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Long run and short run dynamics in italian manufacturing labour productivity

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Abstract

This paper examines structural changes in the Italian manufacturing sector, focusing on labour productivity in recent decades. To this end it distinguishes between trend and cyclical movements in the data using a multivariate unobserved components model. Changes in the relative importance of cyclical and trend components in labour productivity allow discrimination among the impacts of the factors affecting the performance of the Italian manufacturing sector during the 1980s, 1990s and in the more recent period.

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1. Introduction

In recent years, labour productivity growth in Italian industry has decelerated. There has been much debate concerning the possible causes of this phenomenon (i.e. Sgherri, 2005, Daveri and Jona Lasinio, 2005). One explanation put forward concerns the de-industrialisation process driven by a progressive reduction in the manufacturing sector's share of value added in the main industrialised countries (see, e.g. Baumol, 1967). Other reasons relate to the loss of competitiveness due to the higher incidence of emerging markets, such as the Asian and Chinese economies, as a consequence of globalisation.

In this paper we investigate the behaviour of labour productivity in Italian industry during the last decades, analysing its long- and short-run dynamics. Changes in the relative importance of the cyclical and trend components enable us to distinguish among the impacts of different factors affecting the performance of the manufacturing sector during the 1980s and 1990s and in the more recent period.

Whereas the long-run labour productivity evolution is assumed to be mainly due to the effect of structural changes (i.e. institutional reforms to liberalise part-time and fixed-term labour contracts agreed in the mid-1990s), its cyclical component may be mainly associated with macroeconomic factors that only temporarily affect its dynamics (see, Inklaar and Guckin, 2003 and Baily, Bartelsman, Haltiwanger, 2001).

In order to distinguish between trend/cycle dynamics in labour productivity, we use a multivariate unobserved components model *à la* Clark (1989). This approach has several advantages.

First, compared with univariate techniques, the use of a multivariate setting can yield additional information on the dynamics of each component through consideration of more than one variable. Second, the approach displays considerable flexibility in modelling the cyclical and trend components in the data. Third, it allows one to estimate the parameters consistently with each other, given that the equations of the system are estimated simultaneously through an iterative procedure based on the Kalman filter.

According to our evidence, the labour productivity deceleration experienced in the 1980s and 1990s seems to be mainly determined by a progressive deterioration in the cyclical component growth rate. In contrast, in the more recent period (2000-06) the decline seems to be attributable to the effect of a negative cyclical phase generated by a stronger role of transitory shocks, and to the contribution of trend reduction.

The rest of the paper is structured as follows: section 2 introduces the econometric model; section 3 reports the empirical results and puts forward some considerations from a policy perspective; section 4 contains conclusions.

2. Econometric specification

One of the main difficulties associated with the investigation of labour productivity dynamics is estimation of its long- and short-run components. Univariate detrending methods (i.e. filters) are the techniques usually implemented to distinguish trend/cycle components in the data. However, the application of filters has a number of drawbacks. The most important of these is known as the "end-point problem", connected with the uncertainty of the estimates at the end of sample due to the use of both past and future information to estimate current data.

In order to overcome these shortcomings we estimate trend and cyclical components of manufacturing labour productivity, using a multivariate unobserved components model with common cycles *à la* Clark (1989). This approach has several advantages. First, by comparison with univariate detrending methods, it takes into account information derived from more than one variable in order to identify each component of the data. Second, it allows one to assign a quite flexible "*a priori*" structure to trend and cyclical components. Third, it permits estimation of parameters simultaneously and consistently with each other by means of a maximisation procedure based on the likelihood function.

The labour productivity measure that we investigate here is the ratio between value added and employment[1] in the Italian manufacturing sector. According to this measure, the benchmark model includes manufacturing value added (y_t), manufacturing employment (O_t) and the degree of plant utilisation (GU_t). The rationale for including value added and employment as separate components in the model, instead of a direct productivity indicator, is due to the need to capture more accurate information on the different cyclical and trend dynamics in both output and employment. In fact, the inclusion of degree of plant utilisation, given its cyclical profile, makes it possible to identify the short-run pattern of industrial activity and employment by assuming the existence of a common cyclical pattern for the three variables. The multivariate approach makes it possible, in this way, to take account of the underlying cyclical and trend dynamics of each variable. In contrast, extracting the cyclical component directly from a labour productivity indicator does not make it possible to check for these separate dynamics and could lead to unreliable results.

In order to detect the appropriate structure for each component, as a preliminary analysis we investigated the existence of possible stochastic trends in the data. For this purpose standard unit root tests were performed. The results show that manufacturing value added, employment, and degree of plant utilisation display a stochastic trend.

The model is illustrated by three groups of equations. The first group describes the manufacturing value added (y_t):

$$\begin{cases} \mathrm{y_t} = n_t + x_t \\ \mathrm{n_t} = g_{t-1} + n_{t-1} + v_t \\ g_t = g_{t-1} + w_t \\ \mathrm{x_t} = \phi_0 \Psi_t + ey_t \end{cases} \tag{1}$$

where x_t represents the value-added cyclical component that is a function of the degree-of-plant-utilisation cyclical component (Ψ_t), n_t is the value-added trend component described by a local linear trend model, g_t is the stochastic slope of the trend and v_t, w_t, ey_t are stochastic disturbances that are incorrelated and independently distributed with zero mean and constant variance. The employment component (O_t) is described by the following equations:

$$\begin{cases} \mathrm{O_t} = L_t + C_t \\ \mathrm{L_t} = \delta_{t-1} + L_{t-1} + vo_t \\ \delta_t = \delta_{t-1} + u_t \\ \mathrm{C_t} = \alpha_0 \Psi_t + \alpha_1 \Psi_{t-1} + eo_t \end{cases} \tag{2}$$

where L_t is the employment trend component described through a local linear trend model, δ_t is the stochastic slope of the trend, C_t represents its cyclical component, which is a function of degree-of-plant-utilisation cyclical component (Ψ_t), and vo_t, eo_t, u_t are shocks independent and normally distributed with zero mean and constant variance. The degree of plant utilisation

[1] See the empirical section for details on the definition of this variable.

(GU_t) is described by the following equations:

$$\begin{cases} \mathrm{GU_t} = GUTR_t + \Psi_t \\ GUTR_t = B_{t-1} + GUTR_{t-1} + vgu_t \\ B_t = B_{t-1} + z_t \\ \Psi_t = \rho \cos\lambda_c \Psi_{t-1} + \rho sen \lambda_c \Psi^*_{t-1} + \kappa_t \\ \Psi^*_t = -\rho sen \lambda_c \Psi_{t-1} + \rho \cos\lambda_c \Psi^*_{t-1} + \kappa^*_t \end{cases} \tag{3}$$

where $GUTR_t$ represents the degree-of-plant-utilisation trend component, B_t indicates the stochastic slope of the trend, Ψ_t is the cyclical component described by a linear combination of cyclical waves, ρ is the dumping factor corresponding to the amplitude of the cycle, λ_c represents the frequency, with κ_t $\kappa^*{}_t \sim NID(0, \sigma^2_\Psi(1-\rho^2))$ and $\mathrm{cov}(\Psi_0, \Psi^*_0) = 0$, vgu_t and z_t are shocks with zero mean and constant variance. In addition, it is assumed that all the disturbances are mutually independent.

In this case, too, the trend was described by a local linear trend, since, although this variable is expected to be stationary, in the sample considered it exhibits a stochastic trend. The cyclical component of degree-of-plant-utilisation was modelled using a stochastic sinusoidal cycle *à la* Harvey and Jaeger (1993).

On inspection of the system, one notes that the model was built in order to display a common cycle: both the value-added and employment cycles were specified as a linear combination of the cyclical component of the degree of capacity utilisation.

The equations system described has been put in state space form[2] in order to solve the model recursively using the Kalman filter. The measurement and transition equations associated with our model are reported in the appendix.

3. Empirical results

To perform our analysis we used quarterly data covering the period 1986:1-2006:4. The industrial output is measured by manufacturing value added at constant prices obtained from the Italian quarterly national accounts. The degree of plant utilisation comes from the quarterly manufacturing business survey carried out by the Italian Institute for Studies and Economic Analysis (ISAE).

Manufacturing employment is measured in terms of standard labour units (i.e. the number of full-time equivalent employed) also obtained from the Italian quarterly national accounts. Standard labour units provide an estimate of full-time equivalent positions in the labour market, based on labour force survey figures for the number of persons employed in the manufacturing sector and for the type of labour market contract (full-time, fixed-term, part-time). This indicator in fact includes information on the number of hours worked. Furthermore, in Italy the number of employees is officially available on a quarterly basis whereas other employment measures (such as hours worked) are obtainable only annually.

The specification of the model is based on the conjecture that the common cyclical component is driven by the degree of plant utilisation: indeed, this variable is one of the determinants of manufacturing labour productivity, along with hours worked and technical progress (Proietti et al. 2007). Consequently, we expected that a substantial part of the cyclical variations in industrial employment and output would depend, in both cases, on the rate of utilisation of fixed capital in the manufacturing sector. On this view, the co-movements between the reference series at

[2]The variable ranking in the state space form was chosen following Koopman et al. (1998).

business cycle frequencies result from the existence of a common cycle.[3] In this framework, the stochastic cycle of the utilisation rate is generated by the ARMA (2, 1) process (reduced form):

$$(1-\phi_1 L-\phi_2 L^2)\psi_t = (1-\rho\cos\lambda_c L)\kappa_t + \rho\sin\lambda_c \kappa_{t-1}$$
$$\phi_1 = 2\rho\cos\lambda_c,\ \phi_2 = -\rho^2$$

and the roots of AR polynomials are a pair of complex conjugates (modulus $1/\rho$ and phase λ_c), for λ_c that moves in the interval $(0, \pi)$.
Trend components are modelled as local linear trends[4]. The model expressed in state space form is estimated applying the Kalman filter and the associated smoothing algorithms, which enable ML estimation and signal extraction (Harvey, 1989)[5].
To obtain reliable parameter estimates we restrict some sources of variation. First of all, the variance of the shock to the slope of the output trend component is fixed at zero (σ_w^2 =0), so that industrial output evolves as a RW with drift in the long run. We test several specifications for the long-run pattern of employment (L_t) in order to reduce the role of business cycle fluctuations in manufacturing employment time series. The variance of the shock to the slope is estimated as being particularly small, a result very close to that of a deterministic trend.[6]
The final estimation results are reported in table 1 in the appendix. The usual diagnostics are performed, and the fit is generally satisfactory. The common cyclical parameters are estimated to be highly significant and hence to support the existence of a common cycle driven by the degree of plant utilisation. The estimate of cycle loading in the output model is $\hat{\phi}_0$ = 0.076; for standard labour units we also allow for a lagged response to common cycle: factor loadings are $\hat{a}_o$ = 0.021 and $\hat{a}_1$ = 0.038.
The estimated degree-of-plant-utilisation cyclical component displays a periodicity of almost 38 quarters, given the estimated frequency λ_c = 0.165; the inference on the dumping factor is given by ρ = 0.87, which is considerably higher than that obtained from standard univariate models. The variance of the shock to the cyclical component of employment and value added is estimated to be zero. In contrast, for the degree-of-plant-utilisation cyclical component, the disturbance variance is estimated to be equal to $\hat{\sigma}_k^2$ = 164.3x10^{-4}.

[3]This approach has recently been adopted in several business cycle studies (e.g. Harvey and Trimbur, 2003; Proietti, Musso and Westermann, 2007; Runstler, 2002).
[4]This specification is such as to reduce to a RW with constant drift if the slope disturbance variance is null and to an integrated RW with damped slope trend in the case of null disturbance variance for the level component.
[5]Computations were performed using state space routines available in the package SsfPack 2.3 (Durbin and Koopman, 2001, Koopman Shephard, Doornik ,1998) for Ox (Doorink, 2006).
[6]The specification of a deterministic linear trend ($\sigma_{vo}^2 = \sigma_u^2$ =0) leads to analogous results, in terms of in-sample goodness of fit, to that of a random walk with drift, even allowing for slope change.

Figure 1 Cyclical components of Value Added, Labour productivity and Standard Labour Units

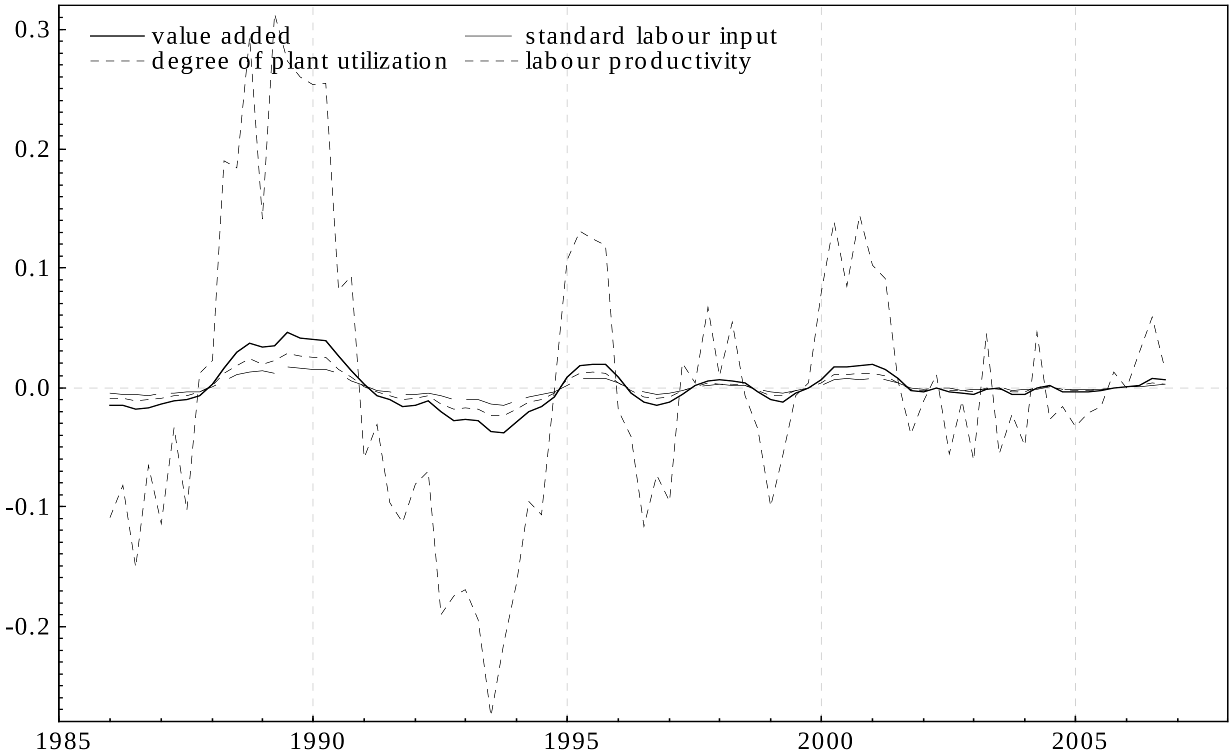

Figure 1 shows the three cyclical components estimated by our model. Specifically, the cyclical and permanent components of labour productivity have been obtained by model estimation. First of all, since the reference variables have been log-transformed, they can be represented as the sum of the corresponding cycle and trend. Overall labour productivity has been obtained as the difference between log(output) and log(employment). Once the multivariate filter has been applied, the labour productivity cyclical component is obtained as the difference between the cyclical components extracted for output and employment, respectively. The same applies in the case of the trend.

The evidence suggests that a large part of the cyclical variation is accounted for by the cyclical features of the degree of plant utilisation, in line with the common cycle setting. Inspection of the graph also reveals a persistent volatility reduction over time in all the cyclical components and shows the existence of a five-year negative cyclical phase in labour productivity during 1990-95, followed by more regular phases of expansion and contraction.

Table 1 Cyclical and trend percentage growth rates of labour productivity in Italy.
Period: 1986Q1-2006Q4.

	1986-89	1990-94	1995-99	2000-06
Actual	2.75	2.57	0.04	-0.29
Cyclical	0.85	-0.59	-0.29	-0.10
Trend	1.95	3.09	0.33	-0.19

Average annual growth rates.

Table 1 reports the annual mean growth rates of labour manufacturing productivity and its estimated components. The results show that labour productivity growth deteriorated progressively over time. In particular, after positive increases in the period 1986-94, growth was zero (0.04%) in 1995-99 and has become negative in the more recent years (2000-06). Looking at the trend/cycle decomposition of the productivity growth rate, one notes that the average annual growth of the productivity cyclical component, which was still positive in 1986-99, becomes negative in the period 1990-94 (-0.6%) and also in the more recent period (2000-06), although less negative in this latter case.
The annual growth of the labour-productivity trend component appears to have been positive in the periods (1986-89) and (1990-94), with average growth of 1.95% and 3.09 % respectively. The trend growth dynamic falls sharply in 1995-99 (0.3%) and becomes negative in 2000-06 (-0.2%). Hence, in the more recent period, structural factors (institutional reforms) have also played a substantial role in explaining the performance of the Italian manufacturing sector.

4. Conclusions

This paper analyses the main changes in labour productivity in the manufacturing sector over the last decades. In particular, we have focused on changes in the relative importance of cyclical and structural factors in Italian labour productivity dynamics.
In order to decompose total labour productivity into trend and cyclical components, we apply a multivariate unobserved component model with common cycle specification *à la* Clark.
According to our findings, labour productivity growth during the period 1986-89 emerges as the effect of a combination of positive trend and cyclical annual growth rates. Labour productivity growth during 1990-94 appears instead to be due to a stronger role of trends and to a negative contribution of the cyclical component growth rates. The results also indicate that the labour productivity deceleration in the period 1995-99 was caused by a trend deceleration and to a negative cyclical component annual growth rate (-0.29%). By contrast, in the most recent period (2000-06), the labour productivity reduction seems to be due mainly to a decline in both trend and cyclical components. This evidence indicates that, in addition to transitory shocks, structural factors (institutional reforms) have also played a significant role in determining the performance of the Italian manufacturing sector.

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Appendix 1

State space form of the system:

$$\begin{bmatrix} y_t \\ O_t \\ GUC_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \alpha_0 & \alpha_1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} n_t \\ L_t \\ GUT_t \\ g_t \\ \delta_t \\ \beta_t \\ \psi^*{}_t \\ \psi_t \\ \psi_{t-1} \end{bmatrix} + \begin{bmatrix} ey_t \\ eo_t \\ 0 \end{bmatrix}$$

Corresponding Transition equation:

$$\begin{bmatrix} n_t \\ L_t \\ GUT_t \\ g_t \\ \delta_t \\ \beta_t \\ \psi^*{}_t \\ \psi_t \\ \psi_{t-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho\cos\lambda_c & -\rho\sin\lambda_c & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho\sin\lambda_c & \rho\cos\lambda_c & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} n_{t-1} \\ L_{t-1} \\ GUT_{t-1} \\ g_{t-1} \\ \delta_{t-1} \\ \beta_{t-1} \\ \psi^*{}_{t-1} \\ \psi_{t-1} \\ \psi_{t-2} \end{bmatrix} + \begin{bmatrix} v_t \\ vo_t \\ vgu_t \\ w_t \\ u_t \\ z_t \\ k^*{}_t \\ k_t \\ 0 \end{bmatrix}$$

Appendix 2

Figure 1 Degree of plant utilisation

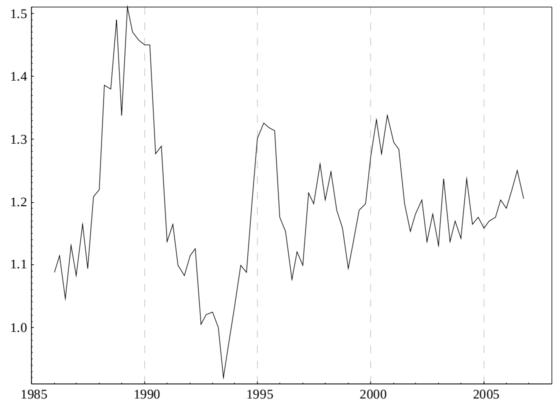


Figure 2 Manufacturing standard labour units

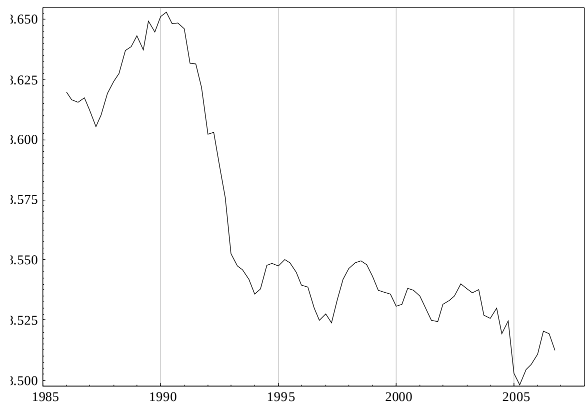


Figure 3 Manufacturing value added

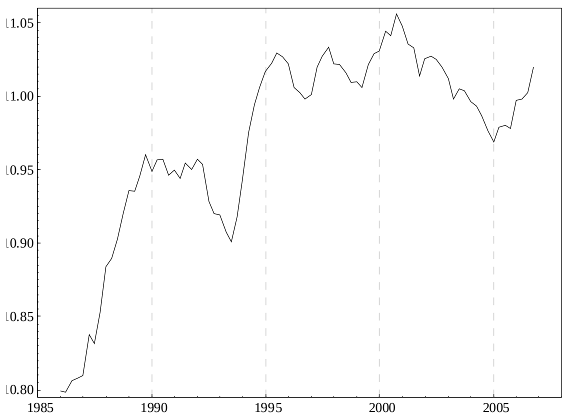
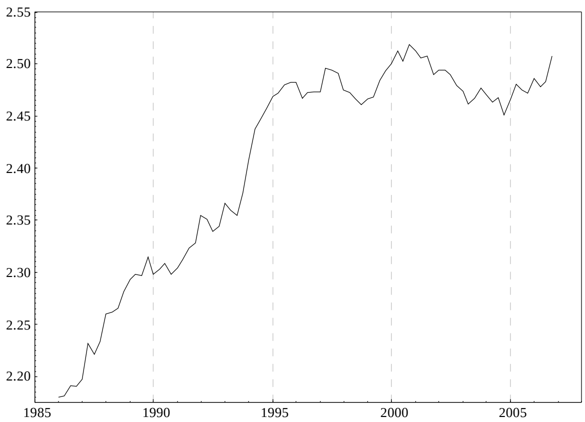


Figure 4 Manufacturing labour productivity



Source: Istat

Table 2: Parameter estimates and diagnostics for tri-variate UC model of Manufacturing Value Added (Y), Employment (O), and Degree of Plant Utilisation (GU). Period: 1986.1-2006.4

	Value	Standard error
Value added equation		
σ_v^2	0.907	
σ_w^2	0	(restricted)
σ_{ei}^2	0	
ϕ_0	0.076	(0.015)
Employment equation		
σ_{vo}^2	0.404	
σ_u^2	0	
σ_{eo}^2	0	
a_o	0.021	(0.010)
a_1	0.038	(0.010)
Degree of plant utilisation		
σ_{vgu}^2	22.23	
σ_z^2	0	
σ_k^2	164.31	(conc)
ρ	0.869	(0.103)
λ_c	0.165	(0.100)
$2\pi / \lambda_c$	38.14	
Diagnostics (*p*-values)		
N	84	
LogLik	655.6	
Q(8) (value added)	0.4189	
Q(8) (employment)	0.1419	
Q(8) (utilisation rate)	0.0010 (**)	
Normality (value added)	0.3144	
Normality (employment)	0.0461	
Normality (utilisation rate)	0.4765	
Q(8) (model)	0.0000 (**)	
Normality (model)	0.0462	

*: significant at 5%; **: significant at 1%
(§): variance parameters are multiplied by 10^4. '(conc)' denotes that the corresponding parameter has been concentrated out of the likelihood. Q(*p*) is the univariate/multivariate portmanteau test for residual autocorrelation, Normality is the Bowman and Shenton normality test.