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

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The decline in Italian Labour Productivity: A Study in Estimation of Total Factor Productivity with Panel Cointegration Methods

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Abstract

The main aim of this paper is to propose a method for obtaining estimates of Total Factor Productivity (TFP) trends (*i*) free from the restrictive assumptions needed by traditional growth accounting and (*ii*) requiring only data on inputs and output flows. The approach proposed relies on recent developments in the analysis of non-stationary dependent panels. The application to the Italian economy for the period 1981-2004, consistently with those obtained through traditional growth accounting methods, 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 of this fall the completion of a factor reallocation process among industries and capital types.

Keywords: Total Factor Productivity, Productivity Slowdown, Italy, Panel Cointegration.

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1 Introduction[1]

The growth of value added per worker (henceforth labour productivity) in Italy since the late 1990's has been abysmal, the poorest in Europe along with Spain[2]: over the period 1995-2004[3] the annual average growth has been just 1.3%, with a falling trend (0.5% per year in 2000-2004). For a comparison, in the USA the growth, about 2.5% a year in 1995-2001, increased to 4% a year in 2001-2004. In fact, the Governor of the Federal Reserve B.S. Bernanke recently stated that "Almost certainly, the most important economic development in the United States in the past decade has been the sustained increase in the rate of growth of labor productivity, or output per hour of work." (Bernanke, 2005). As stressed by Bernanke, labour productivity growth is important not only in the long-run, as the force shaping living standards, but also in the short-run, as one of the determinants of output and employment growth. Hence, understanding the causes of this labour productivity slowdown is a matter of great importance[4].

Formally we can put the question as follows: is the productivity slowdown due to a movement along an isoquant or, rather, to a shift of the isoquant? The former may occur as a consequence of a fall in capital intensity, perhaps linked to a change in relative factor prices; the latter, of a decline in total factor productivity (TFP). Declining TFP will *coeteris paribus* implie lower value added per worker, *i.e.* labour productivity, also. The answer is clearly highly relevant 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, two possibilities arise: either the slowdown reflects the exhaustion of the "quality adjust-

[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 Bank of Italy Capacity Utilisation and Human Capital data, Carlo Altomonte and participants at the Turin February 2007 CNR Meeting of international economics and Brescia 2008 AIEL conference for very helpful comments and suggestions. The usual disclaimers apply.

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

[3] Data limitations for the Capital stock, a key variable of our study, prevent us from considering the period after 2004.

[4] Concern for analogous productiviy slowdown events from the policymaker perspective can be found, *e.g.*, in Dolman, Lu and Rahman (2005) for the Australian economy, and in Centraal Planbureau (1998) for the Dutch economy.

ment" component, linked to reallocation across industries, labour skills, or capital vintages and types (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 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 this issue. More precisely, applying recent non-stationary panel techniques we will examine recent labour productivity patterns in the Italian manufacturing industry and obtain estimates of the underlying aggregate TFP trend valid under very general hypotheses 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. 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). Finally, some conclusions will be drawn (section 3).

2 What do the Disaggregate Data Say? Productivity, Output, Labour and Capital Trends in Italian Manufacturing Industries, 1981-2004

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, are reported in the Data 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 2004, we will examine the period 1981-2004. All details on the data sources and definitions are also reported in the Data Appendix.

The log plots of the aggregate level trends (Fig. **??**, left column) tell an apparently rather clear story: Labour Productivity (measured by the Value Added/labour inputs ratio), Value Added and Capital/Labour ratio (rescaled to account for capacity utilisation) grew more or less steadily, while employment (measured in terms of full time equivalent employees) 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. Thus, the aggregate evidence seems to suggest a decline in capital deepening causing the labour productivity slowdown and acceleration in labour demand (formally, a movement along an isoquant of the production function). Since aggregate trends may hide widely different disaggregate patterns, before jumping to conclusions we should however look at individual industries as well. As it can be appreciated 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[5]. The productivity slowdown and employment acceleration (either faster growth or slower decline) of the 1990's is also evident in all industries but three (Other Manufacturing, Utilities and Transport). The negative partial correlation between Labour Productivity and Employment growth stands out clearly from the cross-plot of the average rates of growth in the individual industries[6] (Fig. 3).

How about capital/labour ratios? Here we find that the disaggregate evidence is at odds with the straightforward factor substitution story suggested by the aggregate data. In fact, from Table 1 we can see that in almost half of the industries examined the average annual rates of growth of Capital endowments per Labour Unit have been *higher* in the second part of the sample, hence accelerating exactly when labour productivity growth slowed down. It is thus not surprising to discover from Fig. 4 that 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: wide ranges of Labour Productivity growth rates appear compatible with approximately similar rates of growth of the Capital/Labour ratio. In fact, the visual inspection of this plot may lead to two radically different conclusions by simply dropping two alternative small clusters of industries:

(*i*) excluding the Chemical, Non-Energy and Wood industries, which had the highest productivity growth of the entire panel in spite of very low capital intensity growth, the correlation is clearly positive;

(*ii*) excluding the Electrical, Transport Equipment and Paper industries, which had high rates of growth of both capital intensity and Labour Productivity, the impression is of no correlation.

The lack of a robust pattern of correlation across industries between the labour productivity and Capital/Labour ratio dynamics leads us to conclude

[5] Average 1981-2004 GDP share 0.7%, 2.8% 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.

[6] Interestingly, this figure closely matches that for the EU economies and the USA reported by Daveri (2004): in the last decade the trade-off between productivity and employment growth seems to be a stylised fact remarkably robust, found in Italian manufacturing industries and european economies alike.

that the simple factor substitution story suggested by the aggregate data is in fact inadequate. Did a shift of the isoquant took place then? To answer to this question a careful analysis of total factor productivity trends is required.

Before moving to this task, we conclude this exploratory section examining 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, which, since the units are dependent, 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 unit root hypothesis, thus confirming the graphical evidence.

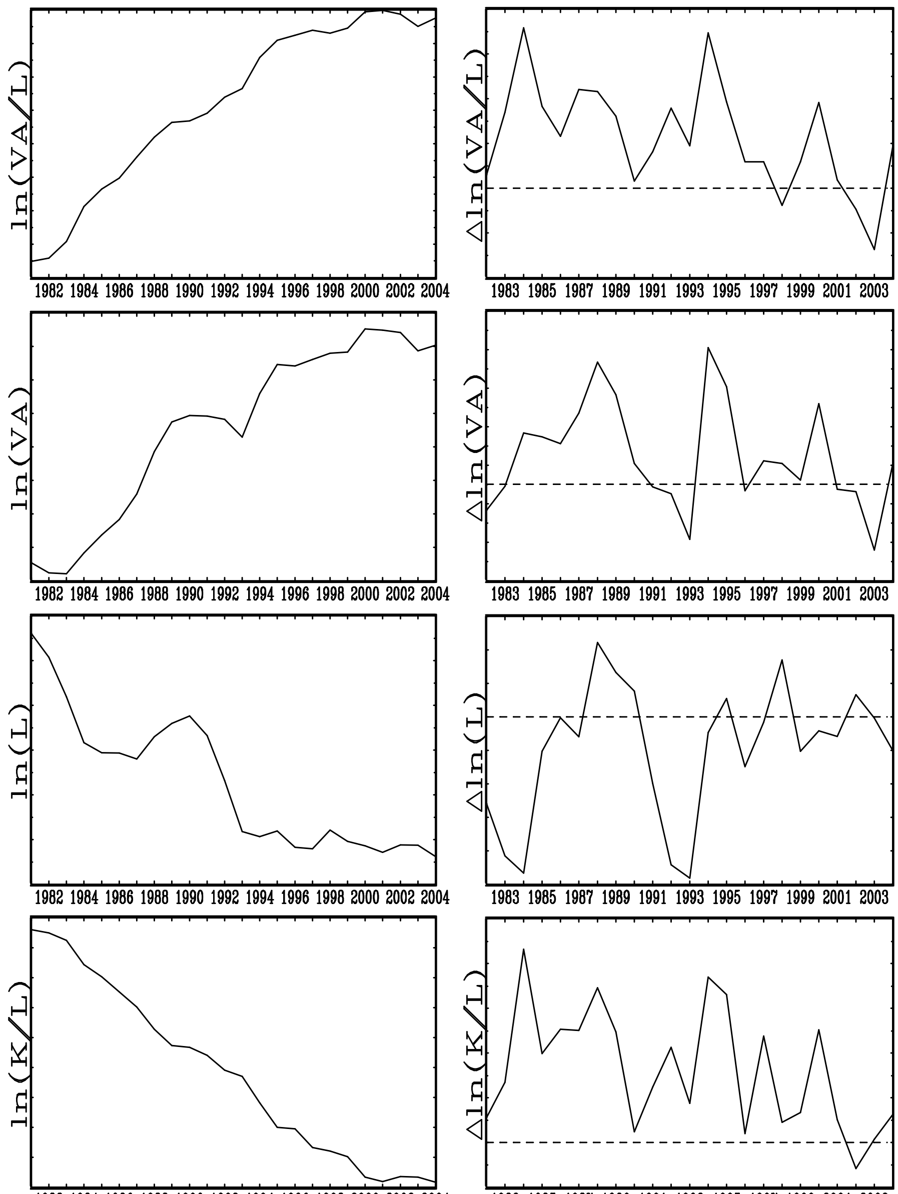

Figure 1: Fig. 1. Mining, Manufacturing and Utilities, 1981-2004. Top to bottom: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit. Left: logs; right: Δ log. Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy Capacity Utilisation Index .

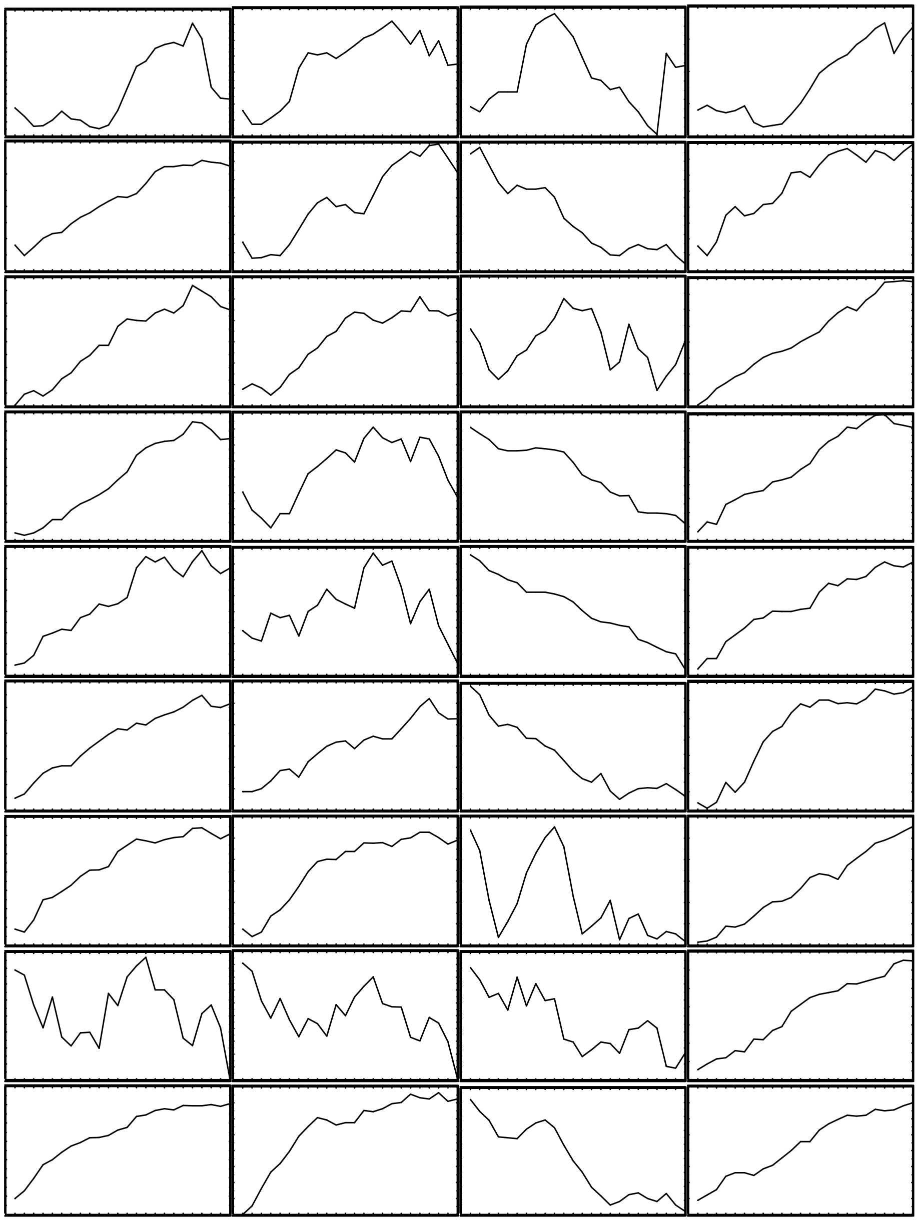

Fig. 2A. Columns, left to right: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit, 1981-2004 (logs; Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy Capacity Utilisation Index); rows, top to bottom: [1] Energy [2] Non-Energy [3] Food [4] Textiles [5] Leather [6] Wood [7] Paper [8] Coke [9] Chemicals (abbreviations: see table A1).

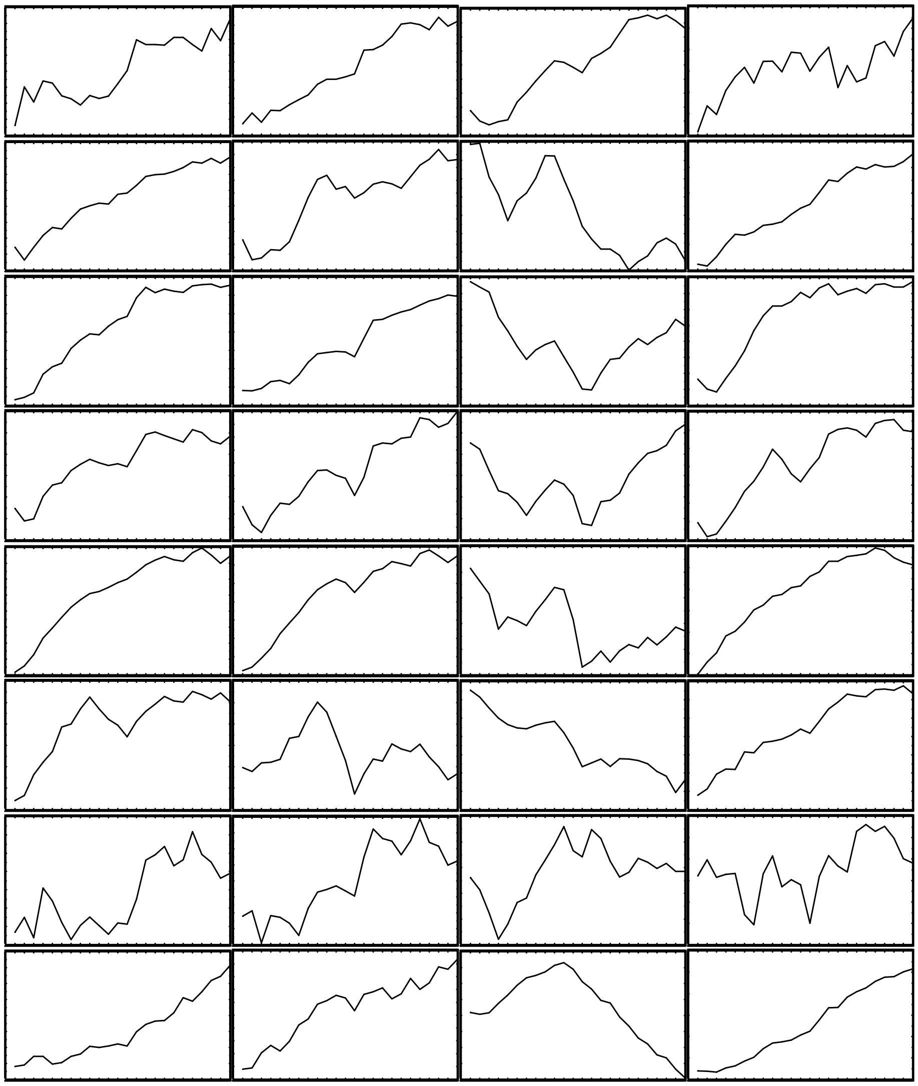

Fig. 2B. Columns, left to right: Value Added per Labour Unit, Value Added, Employment in Labour Units, Gross Capital per Labour Unit, 1981-2004. (logs; Value Added at 1995 prices; Capital at 1995 prices rescaled by the Bank of Italy Capacity Utilisation Index); rows, top to bottom: [1] Rubber [2] Non-metals [3] Metals [4] Machinery [5] Electricals [6] Transport [7] Other [8] Utilities (abbreviations: see table A1).

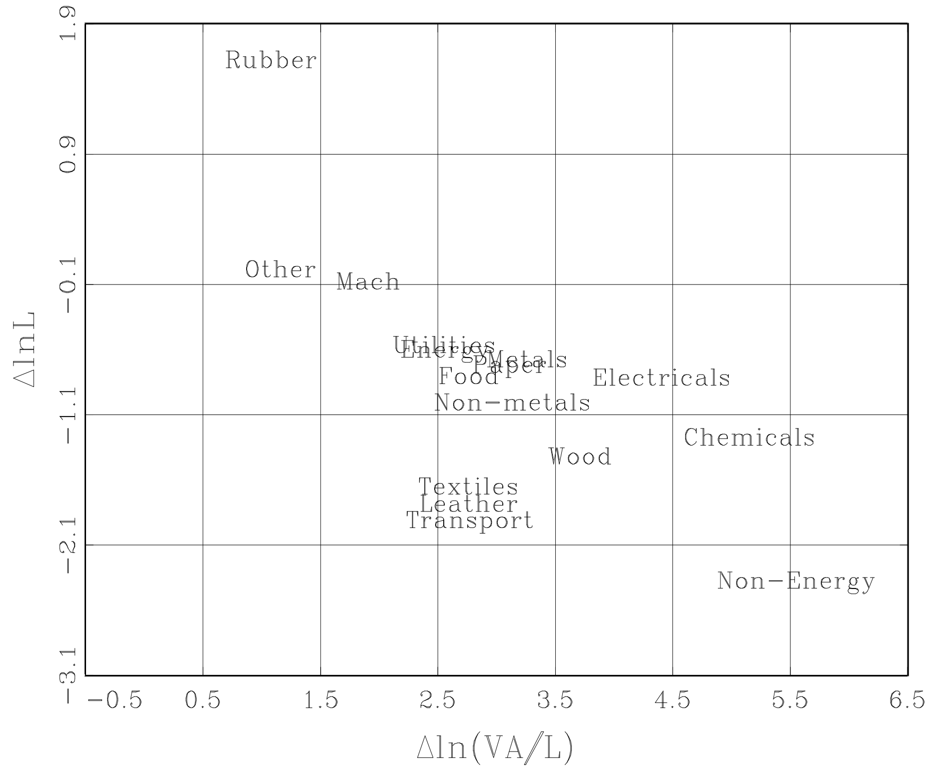

Fig. 3. Annual average rates of growth×100 of Value Added per Labour Unit (VA/L) and Labour Units (L), 1981-2004 (Industries abbreviations: see table A1).

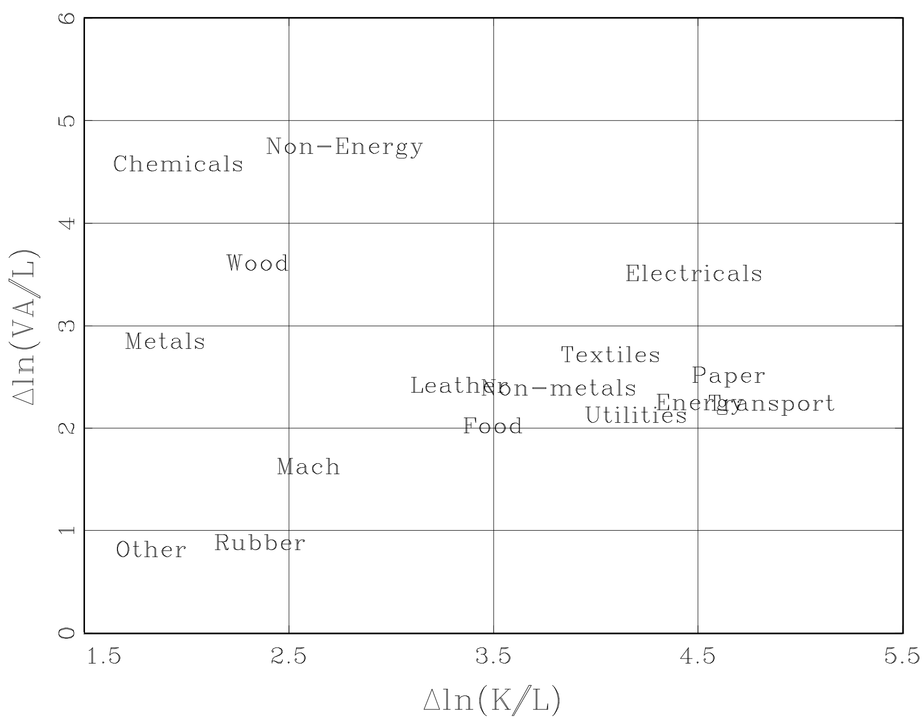

Figure 2: Fig. 4. Annual average rates of growth×100 of Value Added per Labour Unit (VA/L) and Capital per Labour Unit (K/L), 1981-2004 (Industries abbreviations: see table A1).

Table 1
Labour Productivity, Value Added, Labour and Capital
Italian Mining, Manufacturing and Utilities Industries, *1982-2004*
Average annual rates of growth$\times$100

	VA per Labour Unit		Value Added		Labour Units		Capital per Labour Unit	
	82-95	*96-04*	*82-95*	*96-04*	*82-95*	*96-04*	*82-95*	*96-04*
Energy	1.1	1.0	3.3	-2.5	2.2	-3.5	2.4	4.8
Non-Energy	5.3	2.0	1.3	2.5	-3.7	0.4	3.9	-1.2
Food	2.5	1.2	2.2	0.8	-0.3	-0.4	4.0	3.4
Textiles	2.8	1.6	1.0	0.0	-1.8	-1.6	4.1	7.3
Leather	2.7	0.8	0.6	-0.9	-2.1	-1.6	3.4	7.2
Wood	4.2	2.6	1.8	2.7	-2.3	0.1	3.3	-1.6
Paper	2.7	1.2	2.8	0.7	0.0	-0.5	3.7	4.6
Coke	−3.4	-2.1	-4.7	-1.6	-1.4	0.6	5.1	0.5
Chemicals	6.0	0.7	4.4	0.8	-1.5	0.1	2.4	-2.2
Rubber	1.1	-0.2	2.3	1.2	1.2	1.5	0.9	0.7
Non-metals	2.3	1.1	1.7	1.3	-0.6	0.2	3.5	1.4
Metals	3.7	0.6	2.1	1.4	-1.6	0.8	3.7	-2.7
Machinery	2.1	0.0	1.2	1.3	-0.9	1.3	3.5	-0.6
Electricals	4.8	1.1	4.1	1.5	-0.7	0.4	7.3	2.5
Transport	3.0	0.6	0.1	0.3	-2.7	-0.4	6.3	-0.9
Other	1.3	0.0	1.3	-0.1	0.0	-0.2	0.6	1.1
Utilities	1.2	2.6	1.5	0.3	0.3	-2.3	2.6	3.8
Aggregate	2.9	0.8	1.7	0.8	-1.2	-0.1	3.8	1.0

VA: Value Added at 1995 prices;
Labour Unit: full time equivalent employed person;
Capital: Gross Capital at 1995 prices rescaled by the Bank of Italy capacity utilisation index;
NB: 1995 was a peak year according to all dating methods (Bruno and Otranto, 2003).
Source: Istat, *Conti economici nazionali 1970-2007.*

Table 2
Labour Productivity, Labour and Capital/Labour ratio
Panel Unit Root Tests 1981-2004

	VA per Labour Unit	*Labour Units*	*Capital per Labour Unit*
$CIPS^C$	-1.71	-1.23	-1.51
$CIPS^T$	-1.63	-1.46	-1.56

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 (coefficient estimates often non significant, with many implausible values) because of near perfect multicollinearity in almost all industries. This problem is indeed often reported in the literature (see, *e.g.*, Harrigan, 1999, Hsiao, Shen and Fujiki, 2002). The only viable option thus seems to be the Kmenta (1967) linearisation of the CES around the point implying capital-labour elasticity of substitution equal to 1:

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

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:

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

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 nonstationary 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), and which is obviously unobserved. The elusive nature of technical progress is tackled in the production function literature in various, generally unsatisfactory, ways. In time series studies p_{it} is modelled assuming *a priori* a convenient functional form (generally, a linear trend). In panel studies TFP dynamics is typically ignored, and the focus centred on measuring efficiency differentials assumed to be constant over time, hence empirically measured by the fixed effects in panel regressions with homogenous elasticities (e.g., Islam, 1995, and for the Italian case, Marrocu, Paci and Pala, 2001). Finally, a mixture of the two approaches is found in panel studies including linear time trends with coefficients heterogenous across units, as Harrigan (1999). Hence, with scant exceptions such as Kee (2004), the TFP trend is *never* estimated: either assumed or ignored.

We shall now argue that these approaches are uneccessarily restrictive; exploiting the panel structure of the data we can estimate the TFP trend under much looser assumptions. More specifically, similarly to Kee (2004), assume the log TFP index, p_{it}, to admit a decomposition

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

where:

(*i*) θ_t is a, possibly non-stationary, common factor capturing the economy-wide trend in technical progress;

(*ii*) $\psi_{it} = \overline{\psi}_i + \psi'_{it}$ is a stationary industry (log) shift factor capturing the different rates of adoption of the general technical progress in the various industries. Fast growing, high technology industries will have mean (log) shift factor $\overline{\psi}_i > 0$, while for mature industries $\overline{\psi}_i < 0$. Idyosincratic departures from the mean shift factor may be caused by the mean zero, homoskedastic random errors ψ'_{it}.

In other terms, we are assuming that there exists a common trend in technical progress (θ_t), which is transmitted to each industry according to its own rate of adoption, captured by a log-additive shift factor (ψ_{it}), equivalent to a varying slope in natural units. Hence, technology shocks coming from the the common trend have larger impacts on some industries (the high technology ones, where there is much scope for exploiting new products or processes) than in others (the mature industries, where the opposite holds). This approach is consistent with the important recent developments of the literature on non-stationary panels based on the assumption of a common factor to handle dependence (see, *e.g.*, Pesaran, 2006, and Gengenback, Palm, Urbain, 2006).

Substituting (3) into (2) we obtain:

$$\pi_{it} = \alpha'_i + \theta_t + (\beta_{0i} + \beta_{1i} - 1)l_{it} + \beta_{1i}(k_{it} - l_{it}) + \beta_{2i}(k_{it} - l_{it})^2 + \varepsilon'_{it}. \tag{4}$$

where $\alpha'_i = \alpha_i + \overline{\psi}_i$ and $\varepsilon'_{it} = \varepsilon_{it} + \psi'_{it}$.

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:

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

Note that the panel is highly heterogeneous: fixed effects are included, and factor elasticities allowed to vary across industries (contrary to typical panel applications, as *e.g.*, the papers quoted above by Islam, 1995, and Marrocu *et al.*, 2001, where some homogeneity is always assumed). 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 θ_t in model (4). 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.

Since all variables included in (5) should generally be expected, and indeed in our case are, non-stationary, its estimation involves two distinct tasks: (i) testing for cointegration to ensure the relationship is not spurious; (ii) estimating its parameters. The first task requires a panel cointegration test robust to both short and long-run dependence across units (previous studies, such as Marrocu, *et al.*, 2001, ignored this crucial point and used tests valid only for independent units) and, given that in our 1981-2004 panel of the Italian Manufacturing Industries we have $T = 24$ and $N = 15$, able to deliver good small sample performances. While the former requirement is satisfyied by various tests, including asymptotic procedures based on the common factor approach (*e.g.*, Gengenback, Palm, Urbain, 2006), the latter singles out as the only viable option the bootstrap procedure for the mean and median of the individual cointegration ADF statistics proposed by Fachin (2007). The second task, estimation, might in principle be carried out using the OLS estimates computed for the cointegration tests. However, OLS estimates in I(1) regressions are biased, inefficient, and do not converge even asymptotically to a known distribution, so that the point estimates maybe of poor quality and no inference is possible. This suggests that the second task should be carried out using a more suitable method able to account for the non-stationary nature of the data. In principle Fully Modified SUR system estimation (Moon, 1999) may appear the ideal solution. However, in our dataset this is practically unfeasible, as the time dimension only marginally larger than the cross-section dimension makes estimation of the long-run covariance matrix in practice an unfeasible task (Pedroni, 1997, Di Iorio and Fachin, 2008). We shall then apply the following iterative two-steps procedure:

Step A Estimate the panel regression (5) by OLS, and:

- A1. compute the panel cointegration tests by Fachin (2007); details are given in the Appendix;
- A2. recover the TFP trend as the vector of the coefficients of the time dummies D_t ($\widehat{\varphi}$):
- A3. compute the deviations of labour productivity from the TFP trend: $\widetilde{\pi}_{it} = \pi_{it} - \widehat{\varphi}_t$;

Step B 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.

If Step B suggests that some coefficients should be constrained to zero Step A is repeated on the constrained specification, until a satisfactory specification is reached.

Given the small sample size, hence the low power of the significance tests, we chose to delete the labour variable when appropriate (thus moving to a specification implying constant returns to scale), while the capital variables have been excluded only when the coefficients turned out to be negative, clear sign of a spurious relationship. Variables with non-significant coefficients have been retained in a few cases when this delivered overall the most meaningful equations; given the small time sample and the collinearity problems of the dataset at hand this is not unexpected.

The final test statistics and estimates are reported in Table 4, with plots in Fig. 5. To account for possible changes in the industry shift coefficients we split the constant at 1995, a cyclical turning point when TFP growth according to growth accounting estimates slowed down significantly (Istat, 2007). Since no meaningful estimates could be obtained for the residual sector "Other industries" this has been dropped from the panel. Given its composition (it includes activites as diverse as, *e.g*, production of toys and musical instruments and recycling) this is not surprising. 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 below 1% in mean and just above 5% in median, can be safely considered as rejected. The coefficient of labour units is most cases significant, suggesting non-constant returns to scale, mostly decreasing. The quadratic term is generally significant, but the estimates of the elasticity of substitution between labour and capital are far too volatile to be credible. Given that this parameter is a highly non-linear function of the coefficients of the production function this finding is not too surprising; it is also consistent with Balistreri, McDaniel and Wong (2003), who report for 28 US industries over the period 1947-1998 point estimates close to 1 but very wide confidence intervals. 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 3
Modelling Labour Productivity, 1981-2004
Mining, Manufacturing and Utilities

Panel Cointegration Tests		Bootstrap $p-values \times 100$		
		simple	FDB_1	FDB_2
Mean t	-2.73	1.0	0.4	-0.5
Median t	-3.70	11.2	8.7	6.5

FM-OLS estimates
Deviations from estimated TFP trend

Industries	γ_0	γ_1	γ_2	δ_0	δ_1	$ES(K,L)$	Z_α
Non-Energy	0.35	1.99	0.35	3.94	$-$ 0.19	-0.30	-23.93
	(1.60)	(3.57)	(1.80)	(7.28)	(11.11)		
Food	0.72	1.82	0.49	0.57	–	-0.28	-17.80
	(2.51)	(2.55)	(2.54)	(0.41)			
Textiles	–	5.37	1.04	9.72	0.08	-24.74	-10.86
		(10.77)	(10.27)	(16.27)	(4.33)		
Leather	0.66	6.23	0.95	9.31	0.07	-0.08	-11.40
	(4.33)	(5.12)	(4.82)	(6.40)	(4.03)		
Wood	–	1.86	0.38	5.10	-0.08	1.62	-13.77
		(1.86)	(1.58)	(5.01)	(3.87)		
Paper	-0.13	0.17	–	4.48	0.07	1	-14.27
	(0.67)	(6.04)		(4.29)	(3.51)		
Chemicals	0.98	1.43	–	-0.21	0.06	1	-13.06
	(4.63)	(11.60)		(0.20)	(3.69)		
Rubber	-0.70	36.52	12.09	34.74	-0.09	0.06	-13.87
	(0.02)	(5.35)	(5.42)	(6.90)	(4.72)		
Non-metals	0.15	0.83	0.15	3.58	-0.01	-0.44	-19.64
	(4.60)	(6.01)	(4.32)	(18.16)	(2.00)		
Metals	–	3.03	0.69	6.46	–	3.27	-4.64
		(7.60)	(6.78)	(16.82)			
Machinery	–	0.64	0.16	4.09	0.02	1.19	-16.11
		(0.78)	(0.80)	(5.13)	(1.03)		
Electricals	0.30	0.29	–	2.23	–	1	-15.65
	(1.83)	(14.79)		(2.32)			
Transport	0.78	0.17	–	-0.77	–	1	-7.90
	(3.18)	(1.74)		(0.61)			
Utilities	-0.06	1.13	4.34	0.07	–	-7.67	-12.86
	(1.85)	(12.07)	(135.10)	(2.27)			

Model: $\widetilde{\pi}_{it} = \delta_{0i} + \delta_{1i}\tau_t + \gamma_0 l_{it} + \gamma_1(k_{it} - l_{it}) + \gamma_2(k_{it} - l_{it})^2 + \varepsilon_{it}$
$\widetilde{\pi}_{it} = \pi_{it} - \widehat{\varphi}_t$; $\widehat{\varphi}_t$: see equation (5);
$\tau_t = 1$ if $t < 1995$, 0 else;
ES(K,L): Labour-Capital Elasticity of substitution;
Z_α *10% critical point*:-23.54
Bootstrap: 5000 redrawings, block size 4.
FDB_1, FDB_2 : Davidson and McKinnon (2000) Fast Double Bootstrap Type 1 and Type 2.

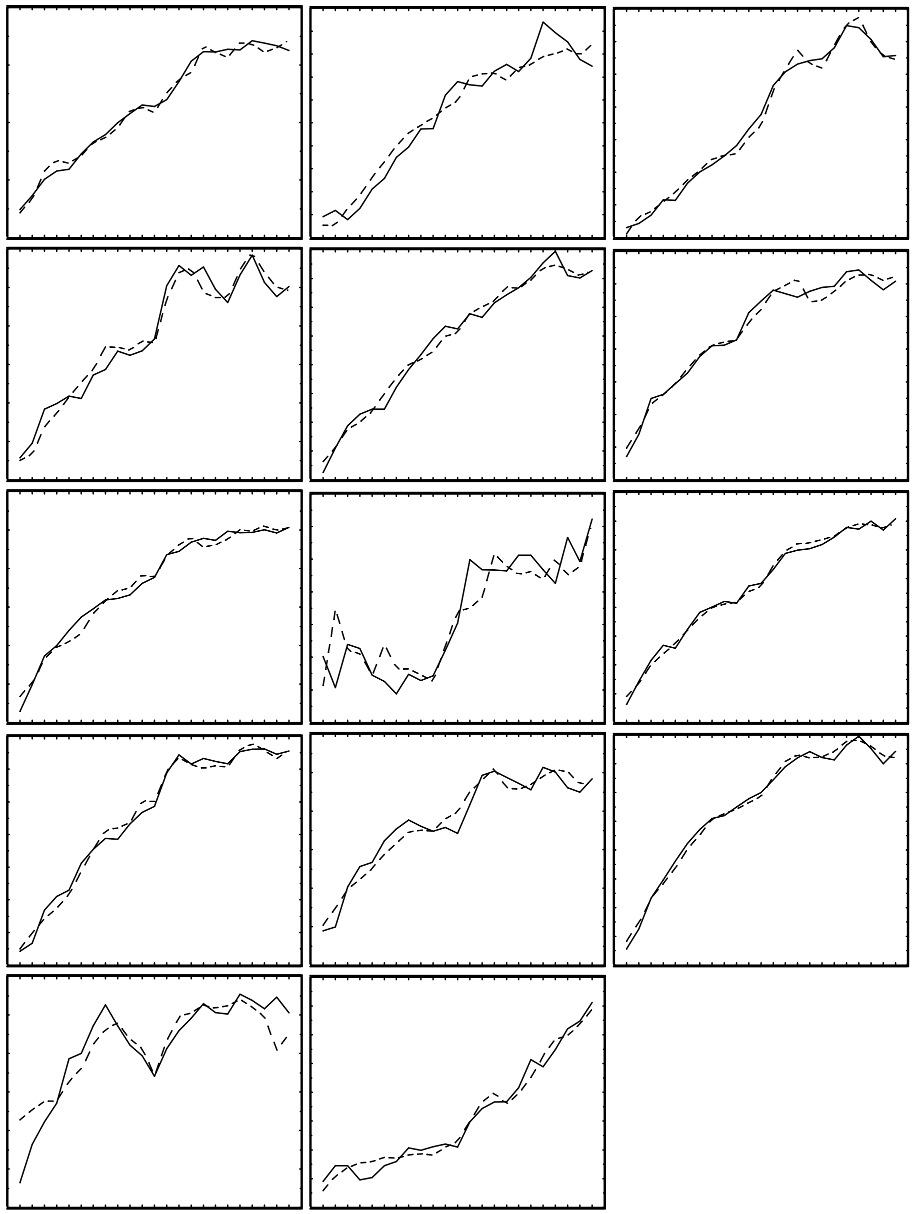

Fig. 5. Value Added per Labour Unit and FM-OLS estimates plus smoothed OLS estimates of common time dummies in model (5), 1981-2004. From left to right and top to bottom (rows in brackets): [1] Non-Energy, Food, Textiles; [2] Leather, Wood, Paper; [3] Chemicals, Rubber, Non-Metals; [4] Metals, Machinery, Electricals; [5] Transport and Utilities (abbreviations: see table A1).

Let us now examine TFP estimates. In Fig. 6 we plotted the first differences of the coefficients along with those obtained following the growth accounting approach by Istat (2007). As w can seen, the results are striking. Following a method entirely different we end up drawing essentially similar pictures: a falling trend reversed only temporarily in the early-'90's. This evidence thus appears to robust to the estimation method adopted.

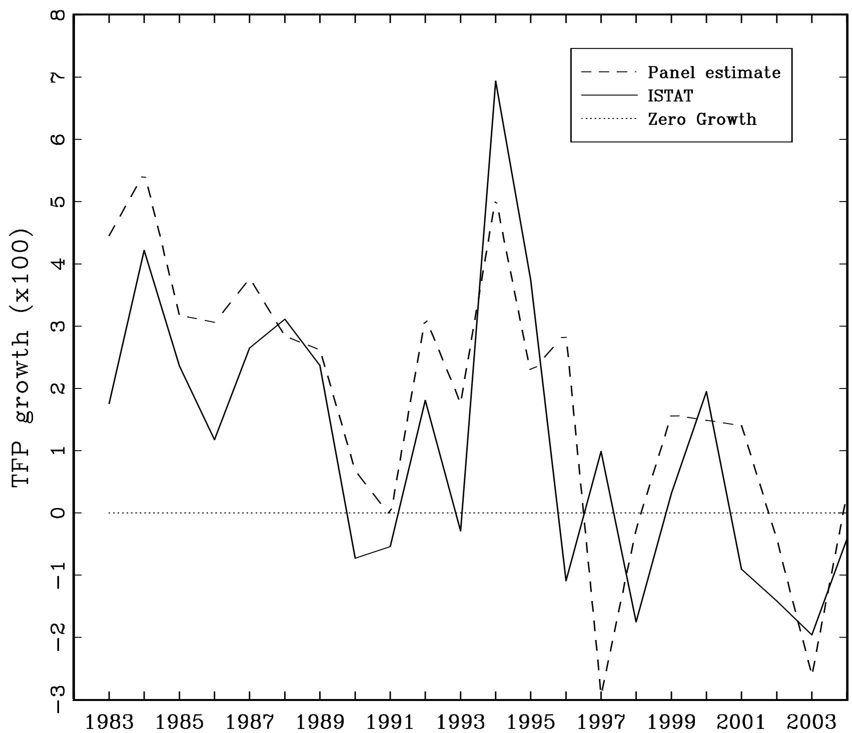

Fig. 6. Alternative estimates of TFP growth rates, 1982-2004. Panel estimates: first differences of coefficients of time dummies in model (5) estimated on all Manufacturing industries except "Energy Mining", "Oil" and "Other Industries". Istat: growth accounting estimates, entire Manufacturing industry (Istat, 2007).

The next natural step is 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, R&D expenditure growth (Δrd), a human capital index (h), and finally,to capture factor reallocation across capital types, the standard deviations across types (machinery, buildings, computers, communication equipment, software, furniture, transportation equipment) of fixed capital growth. To avoid endogeneity all variables have been included with one lag.

The results, reported in Table 4, appear interesting. Factor reallocation, as measured by growth variability across industries, is strongly significant, while there seems to be a weaker but not totally negligible effect of shifts in capital composition. R&D expenditure is not significant, which is not surprising in view of the results reported by Atella and Quintieri (2001). Finally, the failure to detect a significant influence of changes in human capital may be at least partially due to measurement problems.

Table 4
Determinants of TFP growth, 1982-2004

$\sigma_{t-1}^{\Delta l}$	$\sigma_{t-1}^{\Delta(k-l)}$	Δh_{1t-1}	Δh_{2t-1}	Δrd_t	σ_{t-1}^{K}	$const$
1.71 (2.65)	7.62 (3.59)	0.03 (1.08)	0.007 (0.73)	0.09 (0.97)	0.04 (1.38)	−0.21 (−3.95)
$se = 0.02; LM(p) = 0.57$ (0.46)						

Dependent variable: first difference of the coefficients φ of the common time dummies D_t in model (5);
$\sigma^{\Delta x}$ = variance of growth rates of factor x across branches;
Δh_j : log difference of human capital index, $j = 1 : t < 1992$
(break in the series), $j = 2 : t > 1992$;
Δrd : log difference of R&D expenditure;
σ^K : variance of growth rates across capital types;
t-statistics in brackets underneath the estimates;
se : standard error of residuals;
LM: test for no first order autocorrelation (p-value in brackets).

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, building on recent developments in the analysis of non-stationary, dependent panels, we developed a method for obtaining estimates of TFP trends (*i*) free from the restrictive assumptions needed by traditional growth accounting and (*ii*) 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. 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 suggests that the most obvious culprits, namely the completion of a factor reallocation process among industries and capital types, did actually play an important role in this decline.

5 References

Atella, V. and B. Quintieri (2001) "Do R&D expenditures really matter for TFP?" *Applied Economics*, 33, 1385-1389.

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.

Bernanke, B.S. (2005) " Remarks" *C. Peter McColough Roundtable Series on International Economics*, Council on Foreign Relations University of Arkansas at Little Rock Business Forum

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.

Centraal Planbureau "Recent trends in Dutch labor productivity: the role of changes in the composition of employment" Working Paper n. 98 CPB Netherlands Bureau for Economic Policy Analysis, The Hague (NL)

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

Davidson R., and J.G. MacKinnon (2000) "Improving the Reliability of Bootstrap Tests" *Queen's University Institute for Economic Research Discussion Paper* No. 995.

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).

Di Iorio, F. and S. Fachin (2008) "A Note on the Estimation of Long-Run Relationships in Dependent Cointegrated Panels" Working Paper, University of Rome "La Sapienza".

Dolman, B., L. Lu and J. Rahman (2005) "Understanding productivity trends" Australian Treasury.

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.

Gengenback, C., F.C. Palm, J.P. Urbain (2006) "Cointegration Testing in Panels with Common Factors" *Oxford Bulletin of Economics and Statistics*, 768, 684-719.

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

Hsiao, C., Y. Shen and H. Fujiki (2002) "Aggregate vs Disaggregate Data Analysis - A Paradox in the Estimation of Money Demand Function of Japan Under the Low Interest Rate Policy" Working Paper, UCLA (USA).

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

Islam, N. (1995) "Growth Empirics: a Panel Data Approach" *Quarterly Journal of Economics, 110, 1127-1170.*

Istat (2007) "Misure di produttività - Anni 1980-2006" *Statistiche in breve*, 5 Ottobre 2007.

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.

Marrocu, E., R. Paci and R. Pala (2001) "Estimation of total factor productivity for regions and sectors in Italy. A panel cointegration approach" *RISEC*, 48, 533-558.

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

Moon, H.R. (1999) "A note on fully-modified estimation of seemingly unrelated regressions models with integrated regressors" *Economics Letters* 65, 25-31.

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 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, $\{X_1 X_2 \ldots X_N, Y_1 Y_2 \ldots Y_N\}_{t=1}^T$;

2. construct separately by CBB two sets of N pseudo-series, $\{X_1^* X_2^* \ldots X_N^*\}_{t=1}^{T^*}$ and $\{Y_1^* Y_2^* \ldots Y_N^*\}_{t=1}^{T^*}$;

3. compute the Group statistics G^* for the pseudo-data set, $\{X_1^* X_2^* \ldots X_N^*, Y_1^* Y_2^* \ldots Y_N^*\}_{t=1}^{T^*}$;

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 Data

6.2.1 Definitions and Sources

Labour Productivity Value Added per Labour Unit.

Value Added At 1995 prices. Istat, *Conti economici nazionali 1970-2007.*

Labour Units Istat's implementation of the ESA95 concept of full time equivalent employee. Istat, *Conti economici nazionali 1970-2007.*

Capital Gross Capital stock at 1995 prices. Istat, *Conti economici nazionali 1970-2007.*

Capacity Utilisation Bank of Italy Utilisation Index. Because of the lower detail of this index with respect to the data on capital stock 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 manufacturing index has been used for the both the Non metals; (iii) the economy-wide index has been used for the Utilities.

Research and Development expenditure: share of GDP. OECD, *Main Science and Technology Indicators.*

Human Capital Index: Average education of workforce weighted with average net wages, index 1977=100. Brandolini and Cipollone (2001).

6.2.2 Industry Classification

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

	Abbreviation	GDP Share	Share
Section C Mining and Quarrying	*Mining*	*0.5*	*1.9*
Mining and quarrying of energy producing materials	Energy	0.3	1.2
Mining and quarrying, except of energy producing materials	Non-Energy	0.2	0.7
Section D Manufacturing	*Manufacturing*	*20.3*	*90.3*
Food products, beverages and tobacco	Food	2.0	8.4
Textiles and textile products	Textiles	2.1	8.9
Leather and leather products	Leather	0.7	2.7
Wood and wood products	Wood	0.5	2.2
Pulp, paper and paper products; publishing and printing	Paper	1.2	5.1
Coke, refined petroleum products and nuclear fuel	Coke	0.4	1.6
Chemicals, chemical products and man-made fibres	Chemicals	1.5	6.2
Rubber and plastic products	Rubber	0.8	3.4
Other non-metallic mineral products	Non-metals	1.2	4.8
Basic metals and fabricated metal products	Metals	3.0	12.3
Machinery and equipment n.e.c.	Mach	2.4	9.9
Electrical and optical equipment	Electricals	1.9	8.0
Transport equipment	Transport	1.2	4.9
Manufacturing n.e.c.	Other	1.0	4.2
Section E Electricity, Gas and Water Supply	*Utilities*	*1.9*	*7.7*

GDP Share: average 1981-2004 GDP share×100.
Share: average 1981-2004 share×100 of the total value added of Sections C, D and E.
Source: Istat, *Conti economici nazionali 1970-2007.*