The effects of biased technological change on total factor productivity: A rejoinder and new evidence

The effects of biased technological changes on total factor productivity: A rejoinder and new empirical evidence[1]

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ABSTRACT. The paper by Ji and Wang (2013) calls new attention on the analysis of the effects of the direction of technological change. The aim of this paper is to better articulate and test the theoretical arguments that the direction of technological changes has specific effects on the efficiency of the production process and to study the incentives and the processes that lead to its introduction. The decomposition of total factor productivity growth into the bias and the shift effects enables to articulate the hypothesis that the types of technological change whether more neutral or more biased reflect the variety of the innovation processes at work. The evidence of a large sample of European regions tests the hypothesis that regional innovations systems with a strong science base are better able to introduce neutral technological changes while regional innovation systems that rely more upon learning processes and tacit knowledge favor the introduction of directed technologies a form of meta-substitution that aims at exploiting the opportunities provided by the most intensive use of locally abundant factors.

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1 Introduction

Increasing evidence gathered in the international literature shows with clarity at the country level that technological change is not neutral and it is characterized by a strong directionality that has deep economic effects (Hall and Jones, 1999; Caselli and Coleman, 2006; Jerzmanowski, 2007).

Much attention has been paid on the effects of biased technological change on the factor markets (Acemoglu, 1998, 2002, 2003, 2010). Lesser attention has been paid to the effects of biased technological change on the efficiency of the production process in terms of total factor productivity at the microeconomic level. Consequently little analysis has been implemented to understand the determinants of the direction of technological change at the firm level (Ruttan, 1997, 2001).

The paper by Ji and Wang (2013) calls new attention on the analysis of the effects of the direction of technological change. The direction of technological change, i.e. the mix of output elasticity and hence the choice of inputs that, for given levels of costs, are used more intensively, has major economic effects.

The aim of this paper is to provide a reply to the criticisms raised by Ji and Wang (2013) and, in so doing, to better articulate and test the theoretical arguments that: i) the introduction of biased technological changes, able to favor the more intensive use of cheaper inputs, has a clear positive effect on the efficiency of the production process, and ii) the grasping of the effects of biased technological change on the efficiency of the production process enables to better focus the incentives and the processes that lead to its introduction.

Biased technological change can be considered as a meta-substitution process by means of which more expensive inputs are substituted by less expensive ones with positive effects on the efficiency of the production process. The identification of the effects of biased technological change in terms of total factor productivity enables to better grasp the typology of innovation processes that are at the origin of its introduction in terms of (Antonelli, 2002, 2003, 2006, 2012; Antonelli and Quatraro, 2010).

The rest of the paper is organized as it follows. Section 2 presents the notion of technological congruence and its direct relationship with the decomposition methodology of TFP growth. Section 3 applies the results to study the dynamics of biased technological change and its effects in terms of TFP growth in a sample of European regions. The conclusions summarize the main findings of the paper.

2 Theoretical framework

2.1 The direction of technological change and growth accounting

The understanding of the effects of the introduction of biased or directed technological changes on the efficiency of the production process and the articulation of the correct methodology to identify them requires a detailed return to very origins of the notion of efficiency.

It seems appropriate to start with a quote from Robert's Solow founding contribution: "The reader will note that I have already drifted into the habit of calling the curve of Chart 2 $\Delta A/A$ instead of the more general $\Delta F/F$. In fact a scatter of $\Delta F/F$ against K/L (not shown) indicates no trace of a relationship. So I may state as a formal conclusion that over the period 1909-49, shifts in the aggregate production function netted out to be approximately neutral. Perhaps I should recall that I have defined neutrality to mean that the shifts were pure scale changes, leaving marginal rates of substitution unchanged at given capital/labor ratios" (Solow, 1957: 316).

The attentive reading of Solow (1957) makes clear that Solow was well aware that biased technological change does affect output levels. His reading of the empirical evidence for the aggregate production function of the US in the years 1909-49 justifies a growth accounting methodology that does not take into account the effects of biased technological change. According to Solow technological change in the years 1909-1949 has been neutral and this justifies his methodology. It is consequently clear that Solow's methodology applies does not apply when technological change is biased.

According to Solow (1957:313) Euler's theorem enables to check whether technological change is neutral or biased. The application of Euler's theorem, assuming constant returns to scale within the frame of a Cobb Douglas production function, enables to consider the share of revenue distribution as a reliable measure of the output elasticity of each input. All changes in the share of revenue paid to each input denote the introduction of biased technological changes. The next step is to assess whether the introduction of biased- as opposed to neutral- technological change affects output levels.

The notion of technological congruence is relevant to understand whether the introduction of biased technological changes has a direct bearing upon output levels. The matching between the relative prices of production factors and their output elasticity, i.e. the matching between the slope of the isocost and the slope of the isoquant, has clear effects on output levels. The larger is the output elasticity of the production factor that is locally more abundant ad hence cheaper and the larger is the output and hence the efficiency of the production process. The clear understanding of the effects of technological congruence enables to grasp the incentives to the introduction of biased technological changes. Firms based in a labor abundant region have a clear incentive to introduce labor intensive technologies. Firms based in a capital or knowledge abundant region have instead, a clear incentive to introduce respectively capital or knowledge intensive technologies.

Directed technological change exerts a clear meta-substitution process. The increase in efficiency that stems from the introduction of biased technological change in fact is the direct consequence of the substitution of cheaper inputs to more expensive ones. The introduction of biased technological change, in other words, amplifies and magnifies technical substitution with a technological substitution.

Ji and Wang (2013) seem to ignore not only Solow's text (p. 316) but also the famous note to column 7 in Table 1 of Solow (1957: 315) that denotes without ambiguity the use of a Cobb-Douglas production function to measure the residual[2]. Moreover, they fail to appreciate that the integral of Solow's equation (2b) leads to equation (1a) only when and if technological change is neutral. From this viewpoint it can be claimed that $\Delta A/A$ coincides with $\Delta F/F$ if and only if this latter is independent of K and L (Feder, 2014).

In Solow's article, the residual is calculated as the difference between the increase of the actual output historically measured and the expected one. The expected output is calculated as the product of the share of property in income and the increase of the employed capital per man-hour. Consistently with the explicit use of the Euler's theorem Solow uses the share of property in income as a reliable indicator of the output elasticity of capital. Because of the asserted neutrality of technological change in that period of time Solow allows the output elasticities to change

The inspection of table 1 shows indeed that the share of property in income fluctuates from 0.335 in 1909 to a peak of 0.397 in 1932 to decline eventually to 0.326 in 1949. The fluctuation does not allow the identification of a clear trend. This justifies Solow's assumption

[2] Actually the bottom line of Ji and Wang is that the methodology proposed in Antonelli and Quatraro (2010) is wrong because the original was wrong. However, Solow's paper is focused on neutral technological change, as this seemed to be appropriate for analyzing the US evidence. It is a matter of fact that the methodology developed by Solow allows to capture only the shift in the production factor.

that technological change had been neutral in the period 1909-1949. Only because of this specific evidence Solow allows the share of property in income to change year from year in the calculation of the residual.

This procedure for the calculation of the residual enables Solow to measure the shift effects engendered by the introduction of technological change as if it were neutral, but does not grasp the effects of biased technological changes stemming from changing levels of the output elasticity of inputs. Keeping the share of property in income constant at the 1909 level would have enabled Solow to measure the effects of both the shift of the production function and the bias. It is clear, however, that the historical evidence on which Solow works is such that the difference between the two methodologies is absolutely negligible.

When and if the share of property and labor in income exhibits wider changes, the difference between the calculation of the residual respectively with constant and changing levels of output elasticity is larger. The larger is the change in the output elasticity and the larger is the difference between the two procedures. Actually the difference between the two procedures can be regarded as a reliable measure of the extent to which the introduction of biased technological changes affects the efficiency of the production process. The growth accounting procedure with constant output elasticity measures the total effect of technological change, i.e. the sum of shift and bias effects. The growth accounting procedure with changing output elasticity grasps just the shift effects. Their difference measures the biased effects.

The use of the Euler's theorem is crucial for the foundation of this methodology. The use of alternative procedures such as the econometric estimate of translog production functions, as suggested by Ji and Wang (2013)[3]misses completely the point because the identification of the actual output elasticity at each point in time is crucial to appreciate the effects of their own changes (Link, 1987; Bailey, Irz, Balcombe, 2004).

This methodology allows to identifying a variety of effects ranging from pure neutral technological change that engenders only shift effects to pure directed technological change that engenders only bias effects. The range includes a continuum of intermediary effects that

[3] Actually Ji and Wang propose an index to capture both the shift and the bias effect which is exactly the Total Technology Productivity (TTP) index proposed by Barnard and Jones (1996). The idea is modify the Solow's index by freezing the levels of capital and labour, so as to have the very same values for all regions/countries which remain constant over time. However this index allows to disentangling the exact contribution of factor changes, and not the contribution of changes of factors' shares. Moreover, besides the drawbacks already emphasized by Bernard and Jones, it has also undesirable feature to be very sensitive to changes in the conditions of labor markets.

accounts for technological changes that consist in both a shift of the map of isoquants and a change in their slope.

The identification of the specific effects of the introduction of biased technological changes, as distinct from the shift effects enables to try and articulate the analysis of the determinants and incentives to the introduction of either form of technological change.

The exploration of the empirical evidence to confirm whether technological change is substantially neutral as not only Solow on a solid background, but also the following literature has assumed, or instead the introduction of biased technologies has left clear marks on the changes of the shares in income of production factors, is most relevant. In this context it seems necessary to explore as much as possible a disaggregate evidence, such as the regional one, in order to check whether the apparent neutrality at the aggregate level is the result of compensating dynamics at the disaggregate one. The identification of substantial heterogeneity and variance in the changes in the shares in income of inputs would provide the appropriate context to try and explore the determinants of such a variety of types of technological changes at work.

2.2 Microeconomic determinants and effects of the direction of technological change

The economics of innovation and the economics of technical change have grown apart with reciprocal damage. The former specializes in investigations at the macroeconomic and aggregate level. The latter is mainly confined at the firm and industrial level. The crossing of both the tools and the fields of empirical investigation is likely to yield major advantages. Specifically the integration of the debate upon the direction of technological change, and its implication for the growth accounting methodologies, two of the most important legacies of the economics of technical change, with the recent advances of the microeconomics of innovation and knowledge provides important opportunities to identify the variety of types of innovations and knowledge generation processes at work, the related variety of types of technological changes, and their determinants. More specifically the integration of the economics of knowledge and innovation with the economics of technological change enables to identify the matching between the types of technological change being introduced and the types of firms. This in turn enables to appreciate the microeconomic determinants of the direction of technological change appreciating the effects of the sharp differences across regional innovation systems with respect to: i) their structure in terms of size of firms and sectoral composition; ii) the different sources of technological knowledge and the structure of the knowledge base; iii) the variety of types of knowledge generation processes; iv) the different types of knowledge exploitation strategies; v) the different types of production processes; vi) the different types of innovations introduced; and vii) the different types of market forms within product markets.

Within local innovation systems characterized by the small size of firms and the strong role of traditional industries, technological change is mainly biased towards the intensive use of locally abundant inputs. Directed technological change, able to engender only bias effects, can be considered as the result of knowledge generation processes based upon the accumulation of tacit knowledge by means of processes of learning by doing and learning by using and knowledge exploration strategies based upon localized sources of external knowledge (Antonelli, 2008).

Firms try and exploit the new technological knowledge with the introduction of process innovations that rely upon technologies that are better able to take advantage of the local factor markets. Innovation systems that rely more systematically upon the command of localized technological knowledge, based upon internal competence and external tacit knowledge, made available by knowledge interactions with firms co-localized in the same local knowledge pools, can invest lower amount of resources in the knowledge generation processes and can rely on intellectual property rights to a minor extent to exploit it (Stoneman, 2010). Technological change consists mainly of process innovations aimed at reducing production costs in product markets characterized by high levels of price competition. Production processes are characterized by lower levels of capital intensity and hence lower levels of switching costs. As a consequence they are better able to introduce incremental technological innovations that consist of a minor shift and hence a small change in the position of the isoquant, but, being less constrained by switching costs, will find it more convenient to introduce new and superior techniques with a stronger bias towards a direction that enables them to make a more intensive and systematic use of locally abundant production factors (Vaona and Pianta, 2008; Piva, Santarelli, Vivarelli, 2006).

Within regional innovation systems characterized by the role of large firms active in high tech industries technological change is mainly neutral. Neutral technological change, i.e. the one able to engender only shift effects, can be considered as the result of science based innovations. The generation of technological knowledge mainly based upon new scientific breakthroughs is typically introduced by large firms able to search and exploit the science based generation of new technological knowledge (March, 1991). Large firms with a global scope of activity are less rooted in the conditions of their local factor markets. Innovation systems characterized by large firms are better able to impinge upon scientific advances as a major source for technological knowledge and can invest larger resources in formalized R&D procedures and generate new technological knowledge that supports the introduction of radical innovations, can rely upon intellectual property rights to exploit their technological knowledge, face larger switching costs in the introduction of new technologies, the incentives exerted by factor costs account for a small fraction of the overall positive effects of the new technologies. Technological change consists mainly of product innovations that are used in oligopolistic markets to support a strong monopolistic competition based upon product rivalry (Scherer, 1984). The introduction of a superior neutral technology that enables to remain in the close proximity of the previous equilibrium technique is a superior option. These systems will be better able to concentrate their innovation activities towards the localized introduction of major technological changes along the original isocline. Such technological change can be better characterized as a change in the position of the map of isoquants. The new technology will be characterized by much a stronger movement towards the origin accompanied by a negligible change in the output elasticity of inputs consisting in the introduction of labor-intensive or more specifically skill-intensive technologies, rather than capital intensive ones.

The variety of technological activities in regional innovation systems also matters in shaping firms' technological activities. Actually, technological knowledge is the outcome of a collective process, in which the interactions and the access to external knowledge play a key role (Saviotti, 2007; Foray, 2004; Antonelli, 1999). In this direction, the notion of recombinant knowledge is especially relevant This approach views new ideas as being generated through the recombination of existing ideas, under the constraint of diminishing returns to scale in the performance of the research and development (R&D) activities necessary to apply new ideas to economic activities (Weitzman, 1998; Fleming and Sorenson, 2001; Caminati, 2006).

Firms in regional innovation systems therefore produce new knowledge by combining together different knowledge inputs available in the geographic and technological space. The regional knowledge base can be regarded as a heterogeneous construct, which gathers together technologies that establish complementarity and/or similarity relationships amongst themselves. The effectiveness of innovation activities as well as productivity growth (à la Solow) have been found to be positively related to the average degree of integration and complementarity of the knowledge base (Nesta and Saviotti, 2005; Quatraro, 2010). Neutral technological change is more likely to stem from resource intensive innovation activities, which exhibit high effectiveness degree due to exploitation of highly complementary locally available knowledge inputs.

3 Data, Methodology and Empirical Strategy

3.1 The data

In order to investigate the dynamics and the determinants of biased technological change in European regions, we have drawn data from the Eurostat regional statistics, which gathers together statistical information regarding European regions since 1995. Due to data constraints, we focus our econometric exercise on a balanced sample of NUTS II regions across different European Countries, i.e. Austria, Belgium, Germany, Spain, Finland, France, Italy, Hungary, Poland and UK over the period 1996-2004[4].

For what concerns the calculation of the productivity indexes, we needed output, labor and capital services, and the labor and capital shares. As a measure of output (Y_{it}) we used the real GDP (2000 constant prices). Eurostat also provides with estimation of capital stock (K_{it}) and employment, although it does not provide data about hours worked at the regional level. For this reason we used average hours worked at the country level provided by the Groningen Growth and Development Centre (www.ggdc.net), and then calculate total hours worked (L_{it}). Although this does not allow us to appreciate cross-regional difference in average hours worked, nonetheless it allows us to account at least for cross-country differences. The labor share (β_{it}) is calculated using data on the compensation of employees and the GDP according

[4] We acknowledge that the use of administrative regions to investigate represents only an approximation of the local dynamics underpinning economic activities. Indeed administrative borders are arbitrary, and therefore might not be representative of the spontaneous emergence of local interactions. It would be much better to investigate these dynamics by focusing on local systems of innovation. However, it is impossible to find out data at such a level of aggregation. Moreover, the identification of local systems involve the choice of indicators and threshold values according to which one can decide whether to unbundle or not local institutions. This choice is in turn arbitrary, and therefore it would not solve the problem, but it would only reproduce the issue at a different level. Thus we think that despite the unavoidable approximation, our analysis may provide useful information on the dynamics under scrutiny.

to equation (5a), while capital output elasticity has then been calculated following equation (5b).

The data about the unemployment rates across European regions, as well as those concerning population density, the total regional value added and the regional value added in manufacturing industries have been drawn by the Eurostat regional statistics.

For what concerns the role of formalized innovation efforts in the localized introduction of technological change, we decided to use patent applications to European Patent Office (EPO) as proxies of regional innovative activities. The time series provided by the EPO start in 1978, and assign patents to regions according to inventors' addresses. The limits of patent statistics as indicators of innovation activities are well known. The main drawbacks can be summarized in their sector-specificity, the existence of non patentable innovations and the fact that they are not the only protecting tool. Moreover the propensity to patent tends to vary over time as a function of the cost of patenting, and it is more likely to feature large firms (Pavitt, 1985; Griliches, 1990).

Nevertheless, previous studies highlighted the usefulness of patents as measures of production of new knowledge, above all in the context of analyses of innovation performances at the aggregate regional level (Acs *et al*., 2002). Besides the debate about patents as an output rather than an input of innovation activities, empirical analyses showed that patents and R&D are dominated by a contemporaneous relationship, providing further support to the use of patents as a good proxy of innovation (Hall *et al*., 1986).

3.2 Methodology

In order to single out an index for the effects of BTC on TFP, we elaborate upon the so-called "growth accounting" methodology, which draws upon the seminal contribution by Solow (1957) further implemented by Jorgenson (1995) and OECD (2001). In order to confront directly our approach with the seminal contribution by Solow (1957), we shall rely on a Cobb-Douglas production function as in Antonelli and Quatraro (2010 and 2013).

Let us recall the main passages in what follows. The output Y of each region i at time t, is produced from aggregate factor inputs, consisting of capital services (K) and labour services (L), proxied in this analysis by total worked hours. TFP (A) is defined as the Hicks-neutral augmentation of the aggregate inputs. Such a production function has the following specification:

$$Y_{i,t} = A_{i,t} \cdot f(K_{i,t}, L_{i,t}) \tag{1}$$

The standard Cobb-Douglas takes the following format:

$$Y_{i,t} = A_{i,t} \cdot K_{i,t}^{\alpha_{i,t}} \cdot L_{i,t}^{\beta_{i,t}} \tag{2}$$

We can then write TFP as the ratio between the actual observed output and the output that would have been produced through the sheer utilization of production factors:

$$A_{i,t} = \frac{Y_{i,t}}{K_{i,t}^{\alpha_{i,t}} \cdot L_{i,t}^{\beta_{i,t}}} \tag{3}$$

Or in logarithmic form:

$$\ln A_{i,t} = \ln Y_{i,t} - \alpha_{i,t} \ln K_{i,t} - \beta_{i,t} \ln L_{i,t} \tag{4}$$

Where $\alpha_{i,t}$ and $\beta_{i,t}$ represent respectively the output elasticity of capital and labour for each country at each year. It is worth recalling that, according to Solow's formulation, output elasticities of capital and labour are allowed to vary over time. In so doing the effects of their change on productivity are completely neutralized.

Next, following Euler's theorem as in Solow (1957), we assume that output elasticities equal the factors' shares in total income, as we assume perfect competition in both factor and product markets. In view of this, the output elasticity of labour can be expressed as follows:

$$\beta_{i,t} = \frac{w_{i.t} L_{i,t}}{Y_{i,t}} \tag{5a}$$

If we also assume constant returns to scale, the output elasticity of capital can be obtained as follows:

$$\alpha_{i,t} = 1 - \beta_{i,t} \tag{5b}$$

The measure of A obtained in this way, accounts for "any kind of shift in the production function" (Solow, 1957: 312). By means of it Solow intended to propose a way to "segregating shifts of the production function from movements along it". Solow is right if and when technological change is neutral, and/or factors are equally abundant. Instead, the effects of biased technological innovations introduced in countries where factors are not equally abundant, are made up of two elements.

Once we obtain the TFP accounting for the shift in the production function, we can investigate the impact of the bias effect with a few passages. First of all we obtain a measure of the TFP that accounts for the sum of both the bias and the shift effects (for this reason we call it *total-TFP* or *ATOT*), by assuming output elasticities unchanged with respect to the first year observed. This measure can be therefore written as follows:

$$ATOT_{i,t} = \frac{Y_{i,t}}{K_{i,t}^{\alpha_{i,t=0}} \cdot L_{i,t}^{\beta_{i,t=0}}} \qquad (6)$$

The output elasticities for both labour and capital are frozen at time *t=0*, so that at each moment in time the ATOT is equal to the ration between the actual output and the output that would have been obtained by the sheer utilization of production factors, had their elasticities been fixed over time[5]. This index may be also expressed in logarithmic form as follows:

$$\ln ATOT_{i,t} = \ln Y_{i,t} - \alpha_{i,t=0} \ln K_{i,t} - \beta_{i,t=0} \ln L_{i,t} \qquad (7)$$

Next we get the bias effect (*BIAS*) as the difference between *ATOT* and *A*:

$$BIAS_{i,t} = ATOT_{i,t} - A_{i,t} \qquad (8)$$

The index obtained from Equation (8) is straightforward and easy to interpret. Indeed its critical value is zero. When *BIAS* in one country is above (below) zero, then its technological activity is characterized by the right (wrong) directionality, and the slope of isocosts differs from unity.

[5] The differences with the methodology by Ji and Wang (2013) are clear. Actually their index is sensitive to changes in factor prices even if these did not engender any creative reaction aimed at introducing a biased technology. In order Jin and Wang's methodology to hold, factor's costs and firms' budget must be constant. In this sense, while our methodology allows to assessing the extent to which the directionality of biased technological change matched local factor endowments, Ji and Wang's index allows to evaluating the extent to which the change in factors endowments matched the locally available technology. See Feder (2014) for an illustration of such drawbacks.

3.3 Empirical strategy

3.3.1 Conditional average distribution of capital's output elasticity

In order to investigate the dynamics of biased technological change at the regional level we first investigate the evolutionary patterns of the output elasticity of capital (α). Actually, Solow proposed to leave aside any consideration of change in factors' output elasticities due to the specific evidence concerning the US economy in the early 1900s. We intend to show instead that output elasticites do change both across economic units (in our case the regions) and over time.

A first step in this direction consists in the analysis of the conditional average distribution of α. This methodology is usually used to investigate the changing patterns of technological or trade specialization (Cantwell, 1989; Pavitt, 1989; Zaghini, 2005; Uchida and Cook, 2005; Alessandrini and Batuo, 2010; Chiappini, 2013). In line with this literature, we estimate the following equation using the Ordinary Least Square (OLS) estimator:

$$\alpha_i^{03-04} = a + b * \alpha_i^{95-96} + e_i \tag{9}$$

Whereα_i^{03-04} is the average of the distribution of α between 2003 and 2004 for the region *i*, α_i^{95-96} is the average of the distribution of α between 1995 and 1996 of region *i*, *a* and *b* are the coefficients to be estimated and *e* is the error term[6]. Interpretations of the estimation results are as follows. If b = 1, the distribution of α remains stable. If b > 1, α increases in regions already showing high levels of it. If 0 < b < 1, there is a tendency to convergence in the levels of α. This means that on average the value of α has increased in regions where the initial value of the index was low and has decreased in regions for which the initial value of the index was high. If b = 0, there is no relationship between initial and final distribution of α.

Moreover, Cantwell (1989) shows that:

$$\frac{\theta^{2\ 03-04}}{\theta^{2\ 95-96}} = \frac{b^2}{\rho^2} \tag{10}$$

[6] The choice of the time span is shaped by data constraints, which do not allow us to calculate elasticities at the regional level before the year 1995, when Eurostat introduced the standard accounting procedure (ESA).. Ten years can be regarded is a sufficient time spam to allow to appreciating the emergence of structural shifts.

Whereρ is the correlation coefficient obtained from the regression, while $\theta^{2\ 03-04}$ and $\theta^{2\ 95-96}$ are the variance of the dependent and explanatory variable respectively. The correlation coefficient in this empirical setting can be interpreted as a measure of the mobility of regions along the distribution of capital's output elasticities in the two periods. On the basis of the comparison between b and ρ one could observe three different outcomes: i) $b = \rho$, i.e. the dispersion of the variable in the two periods has not changed; 2) $b>\rho$, i.e. the dispersion in the end period is higher than the starting period; 3) $b<\rho$, i.e. the dispersion in the end period is lower than the starting period.

3.3.2 Intra-distribution dynamics of capital's output elasticity

A better way to estimate intra-distribution dynamics and the structural stability of the output elasticity of capital over time is to rely on the General Markov Chain model. Following previous empirical literature (Chiappini, 2013; Mancusi 2001, 2012; Redding 2002; Zaghini 2005; Alessandrini et al. 2007; Alessandrini and Batuo 2010), we implement a Markovian model, which is usually used in the cross-country growth and income literatures but can provide useful insights also in the analysis, at a less aggregate level, of the evolution of cross-regional distribution of other economic variables (Quah 1993, 1996, 1997).

The idea underlying the Markov model is that, in absence of disturbances, the space of possible values of α can be partitioned into a number of discrete intervals. If one let these intervals be the quartiles of the distribution of α, the transition probability matrix P allows to evaluating the probability that the region i, which is located in a given quartile at time t, moves to another quartile at time $t+1$. These probabilities can be estimated by counting the number of transitions out of and into each cell. We can interpret the mobility or persistence throughout the entire distribution of α using the transition probability matrix. Indeed, high values of a transition probability along the diagonal denote high persistence, while higher values of the off-diagonal terms indicate high mobility.

More detailed information on patterns of specialisation can be derived using indices of mobility. Two indices are proposed in the empirical literature (see Shorrocks, 1978) and are easily measurable using the transition probability matrix. The first (M1) evaluates the trace of the transition probability matrix; the second (M2) evaluates the determinant (det) of the transition probability matrix.

$$M_1 = \frac{K - trace(P)}{K - 1} \qquad (11)$$

$$M_2 = 1 - |\det(P)| \qquad (12)$$

For both indices, a higher value indicates greater mobility of the regions throughout the distribution, while a zero value implies complete immobility.

3.3.3 Econometric estimation of the determinants of biased technological change

The previous steps allows to assessing the extent to which the output elasticity of capital (and by symmetry that of labour) are stable or, instead, do change over time and across regions. The evidence about long run changes in these measures suggests that actually technological change, at least in this time period, across European regions did not entail a neutral shift of the production function: On the opposite it exhibited a clear bias that led to a change in the slope of the isoquants..

If biased technological change matters, it seems necessary to enquire into its effects and its determinants. The identification of the effects seems the first necessary step in order to grasp the determinants. To this purpose we calculated the index $R_{i,t}$, which is the ratio between the traditional TFP index and the *BIAS* index:

$$R_{i,t} = \frac{A_{i,t}}{BIAS_{i,t}} \qquad (13)$$

According to the theoretical framework articulated in section 2, the weight of biased technological change in a region's innovation activities is related first of to the changing conditions in factors' markets. For this reason we include the local wage rate ($w_{i,t}$) as an explanatory variable in our empirical model. Moreover, the commitment of resources to R&D activities is also likely to shape the balance between the bias and the shift effect. The intensity of R&D, measured as a share of local GDP, is therefore included in the model ($R\&D_{i,t}$).

Besides this, innovation outcomes like patent applications are also likely to be associated to the variable $R_{i,t}$. Patent applications are indeed a proxy of innovation efforts leading to relevant outcomes. However, a better suitable indicator in this context would be the cost of a patent, measured as the ratio between local R&D expenditures and total patent applications ($PATCOST_{i,t}$). On average, one would expect more expensive patents to yield significant effects on productivity which translate into evident shifts in the production function. Cheaper patents, on the contrary, are more likely to be associated to incremental changes which allow for a better matching between changing conditions in factors' market and firms production plans.

Finally, the average complementarity degree amongst locally available technologies can be proxied by the knowledge coherence index ($COH_{i,t}$). This can be defined as the average relatedness or complementarity of a technology chosen randomly within the sector with respect to any other technology (Nesta and Saviotti, 2005; Nesta, 2008; see Quatraro (2010) for the details of the calculation of the coherence index at the regional level).

Note that this index implemented by analysing the co-occurrence of technological classes within patent applications, measures the degree to which the services rendered by the co-occurring technologies are complementary, and is based on how frequently technological classes are combined in use. The relatedness measure τ_{lj} indicates that utilization of technology l implies use also of technology j in order to perform specific functions that are not reducible to their independent use.

If the coherence index is high, this means that the different pieces of knowledge have been well combined or integrated during the search process. Due to a learning dynamics, the actors in the region have increased capability to identify the bits of knowledge that are required jointly to obtain a given outcome. In a dynamic perspective, therefore, increasing values for knowledge coherence are likely to be associated with profitable technological opportunities. Higher degrees of coherence of the regional knowledge base are expected to lead to the introduction of significant improvements which are conducive to shifts in the production function.

We can now specify the empirical model to be estimated as follows:

$$lnR_{i,t} = c + d_1 ln(R_{i,t-1}) + d_2 \ln\left(w_{i,t-1}\right) + d_3 \ln\left(R\&D_{i,t-1}\right) + d_4 \ln\left(PATCOST_{i,t-1}\right) + \\ + d_5 \ln\left(COH_{i,t-1}\right) + \mu_i + \sum \psi t + \varepsilon_{i,t} \quad (14)$$

Equation (14) can be estimated through dynamic models for panel data. We carried out the empirical test by means of a dynamic panel data regression, using the generalized method of moments (GMM) estimator (Arellano and Bond, 1991). This estimator indeed provides a convenient framework for obtaining asymptotically efficient estimators in presence of arbitrary heteroskedasticity, taking into account the structure of residuals to generate consistent estimates. In particular, we use the GMM-System (GMM-SYS) estimator in order to increase efficiency (Arellano and Bover, 1995; Blundell and Bond, 1998). This approach instruments the variables in levels with lagged first-differenced terms, obtaining a dramatic improvement in the relative performance of the system estimator as compared to the usual first-difference GMM estimator. The error term is therefore decomposed in ρ_i and $\Sigma\psi t$, which are respectively region and time effects, and the error component ε_{it}. Moreover, in order to rule out as much as possible the risk of spurious relationships, all of the explanatory variables have been lagged one year.

4 Empirical Results

4.1 Dynamics of output elasticities

The variance in the observed values of ouput elastiticities is a clear sign of the introduction of biased technological change in the production process. Figure 1 provides a snapshot of the average distribution of output capital elasticity across European regions.

>>>INSERT FIGURE 1ABOUT HERE<<<

The map clearly shows a highly dispersion of the index across the sampled regions, the more peripheral being characterized by higher levels of capital's output elasticity. However, as already stated, the identification of actual output elasticities at each point in time is crucial to appreciate the magnitude of the bias effect of the introduction of new technologies in the production process. For this reason, we have analyzed the change in the conditional average distribution of output capital elasticities over the period analyzed. We implement the method proposed by Cantwell (1989) and Pavitt (1989), by regressing the values observed at the end of the period against those observed at the beginning.

The results of this estimation are reported in table 1. The linear estimation of the coefficient is positive and significant. The magnitude of the coefficient, lower than 1, suggests that the average distribution of capital's output elasticity has changed over time, suggesting a general decrease in the values of α across sampled regions. Moreover, by comparing the estimated OLS coefficient and the correlation coefficient ρ we can also conclude that a convergence process is at stake as far as capital's elasticity is concerned. Actually b is lower than ρ, and this implies that the dispersion at the end of the period is lower than that at the beginning. Thus, this former inspection suggests that the distribution of capital's output elasticity did change over time, and in particular a downwards shift of the distribution can be detected, being α at the end of the period on average lower and less dispersed than the beginning.

>>> INSERT TABLE 1 ABOUT HERE <<<

A graphical representation of this phenomenon can be implemented by resorting to the so-called Salter's curves developed by Salter (1960). Regions are ranked in a descending order according to the beginning of the period capital's output elasticity. The larger is the slope of the curve, the higher is the dispersion of the index across the sampled regions. Salter curves of subsequent periods are plotted with the regions sorted in the same order as that of the first period. Areas of decreasing or increasing heterogeneity can be identified by looking where the Salter curve of a later period lies above or below the Salter curve of the first period.

>>> INSERT FIGURE 2 ABOUT HERE <<<

Figure 2 reports Salter's curves for the period 1995-2000 (solid line) and 2000-2004 (dashed line). The picture clearly suggests the existence of high degree of heterogeneity in the values of capital's output elasticity in the first period. If we look at the position of the curve for the 2000-2004 (the ranking is still based on 1995-2000 values), we can observe that the areas in which the dashed line it is below the solid line is predominant. This is a signal of increasing heterogeneity in the distribution and suggests the existence of high mobility of sampled regions across the distribution.

These methods allow only for a preliminary understanding of the dynamics of capital's output elasticity. In order to capture the evolution of regions across the entire distribution, we rely upon the methodology proposed by Quah (1993, 1996, 1997) in his study of the per capita income convergence.

The results of this methodology, explained in Section 3.3.2, can be found in Table 2. This table reports a four by four transition probability matrix referring to the quartiles of the distribution. The first line of the matrix reports the likelihood to be in one of the four quartiles at the end of the period, given that the region was in the first quartile at the beginning. In the second line, regions at the beginning were in the second quartile, and so on. This means that along the diagonal we have a measure of the persistence of capital's output elasticity in sampled regions.

>>> INSERT TABLE 2 ABOUT HERE <<<

The evidence suggests that there is a fairly high rate of persistence mostly for those regions located in the first quartile at the beginning of the period. It is almost impossible that these regions jump to the third or the fourth quartile. Regions moving from the second quartile show almost the same probability to stay there or to move to the first one at the end of the period. Regions moving from the third and the fourth quartile show almost similar probability to move to the closest lower quartile. The likelihood of larger jumps is very low. It is almost impossible to observe regions moving from the fourth quartile that ends up in the first quartile. This evidence is consistent with the results concerning the average conditional distribution, which suggested that there is a downward convergence in the levels of capital's output elasticities.

Table 2 also reports the results of the calculations for the two mobility indexes described in Section 3.3.2. For both of the two indexes, values close to zero indicate complete immobility. The results of the calculation suggest instead that there has been some mobility of regions across the distribution of capital's output elasticity. This evidence is more striking as far as the index M_2 is concerned.

The European evidence discussed so far shows a situation neatly different from the aggregate US evidence analysed by Solow in the early decades of the 20th century. Actually, the output elasticity of capital (and, by symmetry, that of labour) does change over time in each of the observed regions, so that regions move across the average distribution. The diachronic and synchronic varieties are marked and strictly intertwined. The analysis of the determinants of biased technological change becomes therefore necessary.

4.2 The determinants of biased technological change

Output elasticities in European regions in the period 1996-2004 are not stable over time. This suggests that technological change engendered shifts of the maps of isoquants tightly associated with clear changes in their slope. The methodology described in Section 3.2 allows to grasping the effects of technological change on productivity when neutral shifts are no longer the only viable outcome. The analysis of the determinants of biased technological change as opposed to the neutral one can be carried out through the estimation of equation (13).

>>> INSERT TABLE 3 ABOUT HERE <<<

Table 3 provides the results of the analyses carried out by implementing the GMM system estimator. The first column reports the baseline estimation, in which the $R_{i,t}$ (the ratio between neutral and biased technological change) is regressed against the wage rate and R&D intensity. As expected, both of the coefficients are positive and statistically significant (1%). Regional innovation systems characterized by the commitment of a large amount of resources to formalized research activities are more likely to be featured by the introduction of technological change engendering a shift of the production function. The wage rate is also positive. This evidence is consistent with Antonelli and Quatraro (2013), which found that efficiency wages are likely to exert strong positive effects on productivity growth, especially in contexts characterized by the rigidity of labour markets.

The figures in column (2) concern the model extended so as to include knowledge coherence as an explanatory variable. The sign and significance levels of wages and R&D intensity are unchanged as compared to the previous estimation. Knowledge coherence, as expected, is characterized by a positive coefficient, which is significant at the 10% level. Although weakly significant, the evidence on coherence supports the idea that the higher the average complementarity amongst the technological competences residing in the region, the higher the productivity gains translating into a neutral shift of the production function.

In column (3) we include the unit cost of patents (PATCOST) in the regressor matrix. The coefficients on the wage rate and R&D intensity are pretty stable in terms of sign and significance. Knowledge coherence is now not significant, while PATCOST shows a negative and significant coefficient (1%). The fact that knowledge coherence is no longer significant is not surprising. Actually, the mechanisms behind the effects of knowledge coherence concern the increased effectiveness of the innovation process. This in turn ends up in an increase of productivity growth engendering a shift effect. When patent costs are included in the model, we directly account for the effects of the effectiveness of the innovation process on the introduction of neutral technological change. Actually, the higher the effectiveness of the innovation process, the lower of the unit cost of patents. This explains the negative sign on the PATCOST variable, which is likely to be highly correlated with knowledge coherence.

Finally, in column (4) we drop knowledge coherence from the regressor matrix, in order to check for the stability of the coefficient on PATCOST. It can be observed that all of the coefficients are stable in terms of sign and significance levels, supporting the idea that neutral technological change is better associated to highly effective innovative processes, the commitment of large amounts of resources to formalized R&D activities and high (efficiency) wages. It is also fair to note that the autoregressive term is always positive and significant, although always lower than one. Since all variables are expressed in log, this suggests the existence of a kind of convergence in growth rates of ratio between neutral and biased technological change.

5 Conclusions

The economics of innovation and knowledge has basically ignored the legacies of the economics of technological change, as much as the economics of technological change has ignored the tools and the heuristics of the economics of innovation and knowledge. Little effort has been made to explore the relations between the debates upon the correct growth accounting methodology and the direction of technological change on the one hand and the characteristics of innovation processes at work within innovation systems on the other. As a matter of fact the integration of the microeconomics of innovation and knowledge with the analysis of the direction of technological change and its effects on total factor productivity is a fertile field of investigation that deserves to be better explored. The decomposition of total factor productivity growth into its two key components, the shift and the bias effect, enables to distinguish between types of technological change and to investigate the effects and the determinants of its introduction.

The decomposition of total factor productivity enables, in fact to identify the wide range of types of technological changes comprised between the two extremes of pure neutral and fully directed technological changes. The latter engenders only shift effects based upon the proportionate reduction of inputs necessary for the production of a given output, the former only bias effects based upon the meta-substitution of more expensive inputs with cheaper ones. The exploration of the continuum between the two extremes enables to identify a variety of types of technological changes and relate it to the underlying variety of innovation processes and the typology of knowledge generation processes at work.

The evidence of a large sample of European regions confirms that the direction of technological change as measured by the changes in the output elasticity of inputs is far from negligible. The empirical evidence suggests that a variety of types of technological changes is at work. The empirical evidence at the disaggregate level confirms that technological change is far more directed than standard growth accounting assumes. Underneath the aggregate evidence of small changes in inputs' shares in income, the disaggregate evidence exhibits quite a relevant variance. This is turn has made it possible to investigate the relationship between the types of technological change whether more or less directed and the variety of innovation processes.

The econometric analysis has made it possible to confirm that innovations systems that base their generation of technological knowledge upon learning processes are more likely to introduce directed technologies in order to take advantage of the meta-substitution dynamics. Innovation systems where the generation of technological knowledge can rely upon a strong science base are more likely to introduce neutral technologies.

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Table 1 - Conditional average of the distribution of capital output elasticity (α)

	(1)
$\alpha_{03\text{-}04}$	0.5274^{***}
	(0.0366)
const	0.2395^{***}
	(0.0192)
N	167
R^2	0.558
adj. R^2	0.555
ρ	0.745
b / ρ	0.708

Dep. Var. $\alpha_{95\text{-}96}$
Standard errors in parentheses
$^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table 2 - Intra-distribution dynamics of capital output elasticity (α)

	I	II	III	IV
(167)	0,7436	0,2564	0,0000	0,0000
(167)	0,4167	0,4722	0,1111	0,0000
(167)	0,0732	0,3659	0,5122	0,0488
(167)	0,0000	0,0784	0,3529	0,5686
M_1	0,5678			
M_2	0,9487			

Table 3 - Results of the GMM SYS estimation of equation (13)

	(1)	(2)	(3)	(4)
$\ln(R_{i,t-1})$	0.5214^{***}	0.6731^{***}	0.8178^{***}	0.7542^{***}
	(0.0920)	(0.0887)	(0.0524)	(0.0570)
$\ln(W_{i,t-1})$	0.2441^{***}	0.2081^{***}	0.0719^{**}	0.0821^{**}
	(0.0520)	(0.0560)	(0.0354)	(0.0325)
$\ln(R\&D_{i,t-1})$	0.0465^{***}	0.0430^{***}	0.0338^{***}	0.0403^{***}
	(0.0165)	(0.0138)	(0.0102)	(0.0119)
$\ln(COH_{i,t-1})$		0.0544^{*}	0.0166	
		(0.0303)	(0.0352)	
$\ln(PATCOST_{i,t-1})$			-0.0251^{***}	-0.0262^{***}
			(0.0078)	(0.0088)
Constant	-0.1010	-0.3023^{**}	0.1475	0.1999^{**}
	(0.0872)	(0.1457)	(0.1460)	(0.0920)
Year dummies	Yes	Yes	Yes	Yes
N	724	678	666	700
AR(1)	-4.1606***	-4.3948***	-4.6559***	-4.6543***
AR(2)	-1.2585	-1.3096	0.0291	-0.0394
Sargan Test	1557.6149***	1233.6624***	1196.4304***	1368.3078***

Dep. var.: Ratio between shift and bias effect ($R_{i,t}$)
Robust Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 1 - Changes in the output elasticity of capital (Salter curve)

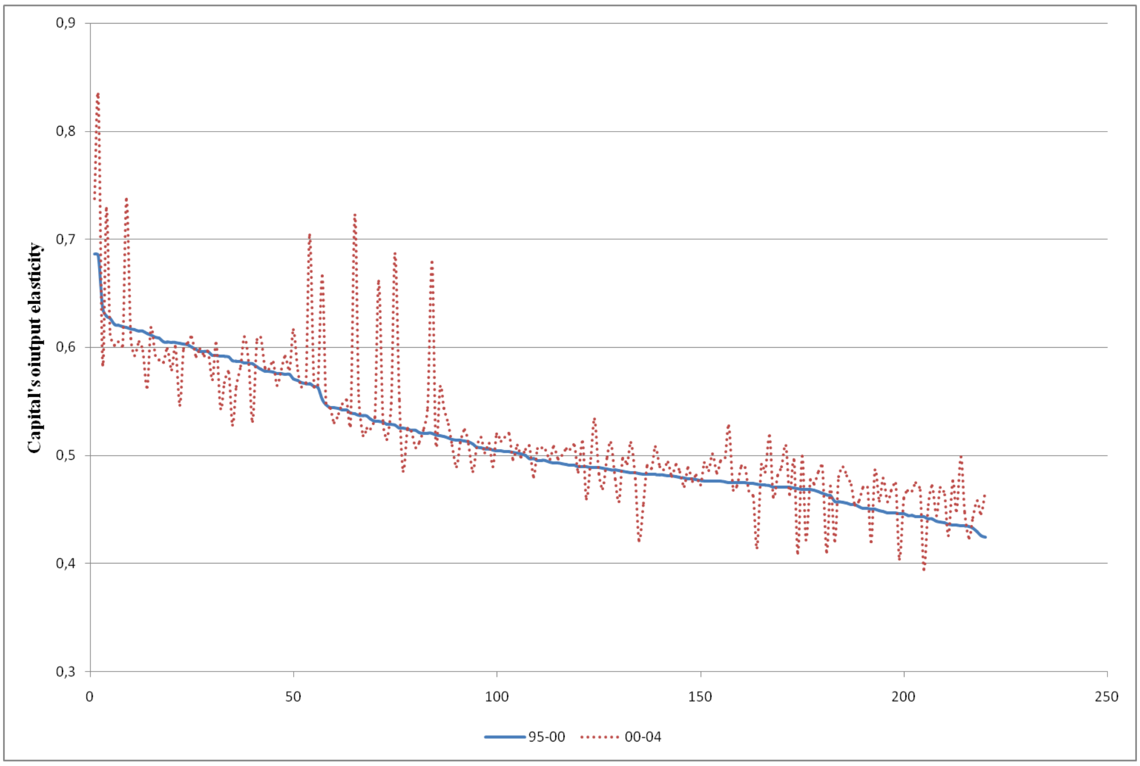

Figure 2 – Regional distribution of capital's output elasticity