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The contribution of physical and human capital accumulation to Italian regional growth: a nonparametric perspective

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Abstract This paper examines changes in the labor productivity, efficiency, technology, and physical and human capital experienced by different regions in Italy between 1980 and 2006. Cobb-Douglas and translog production specifications are not supported by the data. Thus, non-parametric methods are used to compute the Malmquist indices and their components. Moreover, the bootstrap technique allows us to determine the confidence intervals of all components of the labor productivity decomposition. The results suggest that the contributions of efficiency, technology, and physical and human capital accumulation to labor productivity growth differ significantly between Southern Italy and the remainder of the country.

Keywords Total factor productivity (TFP) · Regional convergence · Human capital · Bootstrap · Data envelopment analysis (DEA) · Italian regions

JEL Classification C14 · 047 · R11

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1 Introduction

This paper contributes to the debate on growth and inequality in Italy. Italy represents one of the most interesting cases of a regional divide (Maffezzoli 2006). Although the Northern and Central parts of the country exhibit labor productivity levels comparable to the most industrialized high-income economies, the Southern regions are characterized by labor productivity levels that are similar to those of middle-income countries. This aspect has been investigated in several empirical papers that differ in the periods analyzed and in the techniques employed. The empirical literature is equally divided between parametric and nonparametric models. Despite the relevant number of papers, there is no general consensus on the major research questions. Some of these papers conclude that Italian regions do not display a common process of convergence; at best, only club convergence can be observed (Byrne et al. 2009; Piacentino and Vassallo 2011). In contrast, Maffezzoli (2006) found evidence of absolute β- and σ- convergence. Furthermore, the roles played by total factor productivity (TFP), technological catch-up, technological change, and physical and human capital accumulation as determinants of economic growth remain unclear. For instance, the results of Maffezzoli (2006), Di Liberto et al. (2008), and Conti (2009) suggest a strong impact of TFP on labor productivity, whereas Scoppa (2007) and Piacentino and Vassallo (2011) show that the role of TFP is reduced when human capital is taken into account.

From a methodological point of view, most of these papers are in accordance with growth accounting literature, which assumes a Cobb-Douglas production function. However, the use of a Cobb-Douglas specification can create misleading assumptions because the neutrality of the technology changes and yields biased results in the presence of inefficiencies (Färe et al. 1994).[1] In contrast, Data Envelopment Analysis (DEA) is a nonparametric technique that does not require an a priori specification of the functional form and allows inferences to be drawn when it is used in a bootstrap setting (Simar and Wilson 2008).

In this paper, DEA is employed to analyze the evolution of the labor productivity of 20 Italian regions from 1980 to 2006. Based on papers by Kumar and Russell (2002) and Henderson and Russell (2005), labor productivity is reassessed as efficiency changes (the change in the distance from the best-practice frontier), technology changes (shifts of the frontier), and physical and human capital change (movements along the frontier due to changes in the level of physical and human capital).

A further contribution of this study is that the distribution of regional output per worker and its dynamics between 1980 and 2006 are examined in detail. In fact, as discussed by Quah (1997) and Kumar and Russell (2002), approaches based only on the first moment of labor productivity distribution provide only a partial view of the process of growth. Instead, we analyze the effects of the four components of decomposition on the evolution of the distribution of regional labor productivity. Nonparametric kernel methods are also applied to test for the significance of the relative contribution of each component for changes in the shape of the distribution.

The primary results are as follows: (1) the differences in physical capital accumulation between Southern regions and the remaining areas of the country are the most important determinants of the Italian economic regional divide; (2) the human capital accumulation is the most important source of growth in the South of Italy; (3) two high-income regions (Lazio and Liguria) exhibit significant technological regress; and (4) the analysis of the density distribution of labor productivity reveals the presence of two convergent clubs. The results of (1) and (2), on the one hand, are the direct consequence of policies in the 1990s, which were devoted to reducing public capital funds and increasing the role of human capital in Southern Italy; on the other hand, they leave open the question of future government intervention to reduce the productive gap in the Southern regions. Result (3) indicates that the wealthiest Italian regions are not able to stimulate growth through innovation.

The rest of the paper proceeds as follows. Section 2 describes the applied methodologies used to categorize the production frontier. Section 3 presents the data. The empirical results are presented in Sect. 4. Finally, Sect. 5 concludes.

2 Methodology

Following Färe et al. (1994), Kumar and Russell (2002), Henderson and Russell (2005), DEA is used to decompose labor productivity growth into indices that describe changes in technology, efficiency, and physical and human capital accumulation. Once the productivity indices are calculated, their confidence intervals are estimated using bootstrap techniques (Simar and Wilson 1999).

Let K_t and L_t be the inputs used in the production process, capital, and labor at time t, and let Y_t be the output. Then, following the literature on regional growth, human capital is included in the production function as a multiplicative augmentation of the physical labor input. Thus, the amount of the augmented labor input for region i at time t is given by $\hat{L}_{it} = L_{it}h_{it}$, where h_{it} is the average level of human capital.

Let $e_{i,12}$ be the distance function for region i at time t_1 relative to the technology existing at time t_2. In the same manner, $e_{i,21}$ denotes the distance function for region i at time t_2 relative to the technology t_1. Then, following Färe et al. (1994), the Malmquist productivity index between period t_1 and period t_2 is given by

$$PROD = \mathcal{M}(t_1, t_2) \equiv \frac{e_{22}}{e_{11}} \times \left[\frac{e_{21}}{e_{22}} \times \frac{e_{11}}{e_{12}}\right]^{\frac{1}{2}}, \quad (1)$$

where the ratio outside the square brackets measures the change in the output-oriented measure, i.e., the efficiency change (technological catch-up), and the remaining part is a measure of the shift in technology, i.e., technological change.

Under the assumption of constant returns to scale,[2] the production set can be reduced to a two-dimensional space, with $\hat{y} = Y/\hat{L}$ and $\hat{k} = K/\hat{L}$. Thus, the potential outputs per efficiency units of labor in period t_1 and t_2 are computed by $\bar{y}_1(\hat{k}_1) = \hat{y}_1/e_{11}$ and $\bar{y}_2(\hat{k}_2) = \hat{y}_2/e_{22}$. Similarly, $\bar{y}_1(\hat{k}_2)$ denotes the potential output per efficiency unit of labor at period t_2 of capital intensity using the technology existing at time t_1 and $\bar{y}_2(\hat{k}_1)$ denotes the potential output per efficiency unit of labor at period t_1 relative to the technology at time t_2. Finally, let $\tilde{k}_1 = K_1/(L_1 h_2)$ be the ratio of capital to labor at period t_1 if human capital does not change in period t_2. Then, $\bar{y}_2(\tilde{k}_1)$ is the potential output per efficiency

[1] Papers by Kneller and Andrew Stevens (2003) and Henderson and Kumbhakar (2006) show cases in which the Cobb-Douglas or the more flexible translog specifications are unable to represent the productive process at the country level.

[2] The Malmquist productivity index is defined on a benchmark technology satisfying constant returns to scale (CRS). It provides an accurate measure of productivity change if, and only if, the index is defined on a technology exhibiting constant returns to scale (Färe et al. 1994).

unit of labor at $\tilde{k}_1$ using the technology at time t_2. Similarly, $\bar{y}_1(\tilde{k}_2)$ denotes the potential output per efficiency unit of labor at $\tilde{k}_2$ using the technology at time t_1, where $\tilde{k}_2 = K_2/(L_2 h_1)$ is the ratio of capital to labor at period t_2 if human capital is equal to the level at period t_1. Under the above conditions, the labor productivity index can be decomposed as follows (Kumar and Russell 2002; Henderson and Russell 2005):

$$\begin{aligned} LABPROD = \frac{y_2}{y_1} = \frac{e_{22}}{e_{11}} \times \left[\frac{\bar{y}_2(\hat{k}_2)}{\bar{y}_1(\hat{k}_2)}\frac{\bar{y}_2(\hat{k}_1)}{\bar{y}_1(\hat{k}_1)}\right]^{\frac{1}{2}} \times \left[\frac{\bar{y}_1(\tilde{k}_2)}{\bar{y}_1(\hat{k}_1)}\frac{\bar{y}_2(\hat{k}_2)}{\bar{y}_2(\tilde{k}_1)}\right]^{\frac{1}{2}} \\ \times \left[\frac{\bar{y}_1(\hat{k}_2)}{\bar{y}_1(\tilde{k}_2)}\frac{(h_2)^2}{(h_1)^2}\frac{\bar{y}_2(\tilde{k}_1)}{\bar{y}_2(\hat{k}_1)}\right]^{\frac{1}{2}} \\ := EFF \times TECH \times KACC \times HACC \end{aligned} \quad (2)$$

where *EFF* represents the efficiency change (technological catch-up), *TECH* identifies the technological change, and *KACC* and *HACC* are the physical and human capital accumulation, respectively.

However, Eqs. (1) and (2) do not determine whether the changes in productivity and efficiency are real or merely artifacts. The true production frontiers are unknown and must be estimated from finite samples. Thus, following papers by Simar and Wilson (1998, 1999), a consistent bootstrap estimation procedure is employed to obtain bias-corrected confidence intervals. The idea underlying the bootstrap technique is to approximate the sampling distributions of the indices by simulating the data-generating process (DGP). In the case of individual distance function estimates, the corresponding bias may be substantial. However, as noted by Simar and Wilson (1999), because the components of the Malmquist index, as well the terms in relation (2), are ratios of distance functions, their overall bias may be less than for individual distance function estimates; both the numerator and the denominator are biased in the same direction. Moreover, in relation (2), there is a time dependence that must be taken into account when the efficiency scores are bootstrapped. To accomplish this, the smoothing kernel method is employed to estimate the joint density of efficiency scores in periods t_1 and t_2 [see Simar and Wilson (1999) and “Appendix A” for details)[3].

3 Data

The panel data set used in this work covers 20 Italian regions from 1980 to 2006. The main data sources are statistics provided by the Italian National Institute of Statistics (ISTAT). In particular, the value added (Y) at the constant 1995 price and the number of workers (L) in a full-time standard measure are obtained at the regional level from regional economic accounts (ISTAT 2006a). The average level of human capital employed in the determination of the augmented labor input (see Sect. 2) is given by $h_{it} = e^{w_i s_{it}}$, where w_i represents the time-invariant regional-specific return to schooling estimated by Ciccone (2004) and s_{it} are the regional average years of schooling at time t, which are calculated based on the labor force drawn from the ‘ISTAT Labor Force Survey’ (ISTAT 2006b) by applying the methodology used by Bronzini and Piselli (2009). In particular, we attribute 0 to a person with no qualifications, 5 for completing primary school, 8 for lower secondary school, 10.5 for a professional diploma, 12.5 for people completing secondary education, 15.5 for a “short” degree (*laurea breve*), and 18 for a standard degree.

Because ISTAT only publishes data on the national stock of net physical capital, the regional stock at the constant 1995 price is obtained from the methodology described by Byrne et al. (2009), who use a matrix of regional shares to disaggregate national stock. In particular, the regional subdivision is based on the regional average share of investments (weight 0.75) and labor units (weight 0.25) in the preceding 15 years (Paci and Pusceddu 2000). Let NK_t denote the net capital stock at the national level at time t, let $I_{i,t}$ denote the investment in physical capital for region i at time t, and let $L_{i,t}$ denote the number of workers for region i at time t. The stock of physical capital for region i at time t is equal to

$$K_{i,t} = \left(0.75 \times \overline{IS}_{i,t} + 0.25 \times \overline{L}_{i,t}\right) \times NK_t, \quad (3)$$

where the regional average share of investments ($\overline{IS}_{i,t}$) and labor ($\overline{L}_{i,t}$) at time t are computed as follows:

$$\overline{IS}_{i,t} = \left(\sum_{t-14}^{t} \frac{I_{i,t}}{\sum_{i=1}^{20} I_{i,t}}\right)/15, \quad \overline{L}_{i,t} = \left(\sum_{t-14}^{t} \frac{L_{i,t}}{\sum_{i=1}^{20} L_{i,t}}\right)/15.$$

Table 1 shows the summary statistics of the variables considered in the analysis. The variables are divided by a scale factor by region, setting the national average equal to 100.

4 Empirical results

4.1 Decomposition of the factors affecting labor productivity

Various approaches exist to estimate regional growth. In the traditional growth accounting literature, Cobb-Douglas

[3] The smooth bootstrap procedure for efficiency measures was implemented using FEAR package (Wilson 2008). The results are obtained from 5,000 bootstrap iterations.

Table 1 Summary statistics

Region	CODE	Geographical location	1980			2006		
			Output per worker	Capital per worker	Years of schooling	Output per worker	Capital per worker	Years of schooling
Abruzzo	ABR	S	93.5	104.6	97.0	94.1	98.8	103.3
Basilicata	BAS	S	78.9	112.0	89.8	93.5	108.9	98.9
Calabria	CAL	S	81.3	95.2	97.9	82.8	95.3	99.5
Campania	CAM	S	87.1	96.2	98.2	91.2	92.8	97.7
Emilia-Romagna	EMR	N	109.0	102.4	99.6	107.6	99.4	100.7
Friuli-Venezia-Giulia	FVG	N	94.1	107.7	107.4	109.4	99.6	102.1
Lazio	LAZ	C	117.5	82.9	115.5	108.3	90.1	107.2
Liguria	LIG	N	112.2	78.2	109.9	110.3	89.3	103.6
Lombardia	LOM	N	113.9	97.8	104.7	113.1	98.8	100.6
Marche	MAR	C	89.4	89.1	92.1	97.4	89.3	101.4
Molise	MOL	S	84.5	112.3	90.9	95.1	103.1	100.9
Piemonte	PIE	N	107.3	98.8	100.7	107.1	105.2	99.4
Puglia	PUG	S	84.2	92.4	93.0	86.8	84.9	95.9
Sardegna	SAR	S	103.8	120.7	100.0	88.8	106.8	95.1
Sicilia	SIC	S	100.3	110.3	98.0	93.7	94.5	97.3
Toscana	TOS	C	103.3	89.9	100.7	100.4	89.1	100.3
Trentino-Alto Adige	TRA	N	115.8	116.2	102.7	108.6	132.5	96.8
Umbria	UMB	C	100.4	94.5	98.2	96.9	94.2	105.0
Valle d'Aosta	VDA	N	120.7	103.1	104.1	110.2	127.2	96.2
Veneto	VEN	N	102.8	95.5	99.7	104.7	100.2	98.0
North (average)	N		109.5	100.0	103.6	108.9	106.5	99.7
Center (average)	C		102.7	89.1	101.6	100.8	90.7	103.5
South (average)	S		89.2	105.5	95.6	90.7	98.1	98.6
Italy (average)	ITA		100.0	100.0	100.0	100.0	100.0	100.0

Source Author's computations on ISTAT data. Italy, North, Center and South refer to the average across regions (Italian mean = 100)

or translog specifications are often used. In this paper, we test both the Cobb-Douglas and translog production functions using the procedure proposed by Hsiao et al. (2007). In particular, the test by Hsiao et al. reveals that both the Cobb-Douglas and translog specifications are not appropriate functional forms for describing the productive process at the regional level in Italy.[4]

Thus, the nonparametric technique described in Sect. 2 is employed to determine the labor productivity evolution in Italian regions. Table 2 shows the bias-corrected efficiency scores and the estimated 95 % confidence intervals in 1980 and 2006. The table highlights that Southern regions are characterized by a lower level of efficiency, although their efficiency gap was reduced from 1980 to 2006. We show that Liguria, Lazio, and Valle D'Aosta are the most efficient regions, in line with the results obtained by Maffezzoli (2006) and Piacentino and Vassallo (2011). However, with the exception of Sicily, these regions do not appear to be significantly more efficient than regions located in the Center and North of the country (see Table 2). Furthermore, it is interesting to note that if the DEA efficiencies are considered as estimates, as in the present paper, and the confidence intervals are obtained accordingly, discussion of the regional efficiency rankings may be meaningless.

The components of the labor decomposition from 1980 to 2006 for the 20 regions are reported in the first part of Table 3. Moreover, in the second part of Table 3, the evolution of labor productivity for the three macro-areas (North, Center, and South) are reported by considering two averaging methods: the geometric and the weighted average (Zelenyuk 2006). Because the two aggregation methods produce similar outcomes, we will refer to the results obtained by applying the geometric average.

[4] Specifically, we test the Cobb-Douglas (translog) model against a fully nonparametric alternative. The null hypothesis of the test is that the parametric specification is correct and the alternative is a fully nonparametric model. We reject the parametric specifications at the 1 % level. Additional details and discussion are provided in "Appendix B" of Supplementary material.

Table 2 Efficiency scores with estimated 95 % confidence intervals

Region	1980				2006			
	Eff. scores	Bias corrected eff. scores	Lower bound	Upper bound	Eff. scores	Bias corrected eff. scores	Lower bound	Upper bound
ABR	0.875	0.870	0.859	0.875	0.872	0.862	0.848	0.871
BAS	0.782	0.778	0.769	0.782	0.918	0.905	0.888	0.917
CAL	0.741	0.734	0.720	0.741	0.768	0.758	0.744	0.767
CAM	0.818	0.812	0.799	0.818	0.892	0.883	0.869	0.891
EMR	0.982	0.976	0.961	0.982	0.981	0.970	0.955	0.979
FVG	0.818	0.813	0.801	0.818	0.991	0.980	0.965	0.990
LAZ	1.000	0.934	0.854	0.998	0.993	0.960	0.925	0.991
LIG	1.000	0.940	0.849	0.998	1.000	0.953	0.916	0.998
LOM	0.965	0.949	0.921	0.964	0.992	0.978	0.954	0.991
MAR	0.855	0.845	0.827	0.854	0.935	0.919	0.894	0.934
MOL	0.825	0.821	0.811	0.825	0.905	0.890	0.874	0.903
PIE	0.953	0.944	0.927	0.953	0.960	0.945	0.929	0.958
PUG	0.820	0.813	0.800	0.819	0.889	0.876	0.857	0.887
SAR	0.963	0.958	0.947	0.962	0.864	0.852	0.836	0.864
SIC	0.948	0.943	0.932	0.948	0.919	0.908	0.893	0.918
TOS	0.946	0.929	0.900	0.945	0.963	0.946	0.919	0.961
TRA	0.981	0.976	0.963	0.981	0.939	0.927	0.909	0.939
UMB	0.981	0.975	0.960	0.981	0.956	0.944	0.928	0.955
VDA	0.987	0.974	0.950	0.986	0.917	0.905	0.887	0.916
VEN	0.954	0.947	0.930	0.954	1.000	0.982	0.965	0.997

From the last two columns of Table 3, it can be observed that both the physical and human capital accumulations are powerful determinants of economic growth in the three Italian macro-areas. However, the growth resulting from physical capital accumulation in the South (+11.56 %) is less than that registered in the Center (+22.50 %) and the North (+19.88 %) of the country. Figure 1 shows the physical capital growth of the three macro-areas. The Northern and Central regions show an annual percentage growth of 3.20 and 3.67 %, respectively, whereas the Southern regions are characterized by a slower annual percentage growth (2.03 %), especially after the 1990s, when public capital investments were drastically reduced (Picci 1999; Mastromarco and Woitek 2006; Montanaro 2003; Bronzini and Piselli 2009). In particular, it is interesting to compare the physical capital growth and the changes in capital accumulation over 2-year periods.[5] Even without testing the effectiveness of public capital on economic growth, the comparison of Fig. 1 and the results in "Appendix C" clearly confirm that the reduction of public intervention has had a negative impact on growth (Mastromarco and Woitek 2006).

The human capital accumulation shows slight differences among the three macro-areas.[6] However, in the South, human capital accumulation has a greater impact on labor productivity growth than in the remainder of the country. This finding supports the policy devoted to reducing the gap in education levels between the South and the rest of the country.[7] Moreover, as noted by Di Liberto et al. (2008), the human capital accumulation increases the capacity of a region to absorb new technologies from its neighbors, fostering the process of convergence.

The average contribution of the total factor productivity component to labor growth differs broadly between the three macro-areas. In the South, the value of the component, which is far above the national average, is mostly attributable to the efficiency change. This finding seems to confirm the existence of a moderate process of technological catch-up, on average, between the South and the

[5] Results are given in a separate "Appendix C" of Supplementary material.

[6] Since the results on human capital accumulation may depend on the regional rates of return on schooling employed, the analysis is repeated using an unique parameter for all the regions estimated by Brunello and Miniaci (1999). These results, omitted for brevity, do not differ and are available from the authors upon request.

[7] In the southern regions, the average years of schooling increase from 7.1 to 10.9 during the period 1980–2006, against the 7.5–11.1 registered at the national level.

Table 3 Percentage change of decomposition of labor productivity growth

Region	LABPROD	PROD—1 × 100	EFF—1 × 100	TECH—1 × 100	KACC—1 × 100	HACC—1 × 100
ABR	39.85	7.20***	−0.34	7.57***	14.41***	14.02***
BAS	64.80	28.96***	17.33***	9.91***	7.49***	18.89***
CAL	41.53	4.99***	3.59***	1.35*	19.93***	12.40***
CAM	45.58	13.34***	9.10***	3.89***	16.13***	10.61***
EMR	37.31	4.75***	−0.16	4.92***	16.68***	12.34***
FVG	61.66	27.93***	21.14***	5.60***	14.10***	10.74***
LAZ	28.21	−10.15***	−0.71	−9.50***	29.29***	10.37***
LIG	36.80	−10.30***	0.00	−10.30***	37.30***	11.07***
LOM	38.02	1.52***	2.81**	−1.25	21.65***	11.75***
MAR	51.48	9.35***	9.36***	−0.01	21.85***	13.69***
MOL	56.43	20.31***	9.62***	9.75***	9.03***	19.26***
PIE	38.77	3.75***	0.71	3.01***	19.74***	11.71***
PUG	43.37	11.67***	8.44***	2.98***	15.83***	10.84***
SAR	19.06	−1.20***	−10.20***	10.03***	3.97	15.89***
SIC	29.85	5.19***	−3.09***	8.54***	8.34***	13.95***
TOS	35.12	−0.04**	1.76	−1.77	21.37***	11.36***
TRA	30.42	3.79***	−4.27***	8.42***	12.38***	11.81***
UMB	34.23	2.73***	−2.53**	5.40***	16.70***	11.96***
VDA	26.93	−5.94***	−7.08***	1.22*	21.62***	10.96***
VEN	41.55	8.74***	4.77**	3.79***	17.96***	10.35***
Geometric average						
North	38.61	3.77***	1.95	1.78**	19.98***	11.34***
Center	37.00	0.22**	1.87	−1.62	22.22***	11.84***
South	41.93	10.95***	3.98***	6.70***	11.77***	14.44***
All	39.60	5.85***	2.74**	3.02***	17.06***	12.67***
Weighted average						
North	39.12	4.02***	2.54**	1.44*	20.43***	11.36***
Center	34.32	−3.15	1.34	−4.43*	24.89***	11.59***
South	38.64	8.83***	3.04**	5.62***	12.92***	12.62***
All	38.39	4.12***	2.61**	1.47*	19.50***	11.79***

Statistical significance: *** statistically significant at a 1 % level, ** statistically significant at a 5 % level, * statistically significant at a 10 % level according to the bootstrap confidence intervals

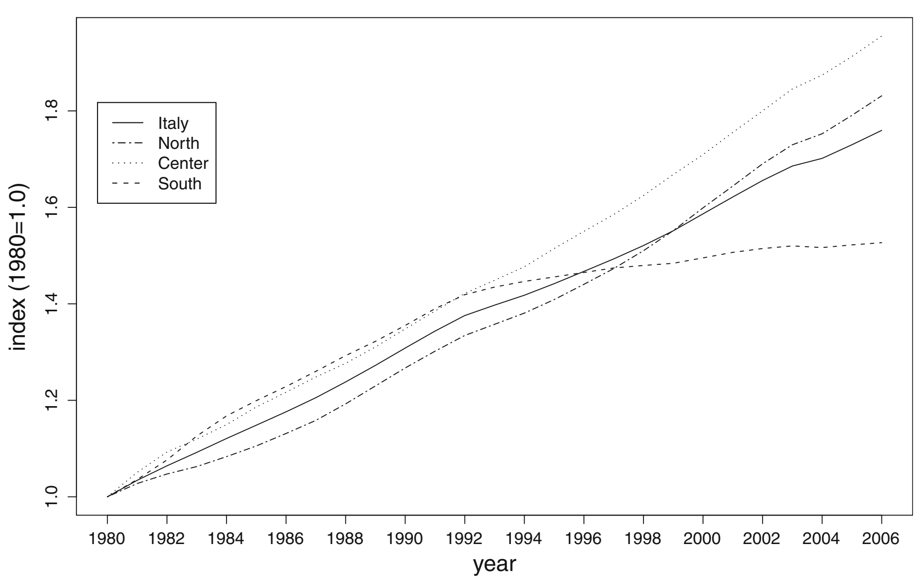

Fig. 1 Physical capital growth, 1980–2006

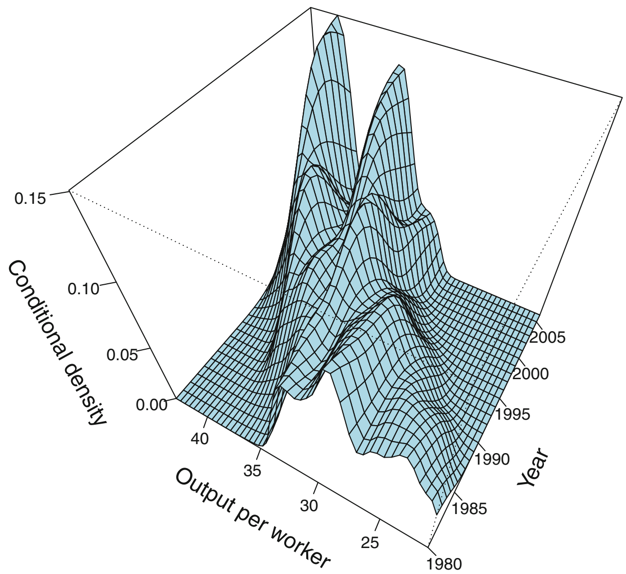

Fig. 2 Nonparametric conditional density $f(y|year)$. *Notes* Likelihood cross-validation method is used to obtain the bandwidths, with $h_y = 0.661$ and $h_{year} = 2.255$

remaining areas of the country from 1980 to 2006. The results of technological change differ from those obtained in previous papers, which considered a different period of analysis (Maffezzoli 2006; Piacentino and Vassallo 2011). In particular, we discovered that the South has experienced significant technological progress; in other words, the poorer regions seem to have benefited from technology transfer (Bronzini and Piselli 2009). For the two remaining areas, there are no significant changes, and we cannot draw any definitive conclusions. However, it is interesting to note that two wealthy regions (Lazio and Liguria) exhibit a significant technological regress. The technological decline may be the consequence of several factors (that are not mutually exclusive): an input-biased technical change caused by non-neutral technical change (Färe et al. 1997), a different sectoral composition of the regional economies, a different relationship between investments in R&D and productivity, which is stronger in the high-tech sectors (Ortega-Argilés et al. 2010), or a reduction of exports, which is an important factor in stimulating innovation in Italy (Basile 2001). In the cross-country growth literature, technological regression was also found by Kumar and Russell (2002), Färe et al. (2006), Badunenko et al. (2008) and Ceccobelli et al. (2011, 2012). In these studies, the explanations provided for this result differed: for Färe et al. (2006) and Badunenko et al. (2008), the implosion of the frontier could be interpreted as an efficiency decline rather than a real technological regress; in the works of

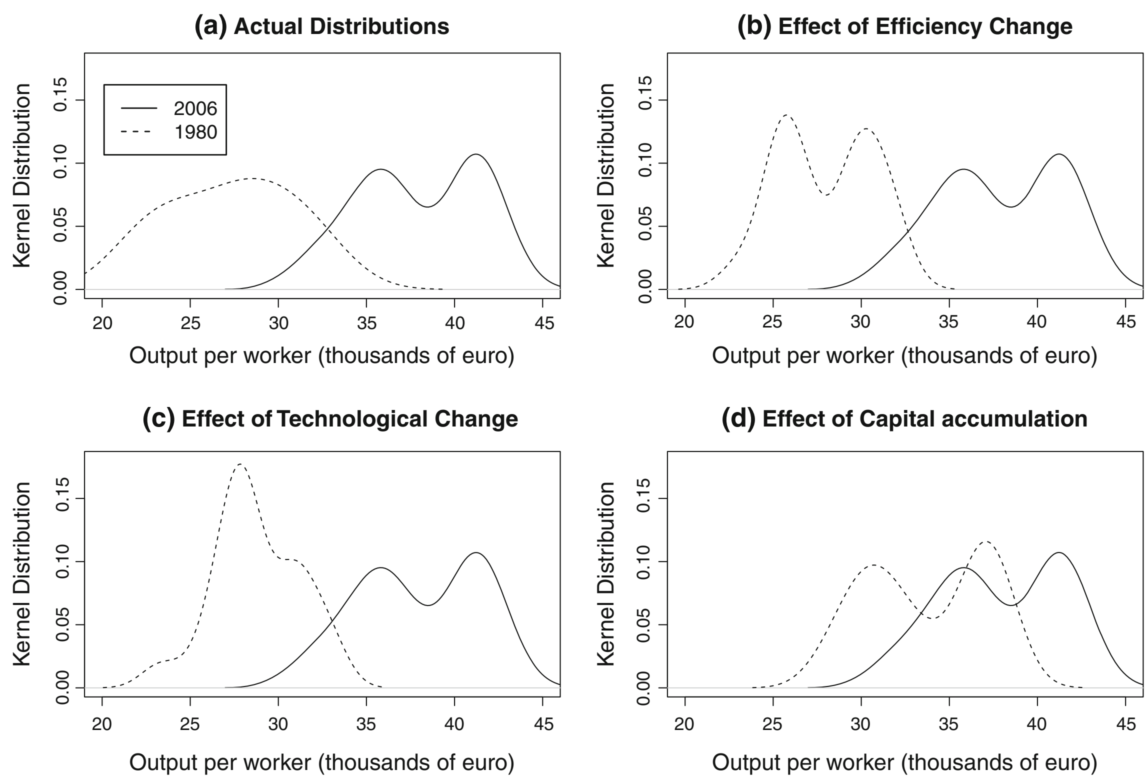

Fig. 3 Counterfactual distributions of output per worker. *Notes* in each panel, the *solid curve* is the actual 2006 distribution of output per worker. In panel **a**, the dashed curve is the actual 1980 distribution of output per worker. The *dashed curves* in panels **b**, **c** and **d** are counterfactual distributions isolating, sequentially, the effects of efficiency change, technological change and physical capital accumulation for the 1980 distribution of output per worker

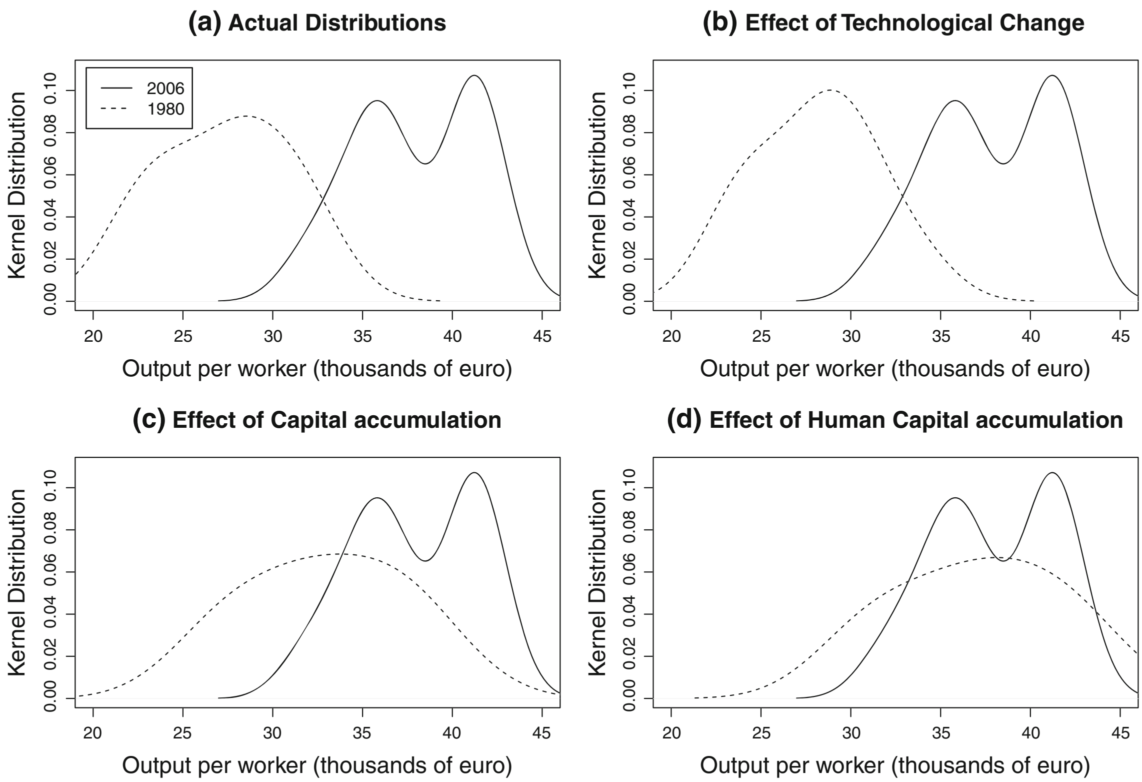

Fig. 4 Counterfactual distributions of output per worker. *Notes* in each panel, the *solid curve* is the actual 2006 distribution of output per worker. In panel **a**, the dashed curve is the actual 1980 distribution of output per worker. The *dashed curves* in panels **b**, **c** and **d** are counterfactual distributions isolating, sequentially, the effects of technological change, physical and human capital accumulation for the 1980 distribution of output per worker

Ceccobelli et al. (2011, 2012), technological regress is the consequence of a declining level of capacity utilization of ICT technologies.

Finally, because the findings obtained from the analysis of Table 3 may depend on the choice of the initial and final time periods, the analysis is repeated over 2-year periods, and the results largely confirm the above conclusions.[8]

4.2 Analysis of productivity distributions

Here, the paper turns to an analysis of the distribution dynamics of labor productivity, which is likely to be more informative than summary measures. We demonstrate the evolution of the distribution of labor productivity in the sample period, and we evaluate the degree to which each of the components of productivity change account for the change in the distribution of labor productivity between 1980 and 2006. We estimate the density of output per worker conditional on the year and present the resulting conditional density *f*(*y*|*year*) in Fig. 2. This figure indicates that the period of study was characterized by a labor productivity improvement, marked by rightward shifts of the respective distributions over time. Moreover, in line with the results of Piacentino and Vassallo (2011), the distribution of labor productivity tends toward a bimodal shape (polarization of the distribution),[9] highlighting the importance of conducting a distributional analysis.

By using the decomposition of labor productivity growth, it is possible to explore how each of the components affects the productivity distribution over the period. Following Henderson and Russell (2005), labor productivity in 1980 is multiplied by each of the components, introduced in sequence. Figures 3, 4, 5, and 6 show the shifts in the distributions by sequential introduction of the four components of labor productivity. For instance, $y^E = EFF \times y_{1980}$ is the counterfactual distribution of labor productivity, which isolates the effect on the distribution of changes in efficiency, assuming no physical and human capital accumulation and no technological change. This counterfactual distribution is shown as a dashed curve in Panel B of Fig. 3, along with the distribution in 2006. In Panel A, the labor productivity distributions in 1980 and

[8] These results are given in a separate “Appendix C” of Supplementary material.

[9] To confirm this fact, we use the test for unimodality of Silverman (1981). We reject unimodality in 2006 at the 5 % level, while we cannot reject unimodality in 1980; the *p* values of the tests for 1980 and 2006 are 0.361 and 0.041, respectively.

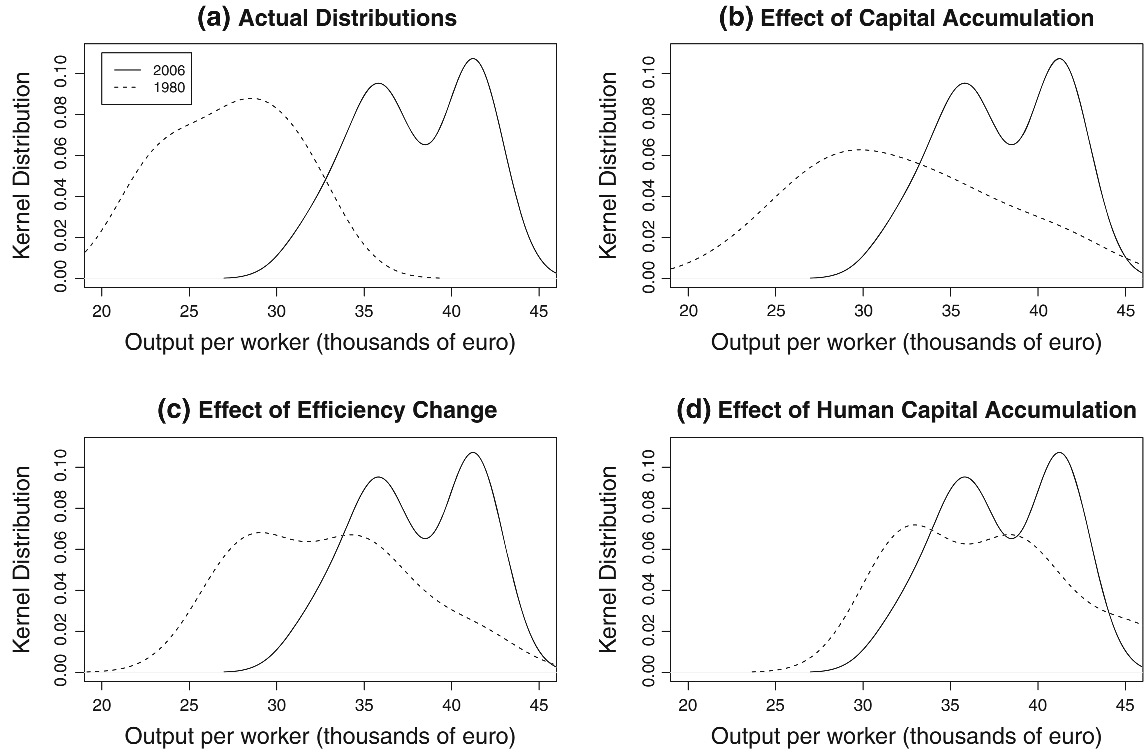

Fig. 5 Counterfactual distributions of output per worker. *Notes* in each panel, the *solid curve* is the actual 2006 distribution of output per worker. In panel **a** the *dashed curve* is the actual 1980 distribution of output per worker. The *dashed curves* in panels **b**, **c** and **d** are counterfactual distributions isolating, sequentially, the effects of physical capital accumulation, efficiency change and human capital accumulation for the 1980 distribution of output per worker

2006 are shown.[10] The counterfactual distribution of the variable $y^{ET} = EFF \times TECH \times y_{1980}$ isolates the effect on the distribution of changes in efficiency and technology, assuming no physical and human capital accumulation. This counterfactual distribution is shown as a dashed curve in Panel C of Fig. 3, along with the distribution in 2006. Similarly, Panel D of Fig. 3 highlights the effect on the distribution of capital accumulation, and Figs. 4, 5 and 6 show other sequencing combinations.

The efficiency change shifted the tails of the distribution, reducing the dispersion of productivity but creating a bimodal distribution.[11] Using different sequencing combinations, it is evident that no other component leads to bimodality of the distribution[12]. In fact, when the effect of efficiency change is not introduced (see Fig. 4), the bimodal distribution does not emerge.

Technological change seems to play a minor role in the increase of the output per worker. The only visible change is the reduction of the lower tail, confirming the technological progress of the low-income regions. However, physical capital accumulation is the driving force that contributes to increasing the dispersion of the productivity level between high- and low-income regions.

Human capital accumulation also shifts the productivity distribution toward the upper levels. Unlike physical capital, it seems that human capital does not change the shape of the labor productivity distribution. In other words, human capital accumulation has allowed the labor productivity level to increase without a difference across Italian regions.

To complete the previous graphical analysis, we test for the statistical significance of differences between actual and counterfactual distributions. We use the test proposed by Li et al. (2009). The null hypothesis states that the two distributions can be considered equal. The results of the test in Table 4 allow us to reject the null hypothesis that each of the components is solely responsible for moving the 1980 distribution to that of 2006. This is confirmed by the fact that the test fails to reject the null hypothesis only when the combined effect of technical change and physical and human capital accumulation are included.

[10] All the estimated distributions in Figs. 3, 4, 5, and 6 are nonparametric kernel density estimates, using Gaussian kernel and the method of Sheather and Jones (1991) to select the bandwidth.

[11] We reject unimodality of the counterfactual distribution $y^E = EFF \times y_{1980}$ at the 5 % level, the p-values of the Silverman test is 0.017.

[12] We do not reject unimodality introducing the other components separately, the p-values of the Silverman tests for $y^T = TECH \times y_{1980}$, $y^K = KACC \times y_{1980}$ and $y^H = HACC \times y_{1980}$ are 0.428, 0.674 and 0.407, respectively.

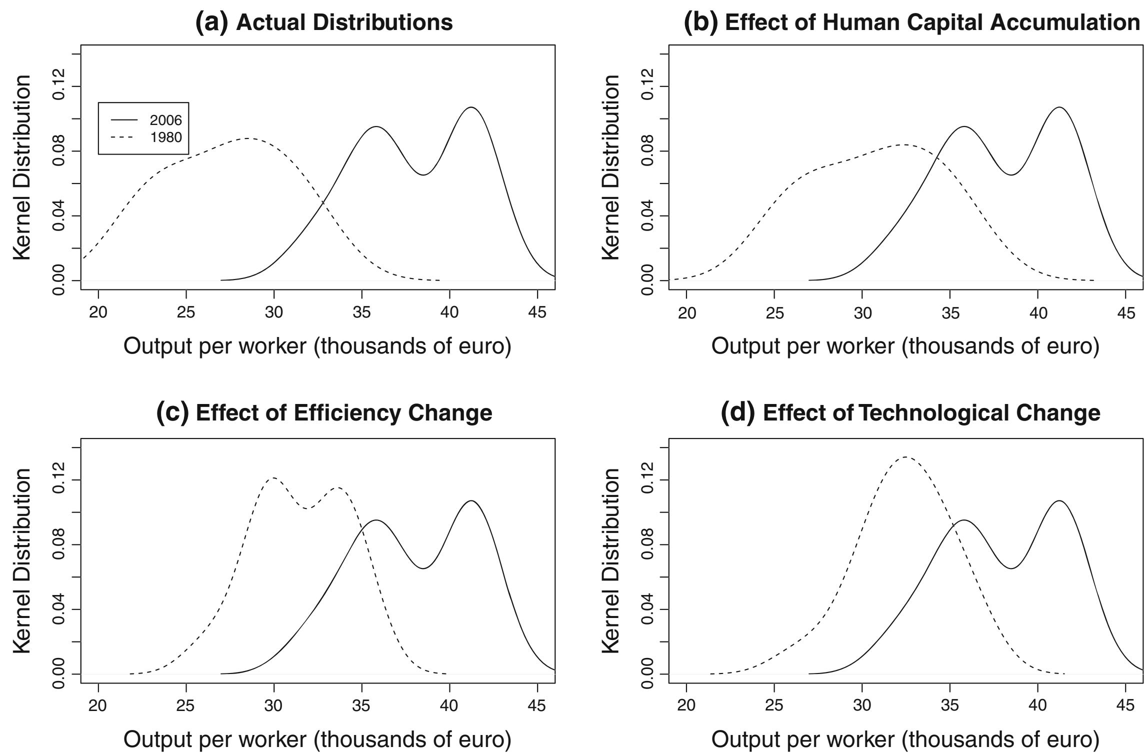

Fig. 6 Counterfactual distributions of output per worker. *Notes* in each panel, the *solid curve* is the actual 2006 distribution of output per worker. In panel **a** the dashed curve is the actual 1980 distribution of output per worker. The *dashed curves* in panels **b**, **c** and **d** are counterfactual distributions isolating, sequentially, the effects of human capital accumulation, efficiency change and technological change for the 1980 distribution of output per worker

Table 4 Distribution hypothesis tests

Null hypothesis ($H0$)	Tn statistic	Bootstrap P value
$f(y_{2006}) = g(y_{1980})$	9.845	0.000
$f(y_{2006}) = g(y_{1980} \times EFF)$	10.174	0.000
$f(y_{2006}) = g(y_{1980} \times TECH)$	9.703	0.000
$f(y_{2006}) = g(y_{1980} \times KACC)$	2.584	0.004
$f(y_{2006}) = g(y_{1980} \times HACC)$	4.844	0.000
$f(y_{2006}) = g(y_{1980} \times EFF \times TECH)$	10.922	0.000
$f(y_{2006}) = g(y_{1980} \times EFF \times KACC)$	2.247	0.012
$f(y_{2006}) = g(y_{1980} \times EFF \times HACC)$	5.782	0.000
$f(y_{2006}) = g(y_{1980} \times TECH \times KACC)$	2.647	0.016
$f(y_{2006}) = g(y_{1980} \times TECH \times HACC)$	4.698	0.000
$f(y_{2006}) = g(y_{1980} \times KACC \times HACC)$	2.058	0.011
$f(y_{2006}) = g(y_{1980} \times EFF \times TECH \times KACC)$	3.469	0.001
$f(y_{2006}) = g(y_{1980} \times EFF \times TECH \times HACC)$	4.670	0.000
$f(y_{2006}) = g(y_{1980} \times EFF \times KACC \times HACC)$	2.112	0.021
$f(y_{2006}) = g(y_{1980} \times TECH \times KACC \times HACC)$	-0.307	0.328

The function $f()$ and $g()$ are kernel distribution functions. We used the bootstrapped Li et al. (2009) test with 499 bootstrap replications

5 Conclusions

Using non-parametric methodologies, this paper investigated the role played by efficiency, technology, and physical and human capital as determinants of economic growth in 20 Italian regions. Cobb-Douglas and translog specifications of the production function were statistically rejected by the data. The methodology described by Henderson and Russell (2005) was applied to decompose the labor productivity of Italian regions from 1980 to 2006, and confidence intervals for the indices were obtained through a bootstrap approach. In some instances, the changes were not significant; thus, it is not possible to draw definitive conclusions. Consequently, any findings based on the original point estimates should be employed with caution.

In particular the empirical analysis has shown that, on average, physical and human capital accumulation are the main determinants of labor productivity growth in Italy. However, in the Northern and Central regions, labor productivity growth is driven primarily by physical capital accumulation, whereas in most of the Southern regions, it is driven by human capital accumulation. The analysis of the counterfactual distributions reveals that physical capital accumulation accounts for the increased dispersion of labor productivity. On average, a slow process of technological catch-up between the South and the remaining areas of the country was found, but the analysis of distribution dynamics shows that efficiency change seems to be the driving force behind the change in distribution from unimodal to bimodal (convergence clubs). From a policy perspective, we can argue that future policy interventions devoted to reducing regional gaps should be oriented toward supporting innovation and promoting investment in physical capital in the Southern regions.

Finally, the main limitations of the research are related to the use of a small sample and to the assumption of constant returns to scale, which is required to define Malmquist productivity index and to decompose labor productivity growth.

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Appendix A

Given the estimates $\widehat{\mathcal{M}}(t_1,t_2)$ of the unknown true values of $\mathcal{M}(t_1,t_2)$, we generate, through the DGP process, a series of pseudo-datasets to obtain a bootstrap estimate $\widehat{\mathcal{M}}^*(t_1,t_2)$. Simar and Wilson (1998) discussed the problems that arise for bootstrapping in DEA models, and they suggested the use of a smooth bootstrap procedure. In addition, the Malmquist index uses panel data, with the possibility of temporal correlation. For this reason, Simar and Wilson (1999) modified the bootstrap algorithm for efficiency scores to preserve any temporal correlation present in the data by applying a bivariate smoothing procedure. The procedure can be summarized as follows:

1. Compute the Malmquist productivity index $\widehat{\mathcal{M}}_i(t_1,t_2)$, for each region $i = 1,\ldots,20$, by solving the DEA models and using Eq. (1), as described in Färe et al. (1994).
2. Calculate the pseudo-dataset $\left\{\left(\boldsymbol{X}^*_{it}, Y^*_{it}\right); i = 1,\ldots, 20; t = 1,2\right\}$ to obtain the reference bootstrap technology using bivariate kernel density where the bandwidth was selected following the normal reference rule.
3. Compute the bootstrap estimate of the Malmquist index $\widehat{\mathcal{M}}^*_{i,b}(t_1,t_2)$ for each region through the pseudo-sample obtained in step 2.
4. Repeat steps 2 and 3, B times (number of bootstrap replications) to obtain the bootstrap sample $\left\{\widehat{\mathcal{M}}^*_{i,1}(t_1,t_2),\ldots,\widehat{\mathcal{M}}^*_{i,B}(t_1,t_2)\right\}$.
5. From the bootstrap sample, compute the confidence intervals for the Malmquist index by selecting the appropriate percentiles.

The construction of the confidence intervals is obtained by sorting the values $\left\{\widehat{\mathcal{M}}^*_{i,b}(t_1,t_2) - \widehat{\mathcal{M}}_i(t_1,t_2)\right\}_{b=1}^{B}$ in increasing order and deleting the $\left(\frac{\alpha}{2}\cdot 100\right)$-percent of the elements at either end of the sorted list. Then, for setting $-\widehat{a}^*_\alpha$ and $-\widehat{b}^*_\alpha$ (with $\widehat{a}^*_\alpha < \widehat{b}^*_\alpha$), which is equal to the endpoints of the sorted array, the estimated $(1-\alpha)$-percent confidence interval for the productivity index is:

$$\widehat{\mathcal{M}}_i(t_1,t_2) + \widehat{a}^*_\alpha \le \mathcal{M}_i(t_1,t_2) \le \widehat{\mathcal{M}}_i(t_1,t_2) + \widehat{b}^*_\alpha \quad (4)$$

The relation (4) is similarly computed for the other components of the labor productivity decomposition: efficiency change (*EFF*), technological change (*TECH*), capital (*KACC*) and human capital accumulation (*HACC*).

References

Badunenko O, Henderson DJ, Zelenyuk V (2008) Technological change and transition: relative contributions to worldwide growth during the 1990s. Oxf Bull Econ Stat 70(4):461–492

Basile R (2001) Export behaviour of italian manufacturing firms over the nineties: the role of innovation. Res Policy 30(8):1185–1201

Bronzini R, Piselli P (2009) Determinants of long-run regional productivity with geographical spillovers: the role of R&D, human capital and public infrastructure. Reg Sci Urban Econ 39(2):187–199

Brunello G, Miniaci R (1999) The economic returns to schooling for italian men. An evaluation based on instrumental variables. Labour Econ 6(4):509–519

Byrne JP, Fazio G, Piacentino D (2009) Total factor productivity convergence among Italian regions: some evidence from panel unit root tests. Reg Stud 43(1):63–76

Ceccobelli M, Gitto S, Mancuso P (2011) Ict e crescita: un'analisi dea per 14 paesi oecd. L'Industria 3:435–454

Ceccobelli M, Gitto S, Mancuso P (2012) Ict capital and labour productivity growth: a non-parametric analysis of 14 OECD countries. Telecommun Policy 36:282–292

Ciccone A (2004) Human capital as a factor of growth and employment at the regional level. The case of Italy. Mimeo

Conti M (2009) The Italian productivity decline: evidence from regional data. Giornale degli Economisti e Annali di Economia 68(3):269–309

Di Liberto A, Pigliaru F, Mura R (2008) How to measure the unobservable: a panel technique for the analysis of TFP convergence. Oxf Econ Pap 60:343–368

Färe R, Grosskopf S, Norris M, Zhang Z (1994) Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 84:66–83

Färe R, Grifell-Tatje E, Grosskopf S, Lovell C (1997) Biased technical change and the malmquist productivity index. Scand J Econ 99(1):119–127

Färe R, Grosskopf S, Margaritis D (2006) Productivity growth and convergence in the European union. J Prod Anal 25(1):111–141

Henderson DJ, Kumbhakar SC (2006) Public and private capital productivity puzzle: a nonparametric approach. South Econ J 73(1):219–232

Henderson DJ, Russell RR (2005) Human capital and convergence: a production-frontier approach. Int Econ Rev 46(4):1167–1205

Hsiao C, Li Q, Racine JS (2007) A consistent model specification test with mixed discrete and continuous data. J Econom 140(2):802–826

ISTAT (2006a) Conti Economici regionali anni 1980–2006

ISTAT (2006b) Rilevazione sulle forze di lavoro anni 1980–2006

Kneller R, Andrew Stevens P (2003) The specification of the aggregate production function in the presence of inefficiency. Econ Lett 81(2):223–226

Kumar S, Russell RR (2002) Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. Am Econ Rev 92(3):527–548

Li Q, Maasoumi E, Racine JS (2009) A nonparametric test for equality of distributions with mixed categorical and continuous data. J Econ 148(2):186–200

Maffezzoli M (2006) Convergence across Italian regions and the role of technological catch-up. Topics Macroecon 6(1), article 15

Mastromarco C, Woitek U (2006) Public infrastructure investment and efficiency in italian regions. J Prod Anal 25:57–65

Montanaro P (2003) Lo stock di capitale pubblico: una stima per regione e per tipologia di bene. Rivista economica del Mezzogiorno, pp 423–462

Ortega-Argilés R, Piva M, Potters L, Vivarelli M (2010) Is corporate r&d investment in high-tech sectors more effective. Contemp Econ Policy 28(3):353–365

Paci R, Pusceddu N (2000) Una stima dello stock di capitale per le regioni italiane: 1970–1994. Rassegna Economica, Quaderni di Ricerca 4:97–118

Piacentino D, Vassallo E (2011) Exploring the sources of labour productivity growth and convergence in the italian regions: some evidence from a production frontier approach. Ann Reg Sci 46:469–486

Picci L (1999) Productivity and infrastructure in the Italian regions. Giornale degli Economisti e Annali di Economia 58:329–353

Quah DT (1997) Empirics for growth and distribution: stratification, polarization, and convergence clubs. J Econ Growth 2(1):27–59

Scoppa V (2007) Quality of human and physical capital and technological gaps across Italian regions. Reg Stud 41(5):585–599

Sheather SJ, Jones MC (1991) A reliable data-based bandwidth selection method for kernel density estimation. J R Stat Soc Ser B 53:683–690

Silverman BW (1981) Using kernel density estimates to investigate multimodality. J R Stat Soc Ser B 43(1):97–99

Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manage Sci 44:49–61

Simar L, Wilson PW (1999) Estimating and bootstrapping Malmquist indices. Eur J Oper Res 115:459–471

Simar L, Wilson PW (2008) Statistical inference in nonparametric frontier models: recent developments and perspectives. In: Fried H, Lovell CAK, Schmidt S (eds) The measurement of productive efficiency, chap 4, 2nd edn. Oxford University Press, Oxford, pp 421–521

Wilson PW (2008) FEAR: A software package for frontier efficiency analysis with R. Socio-Econ Plan Sci 4:247–254

Zelenyuk V (2006) Aggregation of malmquist productivity indexes. Eur J Oper Res 174(2):1076–1086