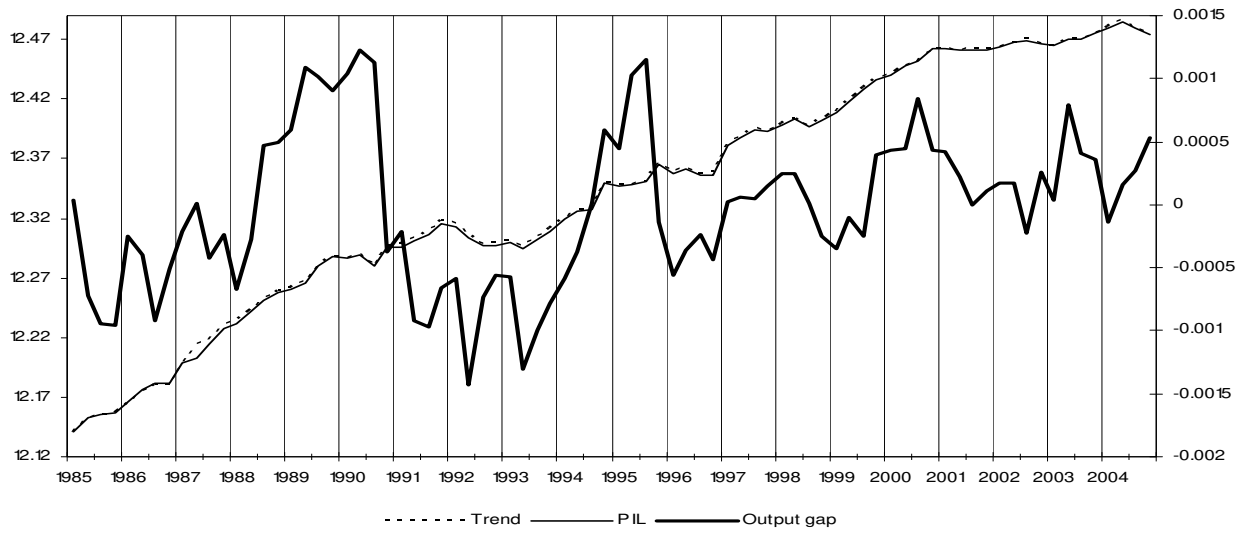
4 Data revisions impact

A major aspect in the evaluation of a decomposition method performance is the data revision impact on the reliability of the end-of-sample estimates of the trend/cycle components.

Indeed, the end-of-sample estimates are subject to revision when new data become available. This updating process generates uncertainty on the real-time estimates that are of the utmost importance for policy-makers' decisions (van Norden, 1995). To this end in what follows we assess, the stability of the output gap estimates with respect to data revisions.

In our analysis, only the revisions due to new data availability are taken into account, while the impact on official data of the uncertainty estimates due to *ex post* revisions is not considered. This allows to evaluate the effect of the end-of-sample revisions due to new data availability. However, on the basis of the evidence provided by Orphanides and van Norden (1999), the effect of National Accounts revisions on the output gap estimates should not be significant.

The reliability of real-time estimates is evaluated by quantifying the impact of 9-step-ahead data revisions on the output gap estimates referred to 2002 Q4. The revisions are computed with respect to 9 quarters starting from 2003:1 to 2005:1 using the following formula:

$$(|y_{t/t+T} - y_{t/t+i}| \cdot 100) \tag{18}$$

where $y_{t/t+T}$ indicates the estimates at time t, including only the information available at time $t+T$ and $y_{t/t+i}$ indicates the estimates in t, obtained through the information available at $t+i$ with $i < T$.

In our case, the 1-step-ahead revisions $(t+1)$, as against to the estimates of 2002 Q3, are obtained as the difference between the estimates referring to 2002 Q4, made using all the information available at 2005 Q1 ($y_{2002q4/2005q1}$), and the estimates of 2002 Q4, based on the information available at 2003 Q1 ($y_{2002q4/2003q1}$).

Table 1 provides the data revisions of the output gap indicators obtained using linear and quadratic trend, the Hodrick-Prescott (1997) filter and the SVAR model. The impact evaluation of data revisions on the output gap real-time estimates shows that the estimates based on Linear trend and on the Hodrick-Prescott filter experienced the highest revisions. The revision amplitude at the end of period for those methods is equal to +1.035 and 0.84 respectively. Quite the reverse, the SVAR model revisions indicate a marginal impact on the estimates. Indeed, the amplitude of the highest revision equals 0.015.

Table 1 Data Revisions referring to 2002 Q4 estimates (% variations as against 2002 Q4)

t=2002:4	Pt/t+9-Pt/t+1	Pt/t+9-Pt/t+2	Pt/t+9-Pt/t+3	Pt/t+9-Pt/t+4	Pt/t+9-Pt/t+5	Pt/t+9-Pt/t+6	Pt/t+9-Pt/t+7	Pt/t+9-Pt/t+8	Pt/t+9-Pt/t+9
Sample	**1980:1 2003:1**	**1980:1 2003:2**	**1980:1 2003:3**	**1980:1 2003:4**	**1980:1 2004:1**	**1980:1 2004:2**	**1980:1 2004:3**	**1980:1 2004:4**	**1980:1 2005:1**
Linear trend	1.035	0.895	0.776	0.646	0.520	0.401	0.296	0.163	0.000
Quadratic trend	0.542	0.446	0.384	0.296	0.245	0.210	0.186	0.108	0.000
H-P filter	0.840	0.552	0.390	0.230	0.155	0.116	0.108	0.061	0.000
SVAR	0.015	0.016	0.010	0.008	0.008	0.010	0.008	0.007	0.000

These results corroborate the view whereby the output gap estimates obtained using VAR models are more reliable at the end of sample. The accurateness and reliability of SVAR estimates compared to univariate detrending methods makes these models particularly suitable for short-term analysis purposes.

5 *Business cycle chronology*

To evaluate whether the estimated GDP cyclical components accurately indicate business cycle turning points, we make a comparison between the peaks and troughs identified through different output gap estimates and the turning points obtained through official cyclical Italian chronology. In particular, the output gap estimates obtained using a quadratic trend, the Hodrick-Prescott (1997) filter with a lambda parameter set to 1600, and the SVAR specification are compared. The sample period is 1985-05.

The Italian cyclical chronology used here comes from Altissimo, Marchetti and Oneto (1999). This methodology detects turning points and cyclical phases on the basis of the coincident indicator absolute variation level[4] and it is based on the classical cycle definition by Burns and Mitchell (1946).

**Table 2 Maximum and minimum turning points. Italian cyclical chronology**

	Initial Minimum	Maximum	Final Minimum	PHASES (in months) Expansion	Recession	Total Cycle
VIII	dic-77	mar-80	mar-83	27	36	63
IX	mar-83	mar-92	july-93	108	16	124
X	july-93	nov-95	nov-96	28	12	40
XI	nov-96	gen-01		49		

Source: ISAE

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[4] Variables included in the coincident indicator are GDP, the industrial production index, imports of investment goods, the share of overtime hours, railway transport, machinery and equipment investments and the market services' value added.

Table 2 reports maximum and minimum turning points of the official Italian cyclical chronology, together with the length (in months) of the expansion and recession periods. The output gaps obtained with different detrending methods are evaluated so as to compare the different cyclical GDP components and turning points.

Figure 3 Cyclical chronology (recession periods: grey area/expansion periods: white area).
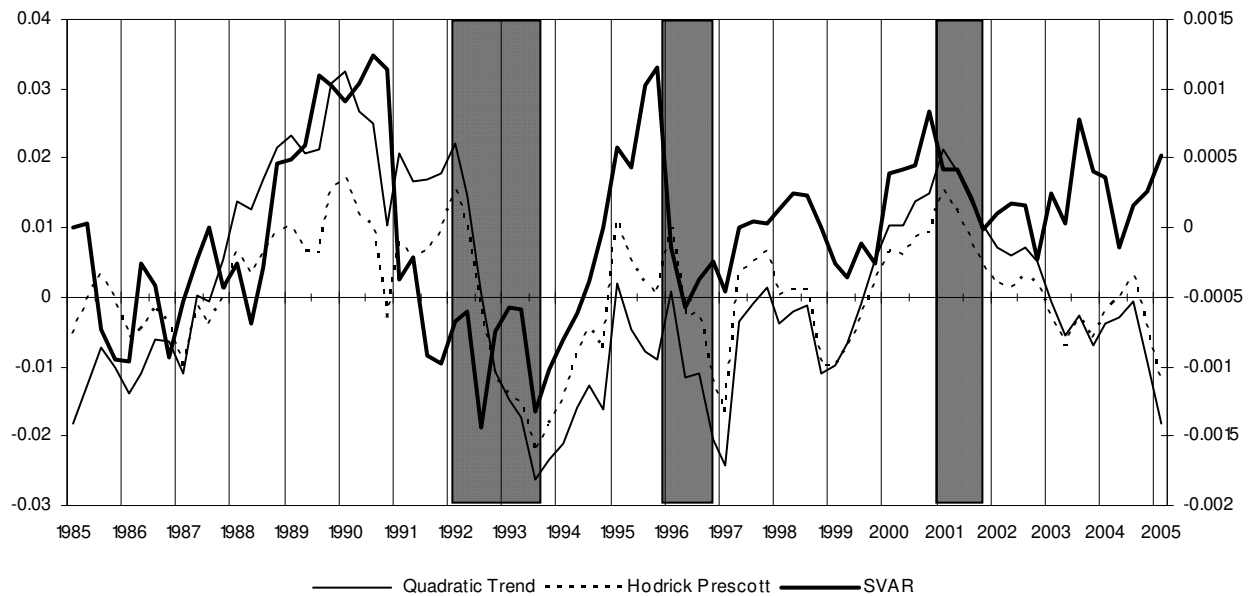
Looking at the graph (Fig. 3), we notice that all the output gap estimates are able to indicate quite precisely the business cycle turning points, even though each estimate differs from the other in the dynamics displayed into the expansion and recessions zones. Moreover, the results show that, although the quadratic trend and the Hodrick-Prescott evolutions are relatively similar, the SVAR model estimates differ from those methods, particularly starting from 2001. The output gap, which is negative from 2001 to 2005 when using univariate estimates, seems positive in the same period when adopting the VAR model estimates. The difference in the two output gap indicator dynamics of SVAR as against the univariate methods stems from the use of an external signal (i.e. coming from business survey data).

6 Conclusions

This paper investigates the effects of a decomposition of real GDP into its trend and cyclical components by using a multivariate decomposition. In particular, we focused on the possibility to obtain reliable estimates of potential output and output gap using structural VAR models including data from business surveys.

From an economic point of view those models provide an economic interpretation to the structural shocks. Furthermore, given that restrictions to shape the structure of each component are not required, the methodology does not impose an *a priori* limitation to modelling trend and cycle dynamics in the data. In this sense, while most detrending methods assume a random walk process for the trend component, the VAR decomposition does not involve a similar assumption. Since the cyclical position can be identified more precisely when new data are available, an sensitiveness evaluation of the different output gap estimates with respect to data revisions is performed.

In our findings, the estimated output gap indicator is able to indicate quite precisely the turning points over the expansions and recessions periods of the Italian official chronology. The results show that, compared to other standard detrending methods, the output gap estimates based on SVAR model seems to have a negligible impact on data revisions at the end of sample. The results confirm the strength of this decomposition technique used in short-term analysis.

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Appendix

Table 3 Portmanteau Test VAR model

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.950138	NA*	1.974824	NA*	NA*
2	2.486994	0.6470	2.525445	0.6401	4
3	12.95609	0.1134	13.40243	0.0987	8
4	15.75192	0.2029	16.34541	0.1759	12
5	20.81236	0.1858	21.74321	0.1517	16
6	22.26165	0.3265	23.31001	0.2738	20
7	22.55443	0.5462	23.63086	0.4829	24
8	27.61519	0.4850	29.25393	0.3997	28
9	30.22760	0.5564	32.19749	0.4570	32
10	32.21071	0.6495	34.46391	0.5417	36
11	33.46755	0.7576	35.92111	0.6544	40
12	37.12075	0.7591	40.21899	0.6344	44
13	40.26798	0.7784	43.97687	0.6384	48
14	44.28770	0.7676	48.84927	0.5986	52
15	50.78118	0.6721	56.84124	0.4435	56
16	60.08622	0.4726	68.47254	0.2119	60
17	63.52040	0.4934	72.83340	0.2102	64
18	65.47009	0.5645	75.34913	0.2529	68

H0: no residual autocorrelations up to lag h
Sample: 1985q1 2005q1
Included observations: 80
*The test is valid only for lags larger than the VAR lag order.
df is degrees of freedom for (approximate) chi-square distribution

Table 4 Lag selection criteria-VAR model

Endogenous variables: delta y and degree of plants utilization
Exogenous variables: C
Sample: 1985q1 2005q1
Number of observations included:74

Lag	LogL	LR	FPE	AIC	SC	HQ
0	110.6097	NA	0.000182	-2.935397	-2.873125	-2.910556
1	162.0656	98.73970	5.05e-05*	-4.217989*	-4.031173*	4.143465*
2	163.2966	2.295634	5.44e-05	-4.143151	-3.831790	-4.018945
3	169.6471	11.49955*	5.11e-05	-4.206678	-3.770773	-4.032790
4	170.3205	1.182988	5.60e-05	-4.116769	-3.556321	-3.893200
5	172.9084	4.406566	5.83e-05	-4.078607	-3.393614	-3.805355
6	174.2266	2.173153	6.29e-05	-4.006124	-3.196588	-3.683190
7	174.6483	0.672520	6.95e-05	-3.909414	-2.975334	-3.536798

* lag order selection criterion
LR: sequential modified LR test statistic (each test at 5% level)
 FPE: Final prediction error
AIC: Criterio di informazione di Akaike
SC: Criterio di informazione di Schwartz
HQ: Criterio di informazione di Hannan-Quinn