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Measuring capacity utilization in the Italian manufacturing sector: a comparison between time series and survey models in light of the actual economic crisis

by

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ABSTRACT

The aim of this paper is to make a comparison between survey and time series-based estimates of capacity utilization for the Italian manufacturing sector. The comparison is focused on the actual economic crisis. Two kinds of empirical evaluation are implemented: the ability of the series to correctly track cyclical turning points and their contribution in explaining CPI inflation. The ISAE survey measures results to be lagging, especially at troughs, and moreover time series-based measures generally outperform the survey in explaining inflation.

Keywords: Capacity utilization, cointegration, unobserved component models, VAR.

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CONTENTS

1. Introduction[1]

Capacity utilization plays an important role in the evaluation of economic activity, contributing to explain the behaviour of investment, inflation, productivity, profits and output (see for example Abel (1981), Greenwood et al. (1988), Corrado and Mattey (1997), Jorgensen et al. (2009)). However, an official statistical measure of capacity utilization does not exist: for the manufacturing sector, it is normally obtained from firm-level surveys, where firms are asked to indicate their current operating rate. Alternatively, measures of capacity utilization may be derived using time series methods, the latter option having the advantages of being free to generate, easily reproducible, and consistently measured over time.
The aim of this paper is to discuss the empirical properties of the survey measure of capacity utilization realized for Italy by ISAE, and to compare them with those obtainable from time series estimates. Various methods to estimate capacity are discussed in section 2, while section 3.1 checks for the ability of the various measures to correctly gauge cyclical turning points and their explicative power with respect to consumers' inflation[2]. Indeed, the most used method to evaluate the explicative power of capacity consists of estimating a single equation in which capital utilization is considered as exogenous (see for example McElhattan (1985) and Garner (1994)). Treating capacity as exogenous may, however, be incorrect: in fact, a change in price inflation is also likely to affect capacity utilization, especially in the case of supply shocks. Therefore, a single equation does not provide an adequate framework for analyzing how changes in capital utilization affect price inflation and a vector autoregression (VAR) approach appears more appropriate. The VAR approach is implemented in section 3.2, where different VARs are estimated up to the fourth quarter of 2007 and inflation forecasts are produced for the eight quarters ahead. Results show that the ISAE survey-based measure of capacity utilization is lagging at turning points and that time series measures generally outperform the survey measure in explaining inflation during the actual recession.

2. Methods for estimating capacity utilization

Capacity utilization measures how close the manufacturing sector is to full capacity: more formally, it is equal to the ratio among actual and potential output:

$$cu = \frac{IP}{cap} \cdot 100 \qquad (1)$$

where cu = capacity utilization; IP = industrial production index; cap = capacity index, or potential output. In (1), the numerator is easily observable, while potential output may be estimated on the basis of some hypothesis on the technology in use, or more generally making use of time series methods: hence, estimates on cu depend upon the assumptions made about the denominator in (1). Indeed, potential output is a vague, hard-to-measure concept which varies over time and according to general economic conditions. In a strict sense, the term refers to the sustainable maximum output that could be produced by an existing (installed) manufacturing plant and machinery; however, sometimes other factors such as labour are taken into account (Johansen (1968)).
Given the difficulties in estimating potential output, a measure of capacity utilization may be alternatively obtained using survey methods, according to which a direct question on the level of capacity utilization is asked to a representative sample of manufacturing firms. In Europe, such a question is administered on a quarterly basis in the framework of the harmonized business survey project of the European Commission;

[1] The authors would like to thank Stefano Costa for his helpful comments.

[2] One of the basic propositions in macroeconomics is that inflation accelerates as capacity utilization moves higher. For empirical studies which examine this evidence see McElhattan (1985), Garner (1994), and Emery and Chih-Ping Chang (1997).

in Italy, the survey is performed by ISAE. In the current version of the questionnaire[3] the exact wording of the question is as follows:

"What is your current rate of capacity utilization (in % of full capacity)?"

Individual answers are given as a percentage of full capacity; data is progressively aggregated to obtain sample averages using information on firm dimension and the relative economic importance of each industry branch as weights.
In the rest of this section, we will derive alternative measures of capacity utilization using time series methods based on the unobserved component model and the cointegration method.

2.1 Unobserved component method

Time series methods may be used to estimate potential output and then derive a measure of capacity utilization on the basis of equation (1). In fact, industrial production, as any other observable time series, can be decomposed in two or more components that are not directly observable, such as the trend, the seasonal component and the cycle. The basic idea is that the unobservable components can be identified by assuming that they affect the variable that can be observed; in addition, the underlying processes behind the unobservable variables have to be specified. After the model has been specified, both the unobservable and the observable variables may be estimated with maximum likelihood methods using the Kalman filter. In the following, we will estimate two different classes of unobserved component models for the industrial production index, alternatively assuming that the unobserved components are autonomously identified (univariate model) or that there exist other variables that are potentially correlated with industrial production (bivariate and trivariate models).

Univariate unobserved component method

The univariate model is based on a simple trend-cycle decomposition of industrial production index:

$$IP_t = T_t + C_t + \varepsilon_t, \varepsilon_t \sim NID\left(0, \sigma_t^2\right) \tag{2}$$

where T_t represents the trend, C_t the cycle, and ε_t the irregular component. The stochastic trend component is specified as:

$$\begin{aligned} T_t &= T_{t-1} + \beta_{t-1} + \eta_t, \eta_t \sim NID\left(0, \sigma_t^2\right) \\ \beta_t &= \beta_{t-1} + \zeta_t, \zeta_t \sim NID\left(0, \sigma_t^2\right) \end{aligned} \tag{3}$$

where β_t is the slope of the trend T_t. The irregular ε_t, the level disturbance η_t and the slope disturbance ζ_t are mutually uncorrelated.
The cycle C_t has the following specification:

$$\begin{bmatrix} C_t \\ C_t^* \end{bmatrix} = \rho_C \begin{bmatrix} \cos\lambda_J & \sin\lambda_J \\ -\sin\lambda_J & \cos\lambda_J \end{bmatrix} \begin{bmatrix} C_{t-1} \\ C_{t-1}^* \end{bmatrix} + \begin{bmatrix} k_t \\ k_t^* \end{bmatrix} \tag{4}$$

where ρ_C is a damping factor; $0 < \lambda_j \leq \pi$ is the frequency of the cycle in radiants; k_t and k_t^* are two mutually uncorrelated NID disturbances with zero mean and common variance σ_k^2. The period of cycle is equal to $2\pi/\lambda_j$[4].

[3] More information on the harmonized project may be found here:
http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm

[4] The decomposition presented above (local linear trend, stationary trigonometric cycle, and an irregular component) is the same applied by Harvey (1989) to the GDP analysis.

Details on estimated output are reported in Table 1. The diagnostic checking rejects the presence of serial correlation, heteroskedasticity and non-normality.

Table 1. Univariate model for log IP (industrial production): main results

	IP
Level	4.48 (0.00)
Slope	-0.01 (0.03)
Cycle component	0.076
Residual tests	
Normality	4.49
DW	1.96
H(64)	0.82
Q(17,12)	12.37
R^2	0.49

Outliers relative to 1969q4, 1972q4, 1973q3, 1974q4, 2009q1 were added in the estimation. The P-values are in parenthesis. The normality test statistic is the Bowman-Shenton statistic having a Chi-square distribution with two degrees of freedom under the null hypothesis of normally distributed errors. We reject the null if the calculated probability exceeds the tabulated ones equal to 5.99 at 5% significance level and 9.21% at 1% significance level. H(h) is the heteroskedasticity test statistics distributed as a F(h,h) with (h,h) degrees of freedom. Under the null of no heteroskedasticity and for h=64, the 5% critical value is 1.51. DW is the classical Durbin-Watson test. Q(P,d) is the Ljung Box statistics based on the sum of the first P autocorrelations and it is tested against a Chi-Square distribution with d degrees of freedom. The null hypothesis of no autocorrelation is tested against the alternative of autocorrelation. The critical value for 12 degrees of freedom is 21.03 at 5% significance level.

Multivariate unobserved component methods

The univariate model can be extended to include other variables that are assumed to contain information about the potential industrial production; in the following, information about unemployment, gross domestic product (GDP) and CPI inflation is included in addition to industrial production (IP) resulting in four different models:

1) a bivariate model considering the relationship between IP and inflation;

2) a bivariate model considering the relationship between IP and the unemployment rate;

3) a bivariate model considering the relationship between IP and GDP; and

4) a trivariate model considering the relationship among IP, GDP, and unemployment rate.

The estimation results are reported in Table 2. In Model 1, inflation is modelled as a local level model as suggested by Cogley et al. (2010); inflation is seasonally unadjusted and, for this reason, a seasonal component is included in the estimates. In models 2 and 4, the unemployment rate is expressed in log as suggested by Chen and Mills (2009); five dummies, all concentrated in the 1960s, are also added to the unemployment equation due to important changes which occurred in the Italian labour market (Modigliani et al., 1986); however, starting the estimation in the first quarter of 1970 does not significantly alter the results. Various dummies are also added to the IP equations in order to account for possible outliers.
The diagnostic checking for Mult2 and Mult3 models are all satisfactory. Mult1 rejects the presence of serial correlation, heteroskedasticity and non-normality for the industrial production equation. Although dummy variables are used to pick up major outliers in the inflation series, normality is still rejected for the inflation residuals; given the erratic movements of inflation in the 1970s and the subsequent sharp fall in the early 1980s, this is not surprising. The diagnostic tests on residuals of Mult4 model are satisfactory for all equations except for the unemployment rate where residuals are non-normal even if several dummies are applied[5].

[5] It is interesting to note that the same problem also emerges in the unemployment residuals in a study by Chen and Mills (2009) conducted on the output gap estimation referring to the entire Euro area.

Table 2. Multivariate models for log IP

Model	Mult 1		Mult 2		Mult 3		Mult 4		
	IP	INFL	IP	Unem	IP	GDP	IP	UNEM	GDP
Level	4.52 (0.00)	1.34 (0.00)	4.53 (0.00)	2.12 (0.00)	4.47 (0.00)	14.02 (0.00)	4.52 (0.00)	14.05 (0.00)	1.99 (0.00)
Slope	-0.01 (0.07)	-	-0.01 (0.04)	0.02 (0.05)	-0.02 (0.01)	-0.01 (0.05)	-0.01 (0.02)	-0.001 (0.36)	0.02 (0.08)
Seasonal Chi^2 test	-	5.38 (0.11)	-	-	-	-	-	-	-
Cycle component	0.099	0.96	0.11	0.049	0.068	0.024	0.094	0.034	0.065
Residual tests									
Normality [(a)]	3.61	15.96	6.11	5.28	5.24	3.31	8.35	2.69	42.66
DW [(b)]	2.07	2.03	1.98	1.97	1.99	1.87	2.07	1.88	2.05
H [(c)]	0.69	0.23	0.55	0.25	0.64	0.37	0.62	0.35	0.21
Q (P,12) [(d)]	10.05	13.85	13.89	20.25	10.31	15.34	8.42	11.82	13.79
R^2	0.54	0.49	0.56	0.61	0.52	0.52	0.56	0.57	0.51

The P-values are in parenthesis.
(a) Bowman-Shenton statistic, Chi-square (2). We reject the null if the calculated probability exceeds the tabulated ones equal to 5.99 at 5% significance level and 9.21% at 1% significance level.
(b) Durbin-Watson test.
(c) H(h) is the heteroskedasticity test statistics distributed as a F(h,h) with (h,h) degrees of freedom. H=62 (model 1, 3 and 4 and H= 61 (model 2). Under the null of no heteroskedasticity the 5% critical value is 1.52 and for h=62 and 1.53 for h=61.
(d) Ljung Box statistics based on the sum of the first P autocorrelations and it is tested against a Chi-square (12). The critical value for 12 degrees of freedom is 21.03 at 5% significance level.

Shaikh–Moudud (SM) cointegration method

An alternative way to estimate potential output is to use the cointegration approach introduced by Shaikh and Moudud (2004). The essential idea is that capacity co-varies with the capital stock over the long run, making the cointegration the natural tool for measuring capacity. The Shaikh–Moudud framework consists of an identity and two behavioural equations. The identity can be stated as $Y_t = (Y/Y^*)\cdot (Y^*/K)\cdot K$, where Y = output of manufacturing firms, Y^* = potential output, K = capital stock of manufacturing firms. If we now define $v = (K/IP^*)$, and cu = capacity utilization rate = (Y/Y^*), then:

$$\log(Y_t) = \log(K_t) - \log(v_t) + \log(cu_t) \tag{5}$$

The IP index (Y) and capital stock (K) are observed variables, but to turn the previous identity into a model we need to specify capacity utilization (cu) and capital to capacity ratio (v). As for the first point, Shaikh–Moudud assumes that Y fluctuates around capacity over the long run, so that the actual cu fluctuates around some desired or normal rate of capacity utilization. This means that manufacturing firms are able to maintain some correspondence between manufacturing capacity and actual production. In log terms, this implies that:

$$\log(cu_t) = e_{cu,t} \tag{6}$$

where $e_{cu,t}$ is a random error term.
Moreover, Shaikh–Moudud assume that the capital-capacity ratio (v) changes over time, in response to autonomous (coefficient b_1) and embodied technical change; the latter in turn depends on the rate of capital accumulation (coefficient b_2). Letting g_v = growth rate of the capital capacity ratio v and g_K = growth

rate of the capital stock *K*, we have $g_v = b_1 + b_3 \cdot g_K$. In log terms, with an added random error term $e_{v,t}$, this leads to the following equation:

$$\log(v_t) = b_0 + b_1 \cdot t + b_2 \cdot t^2 + b_3 \cdot \log(K_t) + e_{v,t} \tag{7}$$

where it is assumed that an autonomous technical change follows a quadratic trend. Equations (5)-(7) form a general model of the relationship among industrial production and the capital stock, given technical change and fluctuating capacity utilization. Combining (5)–(7) we obtain the following estimable equation:

$$\log(Y_t) = a_0 + a_1 \cdot t + a_2 \cdot t^2 + a_3 \cdot \log(K_t) + e_t \tag{8}$$

where $a_0 = -b_0$, $a_1 = -b_1$, $a_2 = -b_2$, $a_3 = 1 - b_3$, and error term $e_t = e_{cu,t} - e_{v,t}$.
Equation (8) implies that log Y and log K are cointegrated, up to a linear and quadratic deterministic trend in the data. The estimation output obtained is reported below; the diagnostic ADF test on residuals is satisfactory.

Table 3. Estimation result of the long run relationship (equation (4))

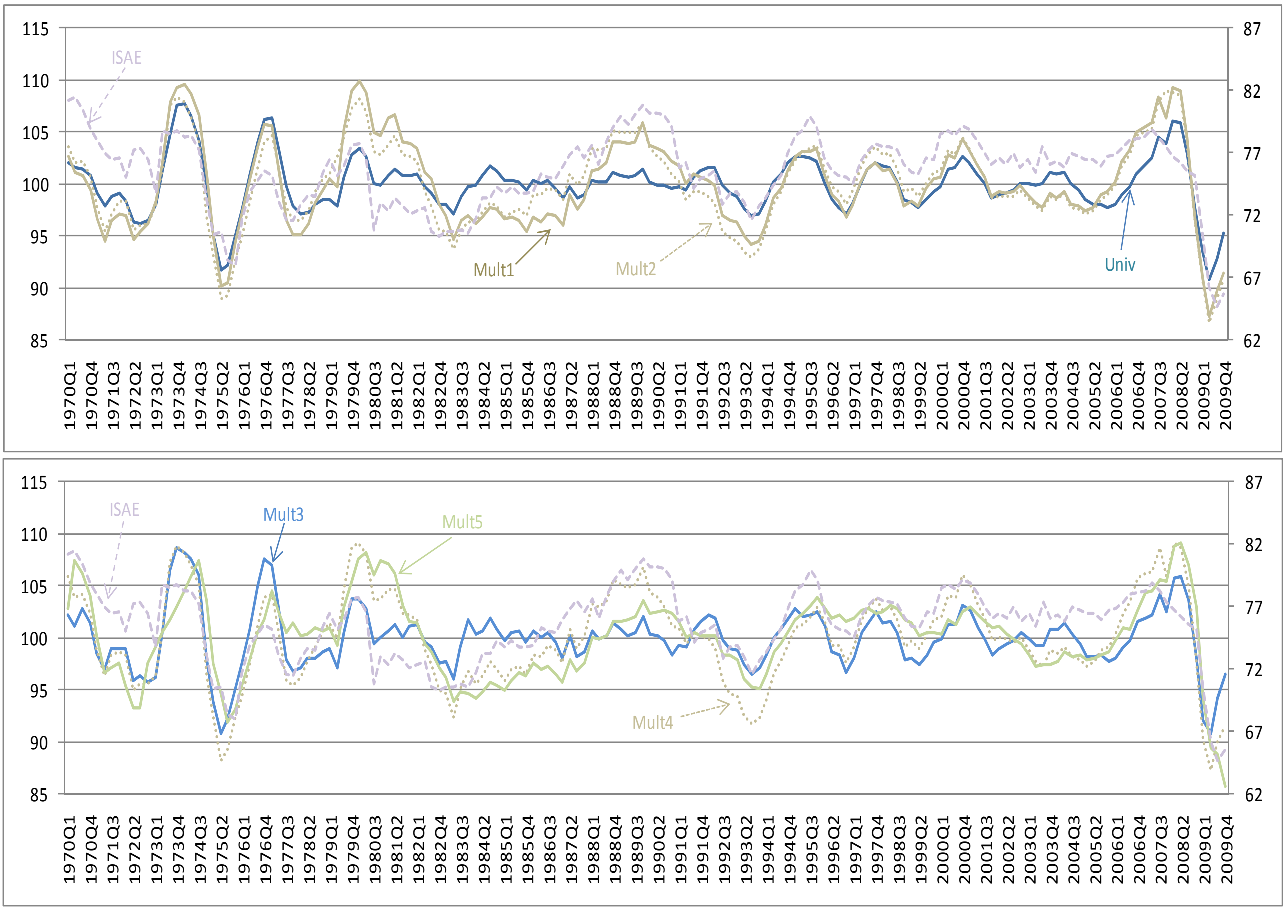
Sample period	a_0	a_1	a_2	a_3
1970q1 - 2009q4	1.97 (1.45)	0.01 (5.72)	-4.40E-05 (6.67)	0.35 (2.89)
Residual ADF t-test	-4.51***			

Note: Y = Value added of manufacturing firms (annual data, source EUKLEMS updated with ISTAT dataset); K = Capital stock of manufacturing firms (annual data, source EUKLEMS updated with ISTAT dataset). The data is transformed in quarterly frequency using the method proposed in Fernandez (1981).
The methodology used is the Engle and Granger approach. This approach consists of estimating a long-run relationship (i.e., the equation (4)) and making an ADF t-test on residuals. For the residual ADF t-test, the lag length is chosen by SIC criteria. Critical values for test are suggested by MacKinnon (1991). Symbols *, **, *** represents, respectively, significance level of 10%, 5%, and 1% of residual ADF t-test. The reported t-statistics (in parenthesis) are corrected for bias stemming from serial correlation and heteroskedasticity by the Newey-West procedure.

3. Comparison of methods

This section compares the various results of capacity utilization estimation with the measure emerging from the ISAE survey on the manufacturing sector. First of all, Figure 1 plots the various measures obtained in section 2 in order to have a first visual appraisement of the difference existing between the various results. All the series show a similar pattern, even if in some cases downturn or upturn phases are under or over-emphasized: this aspect reflects to a certain extent the properties of the individual methods. For example, Univ and Mult4 methods show that the trough reached in the current recession is roughly in line with that of 1975, whereas the other methods pose more emphasis on the recent recession.

Figure 1: Capacity utilization, all methods



Note: Univ = Univariate model for industrial production; Mult1 = Bivariate model for industrial production and inflation; Mult2 = Bivariate model for industrial production and unemployment rate; Mult3 = Bivariate model for industrial production and GDP; Mult4 = Bivariate model for industrial production, unemployment rate and GDP; Mult5 = Shaikh–Moudud cointegration method; ISAE = ISAE's measure of capacity utilization. All series are represented in the left hand axis, except for ISAE which is represented in the right hand axis.

3.1 Business cycle dating

In Table 4 we then report the leads or lags turning points that capacity utilization measures exhibit with respect to the benchmark business cycle dating. The official dating of the Italian business cycle is produced by ISAE (Bruno and Otranto (2008)). Peaks and troughs for the capacity utilization series are identified by means of the Bry-Boschan-Harding-Pagan algorithm (Harding and Pagan (2002)). The output of the algorithm has not been taken at face value: in some cases it did not detect turning points that were instead evident from a visual inspection. In these cases the output is adjusted to consider these points.

The univariate and bivariate IP-GDP methods correctly pick up all the turning points, though with some leads or lags in correspondence of some turning points. The others miss one turning point: three methods miss the peak in the first quarter of 1992, whereas the ISAE survey method misses the peak in the first quarter of 1974. All capacity utilization measures identify extra cycles: univariate series identifies more additional extra cycles with respect to the others (8). As for the values of capacity utilization in correspondence of various peaks, it is interesting to note that only for bivariate IP-UR, trivariate, and Shaikh–Moudud methods are the highest values of capacity utilization reached in the third quarter of 2007.

Table 4. Turning point analysis: Leads (-) and lags (+) with respect to the growth-cycle reference dating

Method	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak
Growth Cycle Reference dating	**1971q4**	**1974q1**	**1975q2**	**1977q1**	**1977q4**	**1980q1**	**1983q1**	**1992q1**
Univariate UC model	-2 (97.78)	0 (**107.78**)	0 (91.77)	0 (106.28)	1 (97.05)	0 (103.35)	1 (97.16)	0 (101.53)
Bivariate IP-INFL UC model	-2 (94.55)	0 (109.52)	0 (90.24)	-1 (105.75)	1 (95.07)	0 (**109.85**)	1 (94.55)	-
Bivariate IP-UR UC model	-2 (95.47)	-1 (108.26)	0 (89)	0 (104.67)	1 (96.46)	0 (108.15)	1 (93.69)	-
Bivariate IP-GDP UC model	-2 (96.88)	-1 (**108.68**)	0 (90.72)	-1 (107.52)	0 (96.86)	-1 (103.79)	1 (95.95)	0 (102.17)
Trivariate IP-GDP-UR UC model	-2* (96.27)	-1 (108.79)	0 (88.22)	0 (104.1)	0 (95.43)	0 (109.08)	1 (92.26)	-
Shaikh–Moudud (SM) method	-2 (96.69)	2 (107.37)	1 (91.84)	0 (104.47)	1 (100.15)	1 (108.14)	1 (93.9)	1 (100.18)
ISAE survey	1 (75)	-	2 (68)	-1 (75.6)	0 (71.5)	0 (77.7)	-1 (70.3)	1 (75.5)

Method	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Number of extra cycles
Growth Cycle Reference dating	**1993q3**	**1995q4**	**1996q4**	**2000q4**	**2003q2**	**2007q3**	**2009q2**	
Univariate UC model	0 (96.87)	-2 (102.66)	0 (97.02)	0 (102.68)	0 (99.87)	2 (105.98)	0 (90.79)	8
Bivariate IP-INFL UC model	0 (94.14)	0 (103.36)	0 (96.8)	0 (104.31)	1 (97.76)	2 (109.24)	0 (87.26)	6
Bivariate IP-UR UC model	0 (92.96)	0 (103.73)	0 (97.99)	0 (104.49)	1 (97.44)	1 (**108.87**)	0 (86.67)	6
Bivariate IP-GDP UC model	0 (96.49)	-3 (102.77)	0 (96.6)	0 (103.1)	0 (99.18)	3 (105.81)	-1 (89.57)	6
Trivariate IP-GDP-UR UC model	0 (91.65)	0 (102.99)	0 (97.53)	0 (105.98)	1 (97.28)	2 (**109.08**)	0 (87.29)	6
Shaikh–Moudud (SM) method	1 (95.12)	0 (103.93)	0 (101.63)	1 (102.97)	0 (97.23)	3 (**109.14**)	-	6
ISAE survey	0 (71.6)	-1 (79.1)	1 (74.5)	0 (**79.1**)	0 (75.4)	-1 (78.9)	1* (64.6)	4

Note: * Indicates the lead or lag (with respect to the reference dating) of capacity utilization that are not classified as such by the Bry-Boschan algorithm but are evident on visual inspection. In parenthesis are reported the values of capacity utilization in correspondence of peaks and troughs. In bold record is reported the maximum value of capacity utilization observed in correspondence of peaks.

Table 5 provides additional information on how well the competing capacity utilization measures track economic fluctuations, focusing in particular on the timelessness of the detection. The empirical evidence suggests that, on average, the univariate series outperforms the others: the mean bias is zero. The trivariate and bivariate IP-UR estimates also show very good tracking properties. The Shaikh–Moudud estimate tends to be lagging at peaks, whereas the ISAE series tends to lag the trough points, being however on average a coincident indicator of the reference cycle.

Table 5. Average lags of the various capacity utilization measures

Method	Average Lag at		
	Peaks	Troughs	All
Univariate UC model	0	0	0
Bivariate IP-INFL UC model	+0.17	+0.12	+0.14
Bivariate IP-UR UC model	0	+0.12	+0.07
Bivariate IP-GDP UC model	-0.43	-0.12	-0.33
Trivariate IP-GDP-UR UC model	+0.17	0	+0.07
Shaikh–Moudud (SM) method	+1.14	+0.29	+0.71
ISAE survey	-0.33	+0.5	+0.14

Note: a positive (negative) sign indicate a lag (lead).

In what follows we focus on the main economic recessions of the last 40 years: 1980–1983 (caused by the 1979 energy crisis); 2001–2003 (caused by the dot-com bubble); 2007-ongoing recession (caused by many factors, including the subprime mortgage crisis and the sharp rise in oil and food prices). The figure below makes a comparison between the recessions (in length and amplitude) of various capacity utilization paths during these phases. All the results are compared with the dynamic capacity utilization measures obtained from the survey (ISAE's capacity utilization). In all measures used, the last cycle is characterized by the most severe recession. The ISAE's capacity utilization shows a recession duration of basically the same size of previous recessions. Referring to this last measure, it is interesting to note that until seven quarters the recession is of the same amplitude of the others and after this point there is a severe slump in capacity utilization.

3.2 Inflation and predictive power of capacity utilization

So far, we have compared the properties of the different capacity utilization measures with respect to the growth cycle dating elaborated by ISAE. An alternative approach is to test to what extent capacity utilization contributes to explain consumer price inflation. The most used method consists of estimating a single equation in which capacity utilization is assumed to be an exogenous variable that explains inflation rate. We guess that bidirectional causality between capital utilization and inflation rate is more consistent with the economic theory.

The linkage between these two variables can be understood using the familiar AD-AS framework. A positive shift in aggregate demand will initially cause output and capacity utilization to rise. As time passes, prices will begin to adjust and inflation will rise. As a consequence of rising prices, output and capacity utilization rates will fall back to their initial levels and inflation will shrink. A shift in aggregate supply affecting prices positively will lead to a reduction in output and in capacity utilization. But reductions in output and capacity utilization will constrain price dynamics and, consequently, lead to output reduction. In the long run no additional capacity will be built up and we expect that capacity and actual output will move in a way that the capacity utilization rate will return to its initial value.

This discussion suggests that a positive demand shock will cause a temporary positive effect on capacity utilization and inflation; whereas a negative supply shock (for example a rise in oil price) will determine a temporary positive effect on inflation and a temporary negative effect on capacity utilization.

VAR and associated impulse response functions are used to study the interaction of different measures of capacity utilization and inflation. The standard form of the VAR model is:

$$\begin{bmatrix} \pi_t^c \\ cu_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \sum_{k=1}^{K} A_k \begin{bmatrix} \pi_{t-k}^c \\ cu_{t-k} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix} \quad (9)$$

where π^c is the cyclical component of the inflation (since that π is I(1)) and *cu* is the capacity utilization. $e_{1,t}$ and $e_{2,t}$ are errors terms which are composed of the structural innovations (that is, demand and supply shocks).

Figure 2. Recessions comparisons

Note: Time on horizontal axis is in quarters.

The theory does not specify a time frame for the relationship between cu and π, so we let the data determine the number k of quarters lags to include. Specifically, we set k basing on the Schwartz Information Criteria (SIC)[6]. On the basis of the VAR model, we employ the impulse response functions to

[6] The SIC model selection criterion is based on the log likelihood function adjusted by a penalty for the number of parameters, and performs well for model selection with large sample sizes (see Lutkepohl (1991)).

illustrate how the two endogenous variables relate to each other over time. The identification of demand and supply shocks is achieved by assuming delayed impacts of demand shock on inflation, i.e. a Cholesky economy[7]. Figure 3 (in the Appendix) shows the results of impulse response functions for different capacity utilization measures. All the capacity utilization measures exhibit an impulse response function in accordance with the theoretical considerations except for univariate and bivariate IP-GDP measures: the response of the capacity utilization to a supply shock is positive for the most part of period.

The last important check is the out-of-sample forecasting performance of inflation. We have estimated each model for the period from the first quarter of 1970 to the fourth quarter of 2007. These estimates are used to predict the observations for the period from the first quarter of 2008 to the fourth quarter of 2009 (the period of current recession). These forecasts are compared with the actual values. The results are reported in Table 6.

Table 6. Out-of-sample performance of various capacity utilization measures

	MAPE	RMSPE	% CDCP
Univariate UC			
Capacity Utiliz.	4.39	0.47	86
Inflation (cycle component)	48.37	6.03	100
Bivariate IP-INFL			
Capacity Utiliz.	6.93	0.77	100
Inflation (cycle component)	74.51	12.61	86
Bivariate IP-GDP			
Capacity Utiliz.	5.63	0.61	71
Inflation (cycle component)	30.70	4.17	86
Bivariate IP-UR			
Capacity Utiliz.	6.21	0.78	71
Inflation (cycle component)	195.89	32.13	86
Trivariate IP-GDP-UR			
Capacity Utiliz.	7.4	0.82	100
Inflation (cycle component)	41.37	6.09	100
Shaikh-Moudud (SM)			
Capacity Utiliz.	7.74	0.94	86
Inflation (cycle component)	76.12	10.91	86
ISAE survey			
Capacity Utiliz.	7.71	1.03	100
Inflation (cycle component)	80.27	9.2	100

Note: MAPE (Mean Absolute Percentage Error) = $\left[\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|\right]\cdot 100$, where A_t is the actual value and F_t is the forecast value. The difference between A_t and F_t is divided by the actual value A_t again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted points n. This makes it a percentage error so one can compare the error of fitted time series that differ in level. RMSPE (Root Mean Square Percentage Error) = $\left[\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{A_t - F_t}{A_t}\right)^2}\right]\cdot 100$. % CDCP (Correct Direction Change Predictions) = $\frac{1}{n}\sum_{t=1}^{n} H_t \cdot 100$, where $H_t = 1$ if $(A_{t+1} - A_t)\cdot(F_{t+1} - F_t) > 0$, otherwise $H_t = 0$. This indicator measures the ability of the model to predict direction changes irrespective of the forecast error magnitude.

The forecasts accuracy indexes show that, in general (with the exception of the bivariate IP-UR capacity utilization estimation), time series capacity utilization estimation exhibits a Root Mean Square Percentage Error (RMSPE) better or, at least, in line with capacity utilization measured by the ISAE survey. Overall, the trivariate capacity utilization estimation has stronger predictive power for the inflation rate.

[7] Details on this point are in the Appendix.

4. Conclusions

This paper makes a comparison between time series and survey-based measures of capacity utilization for Italian manufacturing firms. From turning point analysis of the last 40 years it emerges that the measure obtained from the survey suffers in terms of timely identification of troughs. Moreover, assessments of the various capacity utilization measures, based on the theoretical view that capacity utilization must have good properties in explaining the consumer price inflation, show that the survey measure has performed poorly in forecasting inflation during the current period of recession (the last eight quarters): in fact, a trivariate (industrial production index, GDP, and unemployment rate) time series estimation clearly outperforms the survey index. This confirms the previous result that the survey measure lacks precision in detecting the recession periods. A possible explanation is that firms may have difficulties in fully perceiving their current rate of utilization capacity during the recession phases. The difficulty with surveys is that they do not specify any explicit definition of what is meant by "capacity". Thus the respondents are free to choose between various measures of capacity, and may misperceive the effective utilization rate. For this reason we guess that time series measures can convey important information which can be complementary in respect to survey measures. The Federal Reserve, for example, finds that in some periods the resulting estimates of capacity utilization are not plausible from its point of view, so it further operates to change it using regression methods (Shapiro, 1989).

Appendix: Identification of structural innovations

Our bivariate VAR model can be expressed such as:

$$\pi_t^c = b_{10} - b_{12}\pi_t^c + c_{11}\pi_{t-1}^c + c_{12}cu_{t-1} + \varepsilon_t^S$$
$$cu_t = b_{20} - b_{21}cu_t + c_{21}\pi_{t-1}^c + c_{22}cu_{t-1} + \varepsilon_t^D$$

where it is assumed, for the sake of simplicity, that the lag length is equal to unity[8]. π^c is the cyclical component of the inflation (since that π is I(1)) and *cu* is the capacity utilization. ε^S and ε^D are serially uncorrelated random disturbances, respectively the structural aggregate supply and aggregate demand shocks.

In matrix form the system can be expressed such as:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} \pi_t^c \\ cu_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} \pi_{t-1}^c \\ cu_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^S \\ \varepsilon_t^D \end{bmatrix}$$

Or more simply:

$$BX_t = \Gamma_0 + \Gamma_1 X_{t-1} + \varepsilon_t$$

Pre-multiplying by B^{-1} allows us to obtain the VAR model in the standard form:

$$X_t = A_0 + A_1 X_{t-1} + e_t$$

where

$$A_0 = B^{-1}\Gamma_0; A_1 = B^{-1}\Gamma_1; e_t = B^{-1}\varepsilon_t$$

[8] In the estimation we choose the lag length of the VAR that minimizes SIC information criteria.

These error terms are composed of the structural innovations from the structural system:

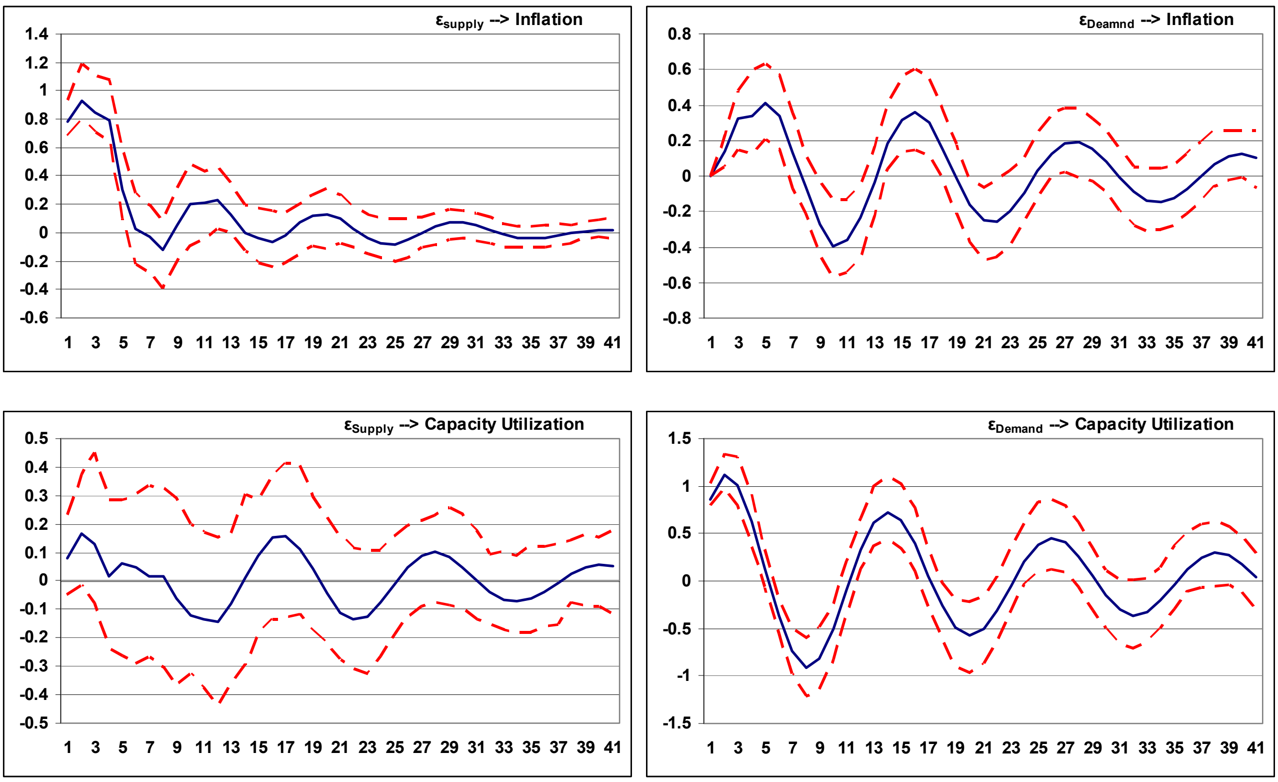
$$e_t = B^{-1}\varepsilon_t \Rightarrow \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \frac{1}{(1-b_{21}b_{12})}\begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_t^S \\ \varepsilon_t^D \end{bmatrix}$$

To get the effect of a structural innovation on *cu* and π^c, we apply the Cholesky decomposition assuming that $b_{12} = 0$. That is, we are assuming that a demand shock does not have any contemporaneous effect on inflation. This assumption is compatible with the economic hypothesis that prices are sticky.

Appendix: SVAR impulse response function

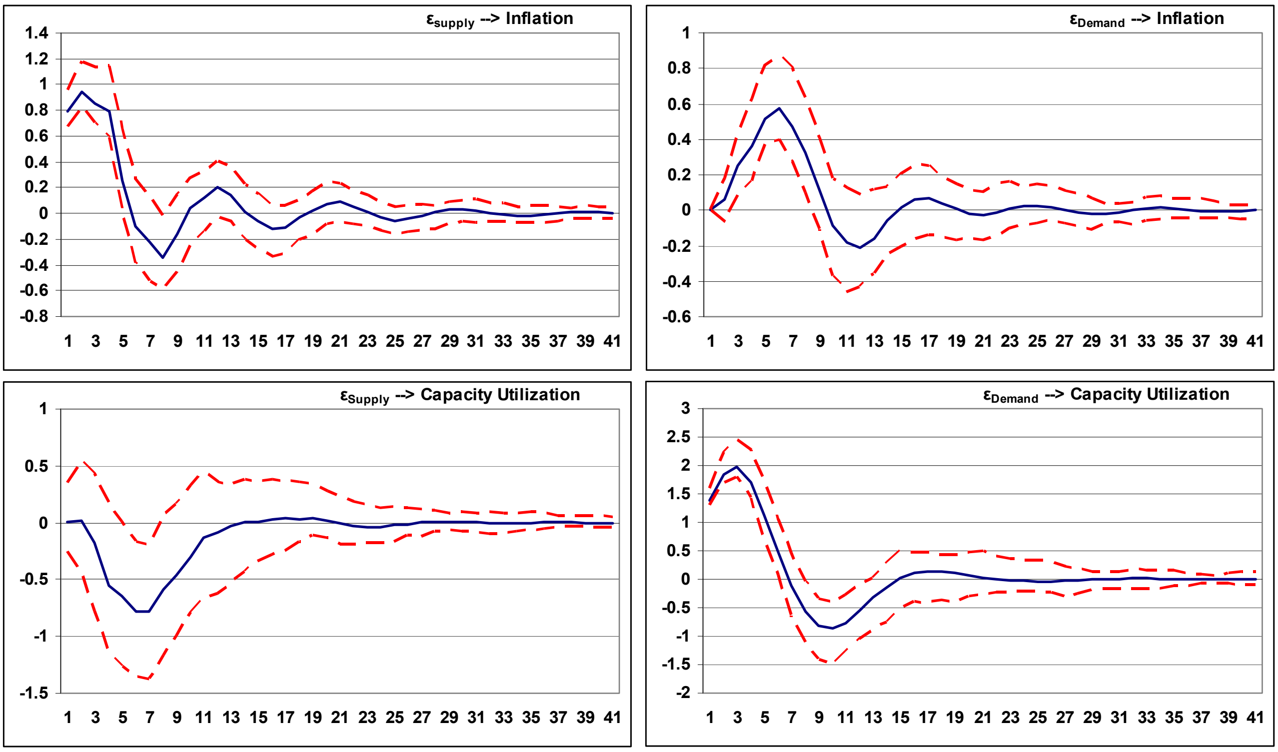
Figure 3. SVAR impulse response function to a demand and supply shocks (Sample 1970q1-2009q4)

Variables: Capacity Utilization (obtained through Univariate UC estimation) and cyclical component of inflation



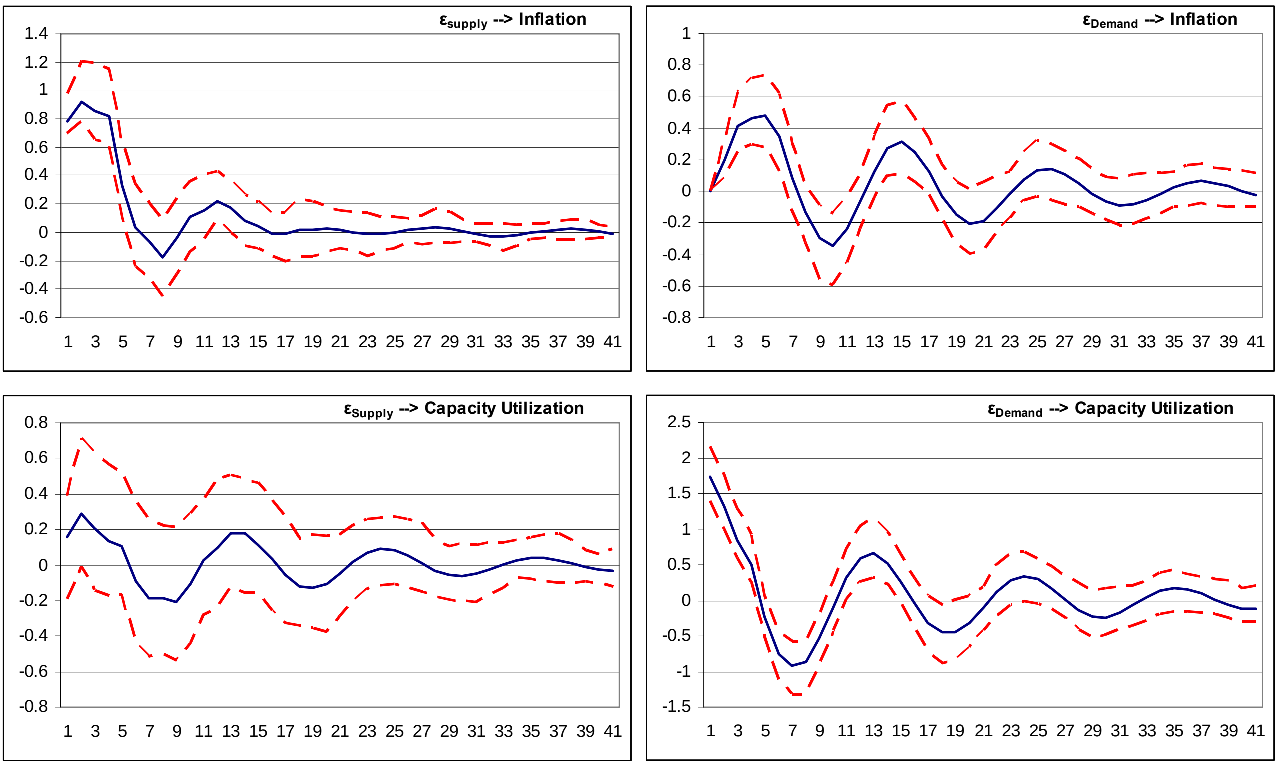
Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (obtained through bivariate IP-UR UC estimation) and cyclical component of inflation



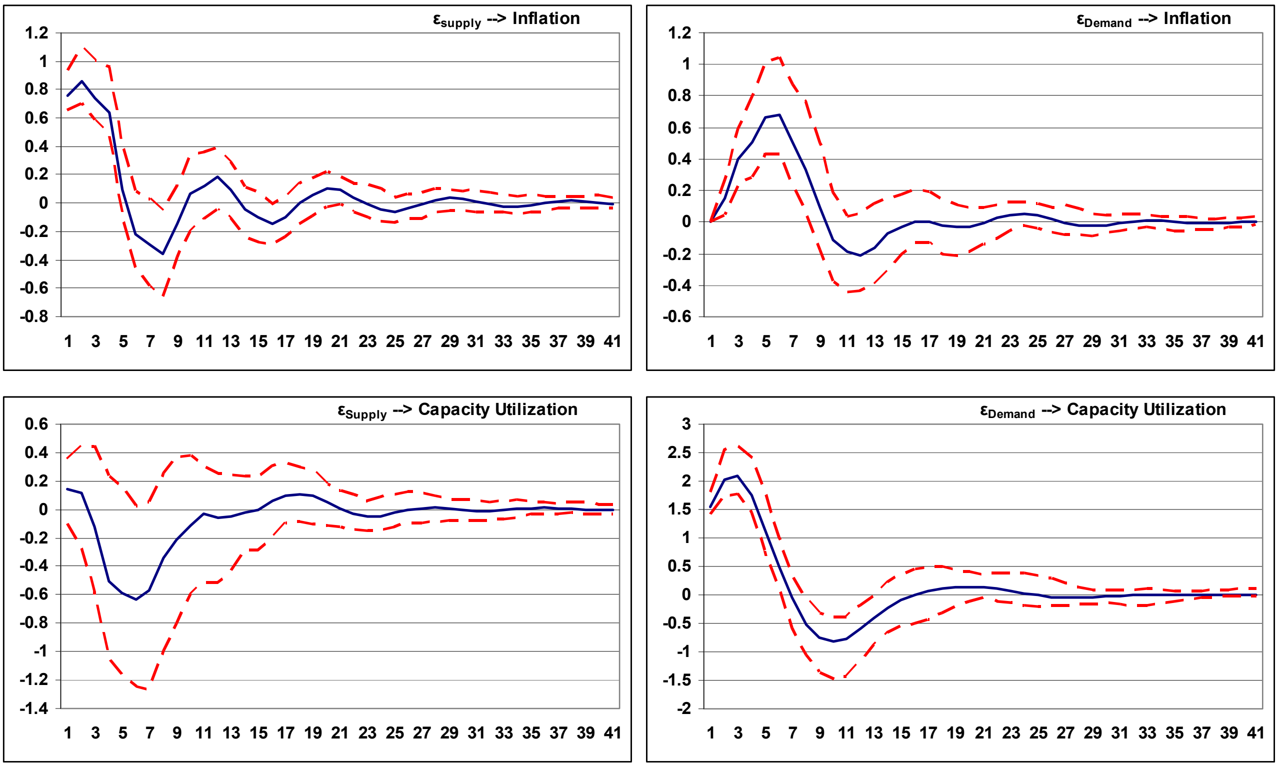
Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (obtained through bivariate IP-GDP UC estimation) and cyclical component of inflation



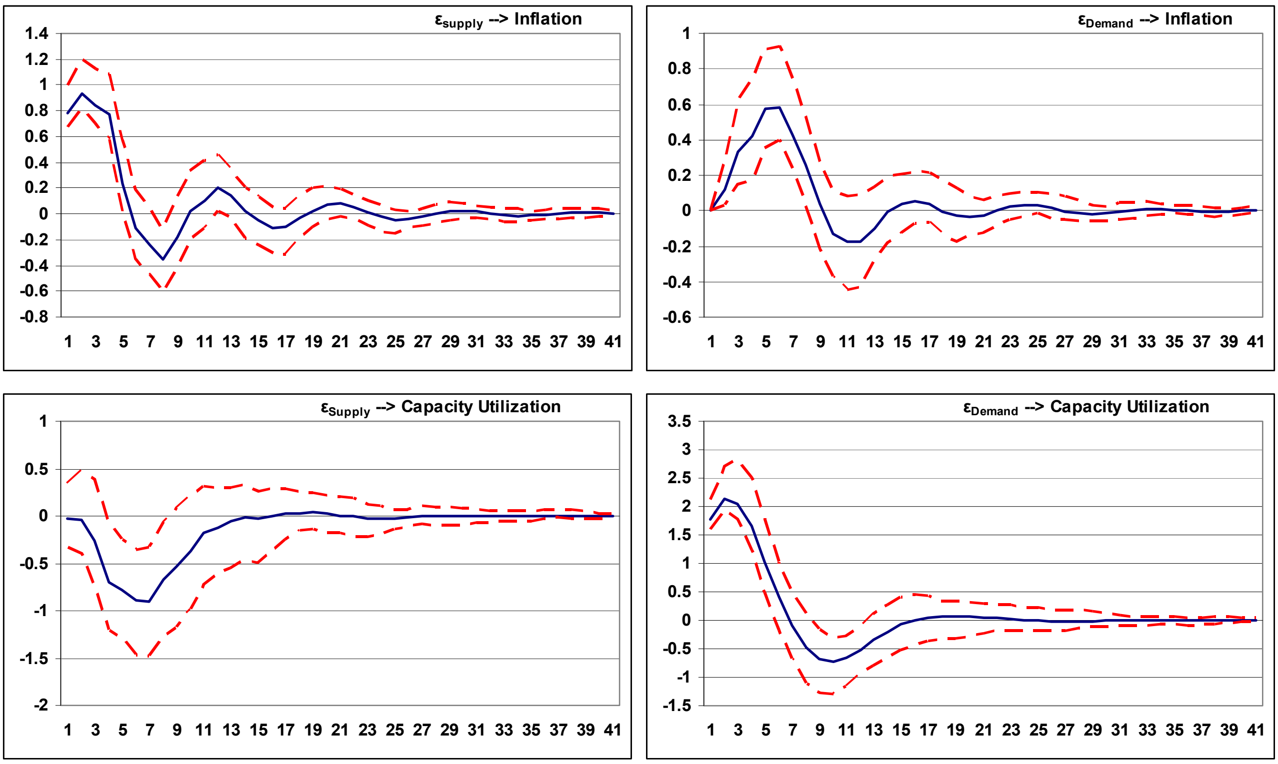
Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (obtained through bivariate IP-INFL UC estimation) and cyclical component of inflation



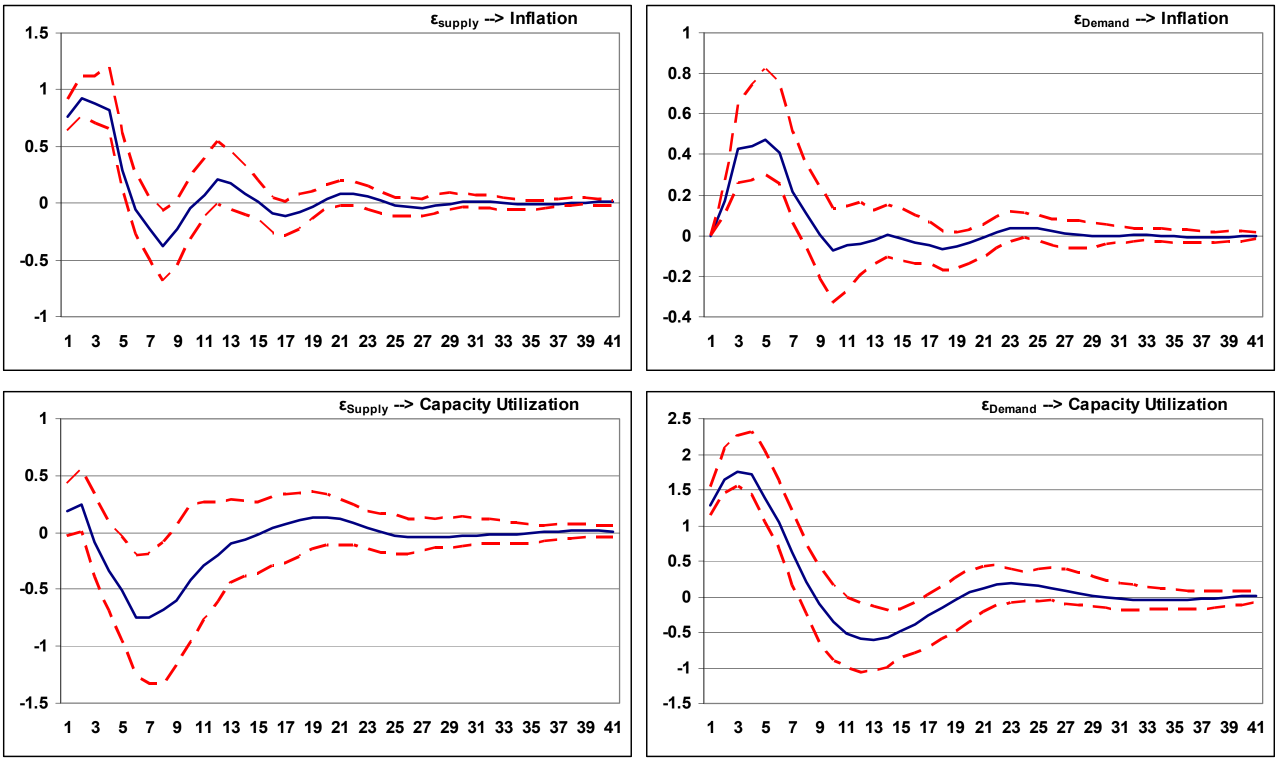
Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (obtained through trivariate IP-GDP-UR UC estimation) and cyclical component of inflation



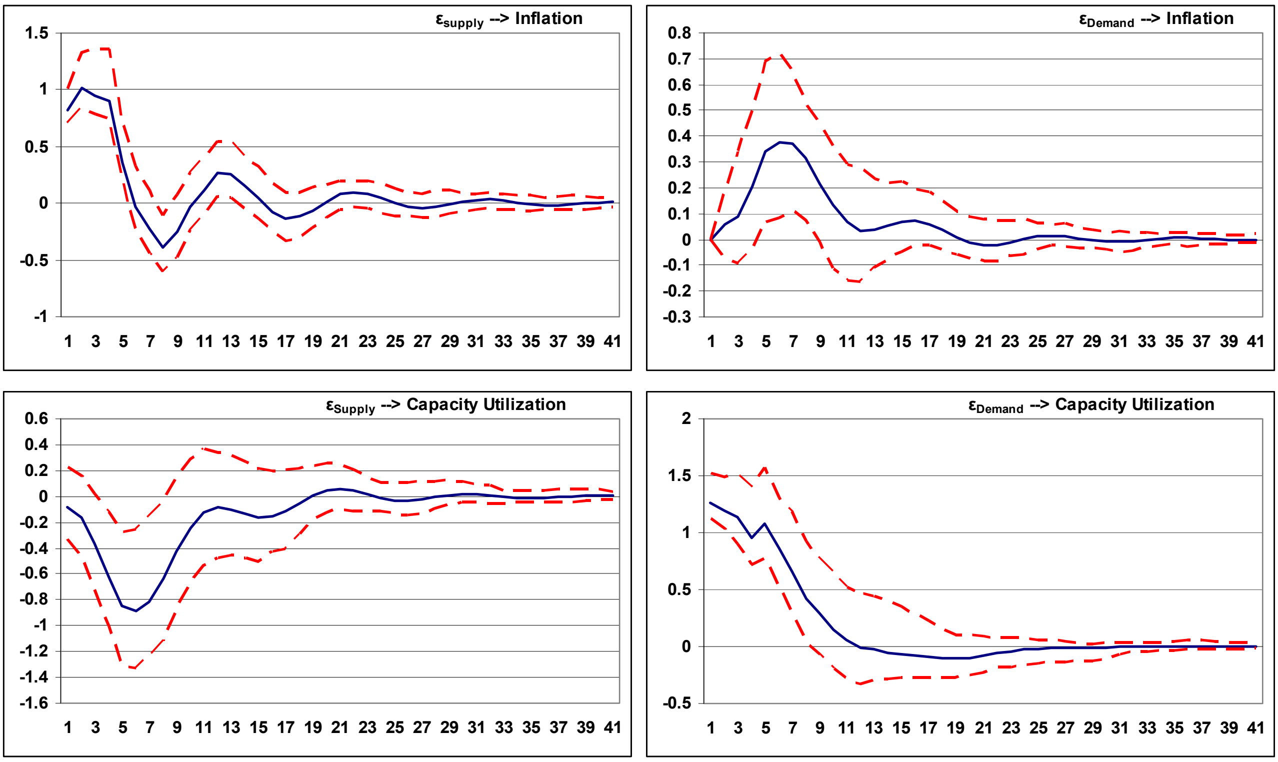
Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (obtained through Shaikh-Moudud method estimation) and cyclical component of inflation



Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

Variables: Capacity Utilization (ISAE series) and cyclical component of inflation



Note: Solid blue line: mean response; Dashed red line: 95% confidence bands.

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