The decline in Italian productivity: a study in estimation of long-Run trends in Total Factor Productivity with panel cointegration methods

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Abstract

The aim of this paper is (*i*) to propose a method for obtaining estimates of long-run total factor productivity (TFP) trends free from the restrictive assumptions needed by traditional growth accounting, requiring only data on inputs and output flows, and able to deliver estimates of long-run TFP trends; (*ii*) to apply it to the Italian manufacturing industries over the period 1980-2001, so to shed some light on the severe productivity slowdown of the last decade. The approach proposed relies on recent developments in the analysis of non-stationary, cross-correlated panels. The empirical application, consistently with growth accounting, supports the view that the decline in Italian labour productivity has been mostly due to a widespread fall in TFP growth. A simple regression points as main causes to the completion of a factor reallocation process among industries and inadequate R&D investment.

Keywords: Labour Productivity, Productivity Slowdown, Italy, Panel Cointegration.

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1 Introduction[1]

The growth of labour productivity in Italy in the past decade has been abysmal, the poorest in Europe together with Spain[2]: from 1995 to 2004, per worker GDP growth was barely 1.3% per annum; from 2000 onward the pace declined to around 0.5%. Such a poor performance raises a fundamental question: is the productivity slowdown due to a fall in capital intensity in the Italian economy, perhaps linked to a change in factor prices vis-à-vis the Eighties (a movement along the isoquant), or is it due to a decline in total factor productivity (a shift in the isoquant)? The answer is clearly very important from a policy perspective. In fact, should the productivity slowdown (consistently with the observed upsurge in employment in the last decade), simply be a consequence of a re-adjustment in the factor mix, there should be no concern. The phenomenon could be seen as a market-driven reaction to an excessive capital intensity of the past. On the other hand, if the problem lies in total factor productivity (henceforth TFP), two possibilities arise: either the slowdown reflects the exhaustion of the "quality adjustment" component, linked to reallocation across industries, labour skills or capital vintages (see the literature dating back to Denison, 1967, and Matthews *et al.*, 1982); or it reflects a decline in pure (disembodied) technological progress, due, say, to fewer research, development and innovation. The latter hypothesis is of particular concern to policy-makers, as it would result in a prolonged competitiveness gap of the Italian industry vis-à-vis other countries, especially within the single currency area. A number of studies have tackled the question: see for instance Bassanetti, Iommi, Jona-Lasinio and Zollino (2004), henceforth BIJZ, and Daveri and Jona-Lasinio (2005). The common conclusion is that most of the decline in productivity since 1995 is due to the decline in TFP. Although there has been some reduction in capital deepening in the period, this has been compensated by an increase in the share of capital in the economy-wide value added. For instance, Daveri and Jona-Lasinio (2005) estimate that 1 out of the 1.2 percentage points reduction in labour productivity growth with respect to the period 1980-95 is accounted for by the decline in TFP in the

[1]The first author acknowledges financial support from University of Rome "La Sapienza" and MIUR. We would like to thank Riccardo Cristadoro and Andrea Brandolini for kindly providing the series of the Bank of Italy Capacity Utilisation Index and Human Capital Index, and Carlo Altomonte, our discussant at the Turin February 2007 CNR Meeting of international economics, for very helpful comments and suggestions. The usual disclaimers apply.

[2]*Inter alia*, Daveri and Jona-Lasinio (2005). For a very recent assessment based on the Groeningen dataset see Conference Board (2007).

overall economy.

Hence, TFP estimation becomes crucial. The debate on this issue was recently revived in a series of papers (see Kee, 2004, and the references cited therein). However, these papers are mostly addressed at comparing the so-called primal and dual growth accounting methods, while the key point is that, as put by Stiroh (2002): "While growth accounting provides a valuable and well-tested means for understanding the proximate sources of growth, additional tests are needed to corroborate those results" (p. 1559). In fact, growth accounting relies on the assumptions of constant returns to scale and perfect competition in both the products and factors markets, hypothesis respectively not guaranteed and very unlikely to hold. Kee (2004) adds an important contribution to the literature by developing a more general approach based upon a structural model requiring neither perfect competition nor constant returns to scale. Although more general than standard growth accounting, his approach restricts the degree of market power to be constant over time. Further, the analysis carried out on first differences, thus leaving open the question on long-run TFP trends.

Summing up, a method for obtaining estimates of TFP long-run trends without overly restrictive assumptions on technology and market structure seems still to be missing. In this paper we address precisely this issue. More precisely, following a largely novel non-stationary panel approach we will examine recent labour productivity patterns in the Italian manufacturing industry and obtain estimates the underlying aggregate TFP trend valid under very general hypothesis on the diffusion of technical progress across industries. Using these estimates we will then (*i*) estimate a simple model relating TFP growth to factors reallocation across industries and factor quality dynamics, and (*ii*) estimate disaggregate production functions and test whether the elasticity of substitution between capital and labour is different from one, an hypothesis of considerable interest for the discussion on the proximate causes of the productivity slowdown[3]. As we will see in more detail below, a non negligible advantage of the proposed approach is that, differently from both standard growth accounting and Kee's structural approach, no information on the rental price of capital is required.

The paper is organised as follows: we shall first examine the data (section 1), then move to modelling issues (section 2, with the technical details of the bootstrap algorithms employed described in the Appendix). Some

[3]Unit elasticity of substitution implies constant factor shares, at least in the long-run. Hence, a labour productivity slow-down would not be surprising in view of the slowdow in in real wages growth which took place in the last decade in Italy.

conclusions will finally be drawn (section 3).

2 What do the Disaggregate Data Say? Productivity, Output, Labour and Capital Trends in Italian Manufacturing Industries, 1980-2001

First of all, let us review the data evidence. Since we will estimate a single TFP trend we will limit the analysis to the Subsections included in the NACE Sections "Mining and Quarrying" (C), "Manufacturing" (D) and "Electricity, Gas and Water Supply" (E, henceforth "Utilities"; the NACE classification with all the abbreviations used as well as, for reference's sake, the average value added shares and capital/labour ratios of all industries, are reported in the Appendix). Agriculture and Market Services, technically far too heterogenous, and, as far as the latter is concerned, plagued by serious productivity measurement problems, have been excluded. As data on Capital are available from 1980, a peak year according to almost all dating methods (Bruno and Otranto, 2003), until 2001, we will examine the period 1981-2001.

The log plots of the aggregate level trends (Fig. 1 left column) tell an apparently rather clear story: Labour Productivity[4], Value Added and Capital/Labour[5] ratio grew more or less steadily, while employment followed an opposite, declining trend. However, looking at the right column of the same figure we can notice that in fact the rates of growth of both labour productivity and capital/labour ratio kept falling throughout the period, while, on the contrary, employment growth accelerated over the last years of the sample.

As it can be appreciate from Figs. 2A-B and Table 1 the aggregate globally positive trend in labour productivity is mirrored in all industries except Energy Mining and Coke, two industries of negligible size[6]. Although

[4]Defined as Value Added per Labour Unit, which is the implementation of the ESA95 concept of full time equivalent employee adopted by Istat, the Italian statistical agency.

[5]Capital rescaled by the Bank of Italy Utilisation Index. Because of the lower detail of the latter in the disaggregate analysis the following approximations have been introduced: (i) the index for "Leather and Textiles" has been used for both the Textile and the Leather industries; (ii) the economy-wide index has been used for the Non metals and the Utilities.

[6]On the average over the period of interest they accounted for 0.16% of the labour inputs used in the entire Italian economy, 0.7% of the Mining, Manufacturing and Utilities aggregate. Considering also that in both cases Value Added fell sharply, while Employment was kept artificially high as a consequence of trade unions and political pressure, we decided to exclude both industries from the main empirical analysis which will follow.

Employment trends are rather varied across industries, growth in the late 1990's has almost in all cases faster (or decline slower) than in the 1980's, with the only exception of the three industries where productivity growth did not fall between the two periods[7]. The negative partial correlation between Labour Productivity and Employment growth suggested by the inspection of the aggregate time series is clearly visibile from the cross-plot of the average rates of growth (Fig. 4), which closely matches that for the EU reported by Daveri (2004).

Differently from what discussed so far, the dynamics of Capital/Labour ratios is rather heterogenous across industries. In fact, average annual rates of growth of Capital endowments per Labour Unit have been higher in the second part of the sample in almost half of the industries. As a consequence, judging from the cross-plot of the disaggregate average rates of growth the partial correlation between the growth in the Capital/Labour ratio and that of Labour Productivity does not appear as obvious as from the aggregate time series. Looking at Fig. 3, we can see that if we exclude the Chemical and Energy industries, outliers for opposite reasons, the correlation is clearly positive. On the other hand, if we treat the Electrical and Transport Equipment industries (which lay at the upper right corner of the plot, with strong positive growth of both Capital/Labour ratio and Labour Productivity) as outliers the impression is of no correlation: an entire range of Labour Productivity growth rates (from slightly negative to strongly positive) is compatible with approximately similar rates of growth of Capital/Labour ratios. The lack of a clearly discernible pattern in the correlation across industries between labour productivity and Capital/Labour ratio dynamics rules out all trivial explanations of former as a mere consequence of the latter. A careful analysis of total factor productivity trends is clearly required.

Before moving to the modelling issue, let us discuss the time series properties of the series. The general impression is obviously of non-stationarity; given the small time sample in order to run a formal test we need to use a panel unit root test, and since the units are obviously not independent it must be robust to cross-correlation. A procedure which appears to be both simple and powerful is Pesaran (2006) CIPS test, which is essentially an average of the Dickey-Fuller tests computed for the individual units (*i.e.*, the popular test by Im, Pesaran and Shin, 2003) augmented with the cross-section means. The results, reported in Table 3, are largely in favour of the

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[7] "Other Manufacturing" and Utilities, where at the end of the 1980's a phase of growth followed a decade of stagnation, and the Transport industry.

unit root hypothesis thus confirming the graphical evidence.

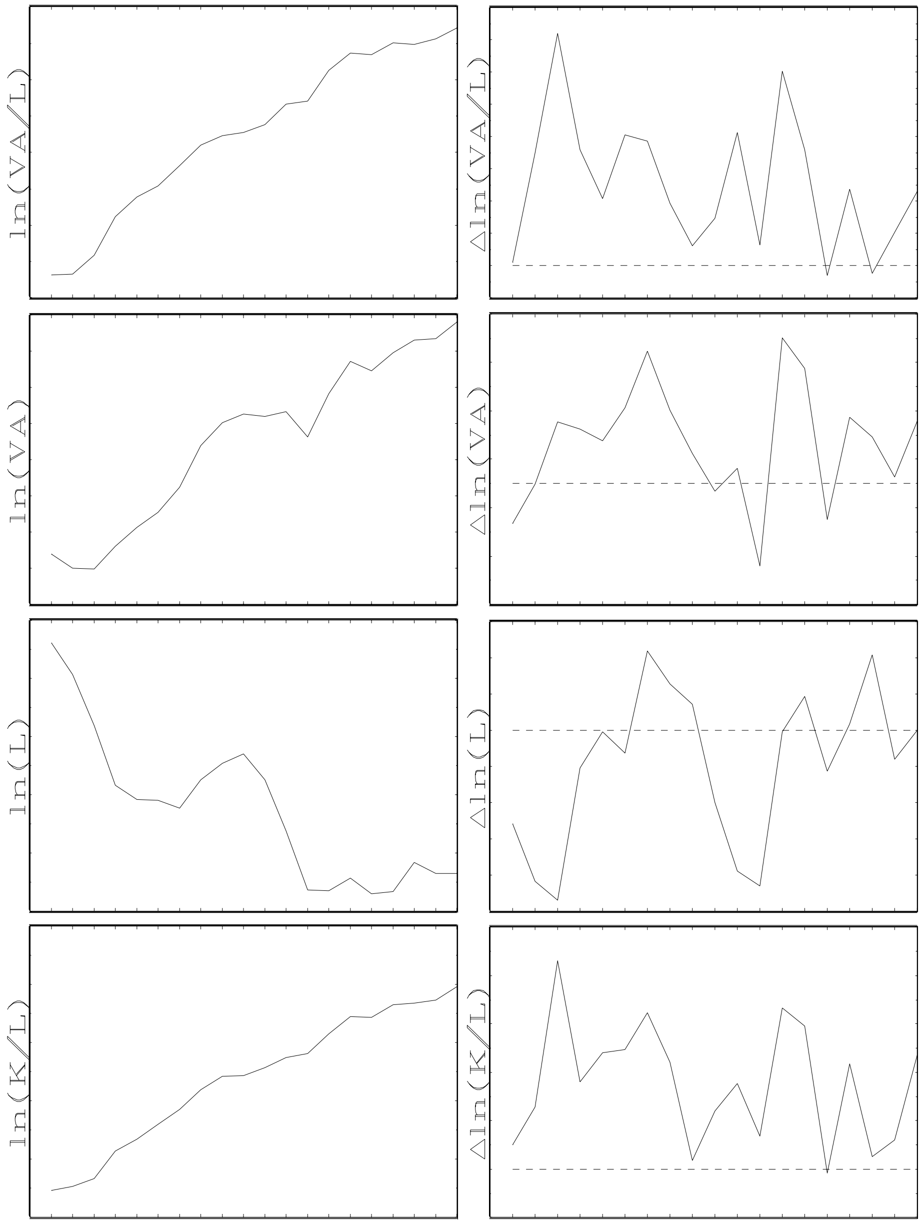

Fig. 1. Mining, Manufacturing and Utilities, 1981-2001. Top to bottom: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit. Left: logs; right: $\Delta \log$. Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy

Capacity Utilisation Index .

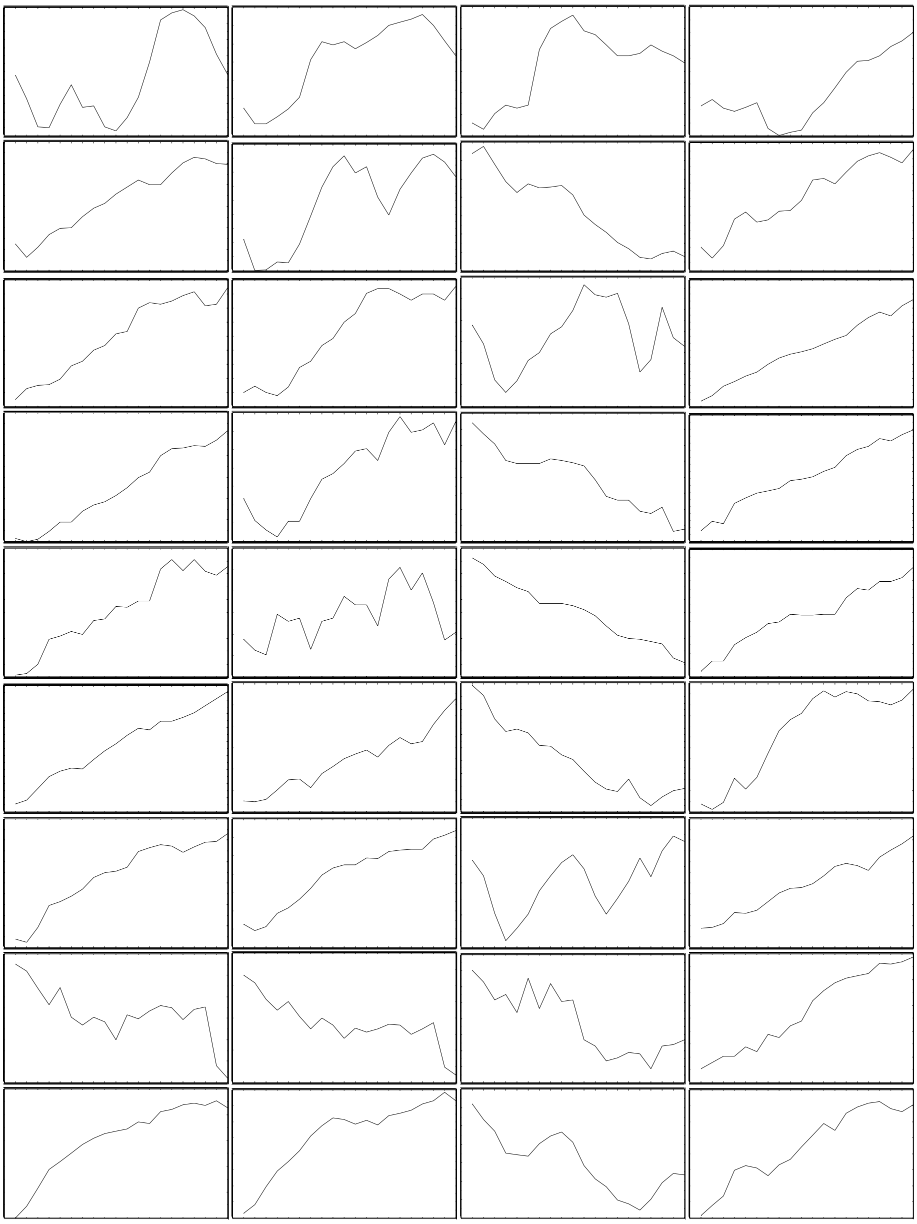

Fig. 2A. Columns, left to right: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit, 1981-2001 (logs; Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy Capacity Utilisation Index); rows, top to bottom: [1] Energy [2] Non-Energy [3] Food [4] Textiles [5] Leather [6] Wood [7] Paper [8] Coke [9] Chemicals (abbreviations: see table A1).

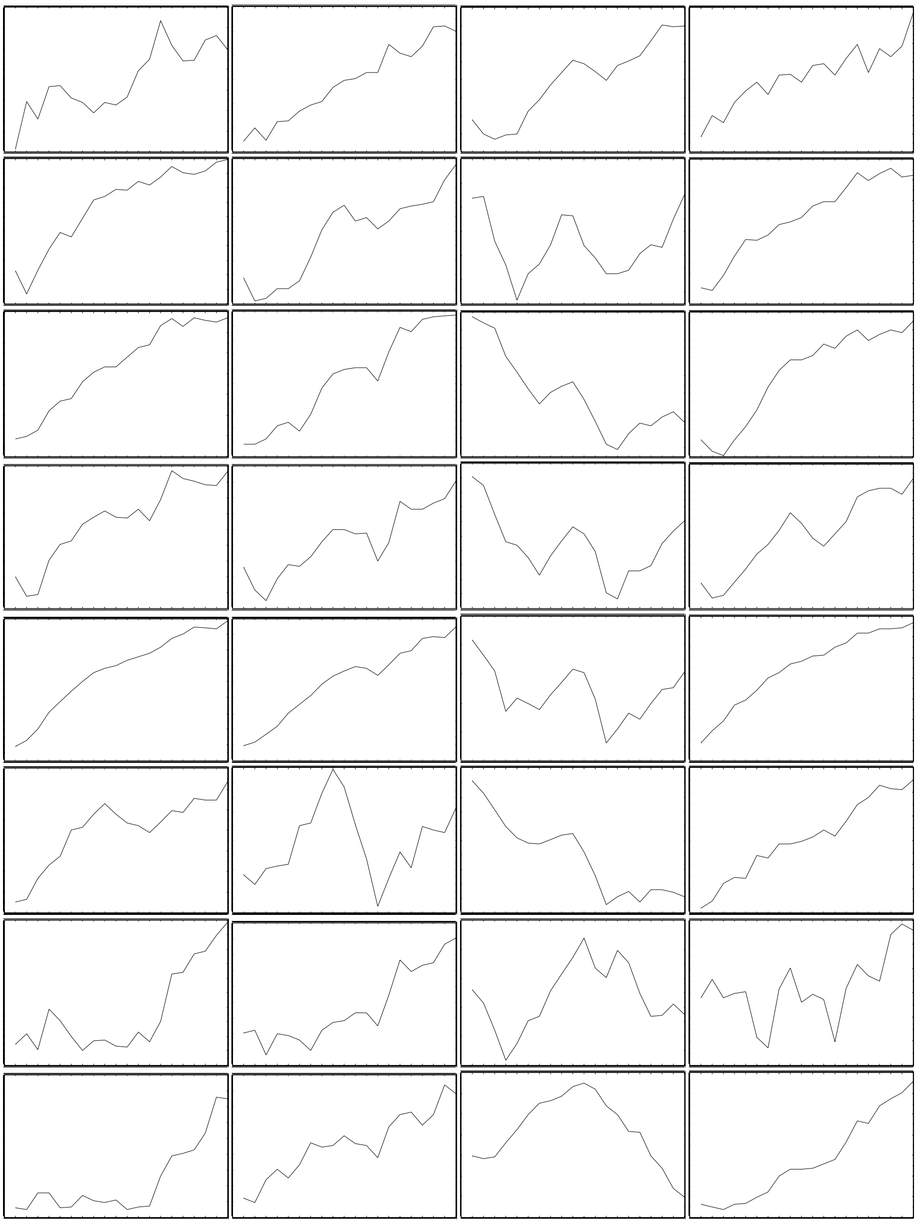

Fig. 2B. Columns, left to right: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit, 1981-2001. (logs; Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy Capacity Utilisation Index); rows, top to bottom: [1] Rubber [2] Non-metals [3] Metals [4] Machinery [5] Electricals [6] Transport [7] Other [8] Utilities (abbreviations: see table A1).

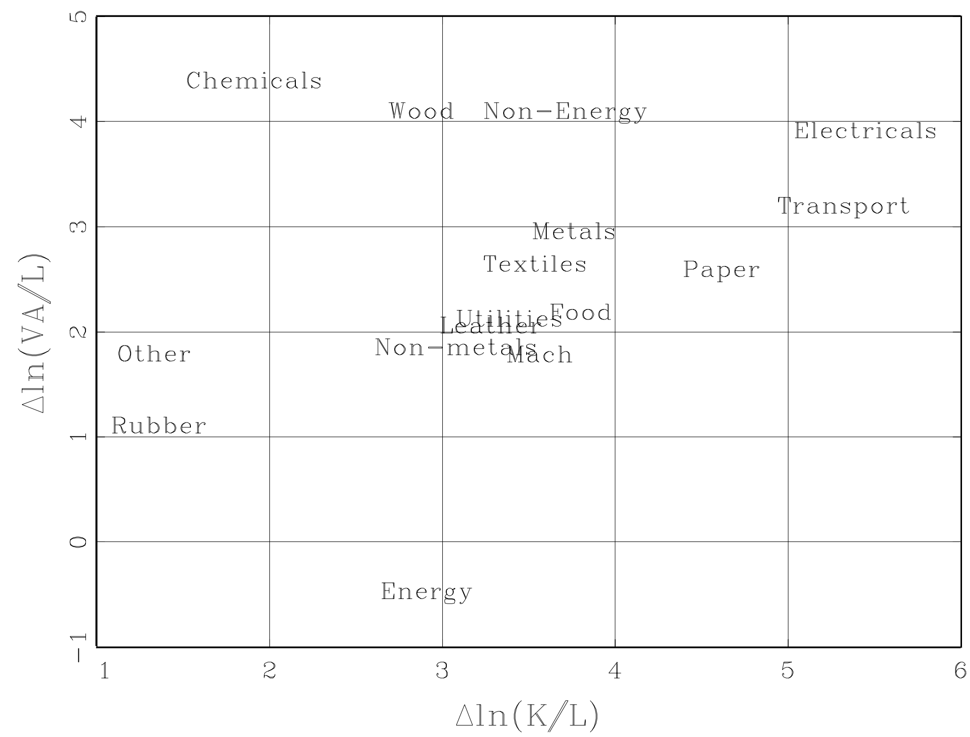

Fig. 3. Annual average rates of growth×100 of Capital per Labour Unit (K/L) and Value Added per Labour Unit (VA/L), 1982-2001 (Industries abbreviations: see table A1). Coke excluded to improve readibility.

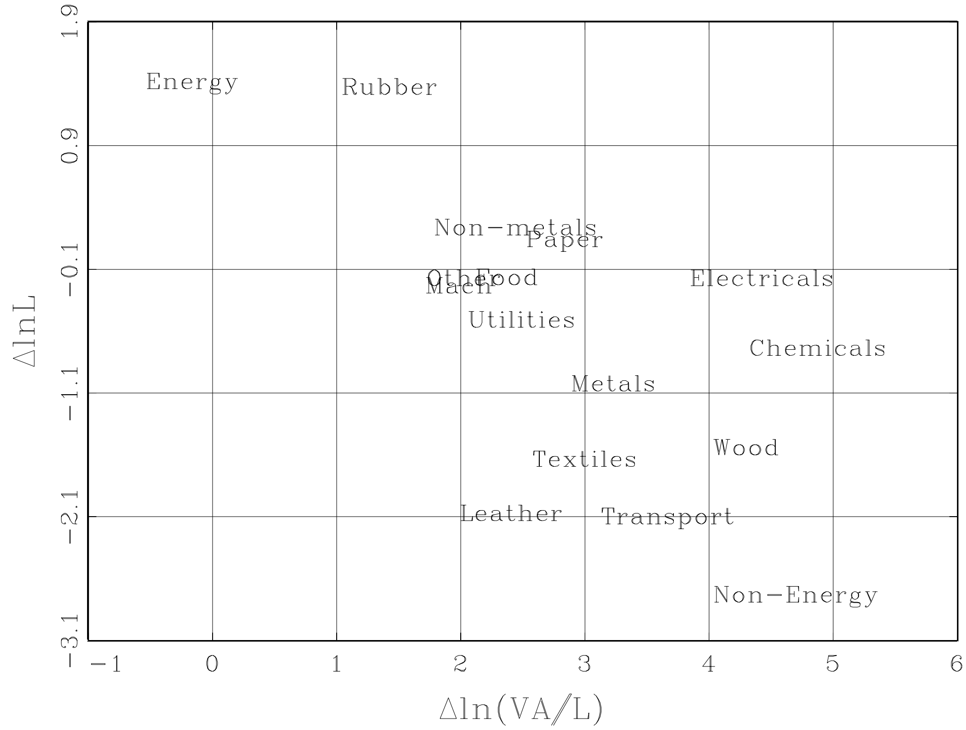

Fig. 4. Annual average rates of growth×100 of Value Added per Labour Unit (VA/L) and Labour Units (L), 1981-2001 (Industries abbreviations: see table A1).

Table 1
Labour Productivity, Value Added, Labour and Capital
in the Italian Mining, Manufacturing and Utilities Industries, *1982-2001*
Average annual rates of growth×100

	VA per Labour Unit		Value Added		Labour Units		Capital per Labour Unit	
	82-95	96-01	82-95	96-01	82-95	96-01	82-95	96-01
Energy	1.1	-5.3	3.3	-6.3	2.2	-1.0	2.4	5.0
Non-Energy	5.3	0.6	1.3	0.7	-3.7	0.1	3.9	0.7
Food	2.5	1.0	2.2	0.9	-0.3	0.0	4.0	3.9
Textiles	2.8	1.8	1.0	0.4	-1.8	-1.3	4.1	2.7
Leather	2.7	-0.3	0.6	-2.5	-2.1	-2.3	3.4	3.5
Wood	4.2	3.6	1.8	4.1	-2.3	0.5	3.3	1.0
Paper	2.7	1.9	2.8	2.2	0.0	0.3	3.7	7.7
Coke	−3.4	-6.3	-4.7	-6.0	-1.4	0.3	5.1	3.0
Chemicals	6.0	-0.5	4.4	0.9	-1.5	1.4	2.4	-0.1
Rubber	1.1	0.8	2.3	2.4	1.2	1.6	0.9	2.6
Non-metals	2.3	0.3	1.7	2.9	-0.6	2.6	3.5	0.2
Metals	3.7	0.5	2.1	0.9	-1.6	0.4	3.7	2.2
Machinery	2.1	0.6	1.2	2.0	-0.9	1.4	3.5	2.1
Electricals	4.8	0.9	4.1	2.2	-0.7	0.2	7.3	1.8
Transport	3.0	3.7	0.1	3.2	-2.7	-0.4	6.3	2.9
Other	1.3	2.9	1.3	2.0	0.0	-0.8	0.6	4.4
Utilities	1.2	4.8	1.5	1.5	0.3	-3.1	2.6	4.8
Aggregate	2.9	1.1	1.7	1.4	-1.2	0.3	3.8	2.7

VA: Value Added at 1995 prices; 1 Labour Unit = 1 full time employee;
Capital: Gross Capital at 1995 prices rescaled by the Bank of Italy capacity utilisation index;
Labour Unit: full time equivalent employed person;
Breakpoint: fixed at 1995, a peak year according to all dating methods (Bruno and Otranto, 2003).
Source: Istat, *Conti economici nazionali 1970-2004*.

Table 2
Labour Productivity, Labour and Capital/Labour ratio
Panel Unit Root Tests 1981-2001

	VA per Labour Unit	Labour Units	Capital per Labour Unit
$CIPS^C$	-1.43	-0.64	-1.81
$CIPS^T$	-1.70	-1.52	-1.65

CIPS: truncated mean of the individual ADF statistics augmented with cross-section means; panel: all industries of the Mining, Manufacturing and Utilities Sections except Energy Mining and Coke ($N = 15$).
$CIPS^C$: CIPS statistic with constant;
$CIPS^T$: CIPS statistic with constant and trend.
Critical values ($T = 20$, $N = 15$):
constant : $5\% - 2.26; 10\% - 2.14$;
trend: $5\% - 2.78; 10\% - 2.67$.

3 Modelling Labour Productivity

Although the economic analysis of productivity is well-known (to say the least) we shall briefly review some basic concepts in order to establish notation.

We are interested in Labour Productivity trends in a panel of N industries over T time periods. Since data on intermediate inputs are not available we measure production by Value Added (Y), rather than the theoretically preferable Gross Output. Denoting by F_i a generic production function for industry i, by L and K, as usual, respectively labour inputs and capital, by P a time-dependent factor capturing Hicks-neutral technical progress, we are essentially interested in estimating the function $Y_{it} = P_{it}F_i(L_{it}, K_{it})$. Since capital-labour substitution is a central issue a Cobb-Douglas specification, which assumes elasticity of substitution equal to 1, is out of question. Some experimentation with the Translog, the most general production function, delivered unsatisfactory results, with erratic and imprecise coefficient estimates likely to be due to multicollinearity problems. The only viable option thus seems to be the well-known Kmenta (1967) linearisation of the CES around the point implying capital-labour elasticity of substitution equal to

1:

$$y_{it} = \alpha_i + p_{it} + \beta_{0i} l_{it} + \beta_{1i} k_{it} + \beta_{2i}(k_{it} - l_{it})^2 + \varepsilon_{it} \qquad (1)$$

where lower-case letters indicate logs and α_i is a scale parameter. Subtracting log labour inputs from both sides of (1) and rearranging we finally obtain an equation for log labour productivity (π) under CES technology with unconstrained returns to scale:

$$\pi_{it} = \alpha_i + p_{it} + (\beta_{0i} + \beta_{1i} - 1) l_{it} + \beta_{1i}(k_{it} - l_{it}) + \beta_{2i}(k_{it} - l_{it})^2 + \varepsilon_{it}. \quad (2)$$

The CES with constant returns to scale and the Cobb-Douglas may be readily obtained from (2) excluding respectively the labour and squared capital-labour ratio terms.

Before examining in detail the issue of technical progress two points must be discussed. First, although (2) allows for an elasticity of substitution different from 1, the linearisation is valid only for small deviations from this value. Thus, although estimates of the elasticity of substitution very distant from 1 have been reported in the literature (for instance, the coefficients estimated by Duffy and Papageorgiu, 2000, implie an elasticity of substitution close to 2.5) the results obtained must be interpreted with great care. Estimated elasticities close to 1 should be regarded as inconclusive, rather than supporting the Cobb-Douglas hypothesis.

Second, since, as we will see below, capital per labour unit is non-stationary the presence of its square brings us into the domain of asymptotics for non-linear transformations of integrated series. Fortunately, things turn out to be very simple, as Park and Phillips (1999) showed that with functions such as the square power of interest here we may expect the OLS estimator to be consistent and mixed normal as in the usual linear cointegrating regression.

Let us now move to technical progress, represented in (2) by the term p_{it} which can be described as a "technology shift parameter" (Mahony and Vecchi, 2003) or a "total factor productivity [TFP] index" (Harrigan, 1999). While in pure time series modelling a functional form for p_{it} must be specified *a priori,* exploiting the panel structure of the data we can obtain unconstrained estimates.

Similarly to Kee (2004), we assume the log TFP index, p_{it}, to admit a decomposition into a possibly non-stationary common factor (θ_t), a stationary common random component with zero conditional mean (γ_t) and a stationary industry proportionality factor (ψ_{it}). The first component measures general technical progress, the second captures random shocks hitting all industries, and the latter the different rates of adoption of this general technical progress in the various industries (fast growing, high technology industries will typically have $\psi_{it} > 0$, while mature industries $\psi_{it} < 0$). Then:

$$p_{it} = \theta_t + \gamma_t + \psi_{it} \tag{3}$$

Writing the industry factor as $\psi_{it} = \overline{\psi}_i + \psi_{it}^{'}$, where $\overline{\psi}_i$ is the mean industry (log) shift factor and $\psi_{it}^{'}$ a mean zero random error, and substituting into (2) we obtain:

$$\pi_{it} = \alpha_i' + (\theta_t + \gamma_t) + (\beta_{0i} + \beta_{1i} - 1)l_{it} + \beta_{1i}(k_{it} - l_{it}) + \beta_{2i}(k_{it} - l_{it})^2 + \varepsilon_{it}'. \tag{4}$$

where $\alpha_i' = \alpha_i + \overline{\psi}_i$ and $\varepsilon_{it}' = \varepsilon_{it} + \psi_{it}^{'}$, with the two random errors ε_{it} and $\psi_{it}^{'}$ assumed to be orthogonal.

In order to estimate model (4) we need to find an empirical counterpart for the unobserved technical progress variable component, θ_t. As mentioned above, exploiting the panel structure of the data this turns out to be a relatively simple task. Define a set of time dummies $D_\tau = 1$ if $t = \tau, 0$ else, $t = 2, \ldots, T$ (one of the time periods must be excluded to avoid singularity); an heterogenous panel long-run model of labour productivity based on (4) including common time dummies is given by:

$$\begin{aligned} \pi_{it} &= \delta_i + \gamma_{0i} l_{it} + \gamma_{1i}(k_{it} - l_{it}) + \gamma_{2i}(k_{it} - l_{it})^2 + \varphi_t D_t + e_{it} && (5) \\ t &= 1, 2, \ldots, T,\ i = 1, 2, \ldots, N && (6) \end{aligned}$$

Note that the panel is highly heterogeneous: fixed effects are included, and factor elasticities allowed to vary across industries; only the coefficients of the time dummies, $\boldsymbol{\varphi} = [\varphi_2 \varphi_3 \ldots \varphi_T]$, are common to all industries. Hence, they measure the shifts in labour productivity which in every period cannot be explained by changes in Capital/Labour ratio and, when $\gamma_{0i} \neq 0$ so that returns to scale are different from one, changes in scale of production, thus corresponding precisely to the term $(\theta_t + \gamma_t)$ in model (4). At this point, to obtain an estimate of the Hicks-neutral trend in TFP we only need to recall that the assumptions underlying (3) imply $\theta_s = E(\varphi_s | t = s):$ an estimate of $\boldsymbol{\theta} = [\theta_2 \theta_3 \ldots \theta_T]$ can thus be simply recovered from a non parametric regression of $\boldsymbol{\varphi}$ on a linear time trend.

Summing up, our identification hypothesis is that technical progress can be decomposed as $p_{it} = \theta_t + \gamma_t + \psi_{it}$, with the components such that:

(*i*) $\psi_{it} = \overline{\psi}_i + \lambda_{it}$, where the error λ_{it} only needs to be orthogonal to the error ε_{it} of the CES equation;

(*ii*) $E(\theta_t + \gamma_t) = \theta_t$.

Clearly, correlation between the common shocks γ and the TFP trend θ would make identification of the later impossible.

Since all variables included in (5) should generally be expected, and indeed in our case are, non-stationary, the equation should be estimated by some suitable estimation method, such as *e.g.*, FM-OLS, and the existence of cointegration tested. However, the estimation of the long-run covariance matrix is practically unfeasible (Pedroni, 1997) unless the time dimension is significantly larger than the cross-section dimension. This is definitely not the case for our 1981-2001 panel of the Manufacturing Industries: $T = 22$, $N = 17$. We then propose to follow the mixed approach applied by Fachin (2007), which involves OLS-based panel cointegration testing coupled with single industry FM-OLS model estimation, with technical progress extracted from OLS panel estimates. More precisely, the approach proposed is the following:

- *TFP extraction.*

1. estimate equation (5) by OLS; let $\widehat{\boldsymbol{\varphi}}$ be the OLS estimate of the vector of the coefficients of the time dummies.

2. compute the Nadaraya-Watson estimator of the regression curve of $\widehat{\boldsymbol{\varphi}}$ on a time trend and obtain the smoothed coefficients $\widetilde{\boldsymbol{\varphi}}$. These are our estimates of the common TFP trend.

- *Estimation of the production functions.*

3. compute the deviations of labour productivity ($\widetilde{\pi}_{it}$) from the smoothed coefficients $\widetilde{\boldsymbol{\varphi}}$: $\widetilde{\pi}_{it} = \pi_{it} - \widetilde{\varphi}_t$; hereafter we will refer to $\widetilde{\pi}_{it}$ as "detrended labour productivity";

4. compute OLS-based panel cointegration tests for model (5); details of the test are given in the Appendix;

5. estimate the equations $\widetilde{\pi}_{it} = \delta_i + \gamma_{0i} l_{it} + \gamma_{1i}(k_{it} - l_{it}) + \gamma_{2i}(k_{it} - l_{it})^2 + e_{it}$ separately for each industry by FM-OLS.

It is worth remarking that, as mentioned in the Introduction, following this approach to obtain a set of TFP estimates we only need data on inputs and output flows. Information on the rental price of capital, always less reliable than these basic flow data and often not even available, is not required.

The estimated and smoothed general[8] TFP trend (obviously non-stationary: for the smoothed series, $ADF = -2.12$, largely in the non-rejection region) and its log difference are plotted respectively in the top and bottom panels of Fig. 5; smoothing has been carried out using a Gaussian kernel and Silverman (1986) bandwidth. From these estimates TFP growth appears substantial (on the average, about 2.8% a year), but declining: from a peak of 3.8% a year in the second half of the 1980's to 1.8% a decade later. It should be remarked that these are estimates of long-run TFP growth, which, contrary to those obtained through by growth accounting, may well be higher than actual productivity growth. With this caveat in mind we can examine Fig. 6, where the average growth of Value Added per labour unit, our estimates of TFP growth and those obtained by growth accounting by BIJZ are compared[9].

The first remark in order is that the estimates of TFP growth from the panel regression are indeed systematically higher than the growth accounting ones. Second, the growth of Value Added per Labour Unit appeared to be lower than the panel estimates of long-run TFP growth in the second half of both the eighties and the nineties, when it was nevertheless less than half that of the former. In fact, the decline of long-run TFP growth rates since the mid-1980's is striking, even more than that of those obtained by growth accounting (which were indeed slightly higher in the second half of the 1980's than in the first half). In order to carry out a more meaningful comparison between the two sets of estimates we centred each on its average (Fig. 7) and computed the changes in the average growth rates from one period to the next (Fig. 8).

The results are in both case striking. Following an entirely different method which does not require the restrictive assumptions of growth accounting, we end up drawing an essentially similar picture of TFP growth patterns in the 1980's and 1990's: close to the average of the period in the early 1980's, then accelerating to reach levels above it in the mid-1980's, decelerating but still above average in the early 1990's, finally since the

[8] Except Energy Mining and Coke, which have been excluded from the panel.

[9] A further note of caution is dictated by the fact that BJIZ analysis covers the entire manufacturing sector, while we excluded Energy Mining and Coke.

mid-1990's falling severely to rates strongly below the period average. The evidence suggesting that TFP growth has been declining since the mid-90's thus appears to robust to the estimation method adopted.

Fig. 5. Estimated (time dummies from OLS panel regression) and smoothed general trend in technical progress. Top panel: level; bottom

panel: rates of growth×100.

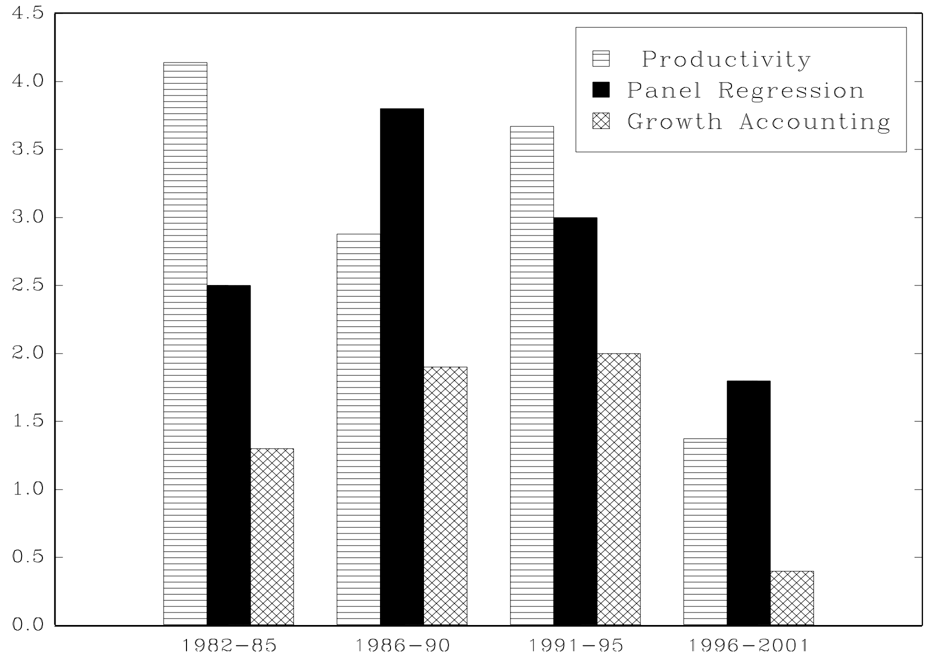

Fig. 6 - Average growth rates×100 of Labour Productivity and estimated TFP. Labour Productivity: Value Added per Labour Unit, all Manufacturing industries except Energy Mining and Oil. Growth accounting: entire Manufacturing Industry, own calculations on estimates by Bassanetti, Iommi, Jona-Lasinio and Zollino (2004), table 5 column I; panel regression: smoothed coefficients of time dummies in model (5) estimated on all Manufacturing industries except Energy Mining and Oil.

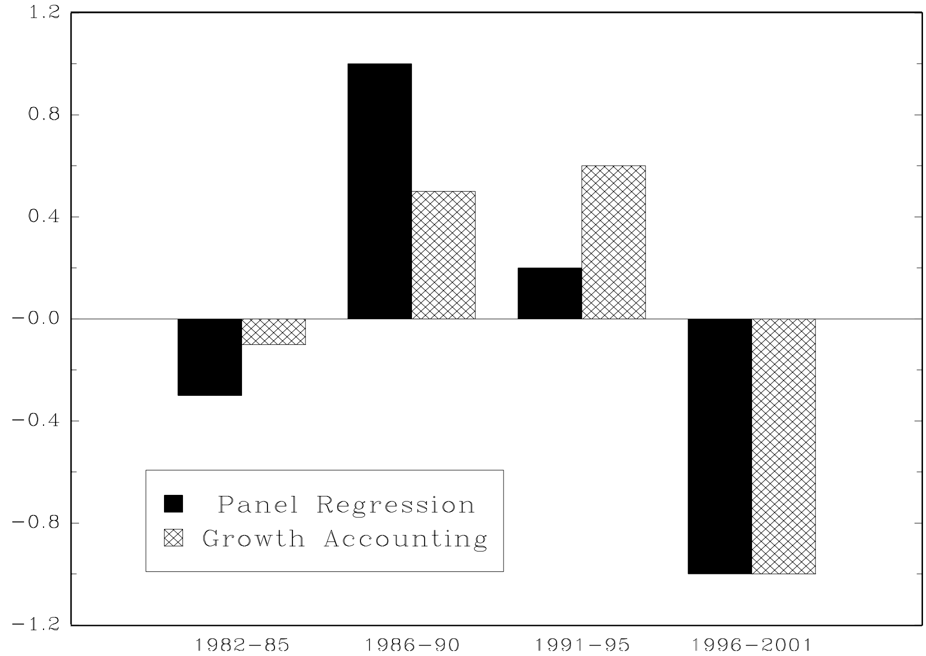

Fig. 7 - Estimated TFP growth rates×100 centred on their 1982-2001 average. Growth accounting: entire Manufacturing Industry, own calculations on estimates by Bassanetti, Iommi, Jona-Lasinio and Zollino (2004), table 5 column I ; panel regression: smoothed coefficients of time dummies in model (5) estimated on all Manufacturing Industries except Energy Mining and Oil.

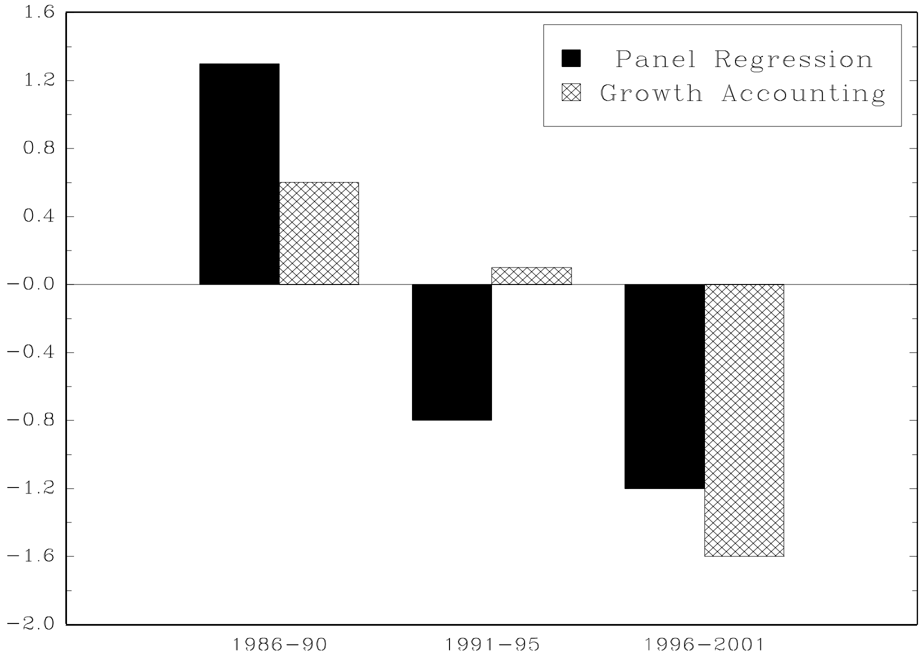

Fig. 8 - Differences between periods of average estimated TFP growth rates×100 (hence, bars for 1986-90 are the difference between average growth rates in 1986-90 and 1982-85, etc.). Growth accounting: entire Manufacturing Industry, own calculations on estimates by Bassanetti, Iommi, Jona-Lasinio and Zollino (2004), table 5 column I; panel regression: smoothed coefficients of time dummies in model (5) estimated on all Manufacturing Industries except Energy Mining and Oil.

Before moving to modelling the deviations of labour productivity from the long-run TFP trend it is worth trying to shed some light on the determinants of TFP growth. To this end we estimated a simple model with a set of explanatory variables including the standard deviations across the I industries of the log differences of labour, $\sigma_t^{\Delta l}$, and capital per labour unit, $\sigma_t^{\Delta(k-l)}$ (*i.e.*, $\sigma_t^{\Delta x} = [I^{-1}\sum_{j=1}^{I}(\Delta x_{jt} - \overline{\Delta x_t})^2]^{\frac{1}{2}}, x = l, (k-l)$), so to capture factor reallocation across industries, and R&D expenditure (rd; source: OECD) and a human capital index (h; source: Brandolini and Cipollone, 2001), both in logs, to measure changes in factors quality. A capacity utilisation index, CU, was also included to account for the cycle. Formally:

$$\Delta\widetilde{\varphi}_t = b_1\sigma_t^{\Delta l} + b_2\sigma_t^{\Delta k} + b_3 rd_t + b_4\Delta h_t + b_5 CU_t + \nu_t.$$

The results, reported in Table 3, are remarkable: reallocation of both factors, as measured by growth variability across industries, is strongly significant. R&D expenditure is also significant, while the failure to detect a significant influence of changes in human capital may be at least partially due to measurement problems.

Table 3
Determinants of long-run TFP growth, 1982-2001

$\sigma_t^{\Delta l}$	$\sigma_t^{\Delta(k-l)}$	Δh_{1t}	Δh_{2t}	rd_t	CU_t
0.42^{***} (2.78)	0.35^{**} (4.85)	-0.42 (-0.41)	0.18 (0.18)	4.29^{*} (2.78)	-0.05 (-0.29)
$se = 1.06; LM = 1.52$ (0.24)					

Dependent variable: first difference of smoothed coefficients of the common time dummies D_t in model (3);
se : standard error of residuals;
LM: test for no first order autocorrelation (p-value in brackets).
Δh_j : log difference of human capital index, $j = 1 : t < 1992$ (break in the series), $j = 2 : t > 1992$;
$\sigma_t^{\Delta x} = [I^{-1} \sum_{j=1}^{I} (\Delta x_{jt} - \overline{\Delta x_t})^2]^{\frac{1}{2}}, x = l, (k - l)$;
rd_t : R&D expenditure;
CU_t : capacity utilisation index.
$t-$statistics in brackets underneath coefficients estimates, robust standard errors;
$^{*},^{**},^{***}$: significant at 10%,5% and 1%.

Let us now move to modelling the deviation of Value Added per Labour Unit from the long-run TFP trend. The plots (Fig. 7) show a variety of patterns: in about half of the cases (Food, Leather, Paper, Rubber, Non Metals, Machinery) there is a clear negative trend, while the opposite holds only for the Non Energy and Wood industries. Breaks are evident in the Textiles, Transport, Metals, Other Manufacturing and Utilities, while a fast growth in the early 1980's followed by stagnation is found for the Chemical and Electrical Industries. Overall non-stationarity prevails: the null hypothesis is never rejected by the CIPS panel unit root test, either with and without a linear trend, with statistics always very distant from the rejection region (respectively, -1.86 and -1.56, with 5% critical values -2.78 and -2.26).

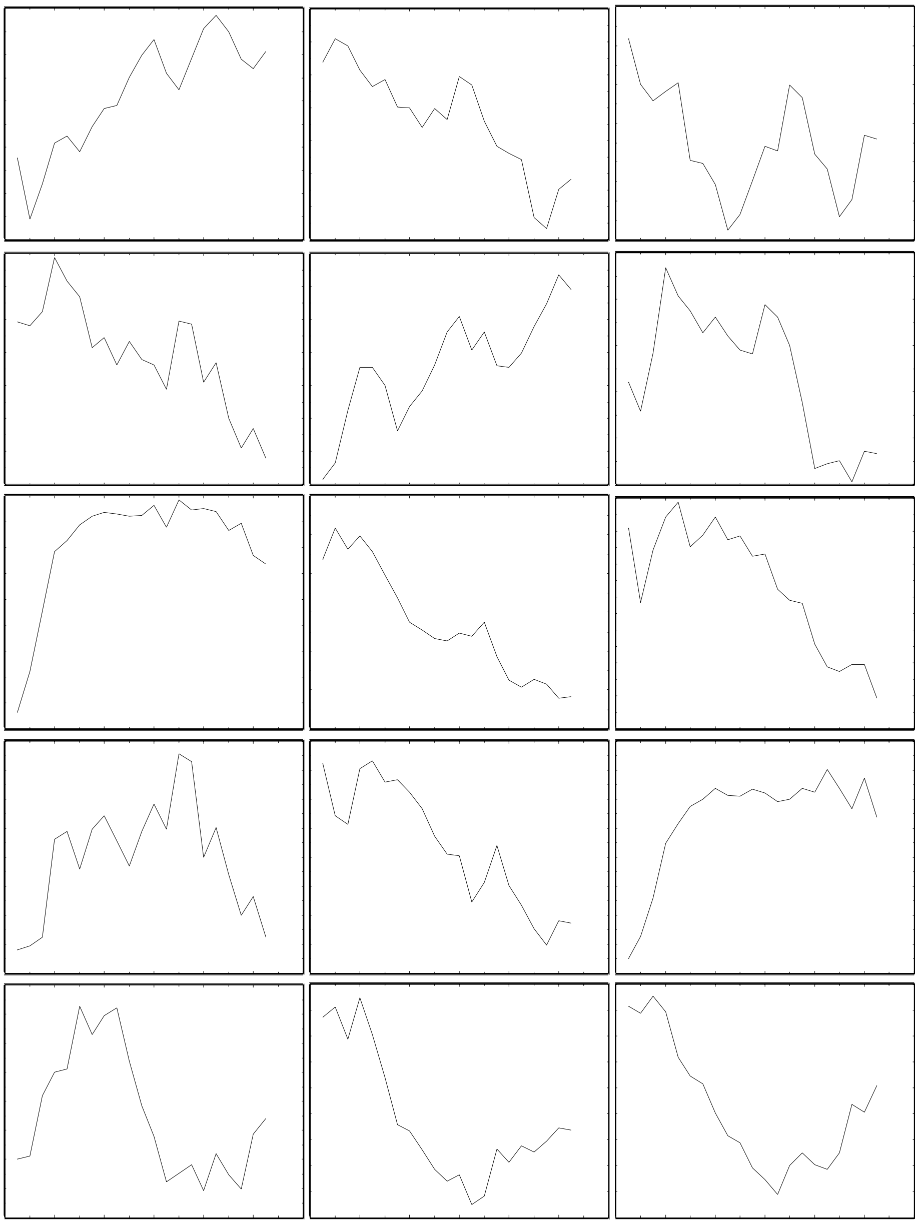

Fig. 7. Deviations of Value Added per Labour Unit from estimated general technical progress (logs). From left to right and top to bottom (rows in brackets): [1] Non-Energy, Food, Textiles; [2] Leather, Wood, Paper; [3] Chemicals, Rubber, Non-Metals; [4] Metals, Machinery, Electricals; [5] Transport, Other, Utilities (abbreviations: see table A1).

Initial estimates are reported in Table 4A and final estimates in Table 4B, with plots in Fig. 8. A critical step of the procedure is the choice of the block size to be used in the bootstrap. In this case the results turned out to be quite robust (details available on request); given the very small sample size we decided to fix the block size at 4 observations. Given the small sample size, hence the low power of the significance tests, we chose to delete only the labour variable when appropriate (thus moving to a specification implying constant returns to scale), while the capital variables have always been retained. Taking into account that with the available sample size the power of the test must to be expected to be rather low (Fachin, 2007) the hypothesis of no panel cointegration for the restricted specification, with p-values definitely smaller than 5%, appears to be strongly rejected both in mean and median. The coefficient of labour units is most cases significant, suggesting returns to scale different from 1. Although the quadratic term is generally significant the estimates of the elasticity of substitution between labour and capital are always very close to 1, with the only exception of the Rubber industry (1.20). To evaluate the uncertainty in the estimates of these highly non-linear functions of the coefficients of the production function we computed bootstrap confidence intervals; the details of the algorithm are documented in the Appendix. The 95% confidence intervals (reported in brackets below the point estimates) always include the point estimates (and 1, except in the Electrical industry) but are often very wide: for instance, in the Machinery Industry the interval is [0.59, 1.63]. Thus, although the point estimates support the hypothesis of a Cobb-Douglas pattern of substitution between labour and capital, the confidence intervals are compatible with very different scenarios with either less or more than proportional substitution between the factors of production. Interestingly, essentially similar conclusions (point estimates close to 1 but very wide confidence intervals) were reached by Balistreri, McDaniel and Wong (2003), who estimated directly the elasticity of substitution for 28 US industries for the period 1947-1998. This suggests that (*i*) our finding of point estimates close to 1 may be more than a mere artifact of the Kmenta linearisation; (*ii*) the strong uncertainty of the estimates is a pervasive problem, common to different periods and countries. A possible explanation may be aggregation bias, with factor reallocation within industries causing the same (different) aggregate combinations of inputs producing different (the same) levels of aggregate output, and ultimately uncertainty in the estimation of the elasticities.

Table 4A

Modelling Labour Productivity, 1981-2001

Mining, Manufacturing and Utilities

Deviations from estimated TFP trend

Panel Cointegration Tests		Bootstrap $p-values \times 100$		
		simple	FDB_1	FDB_2
Mean t	-4.26	11.40	7.94	7.28
Median t	-3.31	26.20	24.64	24.74

FM-OLS estimates

Industries	γ_0	γ_1	γ_2	ES	Z_α
Non-Energy	0.30 (0.79)	9.31 (2.97)	-0.84 (2.61)	0.99 [0.98,1.00]	-13.88
Food	0.30 (0.94)	2.59 (1.25)	-0.30 (1.38)	0.95 [0.79,1.04]	-15.04
Textiles	-0.47 (3.35)	-0.38 (0.56)	0.01 (0.17)	1.04 [0.78,1.65]	-8.25
Leather	0.30 (1.00)	4.30 (3.21)	-0.57 (3.12)	0.97 [0.76,1.20]	-14.57
Wood	-0.06 (0.15)	7.38 (1.36)	0.83 (1.38)	1.01 [0.97,1.10]	-10.91
Paper	-1.08 (4.99)	3.39 (4.45)	-0.39 (4.48)	1.10 [0.71,1.44]	-9.96
Chemicals	-0.51 (3.02)	83.29 (15.40)	-7.60 (15.34)	1.00 [0.99,1.01]	-7.92
Rubber	-1.26 (16.50)	0.10 (0.01)	-0.01 (0.02)	1.20 [0.74,1.31]	-21.82
Non-metals	-0.29 (4.63)	13.04 (12.22)	1.39 (12.48)	0.99 [0.98,0.99]	-11.88
Metals	-0.37 (3.21)	5.58 (6.75)	-0.61 (6.87)	0.96 [0.66,1.18]	-19.80
Machinery	0.11 (0.36)	3.26 (1.38)	-0.41 (1.52)	0.95 [0.70,1.54]	-12.22
Electricals	-0.18 (1.67)	2.84 (9.68)	-0.32 (9.26)	0.92 [0.55,0.96]	-19.58
Transport	1.21 (3.98)	7.14 (4.07)	-0.74 (3.98)	0.99 [0.98,1.00]	-6.42
Other	-3.13 (12.45)	17.14 (4.92)	-2.09 (4.97)	1.00 [1.00,1.01]	-10.21
Utilities	-0.77 (3.52)	-19.33 (3.87)	1.34 (3.75)	1.01 [0.87,1.13]	-12.78

Model: $\widetilde{\pi}_{it} = \delta_i + \gamma_0 l_{it} + \gamma_1(k_{it} - l_{it}) + \gamma_2(k_{it} - l_{it})^2 + \varepsilon_{it}$

ES: Labour-Capital Elasticity of substitution;

Z_α *10% critical point:*-23.54

Bootstrap: 5000 redrawings, block size 4.

Table 4B
Modelling Labour Productivity, 1981-2001
Mining, Manufacturing and Utilities
Deviations from estimated TFP trend

Panel Cointegration Tests		Bootstrap $p-values \times 100$		
		simple	FDB_1	FDB_2
Mean t	-0.78	1.50	0.96	0.74
Median t	-3.51	4.80	3.40	3.44

FM-OLS estimates

Industries	γ_0	γ_1	γ_2	ES	Z_α
Non-Energy	–	9.83 (3.01)	-0.92 (2.85)	0.99 [0.98,0.99]	-12.97
Food	–	5.69 (2.90)	-0.63 (3.04)	0.97 [0.82,1.04]	-15.20
Textiles	-0.47 (3.35)	-0.38 (0.56)	0.02 (0.18)	1.04 [0.78,1.65]	-8.25
Leather	–	5.26 (4.20)	-0.72 (4.38)	0.97 [0.81,1.04]	-15.27
Wood	–	4.31 (0.64)	0.50 (0.67)	1.02 [0.91,1.12]	-10.93
Paper	-1.08 (4.99)	3.39 (4.45)	-0.39 (4.48)	1.10 [0.71,1.44]	-9.96
Chemicals	-0.51 (3.02)	83.29 (15.40)	-7.60 (15.34)	1.00 [0.99,1.01]	-7.92
Rubber	-1.31 (28.32)	-0.10 (0.01)	-0.02 (0.02)	1.20 [0.74,1.31]	-21.82
Non-metals	-0.29 (4.63)	13.04 (12.22)	1.39 (12.48)	0.99 [0.98,1.99]	-11.88
Metals	-0.37 (3.21)	5.58 (6.75)	-0.61 (6.87)	0.96 [0.66,1.18]	-19.80
Machinery	–	2.23 (1.07)	-0.30 (1.22)	0.90 [0.59,1.63]	-11.90
Electricals	-0.18 (1.67)	2.84 (9.68)	-0.32 (9.26)	0.92 [0.55,0.96]	-19.58
Transport	1.21 (3.98)	7.14 (4.07)	-0.74 (3.98)	0.99 [0.98,1.00]	-6.42
Other	-3.13 (12.45)	17.14 (4.92)	-2.09 (4.97)	1.00 [1.00,1.01]	-10.21
Utilities	-0.77 (3.52)	-19.33 (3.87)	1.34 (3.75)	1.01 [0.87,1.13]	-12.78

Model: $\widetilde{\pi}_{it} = \delta_i + \gamma_0 l_{it} + \gamma_1(k_{it} - l_{it}) + \gamma_2(k_{it} - l_{it})^2 + \varepsilon_{it}$
ES: Labour-Capital Elasticity of substitution;
95% bootstrap confidence interval in brackets.
Z_α *10% critical point:* -23.54
Bootstrap: 5000 redrawings, block size 4.

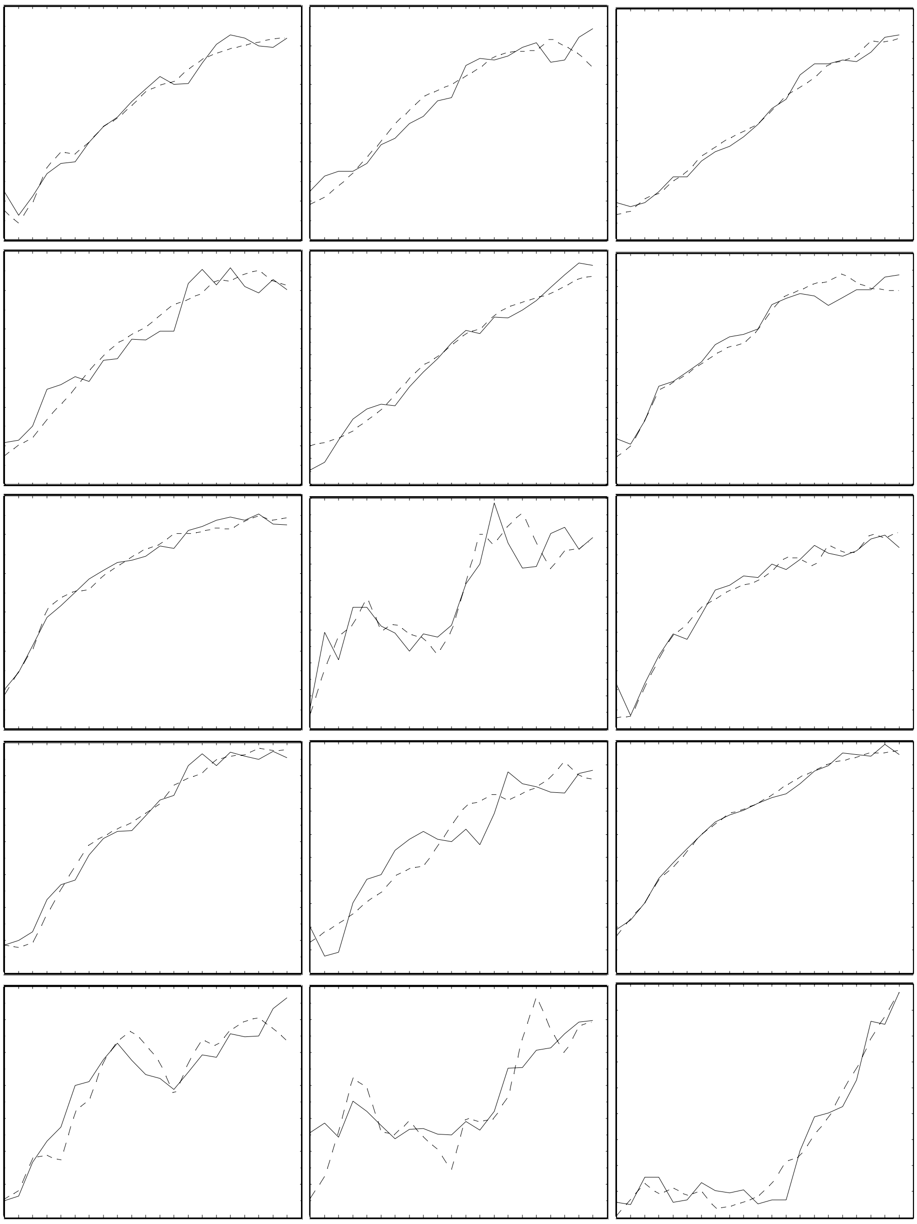

Fig. 8. Value Added per Labour Unit and FM-OLS estimates plus smoothed OLS estimates of general trend in technical progress, 1981-2001. From left to right and top to bottom (rows in brackets): [1] Non-Energy, Food, Textiles; [2] Leather, Wood, Paper; [3] Chemicals, Rubber, Non-Metals; [4] Metals, Machinery, Electricals; [5] Transport, Other, Utilities (abbreviations: see table A1).

4 Conclusions

In this paper we reached conclusions arguably of some interest both from the methodological and the empirical point of view. First of all, we developed a method for obtaining estimates of long-run TFP trends free from the restrictive assumptions needed by traditional growth accounting, requiring only data on inputs and output flows, and able to deliver estimates of long-run TFP trends. It is thus arguably more general than both the growth accounting and Kee's (2004) structural model-based approaches.

Our proposal builds on recent developments in the analysis of non-stationary, cross-correlated panels. Applying it to the Italian manufacturing industries we obtain results confirming the conclusion already reached by growth accounting, *i.e.* that the decline in Italian labour productivity in the past decade has been mostly due to a widespread fall in TFP growth. A simple regression suggest that the most obvious culprits, namely the completion of a factor reallocation process among industries and inadequate R&D investment, did actually play an important role in this decline.

5 References

Balistreri, E.J., McDaniel, C.A., Wong, E.V. (2003) "An estimation of US industry-level capital-labor substitution elasticities: support for CobbDouglas" *North American Journal of Economics and Finance,* vol. 14, 343-356.

Barba Navaretti, G., R. Faini and A. Tucci (2005) "Competitività ed attività internazionali delle imprese Italiane"

Bassanetti, A., M. Iommi, C. Jona-Lasinio and F. Zollino (2004) "La crescita dell'economia italiana negli anni novanta tra ritardo tecnologico e rallentamento della produttività" *Temi di discussione* n. 539, Banca d'Italia.

Brandolini, A., and P. Cipollone (2001) "Multifactor Productivity and Labour Quality in Italy, 1981-2000" Banca d'Italia, *Temi di discussione* n. 422

Bruno, G. and E. Otranto (2003) "Dating the Italian Business Cycle: A Comparison of Procedures" Working Paper, University of Sassari.

Conference Board (2007) "Global Productivity Trends" http://www.conference-board.org/economics/

Daveri, F. (2004) "Why is there a productivity problem in Europe?" *CEPS Working Documents* n. 205.

Daveri, F. and C. Jona-Lasinio (2005) "Italys Decline: getting the facts right" IGIER Università Bocconi, *Working Paper* n. 301.

Denison, E.F. (1967) *Why Growth Rates Differ: Postwar Experience in Nine Western Countries* The Brookings Institution, Washington (USA).

Duffy, J. and C. Papageorgiu (2000) "A Cross-Country Empirical Investigation of the Aggregate Production Function Specification" *Journal of Economic Growth*, 5, 87-120.

Fachin, S. (2007) "Long-Run Trends in Internal Migrations in Italy: a Study in Panel Cointegration with Dependent Units" *Journal of Applied Econometrics, 22,* 401-428.

Harrigan, J. (1999) "Estimation of cross-country differences in industry production functions" *Journal of International Economics*, 47, 267-293.

Im, K., M.H. Pesaran and Y. Shin (2003) "Testing for Unit Roots in Heterogeneous Panels" *Journal of Econometrics*, 115, 53-74.

Kee, H. L. (2004) "Estimating Productivity When Primal and Dual TFP Accounting Fail: An Illustration Using Singapores Industries" *Topics in Economic Analysis & Policy,* vol. 4, article 26.

Kmenta, J. (1967) "On the Estimation of the C.E.S. Production Function" *International Economic Review, 2, 180-89.*

Mahony, M. and M. Vecchi (2003) "Is there an ICT impact on TFP? A heterogeneous dynamic panel approach" *Working Paper*, NIESR.

Matthews, R.C.O., C.H. Feinstein and J. C. Odling-Smee (1982) *British Economic Growth 1856-1973* Oxford University Press, Oxford (UK).

Paparoditis, E. and D.N. Politis (2001) "The Continuous-Path Block Bootstrap" In *Asymptotics in Statistics and Probability. Papers in honor of George Roussas.* Madan Puri (ed.). VSP Publications: Zeist (NL).

Park, J. Y., Phillips, P.C.B. (1999) "Asymptotics for Non-linear Transformations of Integrated series" *Econometric Theory*, 15, 269-298.

Pedroni, P. (1997) "Cross Sectional Dependence in Cointegration Tests of Purchasing Power Parity in Panels" *Working Paper,* Indiana University.

Pesaran, M.H. (2006) "A Simple Panel Unit Root Test in the Presence of Cross Section Dependence". *DAE Working Paper* No. 0346, Cambridge University.

Politis, D.N., Romano, J.P. (1994) The stationary bootstrap, *Journal of the American Statistical Association*, 89, 1303-1313.

Silverman, B.W. (1986) *Density Estimation for Statistics and Data Analysis*, Chapman & Hall, London.

Stiroh, K.J. (2002) "Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?" *The American Economic Review*, 92, 1559-1576.

6 Appendix

6.1 A. A Bootstrap Panel Cointegration Test

A panel cointegration test suitable for our dataset needs to be robust to both short-run and long-run dependence across units, so that the asymptotic tests usually applied in the literature are not suitable. Fachin (2005) put forth a bootstrap test satisfying both requirements. The test is based on the Continuous-Path Block Bootstrap (CBB), which is applied independently to the cross-sections of time-series of the X's, $\{X_1 X_2 \ldots X_N\}_{t=1}^T$ and the Y's $\{Y_1 Y_2 \ldots Y_N\}_{t=1}^T$. Developed by Paparoditis and Politis (2001), the CBB is a block resampling method designed to construct non-stationary pseudodata. The pseudo-series is obtained in two steps: first, a block bootstrap series is constructed integrating within each block the resampled first differences of a series known to be non-stationary; second, the end points of the blocks are chained so to eliminate jumps between blocks (this implies that the pseudo-series are shorter than the original series, as one observation must be deleted when chaining two blocks). As the resampling is applied to the entire cross-section the pseudo-series will clearly preserve the cross-correlation structure of the non-stationary individual time series. On the other hand, the blocks are chosen independently for the $X's$ and the $Y's$, so that the two pseudo-series are independent by design. Denoting by G a group mean statistic the proposed bootstrap procedure includes five simple steps:

1. compute the Group statistic $\widehat{G}$ for the data set under study, $\{X_1X_2 \dots X_N, Y_1Y_2 \dots Y_N\}_{t=1}^{T}$;
2. construct separately by CBB two sets of N pseudo-series, $\{X_1^*X_2^* \dots X_N^*\}_{t=1}^{T^*}$ and $\{Y_1^*Y_2^* \dots Y_N^*\}_{t=1}^{T^*}$;
3. compute the Group statistics G^* for the pseudo-data set, $\{X_1^*X_2^* \dots X_N^*, Y_1^*Y_2^* \dots Y_N^*\}_{t=1}^{T^*}$;
4. repeat steps (2) and (3) a large number (say, B) of times;
5. compute the boostrap significance level; assuming that the rejection region is the left tail of the distribution, $p^* = prop(G^* < \widehat{G})$.

6.2 B. Bootstrap Confidence Intervals for the Elasticity of Substitution

The elasticity of substitution (ES) implied by the linearised CES production function (2) is a highly non-linear function of the function coefficients: $ES = \frac{1}{1+\rho}$, where $\rho = \frac{\gamma_2}{\gamma_1[1-\gamma_1(1+\gamma_0)]}$. To evaluate the uncertainty in the estimates we therefore compute bootstrap confidence intervals according to the following algorithm:

1. estimate the coefficients of the production function ($\delta_i, \gamma_0, \gamma_1, \gamma_2$, some of which may be constrained to zero) and compute the elasticity of substitution $\widehat{ES}$ and the residuals $\widehat{\varepsilon}$;
2. resample the weakly dependent estimated residuals $\widehat{\varepsilon}$ applying a suitable scheme, such as the stationary bootstrap (Politis and Romano, 1994) and obtain a series of pseudo-residuals ε^*;
3. construct the pseudodata: $\pi_t^* = \widehat{\delta} + \widehat{\gamma}_0 l_t + \widehat{\gamma}_1(k_t - l_t) + \widehat{\gamma}_2(k_t)^2 + \varepsilon_t^*$;
4. estimate a CES production function with the same restrictions imposed in step [1] using the dataset (π_t^*, l_t, k_t) and compute the elasticity of substitution ES_b^*;
5. repeat steps (2)-(4) a large number (say, B) of times;
6. compute the extremes of the 2α-level confidence interval for $\widehat{ES}$ as the αB^{th} and $(1-\alpha)B^{th}$ elements of the vector $\mathbf{ES}^* = \left[ES_{1'}^*, \dots , ES_{B'}^*\right]$, where $ES_{1'}^* \leq \dots \leq ES_{B'}^*$.

6.3 C. Industry Classification

The NACE Rev. 1.1 Classification:
Sections C, D and E and their Subsections

	Abbreviation	*Y Share*	*K/L*
Section C Mining and Quarrying	*Mining*		
Mining and quarrying of energy producing materials	Energy	0.3	468
Mining and quarrying, except of energy producing materials	Non-Energy	0.2	88
Section D Manufacturing	*Manufacturing*		
Food products, beverages and tobacco	Food	2.3	60
Textiles and textile products	Textiles	2.8	32
Leather and leather products	Leather	0.7	24
Wood and wood products	Wood	0.6	54
Pulp, paper and paper products; publishing and printing	Paper	1.4	46
Coke, refined petroleum products and nuclear fuel	Coke	0.4	261
Chemicals, chemical products and man-made fibres	Chemicals	1.9	125
Rubber and plastic products	Rubber	0.9	70
Other non-metallic mineral products	Non-metals	1.5	68
Basic metals and fabricated metal products	Metals	3.5	60
Machinery and equipment n.e.c.	Mach	2.7	45
Electrical and optical equipment	Electricals	2.3	44
Transport equipment	Transport	1.7	62
Manufacturing n.e.c.	Other	1.2	40
Section E Electricity, Gas and Water Supply	*Utilities*	1.8	600

Y Share: average GDP share×100, 1981-2001.
K/L: average Capital/Labour Unit ratio, 1981-2001; Capital at 1995 prices, Euros×1000.
Source: Istat, *Conti economici nazionali 1970-2004*.